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Mining Speech Sounds

Machine Learning Methods for Automatic Speech Recognition and Analysis

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Abstract

This thesis collects studies on machine learning methods applied to speech technology and speech research problems. The six research papers included in this thesis are organised in three main areas.

The first group of studies were carried out within the European project Synface. The aim was to develop a low latency phonetic recogniser to drive the articulatory movements of a computer-generated virtual face from the acoustic speech signal. The visual information provided by the face is used as a hearing aid for telephone users.

Paper A compares two solutions based on regression and classification techniques that address the problem of mapping acoustic to visual information. Recurrent Neural Networks are used to perform regression analysis whereas Hidden Markov Models are used for the classification task. In the second case, the visual information needed to drive the synthetic face is obtained by interpolation between target values for each acoustic class. The evaluation is based on listening tests with hearing-impaired subjects, where the intelligibility of sentence material is compared in different conditions: audio alone, audio and natural face, and audio and synthetic face driven by the different methods.

Paper B analyses the behaviour, in low latency conditions, of a phonetic recogniser based on a hybrid of recurrent neural networks (RNNs) and hidden Markov models (HMMs). The focus is on the interaction between the time evolution model learned by the RNNs and the one imposed by the HMMs.

Paper C investigates the possibility of using the entropy of the posterior probabilities estimated by a phoneme classification neural network as a feature for phonetic boundary detection. The entropy and its time evolution are analysed with respect to the identity of the phonetic segment and the distance from a reference phonetic boundary.

In the second group of studies, the aim was to provide tools for analysing a large amounts of speech data in order to study geographical variations in pronunciation (accent analysis).

Paper D and Paper E use Hidden Markov Models and Agglomerative Hierarchical Clustering to analyse a data set of about 100 millions data points (5000 speakers, 270 hours of speech recordings). In Paper E, Linear Discriminant Analysis was used to determine the features that most concisely describe the groupings obtained with the clustering procedure.

The third group belongs to studies carried out within the international project MILLE (Modelling Language Learning), which aims at investigating and modelling the language acquisition process in infants.

Paper F proposes the use of an incremental form of Model-Based Clustering to describe the unsupervised emergence of phonetic classes in the first stages of language acquisition. The experiments were carried out on child-directed speech expressly collected for the purposes of the project.

Papers Included in the Thesis

The papers will be referred to by letters A through F.

Paper A:
Öhman, T. and Salvi, G. (1999) Using HMMs and ANNs for mapping acoustic to visual speech. *TMH-QPSR*, 1-2:45–50.

Paper B:
Salvi, G. 2006 Dynamic behaviour of connectionist speech recognition with strong latency constraints. *Speech Communication*, 48(7):802–818.

Paper C:
Salvi, G. (2006) Segment boundaries in low latency phonetic recognition. *Lecture Notes in Computer Science*, 3817:267–276.

Paper D:
Salvi, G. (2003) Accent clustering in Swedish using the Bhattacharyya distance. *Proceedings of the International Congress of Phonetic Sciences (ICPhS)*, 1149–1152.

Paper E:
Salvi, G. (2005) Advances in regional accent clustering in Swedish. *Proceedings of European Conference on Speech Communication and Technology (Eurospeech)*, 2841–2844.

Paper F:
Salvi, G. (2005) Ecological language acquisition via incremental model-based clustering. *Proceedings of European Conference on Speech Communication and Technology (Eurospeech)*, 1181–1184.

Author's Contribution to the Papers

Paper A:

T. Öhman developed the ANN method and performed the statistical analysis of the results, G. Salvi developed the HMM method, both authors participated in writing the manuscript.

Papers B, C, D, E, F:

The work was carried out entirely by the author, G. Salvi.

Other Related Publications by the Author

Agelfors, E., Beskow, J., Dahlquist, M., Granström, B., Lundeberg, M., Salvi, G., Spens, K.-E., and Öhman, T. (1999a). A synthetic face as a lip-reading support for hearing impaired telephone users - problems and positive results. In *Proceedings of the 4th European Conference on Audiology*, Oulo, Finland.

Agelfors, E., Beskow, J., Dahlquist, M., Granström, B., Lundeberg, M., Salvi, G., Spens, K.-E., and Öhman, T. (1999b). Two methods for visual parameter extraction in the Teleface project. In *Proceedings of Fonetik*, Gothenburg, Sweden.

Agelfors, E., Beskow, J., Granström, B., Lundeberg, M., Salvi, G., Spens, K.-E., and Öhman, T. (1999c). Synthetic visual speech driven from auditory speech. In *Proceedings of Audio-Visual Speech Processing (AVSP)*, Santa Cruz, USA.

Agelfors, E., Beskow, J., Karlsson, I., Kewley, J., Salvi, G., and Thomas, N. (2006). User evaluation of the synface talking head telephone. *Lecture Notes in Computer Science*, 4061:579–586.

Beskow, J., Karlsson, I., Kewley, J., and Salvi, G. (2004). SYNFACE - A Talking Head Telephone for the Hearing-impaired. In Miesenberger, K., Klaus, J., Zagler, W., and Burger, D., editors, *Proceedings of International on Conference Computers Helping People with Special Needs*.

Johansen, F. T., Warakagoda, N., Lindberg, B., Lehtinen, G., Kačič, Z., Žgank, A., Elenius, K., and Salvi, G. (2000a). The COST 249 SpeechDat multilingual reference recogniser. In *Proceedings of XLDB Workshop on Very Large Telephone Speech Databases*, Athens, Greece.

Johansen, F. T., Warakagoda, N., Lindberg, B., Lehtinen, G., Kačič, Z., Žgank, A., Elenius, K., and Salvi, G. (2000b). The COST 249 SpeechDat multilingual reference recogniser. In *Proceedings of the International Conference on Language Resources and Evaluation (LREC)*.

Karlsson, I., Faulkner, A., and Salvi, G. (2003). SYNFACE - a talking face telephone. In *Proceedings of European Conference on Speech Communication and Technology (Eurospeech)*, pages 1297–1300.

Lindberg, B., Johansen, F. T., Warakagoda, N., Lehtinen, G., Kačič, Z., Žgank, A., Elenius, K., and Salvi, G. (2000). A noise robust multilingual reference recogniser based on SpeechDat(II). In *Proceedings of the International Conference on Spoken Language Processing (ICSLP)*.

Salvi, G. (1998a). Developing acoustic models for automatic speech recognition. Master's thesis, TMH, KTH, Stockholm, Sweden.

Salvi, G. (1998b). Developing acoustic models for automatic speech recognition in Swedish. *The European Student Journal of Language and Speech*.

Salvi, G. (2003a). Truncation error and dynamics in very low latency phonetic recognition. In *Proceedings of Non Linear Speech Processing (NOLISP)*, Le Croisic, France.

Salvi, G. (2003b). Using accent information in ASR models for Swedish. In *Proceedings of European Conference on Speech Communication and Technology (Eurospeech)*, pages 2677–2680.

Salvi, G. (2005). Segment boundaries in low latency phonetic recognition. In *Proceedings of Non Linear Speech Processing (NOLISP)*.

Salvi, G. (2006). Segment boundary detection via class entropy measurements in connectionist phoneme recognition. *Speech Communication*. in press.

Siciliano, C., Williams, G., Faulkner, A., and Salvi, G. (2004). Intelligibility of an ASR-controlled synthetic talking face (abstract). *Journal of the Acoustical Society of America*, 115(5):2428.

Spens, K.-E., Agelfors, E., Beskow, J., Granström, B., Karlsson, I., and Salvi, G. (2004). SYNFACE, a talking head telephone for the hearing impaired. In *IFHOH 7th World Congress*.

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[1] IST-2001-33327 `http://www.speech.kth.se/synface`

siasm and devotion to the study of language, and for useful comments and warm encouragement on my work. I wish to thank also the rest of the group at the Department of Linguistics, and in particular *Lisa Gustavsson*, *Eeva Klintfors*, and *Ellen Marklund* for great discussions in a relaxed and friendly atmosphere.

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Free software[2] has been central to my work: all experiments and writing have been performed on GNU[3] Linux systems. The pieces of software that have constituted my daily tools are: Emacs,[4] for anything that involves typing (from writing

[2] `http://www.fsf.org/`
[3] `http://www.gnu.org/`
[4] `http://www.gnu.org/software/emacs/`

e-mails to programming); LaTeX,[5] what you see is what you mean; XFig,[6] for all sorts of schematics and illustrations; Gimp,[7] when you really cannot avoid bitmaps; Perl,[8] text processing has never been this easy; Tcl-Tk,[9] from small scripts to full-featured applications; R,[10] for the statistical analysis, and for being in many respects a great substitute to Matlab®. I am really grateful to all the people and communities that have worked at developing this software. Thanks to *Jonas Beskow* and *Kåre Sjölander* for WaveSurfer[11] and Snack[12] that have been valuable tools for visualising and processing speech. I would like to also thank *Børge Lindberg*, *Finn Tore Johansen*, and the other members of the COST 249 Action for the SpeechDat reference recogniser software,[13] that has simplified my work in many respects. *Nikko Ströms* has done an outstanding job in developing the NICO Toolkit.[14] I am grateful for his recent decision to release NICO under a BSD licence. This work would have taken a much longer time without the Hidden Markov Model Toolkit (HTK).[15]

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[5] http://www.latex-project.org/
[6] http://www.xfig.org/
[7] http://www.gimp.org/
[8] http://www.perl.com/
[9] http://www.tcl.tk/
[10] http://www.r-project.org/
[11] http://www.speech.kth.se/wavesurfer/
[12] http://www.speech.kth.se/snack/
[13] http://www.telenor.no/fou/prosjekter/taletek/refrec/
[14] http://nico.sourceforge.net/
[15] http://htk.eng.cam.ac.uk/

Symbols

$\mathbb{R}$ the field of real numbers

$\mathbb{R}^N$ Nth dimensional space on the field of real numbers

$P(A)$ probability of the event A

$p(x)$ probability density function (PDF) of the variable x

$D(x) = \int_{-\infty}^{x} p(t)dt$ cumulative probability distribution of the variable x

μ vector of means

Σ covariance matrix

$\mathbf{x}^T$ transpose of the vector $\mathbf{x}$

Abbreviations

ANN Artificial Neural Network

ASR Automatic Speech Recognition

BIC Bayes Information Criterion

EM Expectation Maximisation

GMM Gaussian Mixture Model

HMM Hidden Markov Model

HFCC Human Factor Cepstral Coefficients

IPA International Phonetic Alphabet

LDA Linear Discriminant Analysis

LP Linear Prediction

LPA Linear Prediction Analysis

LPC Linear Prediction Coefficients

MFCC Mel Frequency Cepstral Coefficients

MLP Multi-Layer Perceptron

NN Neural Network

PDF Probability Density Function

PLP Perceptual Linear Prediction

PME Perceptual Magnet Effect

RNN Recurrent Neural Network

SAMPA Speech Assessment Methods Phonetic Alphabet

TD(A)NN Time-Delayed (Artificial) Neural Network

Contents

Part I

Introduction

Chapter 1

Outline

Spoken language is, in many situations, the most natural and effective means of communication between humans. All aspects of human activity can be conveniently encoded into spoken utterances and interpreted, often effortlessly, by the listener. Several concurrent messages can be transmitted through a number of different channels. The messages can be linguistic, where a concept is formulated into a sequence of utterances, or paralinguistic, where additional information related to the feelings or intentions of the speaker is encoded using a complex mixture of acoustic and visual cues. The channels can be acoustic, such as the phonetic and prosodic channel, or visual, including speech-related movements and gestures.

The natural ease with which we carry out spoken conversations masks the complexity of language. Diversity in language emerges from many factors: *geographical*, with thousands of languages and dialects; *cultural*, because the level of education strongly influences the speaking style; *physical*, because everyone's speech organs have slightly different shapes; *psychological*, because each person can assume different speaking styles depending on her attitude, emotional state, and intention. This complexity has attracted researchers for centuries, and numerous aspects of language and speech have been described in detail. When trying to build computational models of speech communication, however, many questions are still unanswered. Automatic speech recognition and speech synthesis are still far from imitating the capabilities of humans.

The availability, in the last decades, of large data collections of spoken and written language has opened new opportunities for the speech and language communities, but, at the same time, has implied a challenge, as the task has shifted from the analysis of few examples collected in laboratory conditions, to the study of how language is used in the real world. Machine-learning methods provide tools for coping with the complexity of these data collections.

There are three main areas of applications of these methods. In applied research, they can be used to develop models of astounding complexity that can perform reasonably well in speech recognition and synthesis tasks, despite our incomplete

understanding of the human speech perception and production mechanisms. Machine learning can also be used as a complement to standard statistics to extract knowledge from multivariate data collections, where the number of variables, the size (number of data points), and the quality of the data (missing data, inaccurate transcriptions) would make standard analysis methods ineffective. Finally these methods can be used to model and simulate the processes that take place in the human brain during speech perception and production.

This thesis contains empirical investigation that pursue the study of speech-related problems, from all the above perspectives.

The first group of studies (Paper A–C), was motivated by a practical application and was carried out within the Swedish project Teleface and, subsequently, within the European project Synface. The aim was to develop a low-latency phonetic recogniser to drive the articulatory movements of a computer-generated virtual face from the acoustic speech signal. The visual information provided by the face is used as hearing aid for people using the telephone.

In the second group of studies (Paper D and E), the aim was to provide tools for analysing large amounts of speech data in order to study geographical variations in pronunciation (accent analysis).

The third and last group (Paper F) was carried out within the international project MILLE (Modelling Language Learning), which aims at studying and modelling the language acquisition process in infants.

More in detail, Paper A compares two conceptually different methodologies for mapping acoustic to visual speech. The first attempts to solve the regression problem of mapping the acoustic features to time-continuous visual parameter trajectories. The second classifies consecutive acoustic feature vectors into acoustic categories that are successively converted into visual parameter trajectories by a system of rules.

A working prototype of the system was later developed making use of speech recognition techniques that were adapted to the characteristics of the task. Recurrent multilayer neural networks were combined with hidden Markov modes to perform phoneme recognition in low-latency conditions. This combination of methods gave rise to the studies in Papers B and C. Paper B analyses the interaction between the model of time evolution learned by the recurrent and time-delayed connections in the neural network, and the one imposed by the hidden Markov model. Paper C investigates the properties of the entropy of the posterior probabilities, as estimated by the neural network of Paper B, with respect to the proximity to a phonetic boundary.

Paper D and Paper E contain two variants of a semi-supervised procedure to analyse the pronunciation variation in a Swedish telephone database containing more than 270 hours of recordings from 5000 speakers. Automatic speech recognition methods are used to collect statistics of the acoustic features of each phoneme's accent-dependent allophones. Hierarchical clustering is used to display the differences of the resulting statistical models. Similar allophones are grouped together according to an information theoretical measure of dissimilarity between probab-

ility distributions. Linear discriminant analysis is used to determine the features that best explain the resulting groupings.

Paper F contains a preliminary study that explores the possibility of using unsupervised techniques for modelling the emergence of speech categories from the typical acoustic environment infants are exposed to.

The thesis is organised as follows. Two short introductory chapters summarise the aspects of speech research (Chapter 2) and machine learning (Chapter 3) that are relevant to the thesis. These were included given the multidisciplinary nature of the studies, but are necessarily incomplete and simplified descriptions of the fields. Many references are provided for readers that want to further their understanding of the subjects. Chapter 4 describes the problem of mapping acoustic to visual information in speech, and the results obtained in Paper A–C. Chapter 5 describes the analysis of pronunciation variation in a Swedish database, and the results obtained in Paper D and E. Chapter 6 describes an attempt to model the emergence of acoustic speech categories in infants (Paper F). Finally, a discussion and summary of the thesis is presented in Chapter 7.

Chapter 2

The Speech Chain

This chapter is a brief introduction to speech production, perception, and analysis. It is intended for those with a background in signal processing that are not familiar with speech and voice research and it is limited to those concepts that are relevant to this thesis. The reader is referred to the literature for a more complete review.

An illustration from Denes and Pinson (1993) provides a good map to help navigate through the speech communication mechanism. Figure 2.1 shows a slightly modified version of the picture. The figure depicts two persons, a speaker and a

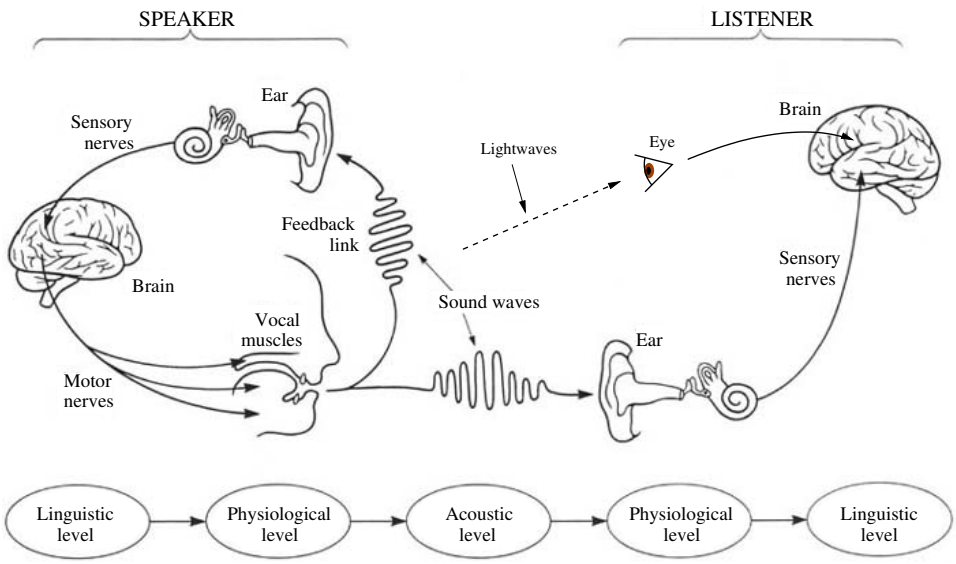


Figure 2.1: The Speech Chain from Denes and Pinson (1993), modified to include the visual path.

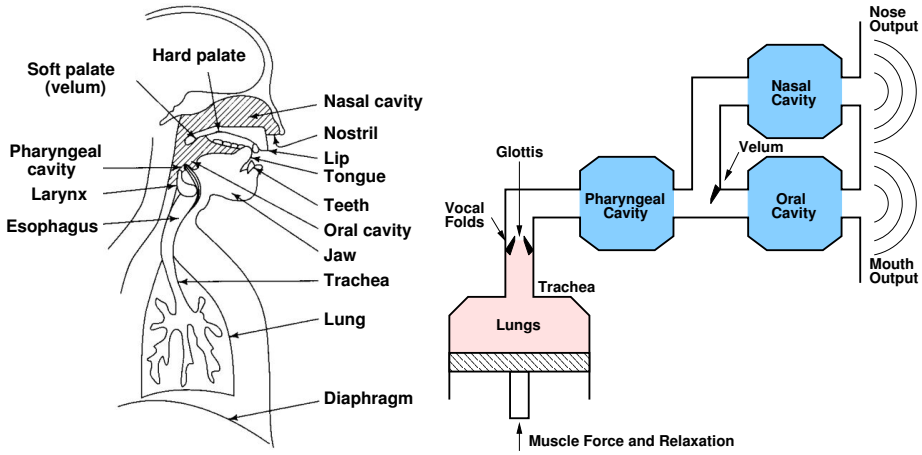


Figure 2.2: Speech production organs and a block diagram depicting their function. From Rabiner and Juang (1993).

listener. We limit the description to the *one-way* speech communication path. However, it is worth noting that many aspects of human-to-human interaction concern the way the speaker's and listener's roles are exchanged, and this picture would be misleading if the focus was on dialogue and dialogue systems research.

At the first level (linguistic), the speaker formulates ideas into language and translates the internal representation of the corresponding utterances into neural signals that control the muscles involved with speech production through the *motor nerves*. The resulting movements (physiological level) of the speech organs produce and modulate the air flow from the lungs to the lips. The modulation of the air flow produces sound waves (acoustic level) that propagate through the air and eventually reach the ears of both the listener and the speaker. At this point, an inverse process is performed. The ear transduces the acoustic signal into neural signals that travel to the brain through sensory nerves. The brain reconstructs the linguistic information with processes that are to a large extent still unknown. In the speaker this information is used as a feedback path to tune the production mechanism.

A visual path has been added to the original figure, to account for the multimodal nature of speech communication, an aspect relevant to the thesis. A number of visual events are used by the listener as a complement to the acoustic evidence during speech understanding, such as facial expressions and gestures of various kinds. The perhaps most important visual information in face-to-face communication comes from articulator movements. Lip reading has been shown to constitute a strong aid to hearing and provides information that is sometimes orthogonal to the acoustic information.

2.1 Speech Production

The processes involved in transforming the neural signals into acoustic sounds are described in this section. The left part of Figure 2.2 shows the organs involved in speech production. The right part of the same figure is a block diagram depicting the functional aspects of each part of the vocal system.

An extensive description of the physiology of speech production can be found in Titze (1994); Rabiner and Schafer (1978); Quatieri (2002). Here it suffices to say that, from the functional point of view, the speaker has control, among other organs, over:

- the air pressure in the lungs
- tension and extension of the vocal folds
- opening of the velum
- position and configuration of the tongue
- opening of the jaw
- protrusion and rounding of the lips

With the exception of click sounds typical of some African languages, speech is produced by inducing a pressure in the lungs, which excites a constriction at the glottis or along the vocal tract. The oral cavities modify the sounds produced at the constriction point by enhancing the contributions close to their resonance frequencies and damping the rest of the spectrum. Depending on the configuration of the articulators along the vocal tract, the resonance frequencies can be varied.

The Source/Filter Model

A simplified but accurate model of these processes is the Source/Filter model (Fant, 1960). The sound generation at the constriction point, and the modulation by the vocal cavities are considered to be independent (Figure 2.3).

The source assumes different states (voiced, fricative, plosive) depending on the place and kind of constriction. These are depicted in the left part of Figure 2.3.

In *voiced* sounds, the constriction is formed by the vocal folds that, due to their elastic characteristics, the lung pressure, and aerodynamic forces, start oscillating and produce a pulse-shaped air flow signal. The dynamics of vocal fold oscillation is a complex phenomenon and have generated a whole field of research (voice research). A popular model of the glottal airflow signal (Fant et al., 1985) models the derivative of the airflow (thus incorporating the effect of radiation at the lips) with a piecewise function controlled by four parameters. An example of flow obtained with the so called Liljencrants-Fant (LF) model is shown in Figure 2.4, where both the glottal flow and its derivative are plotted for three periods of oscillations. Usually, the source signal for voiced sounds is modelled by a Dirac impulse train, followed by a

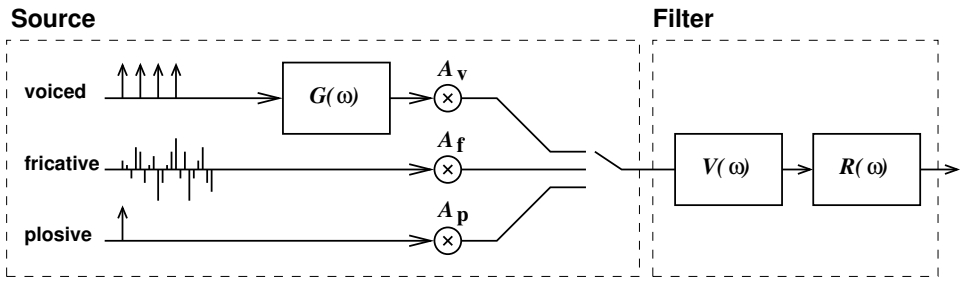


Figure 2.3: Source-Filter model of speech production

filter $G(\omega)$ that reproduces the time evolution of the glottal flow (Figure 2.3). All vowels are voiced sounds. Additionally, vocal fold oscillations are present in voiced consonants, *e.g.* /v/ (compared to /f/) or /b/ (compared to /p/).

Fricative sounds are produced when the constriction is small enough to produce turbulence in the airflow, but the tissues that compose the constriction do not have the physical characteristics to produce oscillations. For example, whispering sounds are produced with a constriction at the glottis, but with a glottal configuration that does not induce vocal fold oscillations. More commonly, fricative sounds are produced with constrictions along the vocal tract. The source, in fricative sounds, is noise-like. Examples of these sounds are /f/ as in "fin", /s/ as in "sin", /ʃ/ as in "shin".

Finally, the constriction can be complete causing pressure to build up in the preceding cavities. At the release a *plosive* sound, such as /p/ or /b/, is produced.

Note that there may be more than one source: in voiced fricatives, for example, there is both turbulence noise at the place of articulation, and excitation from the vocal folds. This explains also why some of the examples above appear in two different categories. For example /b/ is both a voiced sound and a plosive, and /v/ is both a voiced sound and a fricative. Examples of speech sounds in the different categories for Swedish and British English are given in Appendix X.

In each state the source is characterised by a number of parameters: in the case of voiced sounds, for example, the frequency at which the vocal folds oscillate, denominated f_0, is a function of time.

The filter parameters are determined by the configuration of the vocal cavities, *i.e.*, essentially by the velum, the configuration of the tongue, the position of the jaw, and the configuration of the lips. Another factor that determines the filter is the position of the source in the mouth: for example, the resonances in the oral cavity introduce poles in the transfer function for back fricatives excited near the velum, while they act as energy sinks and introduce zeros for front fricatives that are generated near the lips.

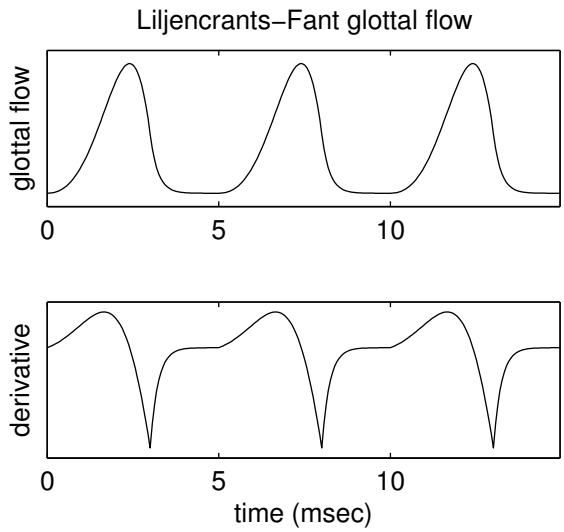


Figure 2.4: Glottal airflow and its derivative obtained with the Liljencrants-Fant model with the following parameters: period 5 msec (fundamental frequency $f_0 =$ 200 Hz), open phase = 0.6, +ve/-ve slope ratio = 0.1, closure time constant/close phase = 0.2.

Solving the wave equation in the vocal tract with a number of simplifying assumptions results in a linear system with transfer function $V(\omega)$ having a number of poles and zeros corresponding to the resonance frequencies of the cavities that are, respectively, in series or in parallel to the path from the source to the radiation point. An additional zero corresponds to the closing condition at the lips, usually referred to as radiation impedance $R(\omega)$.[1]

Both the source and the filter parameters vary continuously in time. The rate of variation is usually considered to be slow when compared to the fluctuations of the acoustic signal. In practise, when modelling the speech signal in statistical terms, short segments of speech are considered to be drawn from a stationary process.

Finally, Figure 2.5 shows an example of a voiced sound at different points in the Source/Filter model. Both the waveform and the spectrum are shown. The impulse train $i[n]$ is filtered successively by the functions $G(\omega)$, $R(\omega)$, and $V(\omega)$. The glottal flow filter $G(\omega)$ is obtained from the LF model. The vocal tract filter $V(\omega)$ is an all-pole model of order 8, obtained with typical values for the first four formants and bandwidths of the Swedish vowel [ɛ].

[1]The contribution of the radiation at the lips is often encompassed in the glottal filter $G(\omega)$, as already noted with regard to the LF model of glottal flow.

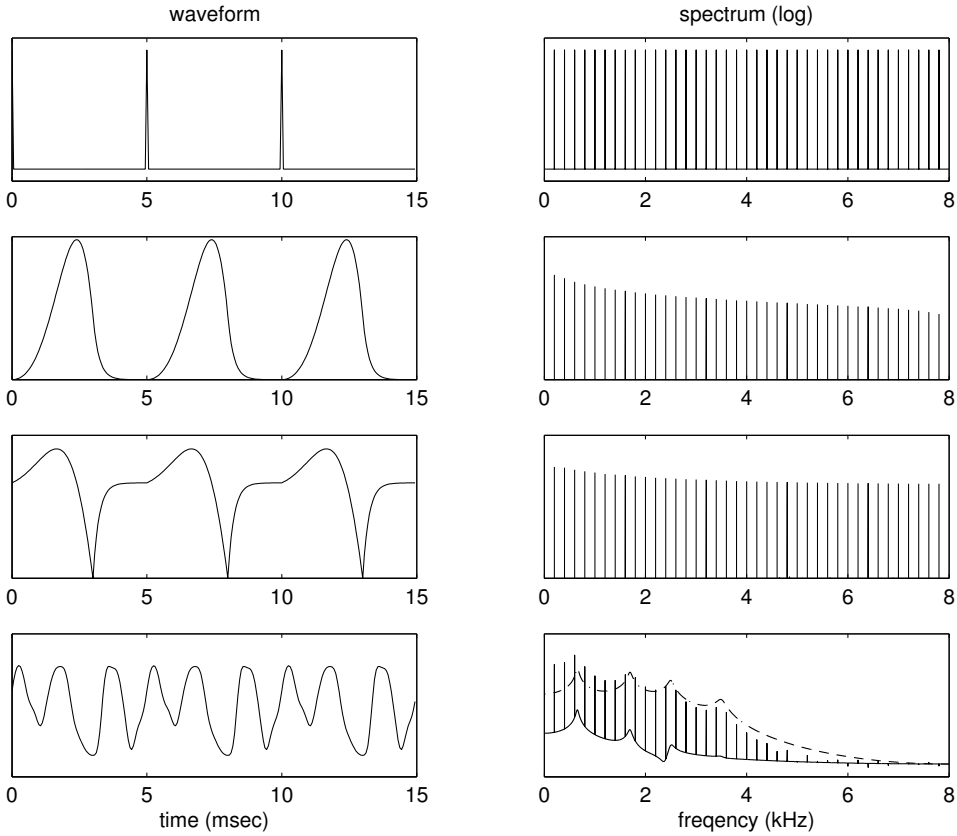


Figure 2.5: Example of a voiced sound at different points in the Source/Filter model. The left hand plots show three periods of the signal, right hand plots show the corresponding log spectrum. From above: 1) impulse train $i[n]$, 2) glottal flow $i[n] \star g[n]$, obtained when filtering $i[n]$ with the glottal shape filter $G(\omega)$ 3) derivative of the glottal flow, can be seen as $i[n] \star g[n] \star r[n]$, *i.e.*, the convolution with the radiation function $R(\omega)$, and 4) after the vocal tract filter: $i[n] \star g[n] \star r[n] \star v[n]$. Source parameters as in Figure 2.4. $V(\omega)$ is an all-pole model of order 8 with formants (bandwidths) in Hz at 654 (50), 1694 (75), 2500 (100), 3500 (150) simulating the vowel [ɛ]. The transfer function of $V(\omega)$ is indicated in the last plot by a dashed line.

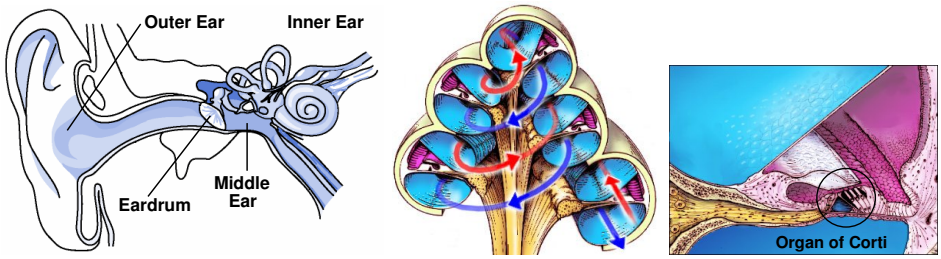


Figure 2.6: Hearing organs, drawings by S. Blatrix (Pujol, 2004), Left: outer, middle and inner ear. Middle: section of the cochlea. Right: detail of a section of the cochlea with organ of Corti.

2.2 Speech Perception

Moving forward along the Speech Chain, the ear of the listener transduces the acoustic wave into neural signals. Many details of this process are still not known. Again, we will describe briefly the results that are relevant to this thesis.

The outer and the middle ear (Figure 2.6, left) work as an impedance adaptor between the acoustic wave travelling in the air and the wave travelling in the inner ear. The inner ear consists of a spiral-formed organ called *cochlea* (Figure 2.6, middle and right), which acts as a pressure-to-neural activity transducer.

Leaving aside nomenclature and details, the cochlea is divided longitudinally into three areas by two membranes (Figure 2.6, right). The two outer areas are filled with incompressible fluid, whereas the inner area hosts the hair cells that stimulate the auditory nerves.

Stimulation of the cochlea by the small bones in the middle ear (ossicles) produces a wave on the thicker of the two membranes (basilar membrane) that propagates along the spiral. Different locations along the basilar membrane have different resonance frequencies, *i.e.*, a sinusoidal stimulus at a certain frequency corresponds to an oscillation that is spatially localised along the membrane. This behaviour is the basis for the ability of the ear to perform a spectral analysis of the incoming signals.

The discrimination of two pure tones is related to the *critical bands* that correspond, for a given frequency f^*, to the range of frequencies around f^* that activate the same part of the basilar membrane. These bands correspond to the same geometrical length in the cochlea, but are nonlinearly mapped in frequency. At high frequencies the discrimination is poorer than at low frequencies. This phenomenon is reflected into the perception of pitch, where test subjects assign the same perceived distance to tones that are further apart at higher frequencies. Stevens et al. (1937) propose a scale based on the perceived pitch called mel scale. The value of 1000 mel is arbitrarily assigned to 1000 Hz. For lower frequencies, the mel and frequency scales coincide. Above 1000 Hz the relationship between mel and fre-

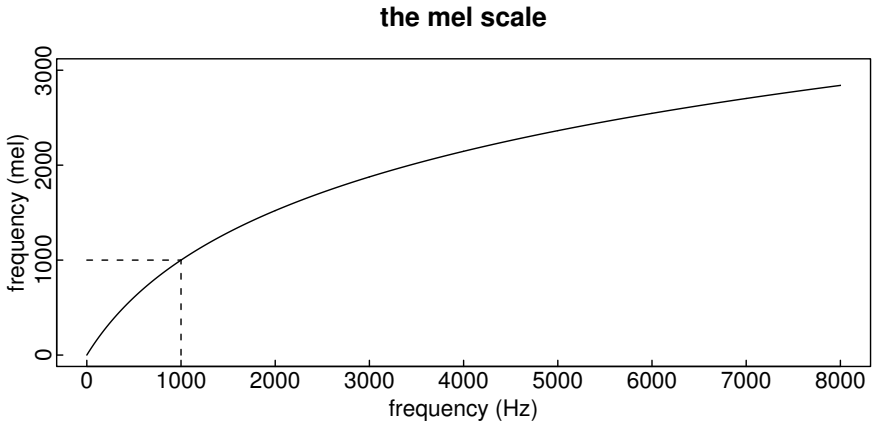


Figure 2.7: The mel scale

quency scale is logarithmic. A common approximation of the mel scale is defined by Stevens and Volkman (1940) as:[2]

$$\text{Mel}(f) = 2595.0 \log_{10}(1 + \frac{f}{700})$$

where f is the frequency in Hz. The mel scale is plotted in Figure 2.7.

The acoustic stimuli that reach the different locations along the basilar membrane are transduced into neural activities by the so called *air cells* in the organ of Corti (see right of Figure 2.6). The air cells fire random neural impulses at a rate that is proportional to the (rectified) pressure signal.

The signals that reach the brain contain both information about the frequency of the acoustic stimulus (carried by the group of nerve fibres that are activated) and temporal information (carried by the time evolution of the density of firings in each nerve fibre).

This gives rise to two groups of models of sound perception. For the first group, called *place models*, sound analysis is entirely based on the position along the basilar membrane from which the neural activities are originated. In practise it states that the brain performs a spectral analysis of the sounds. The second group, called *temporal models*, instead, states that the brain uses the temporal evolution of the firing patterns in each auditory fibre, to characterise sounds.

Most of the processes involved with speech perception are, however, not entirely understood. It is not known, for example, whether and how the sensitivity of the neural transducers along the basilar membrane can be actively controlled, and what

[2]The multiplicative constant should be changed to 1127.0 if the natural logarithm is used.

information from the auditory nerves (place, temporal or both) is used to form the percepts in the higher areas of the auditory cortex.

What most models seem to agree on is that the amplitude spectrum is central for mono-aural perception, whereas, in binaural mode, phase information may be used as well, for example to extract the relative direction between the listener and the sound source.

The Visual Channel

As mentioned in the introduction, the visual channel is a path in the speech communication chain that is relevant to this thesis. When possible, the visual information related to the speaker is integrated with the acoustic information to form a more robust percept. The listener uses, *e.g.*, facial expressions and other gestures to extract paralinguistic information, such as the mood/intention of the speaker, and signals related to turn taking (*i.e.*, when the other person can suitably be interrupted). Information that is more directly coupled to the linguistic content of the speech act is contained in the movements of the visible speech organs: essentially the lip and tongue tip movements and the jaw opening.

In the same way that the acoustic signal is categorised into phonetically relevant classes called phonemes, the visual signal is classified into *visemes*. In speech perception, the information from the acoustic and visual channels is integrated to support one of the possible hypotheses, given the context. This process is exemplified by the McGurk effect (McGurk and MacDonald, 1976) that takes place when inconsistent visual and auditory information is presented to the listener. If, *e.g.*, an auditory /ba/ is combined with a visual /ga/, a /da/ is often heard, suggesting that, among the possible hypotheses, the one that is most consistent with both the auditory and visual information, is chosen.

2.3 Speech Analysis and Acoustic Features

The methods for speech signal analysis are strongly adapted to the concepts of speech production and perception described above.

If we describe the speech signal with an all-pole model (*i.e.*, disregarding the zeros coming from the physics of the production mechanism described above), a powerful analysis tool is *Linear Prediction* (LP). The idea is that, if the system is all poles, the output signal $s[n]$ can be computed as the input signal $u[n]$ plus a weighted sum $\tilde{s}[n]$ of the past samples of the output signal. For voiced sounds, the input signal is modelled as a train of Dirac pulses.[3] Plosive sounds have a single pulse and fricatives have white noise as source signal. In all cases, the model parameters are obtained by minimising the energy of the difference between $s[n]$ and $\tilde{s}[n]$.

[3]provided that the form of the glottal pulse is considered to be part of the filter transfer function.

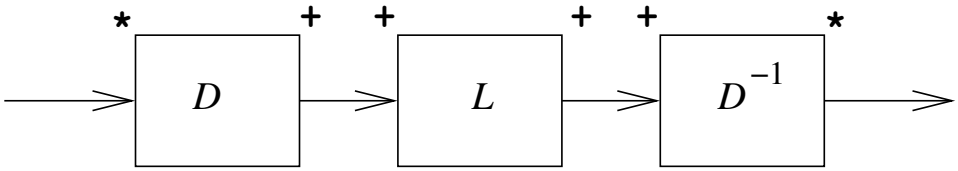


Figure 2.8: Motivation for Cepstral analysis: homomorphic filtering

A limit of Linear Prediction analysis is that zeros in the transfer function cannot be directly modelled, only approximated by a number of poles. Increasing the number of poles reduces the approximation error, but also the accuracy in the model parameter estimation.

A different way to look at the problem is to observe that the signal we try to analyse is a convolution of a number of terms corresponding to the excitation, the glottal shaping filter, and the vocal and nasal tract filtering. An analysis method that can perform deconvolution and does not suffer from the zero-pole limitation of Linear Prediction is Cepstral Analysis. This method is based on the concept of homomorphic filtering.

Homomorphic systems use nonlinear transformations D (see Figure 2.8) to transform the convolution operation into a sum. The convolutive components of the signal correspond, in the transformed domain, to additive components. In the transformed domain, we can use standard linear methods, such as spectral analysis, to analyse the different components of the signal. Moreover, linear filters L can be used to separate the components if these occupy different spectral intervals in the transformed domain. This operation corresponds to a deconvolution in the original domain.

We can find a homomorphic transformation when we notice that the spectrum of the convolution of two signals $x_1[n]$ and $x_2[n]$ is the product of the respective spectra, and that the logarithm of a product of two terms is a sum of the logarithm of the respective terms. We have:

$$\begin{array}{l} D \downarrow \\ \\ \\ \end{array} \left| \begin{array}{lcl} x[n] & = & x_1[n] \star x_2[n] \\ X(\omega) & = & X_1(\omega) X_2(\omega) \\ \log X(\omega) & = & \log X_1(\omega) + \log X_2(\omega) \end{array} \right| \begin{array}{l} \uparrow \\ \\ \\ D^{-1} \end{array}$$

If the aim is to eliminate a convolutive term, *e.g.*, $x_2[n]$, we can use a filter in this domain and then use the inverse transform D^{-1} to obtain an estimation $\hat{x}_1[n]$ of the signal $x_1[n]$ alone. If the aim is to analyse the different convolutive components, we do not need to reconstruct the time varying signal, but simply perform a Fourier analysis in the transformed domain.

original	derived
spectrum	cepstrum
frequency	quefrency
harmonics	rahmonics
magnitude	gamnitude
phase	saphe
filter	lifter
low-pass filter	short-pass lifter
high-pass filter	long-pass lifter

Table 2.1: Terminology in the frequency and quefrency domains

This is the definition of the Complex Cepstrum: the inverse Fourier transform of the logarithm of the Fourier transform of the signal.

$$c[n] = \frac{1}{2\pi} \int_{-\pi}^{\pi} \log(X(\omega)) e^{j\omega n} d\omega$$

If we are not interested in the phase term, we can simplify the complex spectrum $X(\omega)$ in the formula with its modulus $|X(\omega)|$. The result is called Real Cepstrum. Because the function $|X(\omega)|$ is even for real signals, and the logarithm does not change this property, the inverse Fourier transform can be simplified to the cosine transform. Disregarding the phase information is in agreement with models of mono-aural perception, where the amplitude spectrum seems to play the most important role.

The cepstrum has been used in many applications in which the deconvolution of a signal is necessary, *e.g.*, the recovery of old recordings by eliminating the characteristic of the recording channel. To stress the fact that, in the transformed domain, the independent variable does not correspond to time, a new terminology has been introduced, following the way the term cepstrum was coined, *i.e.*, by reversing the first syllable, examples of the terms used in the cepstrum domain are in Table 2.1.

The most commonly used features for speech recognition are the Mel Frequency Cepstrum Coefficients (MFCC, Davis and Mermelstein, 1980). The MFCCs are obtained by applying the cosine transform to the log energies of the outputs of a filterbank with filters regularly positioned along the mel frequency scale. The resulting coefficients can be liftered in order to equalise their range that can vary from low to high order coefficients. The principal advantage of the cepstral coefficients for speech recognition is that they are in general decorrelated, allowing the use of simpler statistical models.

Alternatives to the MFCCs exist that include more knowledge about speech perception. An example is Perceptual Linear Prediction (PLP, Hermansky, 1990; Junqua et al., 1993), which weights the output of the filterbanks by an equal-loudness curve, estimated from perceptual experiments. Human Factor Cepstral

Coefficients (HFCC, Skowronski and Harris, 2004), instead, make use of the known relationship between centre frequency and critical bandwidth obtained from human psychoacoustics, to define a more realistic filterbank. Many studies that compare different features for speech recognition can be found in the literature (Jankowski et al., 1995; Schukat-Talamazzini et al., 1995; Eisele et al., 1996; Nicholson et al., 1997; Batlle et al., 1998; Saon et al., 2000)

2.4 Speech Data

Speech data is usually organised in databases. The recordings are generally carried out in sessions during which a single speaker reads sentences or produces more spontaneous utterances. Short and often unconnected utterances are recorded in a sequence. Depending on the task the database is designed for, more or less realistic scenarios are simulated in the recording sessions.

Databases intended for automatic speech recognition applications are usually divided into different sets of recordings. A *training set* is devoted to building classification models, while a *test set* is dedicated to verifying their quality. The difficulty of the classification task is directly related to the degree of mismatch between the training and test data. The identity of the speakers is one of the factors that usually differentiates training and test set, at least in databases built for speaker independent speech recognition. The orthographic content is also varied for each session of recordings. However, factors as the kind of utterances, the modality of speech production (usually read speech) and the recording conditions (channel and background noise), are often homogeneous withing each database. In these respects, the degree of variation within a database is, therefore, small if compared to the richness of language.

The collection of vast recordings of spontaneous everyday conversations has demonstrated the limit of recognition systems based on words represented as strings of phonemes. Many other aspects, such as the richness in pronunciation variation for each words, the frequent use of corrections and the use of prosody and non linguistic sounds to convey meaning, have begun to be the focus of speech research.

In this thesis, most of the studies are based on data from the Swedish SpeechDat FDB5000 telephone speech database (Elenius, 2000). The database contains utterances spoken by 5000 speakers recorded over the fixed telephone network. All utterances are labelled at the lexical level and a pronunciation lexicon is provided. The database also contains information about each speaker, including *gender*, *age*, and *accent*, and more technical information about the recording, for example the type of telephone set used by the caller.

Additional experiments, often not described in the publications included in the thesis, have been carried out with SpeechDat databases in other languages (English, Flemish) and on the TIMIT American English database. TIMIT and SpeechDat are different in many respects: a) the language (British/American English), b) the quality of the recordings (8kHz, A-law for SpeechDat and 16kHz, 16bit linear for

TIMIT), c) the sentence material, and, perhaps most importantly, d) the detail of the transcriptions. In SpeechDat, only orthographic transcriptions are available, whereas TIMIT provides detailed phonetic transcriptions. This makes the phonetic classification task very different in the two cases: phonetic models built on SpeechDat with the help of a pronunciation dictionary are rich with allophonic variants, and thus closer to phonemic models. In TIMIT, each model represents acoustic realisations (phones) that are more homogeneous. These models are, however, more difficult to use in a word recognition task, because they need accurate pronunciation models to be specified for each phrase.

Another kind of material used in our studies has been collected within the project MILLE (Lacerda et al., 2004a). These recordings are specifically designed to study the interaction between parents and children in their first months. Most of the data consists of child-directed speech by a number of mothers. The specific way that voice and language are used in this situation constitutes the distinctive feature of these recordings. As a reference, the parents are also recorded when speaking with adults.

Chapter 3

Machine Learning

In the last decades, two phenomena have determined the emergence of a new research field. First, the drop of costs involved in electronically collecting and storing observations of the world has brought the need for sophisticated methods to handle the resulting data collections. Both the dimensionality of the data and the number of data points have challenged traditional statistics. Secondly, the study of human behaviour and of human perception (vision, hearing...) has shifted from a descriptive to a quantitative and functional perspective, and researchers have engaged themselves in a challenge to reproduce these abilities in artificial systems.

Data Mining aims at dealing with the first issue by extracting a summarised description of large sets of multivariate observations, to allow for meaningful interpretations of the data.

The second issue is mostly addressed by studies in *Pattern Classification* or *Recognition*, which aim to classify a set of data points into a number of classes. The classes may be predefined according to prior information, or inferred from the data itself.

These two fields are widely overlapping and share the same theoretical foundations. In the following the term Pattern Classification will be used to refer to both areas of investigations, while it should be kept in mind that the *unsupervised learning* methods described in this chapter, are often referred to in the literature as Data Mining methods.

Pattern Classification belongs to a subfield of Artificial Intelligence called *Machine Learning*, that focuses on finding methods for automatically extracting knowledge from sets of observations (so called *inductive learning*). Machine Learning covers a wide range of subjects from theoretical studies aimed at finding general philosophical implications of the concept of learning to more practical studies that try to solve specific learning problems. In all cases, however, the aim is the development of artificial systems (or algorithms) that can improve automatically through experience.

This chapter describes the concepts and the methods that are relevant to this thesis; for a complete account of Machine Learning, the reader is referred to the following books: Duda et al. (2001); Cristianini and Shawe-Taylor (2001); Schölkopf and Smola (2002); Arabie et al. (1996); Gordon (1999); Gurney (1997)

3.1 The Observations

The primary source of knowledge in inductive learning is a set of *observations*. An observation in Machine Learning can be any set of attributes associated to an outcome of a measurement of a certain phenomenon. These attributes can be of many kinds, ranging from *categorical* where the attributes assumes one of a finite number of values, to *ordinal* where the values are ordered, to *interval* where a metric defines the distance between any pair of values of the attribute.

Here we will focus on the cases in which the observations are continuous quantities represented by real numbers. An observation in the following is a set of n measurements (features) that can be represented as a vector $\mathbf{x}$ in $\mathbb{R}^n$ (feature space).

The choice of features is a central problem in pattern recognition. If the learning methods are often independent of the particular domain (*e.g.*, gene classification, speech recognition, or vision), the selection of the features that concisely and robustly convey information about the specific problem often requires deep understanding of the processes involved in it. This is exemplified by noting that, even in human perception, feature extraction is performed by organs (ear, eye, ...) that are hard coded in our genetic heritage, and have been developed through evolution. The classification and recognition tasks are, on the other hand, performed by the same kind of structure (biological neural networks) and are learned in the first years of life.[1]

The studies in this thesis utilise standard features for speech representation, which are described and motivated in detail in Chapter 2.

3.2 The Knowledge

As already stated, machine-learning methods aim at finding structural patterns in a set of observations. The specific learning task is dependent on the kind of knowledge the method aims at extracting from the data. While the observations are the input to the learning procedure, the knowledge is its output. Knowledge can, in this context, be represented in different ways. The learning procedure could, *e.g.*, extract a set of rules that relate different attributes in the observations contained in the data set. It could also assign every observation to a class (*classification*), or relate each observation to a continuous variable (*regression*). Other kind of

[1]The fact that the physiology of the brain is itself a result of evolution, is not in conflict with the point made in the example, as the physiology of the brain corresponds to a particular machine-learning method, while the learning process corresponds to the training a child goes through in the first years of life.

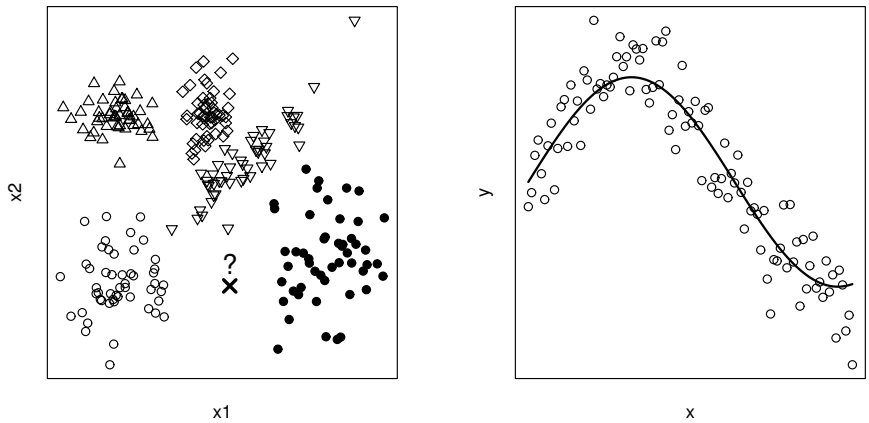


Figure 3.1: Supervised learning: the classification problem (left) and the regression problem (right)

knowledge are graphical models that relate observations with respect to some binary relation (for example a similarity criterion). This is the case of some *clustering* procedures. Methods for classification, regression and clustering will be described in the following.

3.3 Supervised vs Unsupervised Learning

Another central point in machine learning, is whether the knowledge associated with each observation (*i.e.* the right answer) is available to the method during learning. In *supervised learning*, the learning method has access to the right answer for each observation. In *unsupervised learning*, only the set of observations is available, and the learning method has to make sense of them in some way. In most learning situations that we experience, however, both these conditions are extreme cases. *Reinforcement learning* tries to describe a more natural learning scenario, where the learning method is provided with limited feedback.

Supervised Learning

Two possible tasks in supervised learning are supervised classification and regression. These can be seen as two aspects of the same problem. In the first case, we want to assign a new observation to one of C classes that are defined by previously annotated observations, as illustrated in the left part of Figure 3.1. In the second case, we want to assign to any point $\mathbf{x}$ a continuous value for the variable y, having observed a number of examples (right part of Figure 3.1). In both cases, we have

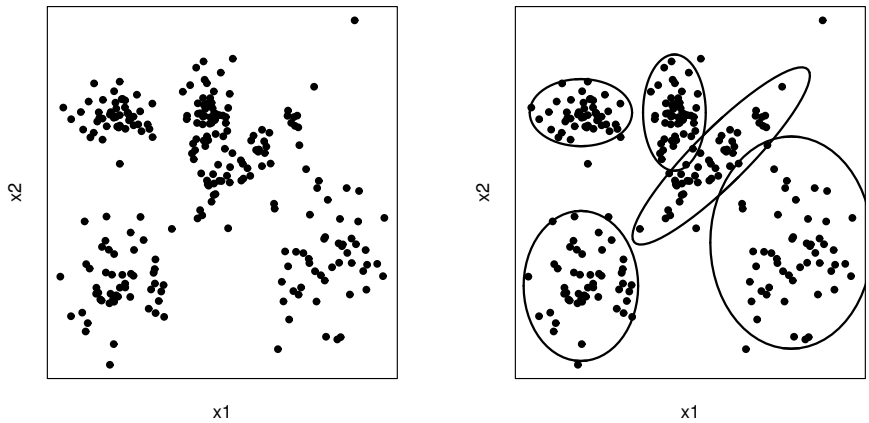


Figure 3.2: Unsupervised learning: the data points are not labelled (left). One of the tasks is, in this case, to find "natural" groupings of the data (right)

a training set that consists of a number of observations $\mathbf{x}_i$ in the input (feature) space X and the corresponding outputs y in the output space Y. X corresponds to $\mathbb{R}^n$ in both cases, whereas Y is a finite set in the case of classification, and the field of real numbers $\mathbb{R}$ in the case of regression.

Unsupervised Learning

When information about the output variable is missing during the training phase (see left plot in Figure 3.2), we talk about unsupervised learning. In this case the possible tasks may be:

- finding the optimal way, with regard to some optimality criterion, to partition the training examples into C classes (see right plot in Figure 3.2),
- finding and displaying relationships between partitions of the data with different cardinality C,
- assigning a new observation to one of the classes in a partition, or
- estimating the optimal number of *natural* classes in a data set.

These tasks are usually referred to as *Clustering* problems in the engineering literature, and simply *Classification* problems in more statistically oriented publications.

Reinforcement Learning

For completeness we give some information about reinforcement learning. This is the learning process that takes place when the learning system has access to

a reward (or penalty) that is somehow related to a series of events. The main difference compared to supervised learning is that the feedback available to the system is not directly related to a specific observation, but rather to a history of events happening in the environment the system lives in, and to the actions that the system has taken as a consequence of these events. It is up to the learning system to interpret the feedback and relate it to its state and to the state of the environment. This kind of task has not been considered in this thesis, but it may be central to one of the problems that will be described in Chapter 6, namely modelling the language acquisition process in an infant.

3.4 Theory behind Pattern Classification

Regardless of the methods used in the pattern classification or regression problem, a number of assumptions about the data generation help to obtain theoretical results of general value, by embedding the problem in a probabilistic framework. In the case of classification, it is assumed that the data is generated by a double stochastic process: first, one of a finite number of states ω_i (called in the following the *state of nature*) is chosen with *a priori* probability $P(\omega_i)$; then, one observation $\mathbf{x}$ is emitted with probability density function $p(\mathbf{x}|\omega_i)$, given that state. In the case of regression, the same model can be used, provided that the discrete states ω_i are substituted by a continuous variable ω with *a priori* density function $p(\omega)$.

Bayes Decision Theory

Bayes decision theory is based on the probabilistic model described in the previous section. If both the *a priori* probabilities $P(\omega_i)$ of each state of nature ω_i and the conditional densities $p(\mathbf{x}|\omega_i)$ of the observations, given the state, are known, using Bayes formula we can derive the *posterior probabilities* $P(\omega_i|\mathbf{x})$ that nature was in state ω_i when we have observed $\mathbf{x}$:[2]

$$P(\omega_i|\mathbf{x}) = \frac{p(\mathbf{x}|\omega_i)P(\omega_i)}{p(\mathbf{x})}$$

The *a priori* density function of the observation $p(\mathbf{x})$ can be computed by summing over all possible states of nature:

$$p(\mathbf{x}) = \sum_{i=1}^{C} p(\mathbf{x}|\omega_i)P(\omega_i)$$

where C is the number of states.

If the stochastic model that has generated the data is fully known, then, Bayes decision theory can be used to find the optimal solution to a decision task given an

[2] If fact that we derive a probability from a density function should not surprise the reader, as the fraction on the right side of the equality could be seen as a limit: $\lim_{dx \to 0} \frac{p(\mathbf{x}|\omega_i)dxP(\omega_i)}{p(\mathbf{x})dx}$

optimality criterion. The criterion can be defined by means of a *loss* function that assigns a penalty $\lambda(\alpha_i, \omega_j)$ to a decision α_i given the state of nature ω_j. Accordingly, a different weight can be assigned to different kinds of errors. The probabilistic model can be used to define a conditional *risk* function $R(\alpha_i|\mathbf{x})$ that relates the risk of taking decision α_i to the observation $\mathbf{x}$, rather than to the state of nature that is, in general, not known. This function is obtained by integrating the loss function over all possible states of nature ω_i, weighted by the posterior probability of ω_i given the observation $\mathbf{x}$:

$$R(\alpha_i|\mathbf{x}) = \sum_{i=1}^{C} \lambda(\alpha_i, \omega_j) P(\omega_i|\mathbf{x})$$

In practical cases, the model of data generation is not completely known. Machine-learning methods attempt, in this case, to estimate the optimal decisions from the available observations.

3.5 Classification Methods

Depending on how the probabilistic description of the data generation is used in the solution of the learning problem we talk about *parametric* and *non-parametric* methods.

Parametric methods rely on a probabilistic model of the process of generating the observations in which probability distributions are described in functional (parametric) form. Learning is, in this case, the process of estimating the model parameters on the basis of the available observations.

There are two kinds of non-parametric methods. The first tries to determine the probabilistic model that has generated the data, but does not assume a functional description of this model. Typical examples are histogram-based methods. Methods of the second kind are based on heuristics and do not directly attempt to estimate a model for the data generation, but, rather, attempt to minimise a criterion that is dependent on the task. Linear discriminant functions, neural networks (or multi-layer perceptrons), and support vector machines are examples of this kind. It should be noted that most of these methods can also be studied and interpreted in probabilistic terms.

Parameter Estimation

Parameter estimation aims at fitting the available probabilistic model to a set of observations, by deriving the optimal set of model parameters. When considering supervised classification, and assuming that observations related to a certain class ω_i give no information about the model for a different class ω_j, the problem can be split into N independent subproblems (N number of classes).

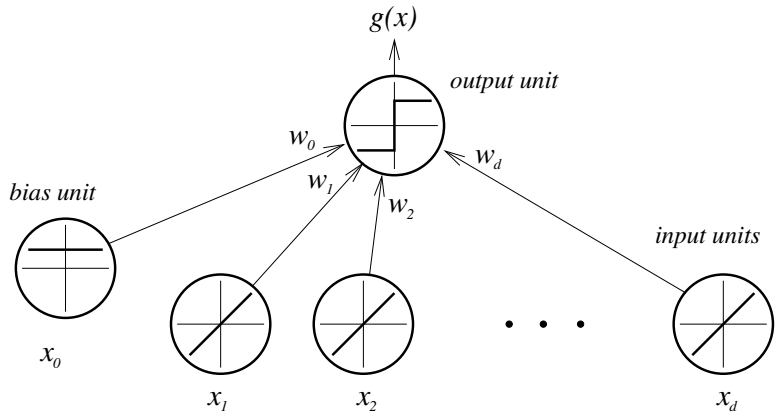


Figure 3.3: A simple linear classifier with $g(\mathbf{x}) = \sum_{k=0}^{d} a_k x_k$. This model can be generalised by using arbitrary functions of the observation $\mathbf{x}$.

Two philosophies can be followed in order to find a solution to this problem. Maximum Likelihood estimation attempts to find the model parameters that maximise the model fit to the data with no *a priori* information. Bayesian estimation, on the other hand, optimises the posterior probability of a certain class given an observation (and the training data). The model parameters are in this case stochastic variables that are characterised by probability distributions. The *a priori* distribution of the model parameters is necessary to apply Bayes theorem and compute the posterior distributions from the likelihoods (that can be computed from the data).

The advantages and disadvantages of these two paradigms are the subject of active discussion in the statistics community, and are not discussed here.

Linear Discriminant Functions

Linear discriminant functions belong to the class of nonparametric methods in the sense that the form of the probability models underlying the data generation need not be known. In reality, the learning paradigm is similar in both parametric and nonparametric models, because, also in the second case, we assume a known form of the discriminant functions (*e.g.*, linear, quadratic, polynomial,...), and we estimate the model parameters from the data. In general, the functions are in the form (often referred to as generalised discriminant functions):

$$g_i(\mathbf{x}) = \sum_{k=1}^{F} a_{ik} y_k(\mathbf{x})$$

where a_{ik} are the weights (or model parameters) that can be trained from the data for each class ω_i, and $y_k(\mathbf{x})$ are F arbitrary functions of $\mathbf{x}$. The fact that these

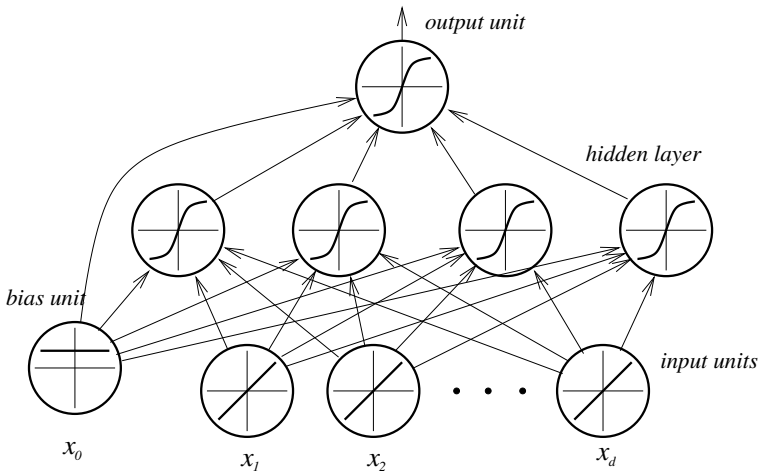


Figure 3.4: Illustration of a multi-layer perceptron.

possibly nonlinear functions are combined linearly is the origin of the name. The functions are used by assigning a point $\mathbf{x}$ to the class ω_i iff $g_i(\mathbf{x}) > g_j(\mathbf{x})$ for all $j \neq i$.

The training procedure is aimed at optimising a criterion (*e.g.*, the training error) and is usually performed with gradient descent procedures. These procedures iteratively move in the model parameter space following the steepest direction with respect to the criterion function. Eventually the procedure finds a local minimum of the criterion function and the iterations are terminated.

Multi-Layer Perceptrons

One of the problems with linear discriminant functions is that they shift the complexity of the pattern recognition task onto the choice of proper discriminant functions, *i.e.*, the transformation of the feature space that makes the classes linearly separable.

One way to let the classification method decide the internal representation of the data is to add a (hidden) layer in the network depicted in Figure 3.3. The result is the multi-layer perceptron shown in Figure 3.4. The weights from the input to the hidden layer (symbolised by arrows in the figure) perform a linear data transformation. The activation functions of each unit in the hidden layer, are usually non-linear functions (s-shaped curves in the figure). The activities at each unit in the hidden layer, obtained by passing the weighted sum of the inputs through the non-linear activation function, can be thought of as an internal convenient representation of the patterns observed by the input layer. The output

layer makes a decision in a manner similar to linear discriminant functions.

The complication of this model, as far as the training procedure is concerned, is that the units in the hidden layer are not directly observable. However, if the so called activation functions are invertible, the error observed at the output node can be propagated to the previous layers using the current estimation of the connection weights. This is the principle of the Back Propagation algorithm, which is the most commonly used training procedure for these models.

3.6 Clustering Methods

Clustering, or unsupervised classification methods, can be divided into a number of classes. The first distinction is based on the use of probability distributions to characterise the clusters, as in Model Based Clustering, or on the use of a pairwise similarity measure, *i.e.*, a relationship between each pair of data points, as in K-means (MacQueen, 1967). It should be noted that, in particular cases, the two approaches coincide, *e.g.*, Gaussian distributions with diagonal covariance matrix in the form λI define spherical shapes equivalent to the ones obtained with the euclidean distance between data points.

Another distinction is between *relocation* and *hierarchical* methods. In the first case, starting from a desired number of clusters, the data points are iteratively relocated between clusters until an optimal partition is found. In the second case the procedure successively merges or splits clusters (agglomerative or divisive clustering), and the result is a tree structure called *dendrogram* that represents the hierarchical relationships between partitions of different orders.

Clustering is a very active research field and many new methods and theories are continuously being developed. For example, Graph Theory (Gaertler, 2002), Self Organising Maps (Kohonen, 1982), and Support Vectors (Ben-Hur et al., 2001) have been applied to the clustering problem. In the following only the methods used in this thesis will be described.

Model-Based Clustering and Gaussian Mixture Estimation

When using parametric models to perform unsupervised classification, we cannot split the problem into a number of subproblems (one for each class), as in the supervised case. The reason is that the assignment of each data point to a certain state of nature (class) that has generated it, is unknown. The parameter estimation procedure must in this case consider all the distributions simultaneously, *i.e.*, it must fit a mixture of distributions to the data.

A solution to this problem is achieved by describing the membership of each data point to each class in probabilistic terms. The union of the original data points, called *incomplete data*, and of the vector of memberships to the classes are called the *complete data*. The Expectation Maximisation (EM) algorithm (Dempster et al., 1977) can be used to compute the model parameter estimate that

Σ_k	Distribution	Volume	Shape	Orientation
λI	Spherical	Equal	Equal	N/A
$\lambda_k I$	Spherical	Variable	Equal	N/A
λDAD	Ellipsoidal	Equal	Equal	Equal
$\lambda_k D_k A_k D_k$	Ellipsoidal	Variable	Variable	Variable
$\lambda D_k A D_k$	Ellipsoidal	Equal	Equal	Variable
$\lambda_k D_k A D_k$	Ellipsoidal	Variable	Equal	Variable

Table 3.1: Parametrisation of the covariance matrix Σ_k in the Gaussian model based on the eigenvalue decomposition, and their geometric interpretation. From Fraley and Raftery (1998).

maximises the likelihood of the model on the incomplete data, by maximising the complete data likelihood. The EM algorithm iteratively finds an estimate of the membership function given the current model parameters (expectation), and the new optimal values for the model parameters given the new membership function (maximisation).

Compared to more traditional clustering methods, such as K-means, which rely on a fixed metric in the feature space, the parametric solution to the clustering problem has the advantage that the form of the clusters can be easily controlled by the shape of the distributions used. For example, in the case of Gaussian distributions, the class of the covariance matrix determines the shape of the distributions as indicated in Table 3.1.

As we will see in the following, this framework also simplifies the task of determining the most plausible number of clusters in the data (Banfield and Raftery, 1993; Dasgupta and Raftery, 1998; Fraley, 1999; Fraley and Raftery, 2003, 2002; Fraley et al., 2003) and the task of comparing different partitions of the same data set (Meilă, 2002).

Hierarchical Clustering

In their classical formulation, hierarchical methods are entirely based on the binary relation between the entities that are to be clustered. In the case of data points spanning a vectorial space, the relation is given by the definition of a metric in that space.

The procedure operates by recursively merging or splitting the clusters according to some optimality criterion. The different variants of this method are dependent on the criterion used to measure the distance between two clusters $d(c_1, c_2)$, given the pairwise distances of their members $d(\mathbf{x}_m, \mathbf{x}_n)$. Examples are given in Table 3.2.

Other formulations operate directly on the data-points. For example Ward's method clusters groups that result in the minimum increase of "information loss", defined in this case as the sum of squared errors from the member average. Hierarchical clustering has also been implemented in the framework of Model-Based

method	distance
single linkage	$d(c_1, c_2) = \min_{\mathbf{x}_m \in c_1, \mathbf{x}_n \in c_2} d(\mathbf{x}_m, \mathbf{x}_n)$
complete linkage	$d(c_1, c_2) = \max_{\mathbf{x}_m \in c_1, \mathbf{x}_n \in c_2} d(\mathbf{x}_m, \mathbf{x}_n)$
average linkage	$d(c_1, c_2) = \frac{1}{\lvert c_1 \rvert \lvert c_2 \rvert} \sum_{\mathbf{x}_m \in c_1, \mathbf{x}_n \in c_2} d(\mathbf{x}_m, \mathbf{x}_n)$
average group linkage	$d(c_1, c_2) = \frac{1}{(\lvert c_1 \rvert + \lvert c_2 \rvert)^2} \sum_{\mathbf{x}_m, \mathbf{x}_n \in (c_1 \cup c_2)} d(\mathbf{x}_m, \mathbf{x}_n)$

Table 3.2: Merging criteria for hierarchical clustering. $|.|$ indicates the cardinality of the set, and $\cup$ the union

Clustering (Fraley, 1999). Note that for diagonal covariance matrices with equal eigenvalues ($\Sigma_k = kI$), Model-Based Hierarchical Clustering is equivalent to Ward's method.

Estimating the Number of Clusters

Guessing the number of *natural groups* from a data set has long been a central problem in statistics and data mining. Here the concept of natural groups or clusters should be considered in a statistical sense.

Intuition suggests that the number of groups in the data is strongly dependent on the degree of detail the analysis is aimed at. For example, when analysing natural language, one could be interested in finding: a) the groups belonging to the same *linguistic family*, b) the *single languages* as defined by political factors, c) *dialectal differences* within the same language, d) personal speaking styles (so called *ideolects*), or even e) variation in *speaking style* of the same person in different contexts. Hence, the problem of finding the *true* number of clusters is strongly influenced by the final goal of the analysis.

However, if we consider the problem in statistical terms, the aim is to establish a methodology that allows an objective interpretation of the data in the same way that hypothesis testing can tell if there are significant differences between the group means in two data samples.

Several methods have been developed by different authors in order to predict the number of clusters. Milligan and Cooper (1985) compared 30 different indexes on a number of synthetic data sets containing from 1 to 5 well-differentiated clusters. They showed how some indexes perform reasonably well under these artificial conditions. Many of these indexes are based on the comparison between the so called scatter matrices. If we call $\mathbf{m}$ the total mean of the data set $\mathcal{D}$, $\mathbf{m}_i$ the mean of the data points belonging to one of k clusters $\mathcal{D}_i$ of size n_i, and $\mathbf{x}$ a generic data point, the scatter matrix of the ith cluster is defined as (T indicates the transpose

operation):

$$S_i = \sum_{\mathbf{x} \in D_i} (\mathbf{x} - \mathbf{m}_i)(\mathbf{x} - \mathbf{m}_i)^T$$

the within-cluster scatter matrix as:

$$S_W = \sum_{i=1}^{k} S_i$$

the between-cluster scatter matrix as:

$$S_B = \sum_{i=1}^{k} n_i (\mathbf{m}_i - \mathbf{m})(\mathbf{m}_i - \mathbf{m})^T$$

and the total scatter matrix as:

$$S_T = \sum_{\mathbf{x} \in D} (\mathbf{x} - \mathbf{m})(\mathbf{x} - \mathbf{m})^T$$

Most of the indexes studied in Milligan and Cooper (1985) use the scatter matrices as a measure of the spread of data points. They usually tend to reduce the within-cluster scatter and increase the between-cluster scatter, in order to produce compact and well-separated groups. Often the indexes have a similar definition, and are, therefore, highly correlated.

Another class of methods to estimate the number of clusters makes explicit use of the probabilistic model used in model-based clustering. These are, *e.g.*, the likelihood and the Bayes Information Criterion (BIC).

The likelihood $l_M(\mathcal{D}, \theta)$ is the evaluation of the density function defined by the clustering procedure on the actual data $\mathcal{D}$. This is seen as a function of the model parameters θ when the data $\mathcal{D}$ is fixed. Given the assumption of independence of each data point $\mathbf{x} \in \mathcal{D}$, the likelihood function can be evaluated as a product of the values of the density function $p(\mathbf{x}|\theta)$ evaluated at each $\mathbf{x}$. For this reason, it is more common to consider the log likelihood that turns the product into a sum, simplifying the computations and avoiding numerical problems. A drawback of the likelihood is that it increases monotonically with the model complexity: more complex models always fit the data equally or better in terms of the likelihood.

The Bayes Information Criterion is an approximation of the Bayes factor, and by definition takes into account the number of parameters and the amount of data that is available for parameter estimation, as well as the model fit to the data. It is defined as

$$BIC \equiv 2 l_M(\mathcal{D}, \theta) - m_M \log(n)$$

where $l_M(\mathcal{D}, \theta)$ is the likelihood of the data $\mathcal{D}$, given the model parameter θ, m_M is the number of free parameters in the model, and n the number of data points.

3.7 Learning Variable Length Sequences

In most machine learning problems, the observations, or data points $\mathbf{x}_i$, are considered to be independently drawn from the probability model described above. As a consequence, the order in which the set of data points is analysed does not matter.

In speech recognition and analysis, and in other areas such as gene sequence classification, on the other hand, the evolution of the sequence of data points carries most of the information. One of the key issues that make these problems exceptional when compared to more traditional pattern classification tasks, is the fact that the sequences may be of variable length. If we could assume sequences of the same length, say S, as might be possible with time sequences in economy, for example, that often follow predefined calendar time intervals, the problem could be folded back to a standard pattern classification. The whole sequence of S points $\mathbf{x}_i \in \mathbb{R}^n$ could in fact be considered, at least in principle, as one point in a space of larger dimensionality $\mathbb{R}^{n \times S}$. The fixed-length assumption would guarantee that any sequence is a point that lies in the same space $\mathbb{R}^{n \times S}$ and thus standard pattern classification methods could be used.

With variable length sequences this is not possible and more sophisticated methods must be used.

Hidden Markov Models

One way to model time-varying processes is with Markov chains. A Markov chain is a process $\{X_n, n = 0, 1, 2, \dots\}$ that assumes one of a finite or countable number of possible values ω_i (called states) at each time step. Whenever the processes is in state ω_i, there is a fixed probability P_{ij} of making a transition to any other state ω_j, *i.e.*

$$P(X_{n+1} = \omega_j | X_n = \omega_i, X_{n-1}, \dots, X_1, X_0) = P_{ij}$$

Another way to express this property is to state that the conditional probability of being in any state at time $n + 1$, given the past states at times $0, 1, \dots, n - 1$ and the present state at time n, is not dependent on past states, but only on the present state. A graphical representation of such a model is shown in Figure 3.5. Each oriented arc in the figure represents a transition probability between the states that the arc connects.

If the sequence of states is not directly observable, but rather we observe the emissions o of a phenomenon that is controlled by the current state, the model can be augmented with conditional *emitting* probabilities $P(o|\omega_i)$, *i.e.*, the probability of emitting a particular observation o when the model was in state ω_i. Because the state is not directly observable, these models are called Hidden Markov Models (HMMs).

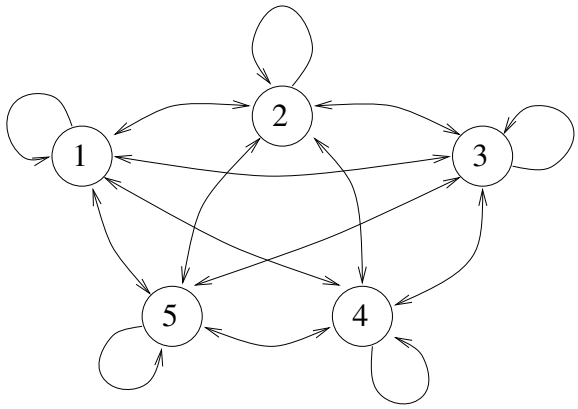


Figure 3.5: A five-state ergodic Markov model

The main tasks when using these models are:

- given a sequence of observations, find the optimal parameters of the model that has generated them (training),
- given a model and a sequence of observations, compute the likelihood that the model has produced the observations (evaluation),
- given a model and a sequence of observations, compute the most likely path through the model that has produced the observations (decoding).

The first of the three tasks is conceptually similar to the task of fitting a mixture of distributions to the data set. The similarity is in the fact that the data is incomplete. In the mixture of distributions case, the missing data is the assignment of each data point to one of the distributions. In the HMM case, the missing data is the sequence of states. Here, a solution to parameter estimation is the forward-backward or Baum-Welch algorithm, which is an instance of the Expectation Maximisation algorithm.

A conceptually simple solution to the *evaluation* problem is performed in two steps: the likelihood can be computed for each possible path through the model by multiplying the corresponding transition and emission probabilities; the total likelihood is then computed by adding the path-specific likelihoods over all possible paths. However, this is prohibitive in most practical applications, because the number of possible paths increases exponentially with the length of the sequence. The forward (or backward) algorithm solves this problem by computing the probabilities iteratively, thus keeping at each time step a number of alternatives equal to the number of states.

A fast algorithm for *decoding* is the Viterbi algorithm (Viterbi, 1967). In this case, at each time step and for each state, we keep track of the probability of the

best path that has taken us to that particular state and retain a pointer to the previous state in the path. When the end of the sequence is reached, the full path can be reconstructed by starting from the last best state, and recursively following the previous best states.

Clustering Variable-Length Sequences

A task that is receiving increasing attention, especially in the field of text processing and gene analysis, is the unsupervised classification of variable-length sequences. As in the supervised case, the most popular models are HMMs.

Oates et al. (1999), for example, apply Dynamic Time Warping to extract information about the possible number of clusters. This information is then used to train one HMM for each hypothesised cluster. The assignment between time series and HMMs can vary in the training phase, based on likelihood measurements.

In Bar-Hillel et al. (2005), the data is first modelled as a mixture of Gaussian distributions and then the parameters of a hidden Markov model are computed as transitions between candidate mixture terms.

Porikli (2004) approaches the problem by training a comprehensive HMM on the data, and then clustering the model parameters by eigenvector decomposition.

Finally, Li and Biswas (1999, 2000, 2002) perform a sequential search, optimising (i) the number of clusters in a partition, (ii) the assignment of each data object to a cluster given the size of the partition, (iii) the HMM size for each cluster, and (iv) the HMM parameters for the individual cluster.

Part II

Contributions of the Present Work

Chapter 4

Mapping Acoustic to Visual Speech

A large part of the work behind this thesis has been carried out within the Swedish project Teleface and the subsequent European project Synface. The aim was to develop a computer-animated talking face that could be used as a hearing aid for persons using the telephone.

As depicted in Figure 4.1, the only input to the system is the acoustic signal received at the hearing-impaired person's end of the telephone line. This paradigm gives a number of advantages, compared to, *e.g.*, video telephony: the telephone

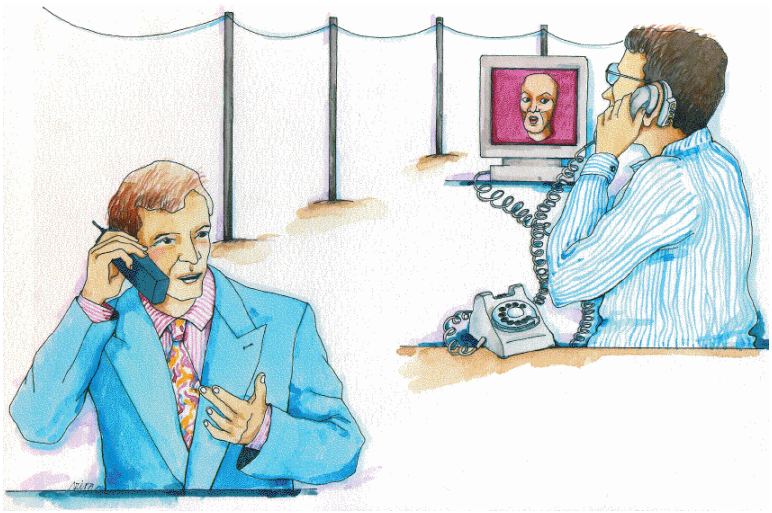


Figure 4.1: The Teleface vision and Synface reality. Illustration by Viera Larsson

line does not need to be changed, the person on the other end of the line needs only a standard telephone, and the hearing-impaired person does not need to make the impairment manifest. On the other hand, this solution requires that the facial movements, and especially the lip movements, be derived from the acoustic signal alone.

The mapping from acoustic to visual information is the focus of this part of the thesis (Papers A–C). The challenge is to produce sufficiently accurate movements, in order to convey useful information to the listener in a *real-time* system with *low latency*.

The real-time requirement arises from the intention to run the system on home computers with no extraordinary processing power. This limits the amount of calculations that can be performed per time unit without overloading the machine, and translates into a constraint on the complexity of the methods employed.

The low-latency requirement is more fundamental and originates from the need to preserve the natural flow of the conversation. Two arguments are responsible for this constraint. Firstly, it is essential that the face movement be synchronous with the acoustic signal. According to, *e.g.*, Grant and Greenberg (2001), the asynchrony between visual and acoustic presentations causes a rapid drop in intelligibility for persons relying on lip reading, especially when the audio leads the video. Secondly, studies (*e.g.*, Kitawaki and Itoh, 1991) have shown that in a communication channel, long round-trip transmission delays (ca 500 milliseconds) cause the natural turn-taking mechanism in a conversation to become troublesome. An everyday example is given by the satellite video connections often employed in TV news programmes, where the delay is in the order of seconds.[1] The first argument requires that the acoustic signal be delayed while the acoustic to visual mapping and the face animation are performed, in order to synchronise audio and video. The second argument imposes a limit to the length of the delay and, therefore, to the latency of the system. As a consequence, the mapping from acoustic to visual information at a certain time may be based on a limited amount of look-ahead, *i.e.*, on a limited amount of future acoustic evidence.

4.1 The Face Model

The face model was developed by Beskow (2003). This section describes the aspects of the model that are useful to understand the acoustic to visual mapping problem addressed in this part of the thesis.

The face model is a 3D graphic model comprised of a large number of polygons controlled by a set of continuous articulatory parameters with values varying in the range $[0, 1]$ (Table 4.1). The time evolution of the value of each parameter

[1] The transmission delay due to wave propagation is about 240 msec for geostationary satellites orbiting at 36,000 km above the earth. Delay due to the transmission protocols and to signal processing must be added.

parameter	description
V0	jaw rotation
V3	labiodental occlusion
V4	lip rounding
V5	bilabial occlusion
V6	tongue tip
V7	tongue length
V8	mouth width
V9	lip protrusion

Table 4.1: Parameters used to control the facial movements

defines movements at a conceptually high level, influencing the trajectory of groups of points in the 3D space.

An alternative higher level control system exists (Beskow, 1995) that is compatible with text-to-speech synthesis engines (*e.g.*, Carlson et al., 1982). This control system accepts as input a string of phonemes/visemes (see Chapter 2) with the corresponding time stamps. For each viseme, a set of target values for the facial parameters is defined. Some of the parameters may be unspecified for a certain viseme when this does not affect the corresponding articulator. In this case, the context must be used to determine the optimal target value. A rule-based system takes as inputs the target values and the time stamps, and performs a linear or spline interpolation, attempting to reach the targets as close as possible while preserving a smooth and consistent movement of the speech organs.

Figure 4.2 displays a subset of the parameters in Table 4.1 for the word "Synface" (/sʏnfɛis/). For each parameter, the target values (when specified) are plotted together with the final parameter trajectories obtained by spline interpolation. In the Swedish-English pronunciation of the word, the first vowel (/ʏ/) is front rounded and activates both the lip rounding and protrusion. The tongue tip is activated by the first and last /s/ and by the /n/. The labiodental occlusion is activated by the /f/, and finally the jaw rotation is moderately active during the whole utterance.

4.2 Regression vs Classification

The first question regarding the solution of the acoustic to visual parameter mapping is whether this map should be achieved directly solving a regression problem, or if the acoustic signal should first be classified into phoneme/viseme classes, after which the face parameters should be computed by means of the rule system described above.

In the first case, the map is a continuous function from the acoustic parameter space $S_p = \mathbb{R}^N$ to the face parameter space $F_p = \mathbb{R}^M$. In the second case, the map

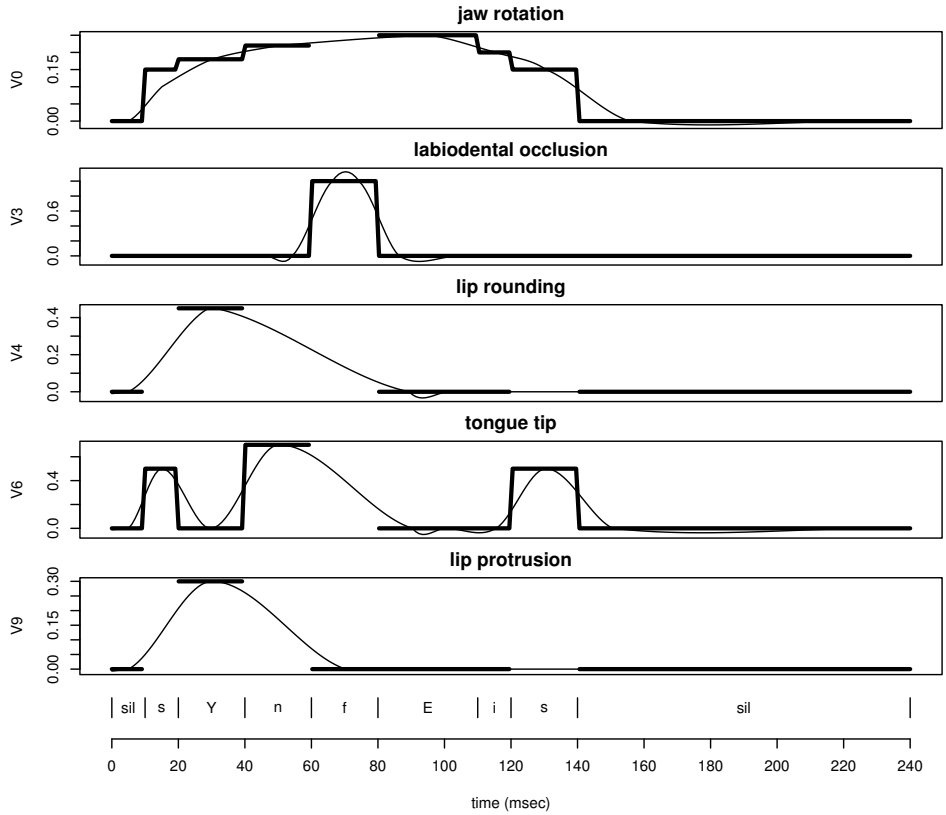


Figure 4.2: Some face parameter trajectories for the word "Synface" (/sʏnfɛis/). Target values (when specified) are indicated by the thicker line. The final parameter trajectories are obtained in this case by spline interpolation.

is a discrete function from the acoustic parameter space to a finite set of symbols $V = \{v_i\}$.

$$S_p = \mathbb{R}^N \longrightarrow F_p = \mathbb{R}^M$$
$$\searrow \quad V = \{v_i\} \quad \nearrow$$

This question was the basis of Paper A. Here, two methods are compared, one aiming at achieving regression by means of a neural network and the other classifying the speech signal into a phoneme string with Gaussian mixture models combined with hidden Markov models.

The neural network is a three-layer perceptron with 13 mel frequency cepstral coefficients (see Chapter 2) as input and the face parameters as output. The network includes both time-delayed and recurrent connections, in an attempt to grasp the time evolution of both the input and the output sequences.

A number of methods were investigated to perform the classification task. The standard scheme uses hidden Markov models with Gaussian distributions as a state-to-output probability model. The different factors that distinguish the methods are the amount of context used in the phonetic models, and whether phonemes are clustered into viseme classes already in the modelling phase or after decoding. The training procedure and the topology of the phonetic models is described in Salvi (1998).

The phonetic models were connected to each other in a free loop. An attempt has been made to define a syllable based topology of the recognition network, but this did not lead to any improvement.

Gender-dependent models have also been tried resulting in a slight improvement when the gender of the model and the test speaker agree; a marked degradation is observed in the case of gender mismatch.

4.3 Evaluation Method

The performance of the different methods can be measured at different points along the processing chain. As the aim of the system is to improve intelligibility in a conversation, the most reliable measure of performance is obtained by performing listening tests with hearing-impaired subjects. Alternatively, normal hearing subjects can be used if the acoustic signal is degraded so as to simulate a hearing impairment. This kind of test usually employs short sentences containing a number of keywords that the subject should detect. The performance is given by the percentage of correctly transcribed keywords. Paper A contains an experiment in which 10 hearing-impaired subjects were asked to repeat the short sentences they were presented with, which contained three keywords each.

Moving backward in the processing chain, an alternative evaluation method is to measure the distance between the target trajectory and the predicted trajectory for each face parameter. This allows for uniform evaluation of both regression and classification methods, but it presents a number of difficulties because the deviations from the target trajectories should be weighted with the potential effect they have on visual perception. For example, in the case of bilabial occlusion, it is essential that the corresponding parameter reaches the maximum value in order to give to the listener the impression that /b/, /p/ or /m/ has been uttered. However, for other visemes, the value of this parameter is less important. In Paper A, only visual inspection has been performed on the parameter trajectories obtained with the different methods.

Finally, classifications methods have a natural evaluation criterion: the number of correctly classified symbols (phonemes or visemes in this case). This evaluation

Example 1

```
ref: AAABBBBCCCCCCCDDDDDEEEEEEE -> ABCDE
rec: AAAAAAAAAABBBBCDEEEEEEEEEE -> ABCDE
res:                             ccccc
fbf: ccc----------c---ccccccc
```

accuracy = 100, % correct = 100%, frame-by-frame = $11/26 \times 100 = 42.3\%$

Example 2

```
ref: AAABBBBCCCCCCCDDDDDEEEEEEE -> A    BC      D E
rec: AFGHIBKDSORFKDKELFDSKDLFID -> AFGHIBKDSORFKDKELFDSKDLFID
res:                             ciiiicsiiiiiiciciiiiiiiii
fbf: c----c----------c-------
```

accuracy = $(4-21)/26 \times 100 = -65.4$, % correct = 80%, frame-by-frame = $3/26 \times 100 = 11.5\%$

Figure 4.3: Scoring examples. Capital letters are result symbols for each frame (observation vector) on the left and as a sequence on the right. `ref` is the reference, `rec` is the recognition output, `res` is the result after alignment (`c` = correct, `i` = insertion, `s` = substitution), and `fbf` is the frame-by-frame result.

criterion is complicated by the fact that classification results come in sequences where both the correctness of the symbol and the time alignment are important. Moreover, given the low-pass filter characteristics of the rule-based visual parameter generation, short insertions do not cause severe degradation to the final facial movements.

A number of standard evaluation methods have been used in Papers A–C. The scores are illustrated in Figure 4.3, where some of their limitations are exemplified. Two scoring methods (*accuracy* and *% correct*) are computed after aligning the sequence of recognised phonemes/visemes to the sequence contained in the reference transcription. The alignment is performed at the symbolic level, with dynamic programming. Although the position of each symbol in the recognition sequence is correlated to its time alignment with the sequence of observations, the above methods disregard the time information contained in the transcriptions. The % correct score is defined as the ratio between the number H of matching symbols after alignment and the total number N of symbols. Accuracy is defined as $\frac{H-I}{N} \times 100$ where I is the number of insertions emerged from the alignment procedure. An additional scoring method (*frame-by-frame correct rate*) simply computes the ratio between number of correctly classified and total number of frames (observation vectors). This method tends to underestimate the importance of short insertions.

As shown in Figure 4.3, these scores can give misleading results in case of phonetic recognition. In the first example, accuracy and % correct give no information about the time misalignment of the recognition sequence and reference sequence in time. The second example shows how % correct can give high scores for random recognition sequences.

4.4 Results of Paper A

The main result of Paper A is that the methods solving the classification problem, referred to as HMM methods in the paper, outperform the ones performing regression (the ANN method). The main reason for this is that the trajectories estimated by the neural network are only able to follow the trend of the target trajectories, but are not sufficiently accurate. The errors committed by the HMM methods are more drastic, because they produce a completely incorrect trajectory. However, these errors are less frequent and more acceptable when considering that, in case of correct classification, trajectories close to the optimum are obtained.

The regression methods have the advantage that the facial parameters can be estimated independently of one another from the acoustic features, and that different articulatory gestures (*e.g.*, with different degrees of articulation) could, in principle, be determined from the sounds they produce. In this application, however, the aim is to achieve stereotypical movements, rather than reproducing realistically the actual movements that produced the sound. In this respect, methods based on classification are more suitable, because they make use of a discrete phonetic representation that standardises the results.

The listening tests show how the synthetic face driven by the correct parameters gives a remarkable improvement over the audio-alone condition, even if it does not help as much as a natural face. The synthetic face driven by the HMM method gives an improvement that is significant compared to the audio-alone condition, whereas the ANN method gives no improvement. The tests also show that these results are highly dependent on the listener.

4.5 Real-Time and Low-Latency Implementation

After the studies described in Paper A, the solution based on regression was discarded and further development, mainly carried out during the Synface project, was focused on solving the classification problem described above in a real-time, low-latency system.

This research has involved both the development of new classification methods and the implementation of a software library that could be integrated with the existing face animation and control module.

The classification methods employed in the Synface prototype use a hybrid of hidden Markov models (HMMs) and artificial neural networks (ANNs). The hidden Markov models define a number of states, corresponding to subparts of

each phoneme and the way these states are traversed in time (transition model). The neural networks are trained to estimate the *a posteriori* probability of a state given an observation (Ström, 1997).

Different topologies for the ANNs, and consequently for the HMMs, have been tested in an initial phase of the project. The simplest models are feed-forward networks trained with one output unit for each phoneme. The neural network is in this case a static model; all the information about time evolution is coded into the HMM in the form of a loop of three-state left-to-right models representing a phoneme each.

A more complex model performs the same task with a time-delayed neural network (TDNN). In this case, several input vectors are considered at every time step by means of delayed connections between the input and the hidden layer. Delayed connections are also present between the hidden and the output layer. All delays are positive, making sure that only the current and past frames are necessary to produce a result at a certain time.

Another model that was trained during this phase extends the output targets in the neural network to context-dependent units. Statistics on the training data were used to estimate which phonemes are more affected by context. This was done with a methodology commonly used in speech recognition based on HMMs and Gaussian mixture distribution models, called phonetic tree clustering (Young, 1996): phonetic knowledge and statistics collected during the training phase are used to build a clustering tree, in which the leaves contain groups of similar states. The procedure can be terminated either based on the likelihood of the data given the model or when the desired number of clusters has been reached. This procedure was used to determine the number of context-dependent output units to be used in the neural network. An example of the distribution of number of output units for each phoneme is given in Figure 4.4, with a total of 376 output units. These models have been trained but never fully tested.

Finally, recurrent neural networks (RNNs) with one output unit per phoneme were trained. These models, thanks to the time-delayed recurrent connections in the hidden layer, can learn more complex time dependencies than TDNNs (Salvi, 2003a). Papers B and C describe experiments based on RNN models.

A real-time modified version of the Viterbi decoder was implemented. This truncates the back-tracking phase to a configurable number of time steps, thus allowing incremental results to be evaluated. The effects of the truncation compared to the standard Viterbi decoder were investigated in (Salvi, 2003a). As expected, the performance drops when the look-ahead length, *i.e.*, the amount of right context, is reduced. Results stabilise for look-ahead lengths greater than 100 milliseconds, for this specific task.

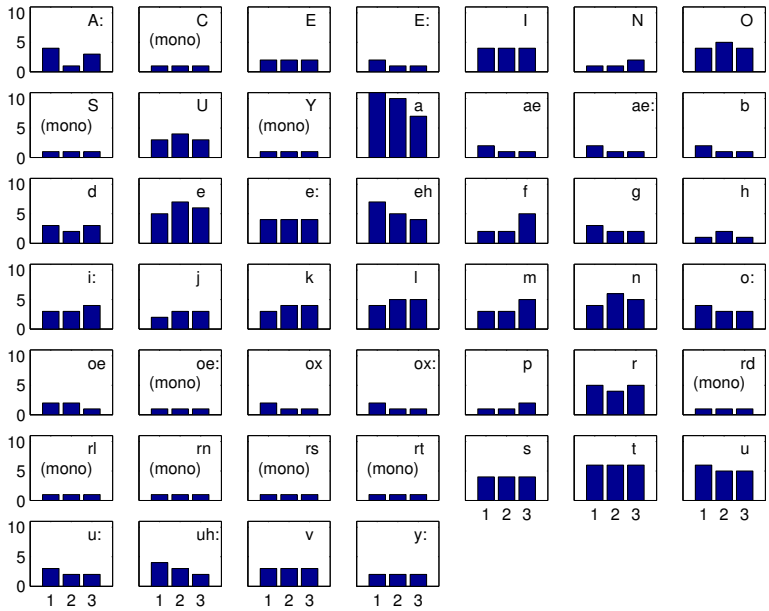


Figure 4.4: The distribution of context-dependent output units of each phoneme and segment position (initial, middle and final), indicated by the numbers 1, 2, 3. The total number of output units is in this case 376. The phonemes with only one output unit per segment are context independent (mono).

4.6 Interaction between the RNN's and HMM's Dynamic Model

As described in detail in Paper B, the use of recurrent and time-delayed neural networks violates the first order Markov chain assumption: each observation is not only dependent on the current HMM state. In other words, both the NNs and the HMMs impose a model of time evolution. Depending on the task, these two models may be conflicting, *e.g.*, if the HMM contains a sequence of states that was not present in the network's training data. The interaction between the two models can be expected to have stronger effects when the time dependencies are longer (RNNs with many delayed connections and HMMs defining word-like sequences rather than a simple loop of phonemes).

Standard analysis tools may not be used to characterise the temporal properties of these models, due to the presence of nonlinearities. A number of studies have been devoted to describing the dynamic properties of non-linear systems analytically (*e.g.*, **??**). In our case, however, the use of a decoder with limited look-ahead complicates this task. Is, for example, the truncation error larger when the time

dependencies in the model are longer?

Paper B tries to answer some of these questions with empirical experiments. Three factors are considered:

1. the length of the time dependencies in the neural network,
2. the length of the time dependencies in the hidden Markov model,
3. the look ahead length.

To vary the first factor, three neural networks were compared: a feed-forward NN (with no time dependencies) and two recurrent networks with different complexities.

The second factor was varied in two ways. In one experiment (denominated word-length test), the topology of the HMM was gradually varied from a free loop of phonemes to a word loop, with words of increasing length in terms of the number of phonemes (up to 7). To achieve this, the words were artificially created by concatenating the phonemes in the transcriptions of each test utterance. In the second experiment (denominated alpha test), the HMM topology was defined as a mixture of a phoneme loop and a forced alignment model, *i.e.*, a model in which the only possible output sequence is the phoneme string from the transcription of each utterance. A parameter sets the relative weight of the two models in the mixture. Note that the alpha test with alpha set to 0 coincides with the word length test with word length equal to 1 because, in both cases, the HMM defines a loop of phonemes.

The third factor is varied by setting the look-ahead length in the decoder from 1 to 20 frames (10 to 200 milliseconds).

4.7 Results of Paper B

The results in Paper B can be summarised as follows:

- In all conditions, longer look-ahead lengths correspond to better performance.
- The word-length test shows this phenomenon in a clearer way than the alpha test.
- The degree of improvement depends on the amount of time-dependent information in the HMM and in the NN.
- When the time dependencies in the HMM are short (word length close to 1 or alpha less then 0.5), the recurrent networks take more advantage of longer look-ahead lengths than do the feed-forward networks.
- When the time dependencies in the HMM are long, the feed-forward networks seem to take more advantage of longer look-ahead lengths, but this outcome is conditioned by the fact that the results obtained with the more complex recurrent networks tend to saturate (approach a 100% correct classification rate).

4.8 A Method for Phonetic Boundary Detection

During the experiments in Paper B, the class entropy, easily estimated from the outputs of the neural networks, was considered as a possible confidence measure for the classification performance. A closer inspection of the time evolution of the entropy suggested another use of this measure. The entropy is a measure of uncertainty, and thus increases when the neural network presents activity in more than one output unit. This usually corresponds to an input that is ambiguous compared to the patterns learned during training. There are many factors that generate ambiguous patterns, *e.g.*, a voice that is particularly hard to recognise or a phoneme in a context underrepresented in the training data. One of the factors that seem to systematically affect the class entropy is the proximity to a phonetic boundary. This can be explained by the fact that the properties of the speech signal vary continuously from one segment to the next, assuming values that are intermediate between the two typical patterns. Even in the case of abrupt transitions, as for plosive sounds, the fact that the signal analysis is preformed over overlapping windows of a certain length causes the corresponding feature vectors to vary gradually.

This phenomenon suggests the use of the class entropy as a segment boundary detector. Paper C shows a preliminary analysis aimed at verifying this possibility.

4.9 Results of Paper C

The results in Paper C can be summarised as follows:

- The entropy of the output activities of the phoneme classification neural network has local maxima corresponding to phonetic boundaries.
- The absolute value of the entropy is strongly dependent on the phonetic content of the segment.
- Averaged over all the speech frames, the absolute value of the entropy and the value of the entropy normalised to the average for each phonetic segment increase close to phonetic boundaries.
- Both the absolute and normalised entropy are nevertheless not sufficient to detect phonetic boundaries efficiently.
- Dynamic entropy measures (first and second derivatives) also carry information on the proximity to a phonetic boundary.
- These preliminary results suggest that peak-picking techniques could be used to accurately detect the boundary positions from the entropy measurements.

Later results (Salvi, 2006), confirm that the phonetic boundaries can be predicted within 20 msec, with 86.4% precision and 76.2% recall, based only on entropy measurements. To be able to compare these results with the literature, it is important to

note that the task of detecting phonetic boundaries is related, but not equivalent, to the task of aligning the speech signal to a reference transcription (*e.g.* Hosom, 2002). In the first case, no information is given about the phonetic content or about the number of boundaries for the speech utterances.

Chapter 5

Accent Analysis

Papers D and E describe studies on pronunciation variation in Swedish due to the speaker's regional accent. The distinctive characteristics of these studies, when compared to more traditional phonetic investigations, is the use of large data sets containing vast populations of subjects (speakers).

Most studies in phonetics use traditional statistics to analyse a limited number of observations collected in well-controlled laboratory conditions. The value of these studies is not questioned, because they provide means to isolate the effect of the variables of interest and eliminate or control disturbing effects. However, the drawback of these studies is the limited amount of observations that can be collected and analysed under controlled conditions, mainly due to the need to carefully annotate the material.

Given the large number of physical, linguistic, and psychological variables that affect speech production, there is a risk that the observations collected in a laboratory are biased towards the phenomena the researcher is investigating. In some cases, the study might reveal, with utmost precision, phenomena that are only valid for the small population of subjects considered and are hard to generalise.

The machine-learning methods used in automatic speech recognition (ASR) represent an alternative analysis framework that helps overcome these limitations. These methods are inherently developed for large data sets that are not accurately annotated. In spite of a reduced control over the experimental parameters, caused by the lower quality of the data, these methods allow the analysis of large populations of subjects and thus lead to results that are more general and representative of the entire population for a certain language. Moreover, if the data set is sufficiently large, the effects of the parameters over which we lack control can be assumed to be randomly distributed and, thus, cancel out in the experiments.

The aim is not to substitute the more traditional methods for speech analysis, but rather to verify results obtained within controlled experiments, and to extend and generalise them to larger populations.

From the point of view of ASR applications, these studies can also throw light on aspects and limits of the models and lead to more "knowledge aware" development, as for example in Salvi (2003b).

5.1 Regional Accent vs Dialect

When talking about geographical variability of language, many linguistic aspects can be taken into account. The hierarchical classification into language families, languages, and dialects is based on a complex mixture of factors such as word forms, grammatical rules, phonetic inventory, and prosodic features.

The only linguistic aspects considered in this thesis are in regard to pronunciation variation within a particular language. The term *accent* will be used to describe a pronunciation variety, according to Crystal (1997, ch. 8, p. 24):

> Dialect or accent?
>
> It is important to keep these terms apart, when discussing someone's linguistic origins. *Accent* refers only to distinctive pronunciation, whereas *dialect* refers to grammar and vocabulary as well. [...]

To avoid confusion, a further distinction needs to be made between the use of the term accent in this thesis and its use in prosodic studies: in the latter case, the focus is on specific patterns of suprasegmental stress.

5.2 Method

The speech signal is represented with regularly spaced feature vectors that constitute data points in the feature space. Each instance of a phoneme (phone) is thus characterised by a variable number of feature vectors or data points, depending on its length in time. This contrasts with the common practise in phonetic experiments of measuring a set of features at suitable points in time chosen by the researcher, or of averaging them over previously annotated segments. As mentioned above, another difference is that, given the size of the recordings we are considering, the number of data points to be analysed can easily reach the order of hundreds of millions.

Both these observations suggest the need for an intermediate level in the analysis, *i.e.*, the analysis is not performed directly on the observations, but on a parametric (statistical) model of the observations. This allows us both to represent phonemes with a fixed-length set of parameters and to drastically reduce the size of the set of observations to be analysed.

Each phoneme, as spoken by each population of speakers from a certain accent area, is represented by a three-state left-to-right hidden Markov model. A multivariate unimodal Gaussian distribution is associated with each state of the model, representing the statistics (means μ and covariances Σ) of the data points associated with it. This is common practise in ASR and guarantees that the model

splits each phone, *i.e.*, each acoustic realisation of each phoneme, into three consecutive segments (initial, middle, and final), thus taking into account the non stationary nature of speech segments. The procedure to initialise and estimate the model parameters is also standard practise in ASR and makes recursive use of the Baum-Welsh algorithm, based on the Expectation-Maximisation paradigm. The input to this procedure, in addition to the current estimates of the model parameters, is simply the sequence of phonemes contained in each utterance, abolishing the need for time-annotated material.

The analysis of differences in the pronunciation of each phoneme is then performed in the model parameter space, rather than in the feature space. This is done either by defining a global distance between model states, *i.e.*, between Gaussian distributions, or by analysing in detail the individual model parameters. In the first case, the metric is used in conjunction with hierarchical clustering to build trees of relationships that show how the model states naturally group depending on their mutual similarity. In the second case, given two groups of states, discriminant analysis is used to rank the model parameters that best explain the separation between the groups.

The Metric

Let $p_1(x)$ and $p_2(x)$ be the two density functions we want to compare; the metric used is the *Bhattacharyya distance* (Bhattacharyya, 1943) defined as:

$$\mathcal{B}(p_1, p_2) = -\ln \int p_1(x)^{\frac{1}{2}} p_2(x)^{\frac{1}{2}} dx$$

This is an example of the Ali-Silvey class of information-theoretic distance measures (Ali and Silvey, 1966), of which the more common Kullback-Leibler and Chernoff distances are members. All these distances carry informations about the classification error of a classifier based on the two distributions considered. The Kullback-Leibler distance, defined as

$$\mathcal{D}(p_1, p_2) = \int p_1(x) \ln \frac{p_1(x)}{p_2(x)} dx$$

has the drawback of being asymmetric, *i.e.*, $\mathcal{D}(p_2, p_1) \neq \mathcal{D}(p_1, p_2)$. The Chernoff distance is a generalisation of the Bhattacharyya distance:

$$\mathcal{C}(p_1, p_2) = \max_{0 \leq t \leq 1} -\ln \int p_1(x)^{1-t} p_2(x)^t dx$$

The Chernoff distance provides a tighter bound on the classification error than the Bhattacharyya distance, but it implies an optimisation.

In the case that $p_1(x)$ and $p_2(x)$ are multivariate Gaussian densities, the Bhattacharyya distance can be computed in terms of the means μ_1, μ_2 and the covariance

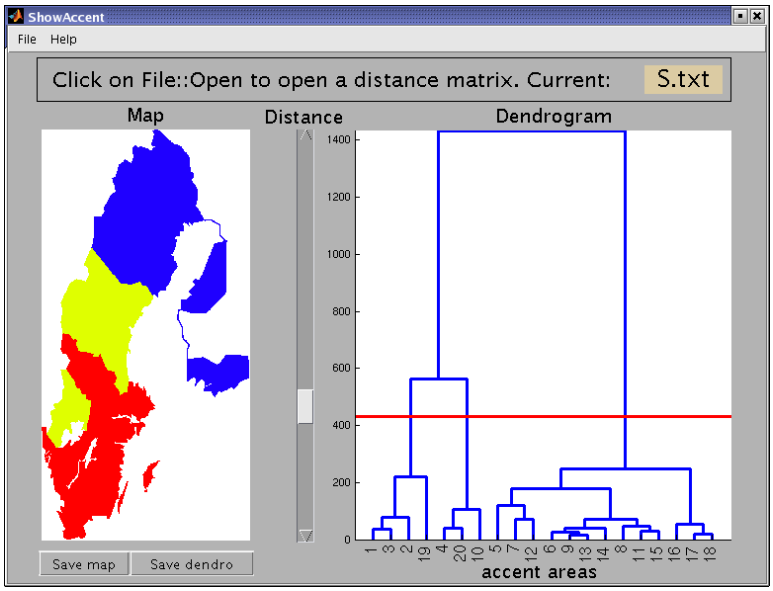


Figure 5.1: The ShowAccent interface. The map on the left displays the geographical location of the clusters for a distance level specified by the slider. On the right, the *dendrogram* is a compact representation of the clustering procedure.

matrices Σ_1, Σ_2:

$$\begin{aligned}\mathcal{B}(\mu_1, \Sigma_1, \mu_2, \Sigma_2) &= \frac{1}{8}(\mu_2 - \mu_1)^T \left[\frac{\Sigma_1 + \Sigma_2}{2}\right]^{-1} (\mu_2 - \mu_1) \\ &\quad + \frac{1}{2} \ln \frac{\left|\frac{\Sigma_1 + \Sigma_2}{2}\right|}{\sqrt{|\Sigma_1||\Sigma_2|}}\end{aligned}$$

The Analysis

The analyses performed in Papers D and E are based on agglomerative hierarchical clustering. The pairwise distances between the distributions corresponding to each HMM state are used to build a dendrogram that represents the hierarchical grouping of the corresponding allophones. The *complete linkage* method has been used to guarantee maximum separation between the clusters.

In Paper D, each phoneme is analysed independently and the distance between two allophones is averaged over the three HMM states. The analysis was performed by visual inspection; a Matlab tool was developed to simplify this task (Figure 5.1). For each phoneme, the tool shows the dendrogram on the right pane, a map on the left pane, and a slider in the middle. The slider can be used to select levels at

Region	Subregions	Subjects
I	15,16,17,18	1044
II	10,11,12,13,14	1098
III	8,9	1332
IV	7	76
V	5,6	307
VI	1,2,3,4	975
VII	19	25

Table 5.1: The number of subjects and the subdivision of the seven main accent areas in Sweden and part of Finland.

which the dendrogram can be cut. The map shows the geographical distribution of the groups of regions obtained cutting the dendrogram at that particular level. No attempt was made in this paper to establish automatically the most plausible number of clusters for each case.

In Paper E, the complete pool of states is clustered simultaneously, allowing distributions belonging to different phonemes to form groups of similarity. In Paper E, moreover, for each split in the binary tree obtained by the clustering procedure, linear discriminant analysis (LDA) is used to rank the model parameters that best explain the split. A number of indexes have been investigated in order to predict the optimal number of clusters from the data. Many of the indexes from Milligan and Cooper (1985) are highly correlated, which Milligan also remarks. Additionally, the Bayes Information Criterion was calculated.

5.3 Data

As in other studies in this thesis, the data is extracted from the Swedish SpeechDat database (Elenius, 2000). Other collections of recordings in Swedish might be suitable for similar investigations. The project SweDia (Bruce et al., 1999), *e.g.*, has collected a remarkable set of recordings with the aim of studying genuine dialects of Swedish. As already explained, the focus in this thesis is rather on accent variation than on dialect analysis. Both the rich phonetic knowledge and the data collected in the SweDia project are, however, precious resources for this kind of studies.

The SpeechDat database contains annotations of each speaker's accent region, as defined by Elert (1995) and illustrated in Figure 5.2. The number of speakers for each accent area (see Table 5.1) is representative of the total population for that region. Other variables, such as gender and age, are well balanced across accent areas. A detailed description of the pronunciation variation for each region is given in Paper D (Figure D.2, page D6).

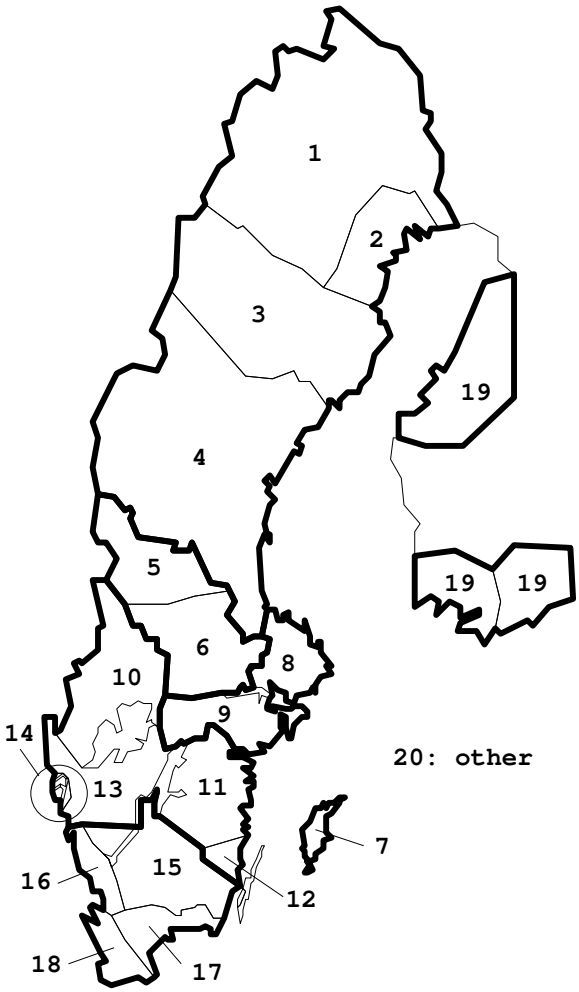


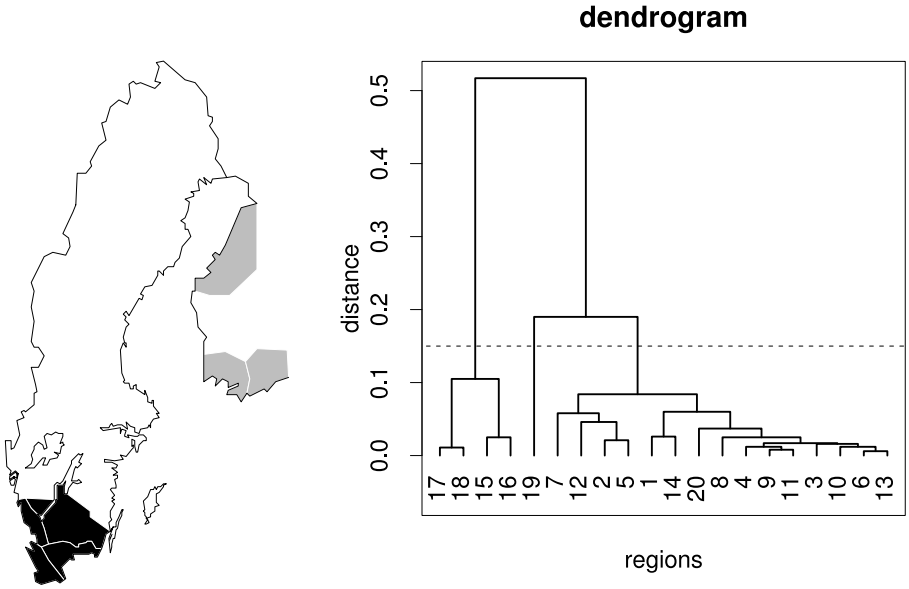
Figure 5.2: Geographic representation of the twenty accent areas in Sweden and part of Finland. The thick borders represent the seven main accent areas.

The official SpeechDat training set was used in the experiments for a total of 4500 speakers and 270 hours of speech. This results in approximately 97 million feature vectors computed at 10 millisecond intervals containing 13 Mel cepstrum coefficients $\{c_0$–$c_{12}\}$, and their first and second order differences $\{d_0$–d_{12}, a_0–$a_{12}\}$.

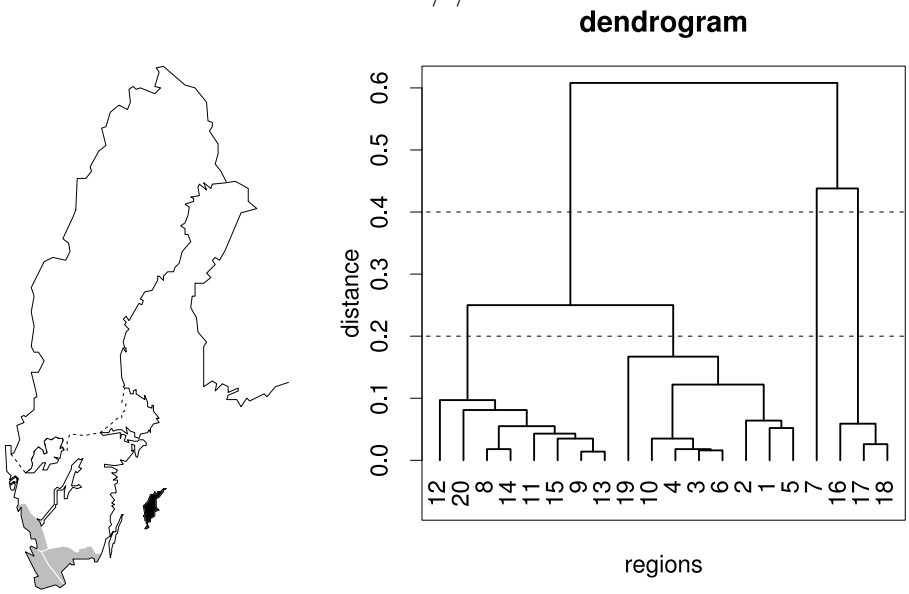
During training, 49 three-state HMM models (46 phonemes, 1 silence, 2 noise models) were trained for each of the 20 regions. This resulted in a total of 2940 states (or distributions). In the analysis of Paper E, the noise models and the retroflex allophone [ɭ] were removed (the last for lack of data points in certain regions). Thus, a total of 2760 states (distributions) were used for the clustering procedure.

5.4 Results of Paper D

Some of the results are reported in Figure 5.3 and can be summarised as follows. In all cases except for the fricative /ç/, the dendrogram shows two or three distinct clusters. In the case of /r/, the retracted pronunciation [ʁ] of the southern regions (15–18) corresponds to a very distinctive cluster in the analysis. Also, the Finnish variant (region 19) could be separated from the more standard pronunciation [ɹ]. For the phoneme /u:/, cutting the dendrogram at distance 0.4, for example, we get three clusters corresponding to the southern regions (16–18) where the vowel is diphthongised, to Gotland (region 7) where it is pronounced as [o:] (Elert, 1995), and to the rest of Sweden and Finland. An alternative partitioning, also plausible considering the dendrogram at distance 0.2, would split the third group with a border indicated by the dashed line on the map. For the fricative /ç/, the dendrogram does not show clearly distinctive clusters; however, a possible partition is the one shown on the map with a group corresponding to the affricate variant as spoken in Finland. Finally, the two clear clusters in the case of the fricative /ʃ/ correspond to the standard velar pronunciation in the central and south part of Sweden [ɧ] and to the more frontal pronunciation in the north and in Finland.

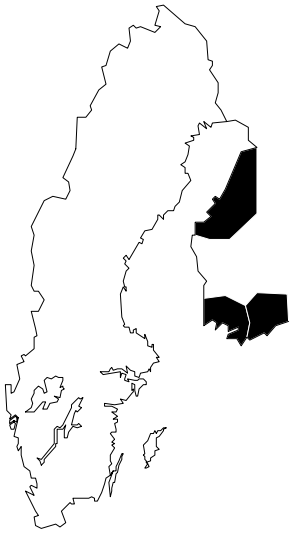


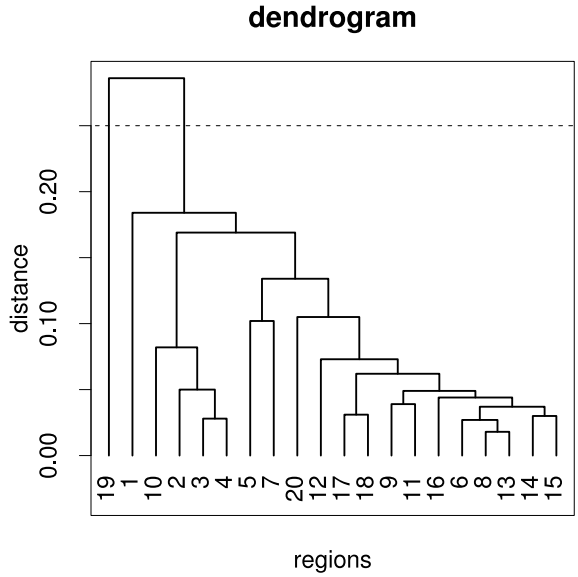
/r/



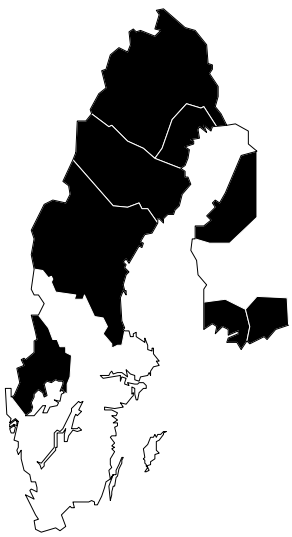
/uː/

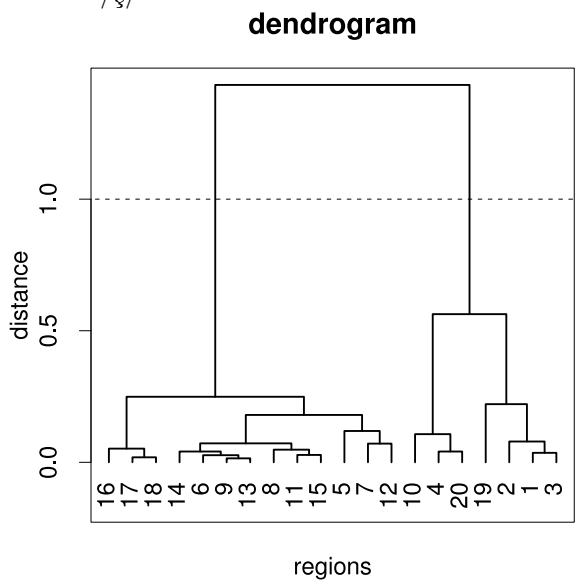
Figure 5.3: Four examples of pronunciation variation across Sweden and part of Finland. White, black, and grey regions represent clusters where the acoustic features are homogeneous. The dashed lines in the dendrograms represent the possible distance levels that produce the clusterings displayed in the maps.





/ç/





/ʃ/

Figure 5.3: (continued)

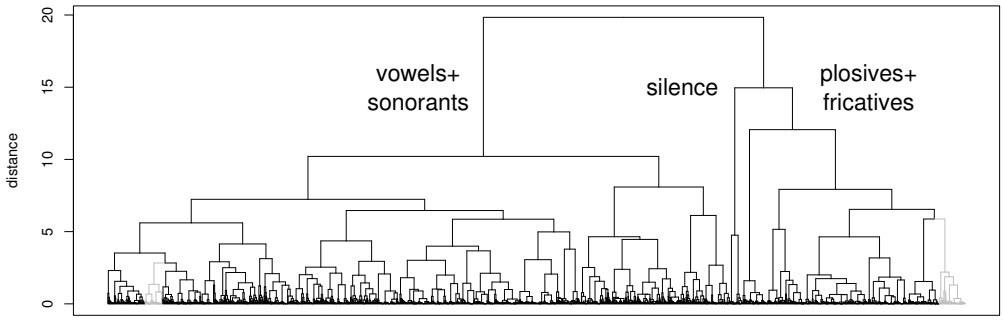


Figure 5.4: Dendrogram of the full clustering tree. The y-axis shows the dissimilarity level; the x-axis shows the states in the form phoneme-segment-region. Given the number of states, it is not possible to display each label. Broad classes are also shown in the picture. An enlargement of the two greyed-out subtrees is given in Figure 5.5.

5.5 Results of Paper E

The complete clustering tree for the 2760 distributions is shown in Figure 5.4. The reader is referred to the paper for a detailed description of the results that can be summarised as follows:

- Given the large number of distributions, it is not possible to visualise all the details simultaneously; one way to eliminate this problem is to split the analysis in two phases by approaching the tree from the top or bottom.
- Starting from the top of the tree we can observe the emergence of broad classes such as vowel/sonorant, plosive/fricative and silence.
- LDA shows that the first cepstral coefficients are mainly responsible for these groupings (mainly related to the energy and spectral tilt).
- Starting from the bottom of the tree, we can observe that the state position (initial, middle and final) and the identity of the phoneme are more prominent variables than the accent region. This means that states in different positions of a segment and belonging to different phonemes are split first, whereas the effect of the accent region comes last. In this case, the subtrees referring to the same phoneme and position can be used to observe relationships between different accent variants in a similar way as in Paper D (see the case of /r/ in Paper E).
- There are exceptions to this regularity that are particularly interesting, because they show the cases in which the pronunciation of one phoneme in the

language is assimilated to the pronunciation of another phoneme that is also part of the phonetic inventory of that language. Paper E gives a number of examples with fricatives and vowels. More examples are given in the following discussion and in Figure 5.5.

- Most of the indexes computed in order to estimate the optimal number of clusters are a monotone function of the number of clusters. This shows that the number of parameters used in the accent-dependent HMM sets is low if compared to the complexity of the problem and to the amount of data available for parameter estimation. This is in agreement with the fact that ASR models are usually some orders of magnitude more complex, by using both context-dependent models and mixtures of up to tens of Gaussian distributions for each state.

Although several interesting cases have been observed in Paper E, these results are not exhaustive and the process of analysing and interpreting the tree in Figure 5.4 continues. In Figure 5.5, we give two examples that did not appear in the papers and that are indicative of some of the above points.

The two dendrograms are extracted from the full tree of Figure 5.4 in which they are greyed out. The left dendrogram shows the clusters of the first states (s1) of three back vowels: two long /oː/, /uː/ and one short /ɔ/. The three vowels appear next to each other if we consider the full tree, but they form distinctive clusters, as the dendrogram illustrates. Exceptions to this are the allophones of /oː/ from the southern regions of Sweden (r16–r18) and the allophone of /uː/ from Gotland (r07); both are more open if compared to the more standard pronunciations, and therefore cluster with /ɔ/.

Similarly, for the right dendrogram in Figure 5.5, the fricatives /s/, /f/, and /v/ form distinctive clusters. However, the pronunciation of /ʃ/ is split into two main allophones: more retracted in middle and southern Sweden and more frontal in the north of Sweden and in Finland. This second allophone clusters with the southern allophone of the phoneme /ʂ/, and successively with the other front fricatives /s/, /f/, and /v/. Note also that the two clusters of the phoneme /ʃ/ are identical to the ones obtained in Paper D (Figure 5.3), where each phoneme was analysed separately, confirming the robustness of the method.

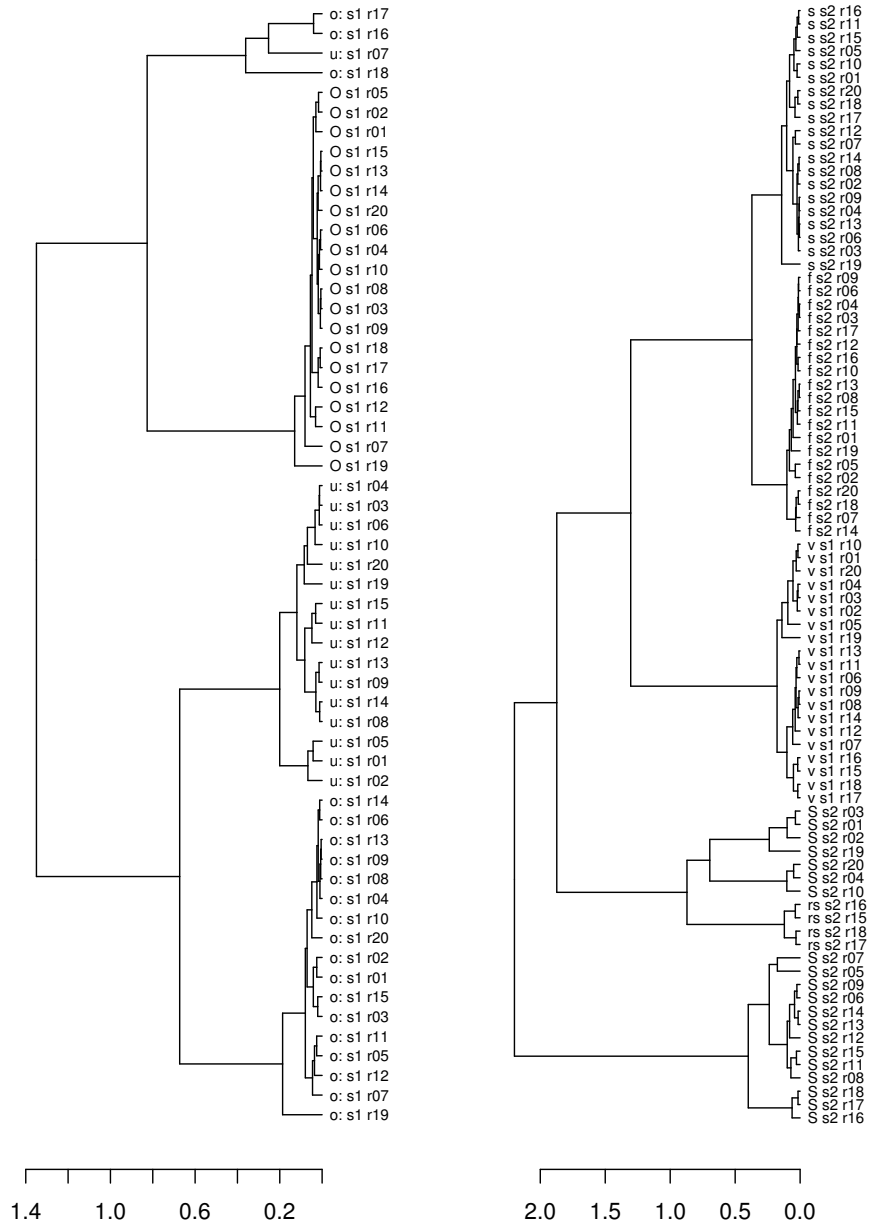


Figure 5.5: Two examples extracted from the complete clustering tree (Figure 5.4), with back vowels (left) and fricatives (right). The labels indicate phoneme (SAMPA), state (s1, s2 or s3), and region (r01–r20). The SAMPA symbols that graphically deviate from IPA are: O → ɔ, S → ʃ and rs → ʂ.

Chapter 6

Modelling Language Acquisition

When we described the speech communication chain in Chapter 2, we assumed that the two interlocutors were familiar with the language they were speaking. This chapter describes a study carried out within the project MILLE (Lacerda et al., 2004b) that aims at studying the phenomena that occur in an infant's attempt to acquire the skills necessary to engage in spoken interaction.

The theoretical standpoint of the project MILLE are the Ecological Theory of Language Acquisition (Lacerda et al., 2004a) and Lindblom's Emergent Phonology (Lindblom, 1999) which claim that very little, possibly only the physiology of the speech and hearing organs and of the brain, is transmitted genetically from generation to generation. The skills to control these organs and to interpret sensory information are not inherited and must be learned from the environment. This is in line with Gibson's Ecological Psychology (Gibson, 1963) that was initially developed for visual perception, and first stressed the importance of the environment in understanding human behaviour.

Figure 6.1 is a modified version of Figure 2.1 (page 7) that takes into account language learning aspects of the speech chain. Here, speaker and listener are replaced by child and parent. The child is exposed both to the sounds she has produced and to the physical environment, which consists mainly of acoustic, visual and tactile stimuli that the parent generates by talking, making gestures, and showing objects to the child. The loop on the left side of the figure, *i.e.*, from the brain of the child/speaker to her vocal muscles, to the speech sounds, to her ear, and back to her brain, is important both for skilled speakers and for speakers taking their first steps in the use of a language.

For the skilled speaker, it can be seen as a control loop in which the speaker's perception of the sounds she has produced is compared to a system of acoustic categories in order to fine-tune her production mechanism (for example, correcting a *tongue slip*). In this case, both the motor control necessary to drive the speech organs and the perceptual acoustic categories are considered to be well established in the speaker's brain.

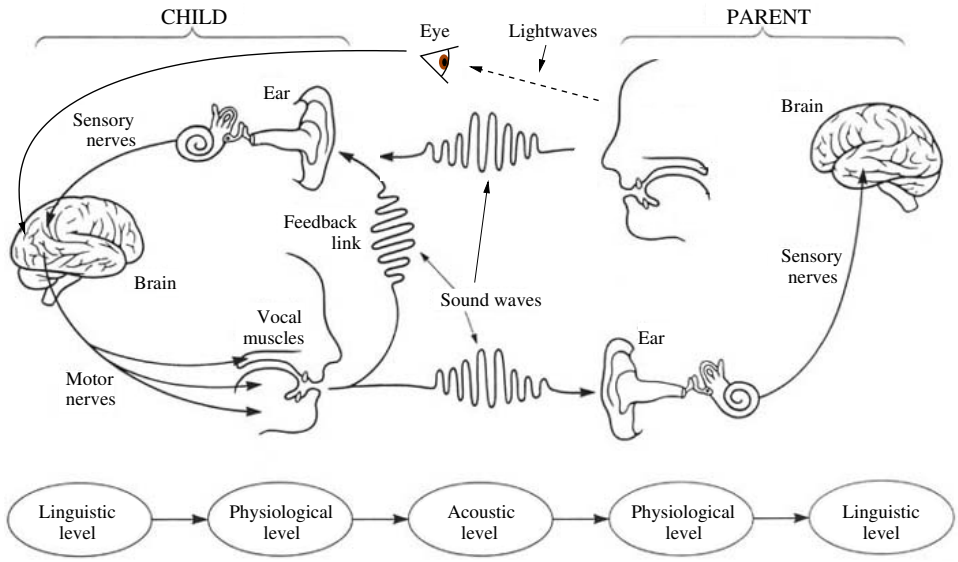


Figure 6.1: The Speech Chain after Denes and Pinson (1993), modified to account for language learning.

In the case of a child learning how to produce speech sounds, this feedback mechanism is equally important. During babbling, infants explore the articulatory and acoustic spaces in an attempt to gain familiarity with their production and sensory organs. An attempt to model this behaviour is Guenther's DIVA model of speech production. In its original formulation (Guenther, 1994), the model was an attempt to show how a child learns the motor control of the speech production organs. The model randomly generates configurations of the vocal tract and adjusts them in order to minimise the distance between the resulting sounds and some reference speech categories. Because the focus of this model is on production, the speech categories that constitute the perceptual reference are assumed to be already established in the child and to correspond to the specific language's phonemes. This is supported by evidence that, by the age of 10–12 months, children already show well-developed phonetic categorisation (Werker and Tees, 1984).

A more realistic model, when focusing on the first stages of language development, considers both the production and perception mechanisms to be in continuous evolution in the infant. Referring to Figure 6.1, the infant at the same time:

- develops acoustic categories (perhaps on a statistical basis),
- compares parent's production to own production, in order to bias her originally random babbling towards language-specific events (*e.g.* syllables), and

- correlates acoustic to visual (and other sensory) information in an attempt to associate linguistic events to a representation of her environment (semantics).

The theoretical standpoint of ecological theories of language acquisition is the assumption that each of these tasks are performed on the basis of very few evolutionary principles, based on statistics and energetics. The latter is supported by a vast body of literature focusing on locomotion in various species, which shows how the locomotive strategies in both animals and humans are optimised in order to minimise energy consumption.

The three points listed above are likely to interact with each other. For example, the phonetic inventory (acoustic categorisation) in a language depends on the contrastive use the language makes of each speech sound. The emergence of acoustic categories is, therefore, guided, not only by the statistical occurrence of each sound (first point), but also by the attempt to relate the acoustic evidence to meaning (third point). This interaction was ignored in the study described in Paper F that only focuses on the first of the three points.

6.1 The Emergence of Speech Categories

The study described in Paper F is an attempt to model the way acoustic categories emerge on the basis of the child's exposure to the linguistic environment mainly produced by the parent's voice. The main constraints to the learning process are:

- learning should be unsupervised because we do not want to assume innate information about speech sounds,
- learning should be incremental because the categorical perception improves with the child's increasing exposure to language, and
- the learning method should be compatible with the psycho-neurological processes that are likely to take place in the child's brain.

With regard to the last constraint, it is important to state the level of detail at which the modelling is aimed. Detailed computational models of neural systems are available for both supervised and unsupervised learning. Guenther and Bohland (2002) simulate the emergence of a phenomenon called Perceptual Magnet Effect (PME), first introduced by Kuhl (1991), in categorical perception of vowels with a self-organising map that closely resembles the functionality of a neural system; Sandberg et al. (2003) simulate in detail the functionality of the working memory, whereas Johansson et al. (2006) model the neurons in the mammalian visual cortex, just to give some examples.

In this phase of the project MILLE, however, the focus is on modelling the phenomenon *per se*, rather than its neurological implementation. Moreover, we are interested in modelling the phenomenon in its entirety rather than focusing on specific details. For this reason, and with the future aim of integrating this computational model into a larger system that would take into account other aspects

of language learning, the methods used are purely statistical. However, both the data representation and the properties of the algorithms are compatible with the real learning processes in many respects.

A problem that is in some respect similar to modelling the emergence of speech categories has been addressed in the last two decades in the field of automatic speech recognition (ASR). This is the data-driven optimisation of the sub-word units that constitute the building blocks of the ASR acoustic models (Holter and Svendsen, 1997; Deligne and Bimbot, 1997; Singh et al., 2002). In these studies, even though the sub-word units are derived from the data, rather than from phonetic knowledge, the target words are defined by orthographic transcriptions, making the methods supervised, from our perspective.

As discussed elsewhere in this thesis, when representing speech with regularly spaced acoustic feature measurements, the resulting feature vectors must be considered as sequences, rather than independent outcomes of some stochastic process. Furthermore, any attempt to relate these observations to meaning (*e.g.*, to build a phonological system out of a set of acoustic features), results in a variable-length sequence matching problem. In spite of this, the study presented in Paper F is limited to the classification of feature vectors in the feature space, and does not consider the time aspects of the problem. The focus here is on incremental, unsupervised classification.

A number of methods for clustering variable-length sequences have been introduced in Chapter 3. Most of the methods have been developed focusing on discrete observations, and are particularly appropriate for applications such as text clustering or gene analysis. None of the methods consider the problem of learning incrementally. Yet, they propose interesting concepts that should be further investigated when the emergence of syllable- and word-like sequences is taken into account.

6.2 Method

The speech signal is represented, as in the other studies in this thesis, by mel frequency cepstral coefficients (see Chapter 2). These are loosely related to the properties of the human ear (Davis and Mermelstein, 1980). Parameterisations that are more closely related to psychoacoustic phenomena exist (*e.g.* Hermansky, 1990; Skowronski and Harris, 2004) and may be considered in future studies. Given the nature of the study in Paper F, the conclusions obtained are likely to generalise to psychoacoustically-based features as well.

The method is based on Model-Based Clustering (Fraley and Raftery, 1998), described in Section 3.5. The algorithm has been modified according to Fraley et al. (2003), in order to account for incremental learning, and can be summarised in the following steps:

1. Start with a Gaussian model.

2. Get new data.
3. Adjust current model parameters to the new data.
4. Divide the new data into well-modelled and poorly-modelled points.
5. Try a more complex model adding a distribution for the poorly modelled points.
6. Choose the best model according to the Bayes Information Criterion (BIC). If the more complex model is best, go to 4; otherwise, go to 2.

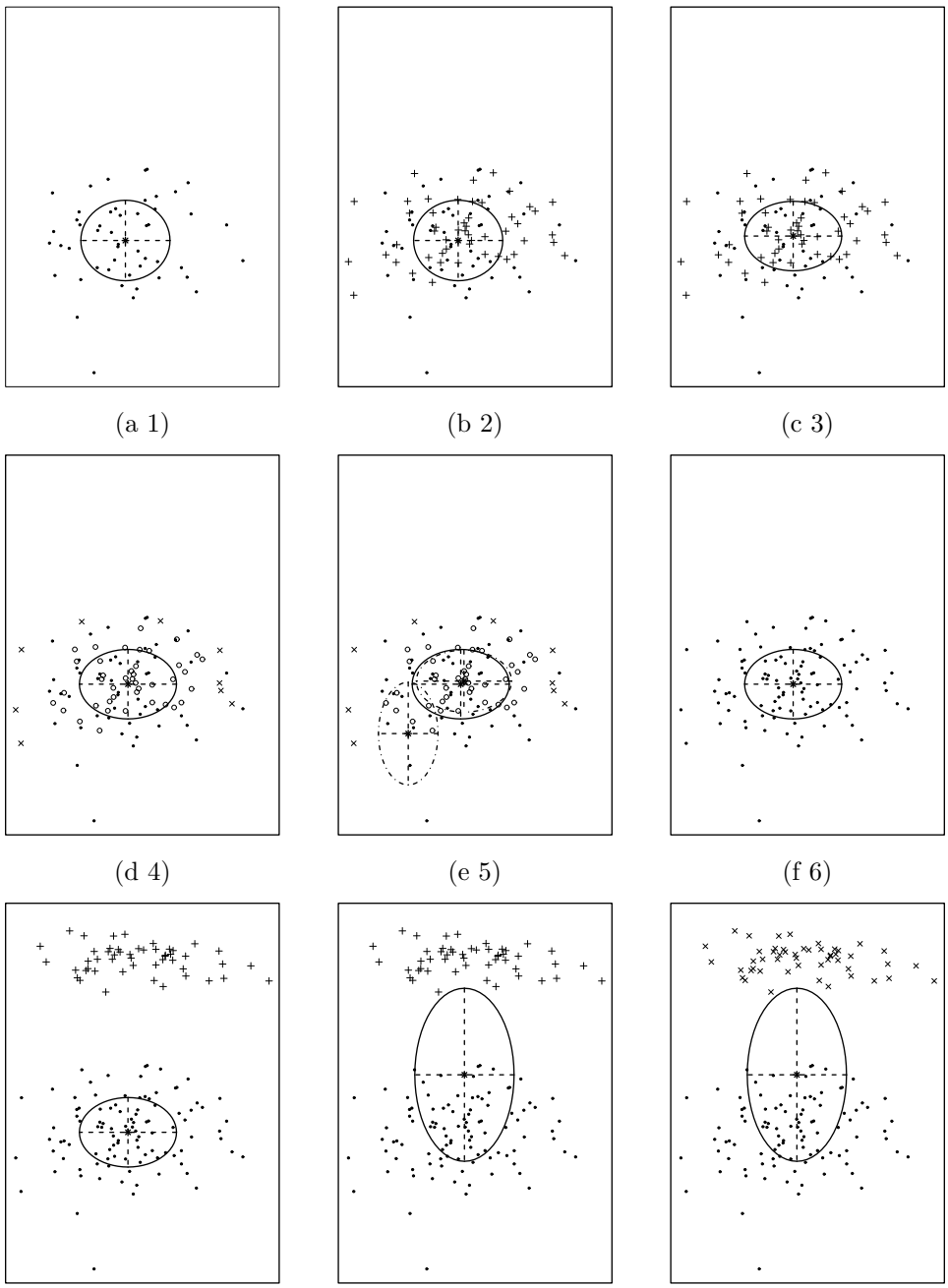
Figure 6.2 illustrates the algorithm with an example. Synthetic data points are drawn from two-dimensional distributions. Each plot is indexed in time by a letter (a–r). An additional number (1–6) refers, for each plot, to the corresponding step in the list above.

New data points are indicated by a "+", well-modelled points by "∘", and poorly-modelled points by "×". The current best model is indicated by one or more ellipses corresponding to the standard deviation of the bivariate multimodal Gaussian distributions. The alternative more complex model introduced by step 5 in the algorithm is represented by a dashed line. The sequence shown in the figures illustrates how the complexity of the best model incrementally follows the characteristics of the data.

6.3 Data

The data used in the experiments is a subset of the recordings done within the project MILLE. The interactions between infants and their parents (predominantly their mothers) are recorded using both the acoustic and visual channel. Conversations between the parents and adults have also been recorded as reference. Only the child-directed acoustic channel has been used in our experiments.

Using this kind of data, as opposed to traditional speech databases, ensures that the method is exposed to a similar environment as the child during learning. This is necessary because child-directed speech has peculiar characteristics if compared to adult-directed speech. The number of repetitions and the similarity of subsequent repetitions in child-directed speech seem to be optimised for facilitating learning. Also, the pseudo words that the parent makes up in their custom language seem to be an attempt to steer the child's random babbling towards syllable-like sequences and to facilitate the association between words and objects through onomatopoeia. An example is the utterance "brummeli, brummeli", which is often used in our material in association with a car toy.

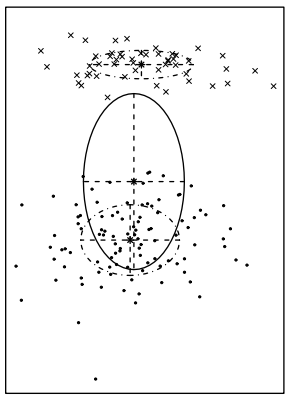


(a 1) (b 2) (c 3)

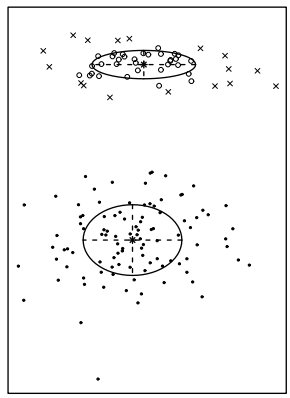
(d 4) (e 5) (f 6)

(g 2) (h 3) (i 4)

Figure 6.2: Illustration of the incremental clustering algorithm on synthetic bi-dimensional data. See the text for a thorough description.



(j 5)



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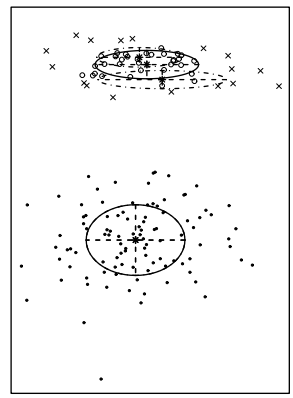

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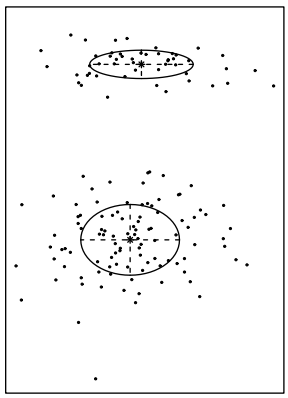

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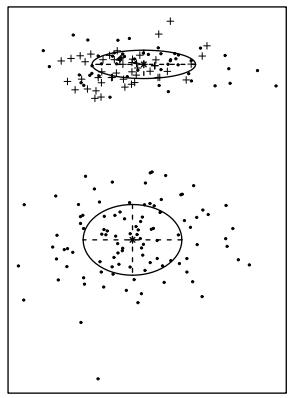
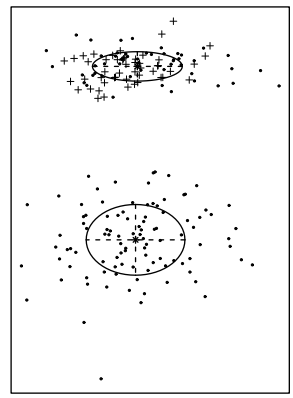
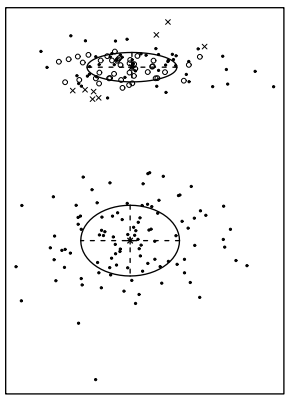


(n 2)



(o 3)



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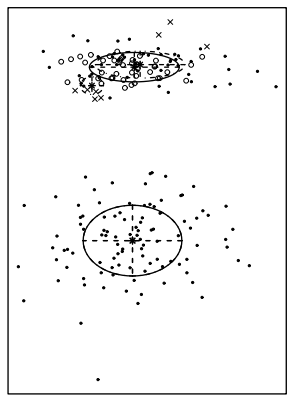

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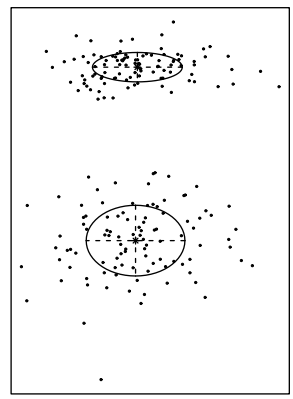

(r 6)

Figure 6.2: (continued)

6.4 Experimental Factors

The effects of two experimental factors have been investigated in the paper:

- The size of the data chunks that are incrementally presented to the algorithm ("frame length" in the paper).
- The size of the feature vectors that constitute a single observation ("number of coefficients" in the paper).

The first factor is related to the length of the auditory store that is available to the child for processing. This is an interesting factor in the light of the various theories on the existence of different auditory "buffers" with different sizes and properties (Cowan, 1984).

The second factor can be related to the amount of information carried by the auditory nerves from the cochlea to the auditory cortex. It is reasonable to assume that the child initially has a coarse perception of the sounds, mainly based on energy levels (or amplitude). This allows her to extract information that is mainly related to the prosody of the language. Later, the perception is refined and an increasing number of "coefficients" are adopted, allowing for a finer classification of the speech sounds.

6.5 Results of Paper F

Paper F is an exploratory study aimed mainly at observing the properties of incremental-model-based clustering on child-directed speech. Given the nature of the data and the task, the results should be compared to perceptual studies on the emergence of speech categories in children, in order to establish the model's predictive ability. The choice made in this study is to measure performance in a relative way by comparing the partitions obtained by the method when the experimental factors are varied. The measure of similarity between two partitions is based on information theoretical concepts described in Meilă (2002). This relative measure can validate the method in terms of stability, with regard to the experimental factors; however, it does not provide information on the method's ability to predict the perceptual data.

The simulations in Paper F show that although the size of the data chunks presented to the clustering algorithm has a relatively little effect on the clustering results, the number of coefficients play a fundamental role.

Another observation is that, in spite of the method not making use of time evolution information, the clusters obtained are stable in time.

The classifications obtained in different conditions, *e.g.*, with different sizes of the data chunks, are also in good agreement, in spite of the fact that the resulting partitions correspond to different total numbers of clusters.

Chapter 7

Discussion and Conclusions

7.1 General Discussion

Two main goals have been pursued in all cases. The first is the characterisation of speech sounds in statistical terms. The purpose of this characterisation has varied from speech recognition applications (Paper A), to the analysis of pronunciation variation (Papers D and E), to simulating the emergence of speech categories in infants (Paper F). The second goal that pervades these studies is the empirical analysis of machine-learning methods on real data over a wide range of problems, including supervised and unsupervised classification and regression.

In all cases, the continuous speech signal has been represented by equally spaced vectors of acoustic features,[1] which has highlighted one of the central problems in speech processing; that is, the need for modelling variable-length sequences.[2] Paper B addresses one aspect of this problem by analysing the behaviour of models that are commonly used in variable-length sequence classification, in specific conditions. Paper C contributes to the studies aimed at finding landmark points in the speech signal (in this case phonetic boundaries).

A common criticism of statistical machine-learning methods is that they provide "black box" solutions to practical problems, without adding any knowledge about the phenomena at hand. The studies described in part of this thesis (Papers D, E, and F) may contribute to showing that this is not necessarily the case, and that models obtained with machine-learning methods can be a valuable source of knowledge.

In the following, each paper is briefly summarised and discussed; see Chapters 4, 5, and 6 for more details.

[1] The fact that the same kind of features has been used consistently throughout this thesis is also a unifying aspect, but of secondary importance, because the methods employed are to a great extent independent of the features.

[2] In this respect, speech research shows similarities with, *e.g.*, gene classification research.

7.2 Paper A

The problem of mapping the acoustic speech signal onto a set of visible articulatory parameters is addressed in this paper. The articulatory parameters are used to animate an avatar that provides a visual aid to hearing-impaired persons using the telephone.

Two methods for acoustic to visual mapping have been investigated. Because both the acoustic signal and the articulatory parameters are represented by vectors of continuous measurements, the task of estimating each articulatory parameter is solved by the first method as a regression problem. The second method classifies the acoustic parameter vectors into visemes, *i.e.*, groups of sounds that share the same target values for the visual articulatory parameters. The parameter trajectories are, in this case, obtained by interpolation of the target values. These two strategies have been implemented by means of recurrent neural networks for regression and hidden Markov models for classification.

The classification method gave a number of advantages over the regression method, mainly because of the lower number of degrees of freedom in this task: in case of correct classification, somewhat stereotypical movements are produced, which simplifies the task of lip reading by the listener; the target values of some critical parameters (such as bilabial occlusion) are fully reached, reducing ambiguity of the movements; the interpolation procedure produces smooth trajectories that are pleasant to see.

An improvement to the regression method could be obtained by imposing constraints on the possible outcome of the mapping function and by smoothing the outputs of the neural network.

7.3 Paper B

Hidden Markov models are widely used in speech recognition. The Markov chain model specifies the time evolution of the speech production process, whereas the state-to-output probability models specify the relationship between states and acoustic observations (feature vectors). When using recurrent neural networks (RNNs) to estimate the state-to-output probabilities, a potential conflict emerges due to the fact that the time evolution model learned by the RNN can be in contrast with the Markov chain structure.

Paper B analyses this phenomenon in a phoneme recogniser with low-latency constrains. The results reveal an interaction between the two dynamic models. The degree of interaction depends both on the complexity of the RNNs and on the length of time dependencies in the Markov chain.

7.4 Paper C

Paper C analyses the phonetic boundaries obtained by the SynFace phoneme recogniser under low-latency constraints. A neural network estimates the posterior probabilities of a phonetic class given the acoustic feature vector (observation). The entropy of the probability estimates is studied in relation to the proximity to a phonetic boundary. Visual investigation shows that the entropy as a function of time assumes local maxima at phonetic boundaries. Results over a number of test sentences confirm that the entropy tends to be higher close to a boundary, even if variation due to other factors is large. The first and second derivatives of the entropy also carry information about the proximity to a boundary. Later studies, not included in this publication, show that the phonetic boundaries can be predicted within 20 msec, with 86.4% precision and 76.2% recall based only on entropy measurements.

7.5 Paper D

Pronunciation variation related to geographical factors is the topic of Paper D. A method is proposed to analyse large amounts of speech data that have not been transcribed at the phonetic level. Automatic speech recognition (ASR) techniques are used to fit a statistical model of the spectral features for each phoneme to the data containing recordings from 5000 speakers. The analysis is then performed on the model parameters, rather than on the data points, with the help of a measure of dissimilarity between probability distributions. Agglomerative hierarchical clustering is used to visualise the results and analyse the groups of similarities that emerge from the data. A few examples are shown where the clusters emerging from this procedure clearly correspond to well-known phenomena of pronunciation variation in Swedish.

7.6 Paper E

Paper E is an extension of Paper D in several respects. The statistics for three segments of each phoneme (initial, middle and final) are considered independently to take into account the dynamic properties of each phonetic segment. The agglomerative clustering procedure is performed on the full pool of distributions, allowing allophones of a certain phoneme to group with allophones of other phonemes, based on their acoustic similarity. An attempt to establish the optimal number of clusters in the data is discussed in the paper. Cutting the clustering tree (dendrogram) at any point results in two groups of distributions. Linear Discriminant Analysis is used to find the spectral characteristics that best explain acoustic differences between the groups so obtained. The results are, in most cases, in agreement with those in Paper D. They also show that the accent variable has usually a weaker influence on the acoustic feature that the phoneme identity and the position within

a phoneme. A few exceptions to this correspond to the cases where the allophonic variation *within* a particular phoneme exceed the variation *between* different phonemes.

7.7 Paper F

An incremental version of Model-Based Clustering has been used to simulate the unsupervised emergence of acoustic speech categories in the early stages of language acquisition in an infant. Preliminary experiments are performed using recordings from a mother talking to her child. The effect of two parameters are considered: the dimensionality of the acoustic features used as observations and the number of data vectors that are presented to the method at each step of the incremental learning procedure. The results are analysed in terms of number of acoustic categories as a function of time and by comparing the classifications obtained in different conditions with an information theoretical criterion. The results show that the acoustic categories emerging from the data are to a high degree consistent across the different experimental conditions. The classes are usually stable in time, *i.e.*, consecutive frame vectors belong often to the same class. The total number of classes is strongly dependent on the dimensionality of the acoustic feature frames, but only weakly dependent on the size of the data chunks incrementally presented to the method.

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Appendix X

Phonetic and Viseme Symbols

In the papers included in this thesis different phonetic symbols are used depending on the focus of the work and on problems related to graphic software. This appendix lists IPA (International Phonetic Alphabet) and SAMPA (computer readable phonetic alphabet) symbols for Swedish and British English with examples. A slightly modified version of SAMPA, here called HTK SAMPA, has been used during the experiments to overcome the limitations of the string definition in the HTK software package.

The definition of the visemic groups used in the Synface project are also given here using HTK SAMPA symbols. Different viseme classifications can be found in the literature with varying degrees of details. Fisher (1968), *e.g.*, defines broad classes based on confusions in perceptual studies. The definitions given here are from Beskow (2004) for Swedish and Siciliano et al. (2004) for English. They were developed in order to control the visual synthesis in the Synface avatar, and are therefore more detailed (22 classes for Swedish and 26 for English, including silence). Broader viseme definitions can be obtained by merging some of the groups presented here.

X.1 Swedish

Plosives, fricatives and sonorants

IPA	HTK SAMPA (SAMPA)	Example	Transcription	
			IPA	SAMPA
6 plosives				
p	p	pil	pi:l	pi:l
b	b	bil	bi:l	bi:l
t	t	tal	tɑ:l	tA:l
d	d	dal	dɑ:l	dA:l
k	k	kal	kɑ:l	kA:l
g	g	gås	go:s	go:s
6 fricatives				
f	f	fil	fi:l	fi:l
v	v	vår	vo:ɾ	vo:r
s	s	sil	si:l	si:l
ʃ	S	sjuk	ʃʉ:k	Suh:k, S}:k
h	h	hal	hɑ:l	hA:l
ç	C	tjock	çɔk	COk
6 sonorants				
m	m	mil	mi:l	mi:l
n	n	nål	no:l	no:l
ŋ	N	ring	ɾɪŋ	rIN
r	r	ris	ri:s	ri:s
l	l	lös	lø:s	lox:s, l2:s
j	j	jag	jɑ:g	jA:g

Vowels

IPA	HTK SAMPA (SAMPA)	Example	Transcription	
			IPA	SAMPA
9 long vowels				
i:	i:	vit	vi:t	vi:t
e:	e:	vet	ve:t	ve:t
ɛ:	E:	säl	sɛ:l	sE:l
y:	y:	syl	sy:l	sy:l
ʉ:	uh: (}:)	hus	hʉ:s	huh:s, h}:s
ø:	ox: (2:)	föl	fø:l	fox:l, f2:l
u:	u:	sol	su:l	su:l
o:	o:	hål	ho:l	ho:l
ɑ:	A:	hal	hɑ:l	hA:l
9 short vowels				
ɪ	I	vitt	vɪt	vIt
e	e	vett	vet	vet
ɛ	E	rätt	ɾɛt	rEt
ʏ	Y	bytt	bʏt	bYt
ɵ	u0	buss	bɵs	bu0s
œ	ox (2)	föll	fœl	foxl, f2l
ʊ	U	bott	bʊt	bUt
ɔ	O	håll	hɔl	hOl
a	a	hall	hal	hal

Allophones

IPA	HTK SAMPA (SAMPA)	Example	Transcription	
			IPA	SAMPA
important allophones				
æː	ae: ({:)	här	hæːɹ	hae:r, h{:r
œ̞ː	oe: (9:)	för	fœ̞ːɹ	foe:r, f9:r
æ	ae ({)	herr	hæɹ	haer, h{r
œ̞	oe (9)	förr	fœ̞ɹ	foer, f9r
ə	eh (@)	pojken	pɔjkən	pOjkehn, pOjk@n
ʂ	rs	fors	fɔʂ	fOrs
less frequent allophones				
ʈ	rt	hjort	jʉʈ	jUrt
ɖ	rd	bord	buːɖ	bu:rd
ɳ	rn	barn	bɑːɳ	bA:rn
ɭ	rl	karl	kɑːɭ	kA:rl

Visemes

name	phonemes
sil	sil fil sp spk
C	C j
A:	A:
e	E e E: eh
e:	e:
i:	I i:
oe	oe ox: ox oe:
u0	u0
ae	ae ae:
g	N g h k S
O	O

name	phonemes
rd	rd rn rs rt
U	U u:
Y	Y y:
a	a
o:	o:
b	b m p
d	d n t
f	f v
uh:	uh:
l	l rl r
s	s

X.2 British English

Plosives, affricates, fricatives and sonorants

IPA	HTK SAMPA (SAMPA)	Example	Transcription	
			IPA	SAMPA
6 plosives				
p	p	pin	pɪn	pIn
b	b	bin	bɪn	bIn
t	t	tin	tɪn	tIn
d	d	din	dɪn	dIn
k	k	kin	kɪn	kIn
g	g	give	gɪv	gIv
2 phonemic affricates				
tʃ	tS	chin	tʃɪn	tSIn
dʒ	dZ	gin	dʒɪn	dZIn
9 fricatives				
f	f	fin	fɪn	fIn
v	v	vim	vɪm	vIm
θ	T	thin	θɪn	TIn
ð	D	this	ðɪs	DIs
s	s	sin	sɪn	sIn
z	z	zing	zɪŋ	zIN
ʃ	S	shin	ʃɪn	SIn
ʒ	Z	measure	meʒə	mezeh, meZ@
h	h	hit	hɪt	hIt
7 sonorants				
m	m	mock	mɒk	mQk
n	n	knock	nɒk	nQk
ŋ	N	thing	θɪŋ	TIN
r	r	wrong	rɒŋ	rQN
l	l	long	lɒŋ	lQN
w	w	wasp	wɒsp	wQsp
j	j	yacht	jɒt	jQt

Vowels

IPA	HTK SAMPA (SAMPA)	Example	Transcription	
			IPA	SAMPA
6 "checked" vowels				
ɪ	I	pit	pɪt	pIt
e	e	pet	pet	pet
æ	ae ({)	pat	pæt	pae t, p{t
ɒ	Q	pot	pɒt	pQt
ʌ	V	cut	kʌt	kVt
ʊ	U	put	pʊt	pUt
1 central vowel				
ə	eh (@)	another	ənʌðə	ehnVDeh, @nVD@
13 "free" vowels				
iː	i:	ease	iːz	i:z
eɪ	eI	raise	reɪz	reIz
aɪ	aI	rise	raɪz	raIz
ɔɪ	OI	noise	nɔɪz	nOIz
uː	u:	lose	luːz	lu:z
əʊ	ehU (@U)	nose	nəʊz	nehUz, n@Uz
aʊ	aU	rouse	raʊz	raUz
ɜː	Eh: (3:)	furs	fɜːz	fEh:z, f3:z
ɑː	A:	stars	stɑːz	stA:z
ɔː	O:	cause	kɔːz	kO:z
ɪə	Ieh (I@)	fears	fɪəz	fIehz, fI@z
eə	eeh (e@)	stairs	steəz	steehz, ste@z
ʊə	Ueh (U@)	cures	kjʊəz	kjUehz, kjU@z

Visemes

name	phonemes
sil	sil fil sp spk
O:	O: Ueh
A:	A: aq
D	D T
I	I ih
ae	ae V ax e eh
g	N g h k
Ieh	Ieh
oh	oh Q
OI	OI
S	S Z dZ tS j
U	U
eI	eI

name	phonemes
u:	u:
b	b m p
d	d l n r t
f	f v
eeh	eeh
i:	i:
ehU	ehU
aI	aI
s	s
Eh:	Eh:
w	w
z	z
aU	aU

Part III

Papers

Paper A

Using HMMs and ANNs for mapping acoustic to visual speech

Tobias Öhman and Giampiero Salvi

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Using HMMs and ANNs for mapping acoustic to visual speech

Tobias Öhman and Giampiero Salvi

Abstract

In this paper we present two different methods for mapping auditory, telephone quality speech to visual parameter trajectories, specifying the movements of an animated synthetic face. In the first method, Hidden Markov Models (HMMs) were used to obtain phoneme strings and time labels. These where then transformed by rules into parameter trajectories for visual speech synthesis. In the second method, Artificial Neural Networks (ANNs) were trained to directly map acoustic parameters to synthesis parameters. Speaker independent HMMs were trained on an orthographically transcribed telephone speech database. Different underlying units of speech were modelled by the HMMs, such as monophones, diphones, triphones, and visemes. The ANNs were trained on male, female, and mixed speakers. The HMM method and the ANN method were evaluated through audio-visual intelligibility tests with ten hearing impaired persons, and compared to "ideal" articulations (where no recognition was involved), a natural face, and to the intelligibility of the audio alone. It was found that the HMM method performs considerably better than the audio alone condition (54% and 34% keywords correct, respectively), but not as well as the "ideal" articulating artificial face (64%). The intelligibility for the ANN method was 34% keywords correct.

A.1 Introduction

In the Teleface project at KTH, we have since 1996 investigated the possibility to use a synthetic face as a speech reading aid for hard-of-hearing persons during telephone conversation. The idea is to use the telephone speech to drive a synthetic face at the listener's end, so that it articulates in synchrony with the speech (Beskow et al., 1997). Earlier related studies where lip movements or face gestures have been generated from the auditory speech signal include work by Yamamoto et al. (1998); Masuko et al. (1998); Morishiba (1998).

The great advantage of using face gestures as the visual code is that it is often already trained by most people, either directly or indirectly, as they lipread as soon as the auditive signal is weak or disturbed. In previous work it was found that the intelligibility of VCV-syllables and everyday sentences was considerably increased, when the auditory speech signal was enriched by synthetic visual speech that was manually synchronised and fine tuned to become consistent with the audio (Agelfors et al., 1998).

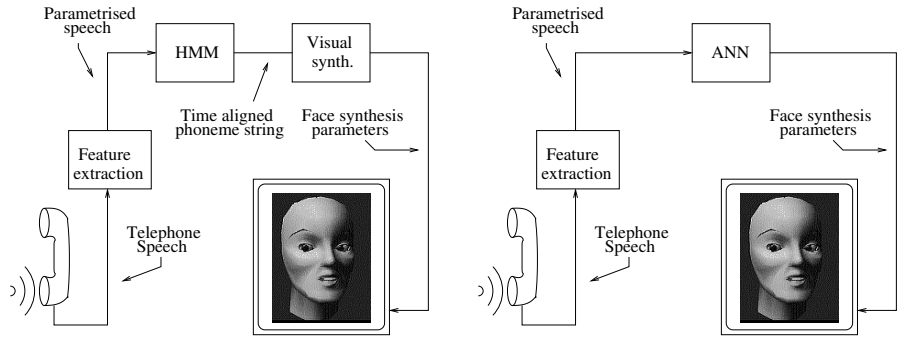

Figure A.1: The HMM method (left) and the ANN method (right) in the intended application where telephone quality speech is mapped to synthetic face movements at the remote side.

This paper describes implementation of algorithms to automatically derive the artificial facial articulations from telephone quality speech. We also present results from tests, where the audio-visual intelligibility of the stimuli created in this way is compared to the intelligibility of the stimuli used in previous tests and to the intelligibility of the audio alone.

In the rest of this paper, an ideal trajectory will refer to parameter values generated by visual speech synthesis rules, for which the input (phoneme strings and time labels) has been manually tuned to be perfectly synchronised and consistent with the audio. In contrast, the term target trajectory will be used when the input to the synthesis rules was generated by applying forced alignment on orthographically transcribed speech material.

A.2 Method

We have developed two methods for mapping the telephone quality speech to synthetic face movements (Figure A.1). Both methods make use of statistical models trained on the same speech material. Utterances containing single words and sentences were selected from the SpeechDat database (Höge et al., 1997). This subset of the database contains about 13,000 recordings of telephone speech from 1000 speakers. For training the HMMs and the ANNs we selected 750 speakers (433 females and 317 males, 14 hours of speech) using a controlled random selection algorithm (Chollet et al., 1998) in order to maintain the same gender and dialect proportions as in the full database. Two hundred of the remaining subjects were used for evaluation. Aligned phonetic transcriptions of the material have been obtained by forced alignment using the SpeechDat orthographic transcriptions. The 8 kHz sampled speech signal was parameterised into 10 ms frames of thirteen para-

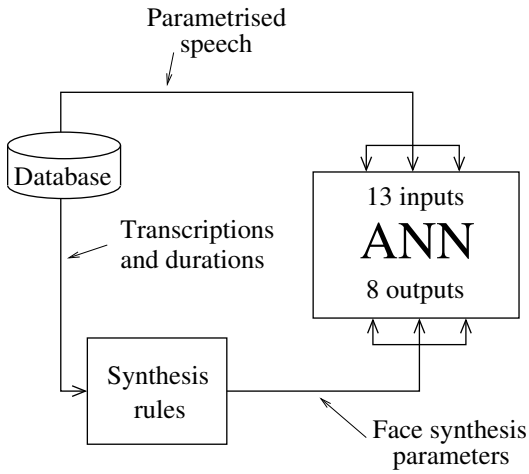

Figure A.2: Procedure to train the ANN. The target values are generated by applying the visual synthesis rules to phoneme strings, which are obtained by forced alignment.

meters (twelve mel-cepstral and energy), which were used as input to the systems. Dynamic parameters (delta and acceleration) were added for the HMM method.

The HMM method

In a first step, the acoustic signal is analyzed and the frames are classified by HMMs into phonetic units. The resulting time aligned transcription is in a second step converted into face parameter trajectories by a rule-based visual speech synthesis system (Beskow, 1995).

Even if HMMs are widely used in speech recognition, their application is usually based on the analysis of long segments of speech. Pure acoustic models, often representing short phonetic units, are concatenated according to grammatical rules into large HMMs. This imposes constraints to the problem that increase classification accuracy and may reduce computational load.

In the Teleface application the recognition task is unspecified, as the system is to be used in free conversational speech. This makes the use of grammatical and lexical constraints troublesome as a general grammar model and a complete lexicon would be required. Furthermore, the latency constraints imposed by the task, limit the effectiveness of language models with long time dependencies. For these reasons the modelling developed in this work is limited to short acoustic segments. The HMMs that model the speech units, are connected to each other in a way that allows any unit to follow any other in a *free loop*.

The result of an analysed utterance is a string of symbols and time stamps that serve as input to the visual speech synthesiser. Phonemes belonging to the same visual class (called viseme) result in the same visual parameter trajectories. For this reason, the classification accuracy is computed according to visemes, i.e. a recognised phone is considered to be correct if it belongs to the correct viseme.

All the experiments can be grouped in two main methods depending on whether the phone to viseme clustering is performed before or after recognition. The first method includes models for monophones and triphones. They are three or four states HMMs, trained on the SpeechDat material (Salvi, 1998) by using the HTK toolkit (Young et al., 1997). The observation probability distribution for each state is modelled by a weighted sum of up to eight Gaussians. In the case of triphone models, context information is taken into account when generating recognition hypothesis. In the attempt to reduce the size of the resulting recognition network, the possibility of using syllabic constraints has been tested, but did not give promising results. In the second method, viseme models are first created on the basis of the monophone models belonging to the same visual class. Each state contains one Gaussian term for each phoneme belonging to the viseme. The number of Gaussian terms is thus different for different viseme models. After retraining, these models have been improved by using up to sixteen Gaussian terms for each state.

The ANN method

An alternative to using the HMM method is to train ANNs to map the audio directly to parameter values of the synthetic face. In this way, no intermediate classification errors come in to play. Another possible advantage is that coarticulation is handled directly, without applying any rules.

To generate the target values for training the ANN, we ran the phoneme strings and time labels of the training speech (obtained by forced alignment) through the visual speech synthesis system. The resulting eight trajectories, one for each visual speech synthesis parameter, were then used for training (Figure A.2).

A three layered net, with thirteen units in the input layer, 50 units in the hidden layer and eight units in the output layer, was created using the NICO toolkit (Ström, 1997). The input speech parameters were the same as the static ones in the HMM method, and each output node corresponds to one visual synthesis parameter. Each layer was connected to the other two, and the hidden layer was also connected to itself (i.e. a recurrent network). A time-delay window of six frames (10 ms per frame) was used. This gives the net three frames of context, both forward and backward in time, for the parameter values at any frame. The total number of connections in the network was 15,636.

Three different speaker independent ANNs with the typology described above were trained on the same speech material as the HMMs; one for males, one for females, and one for mixed speakers.

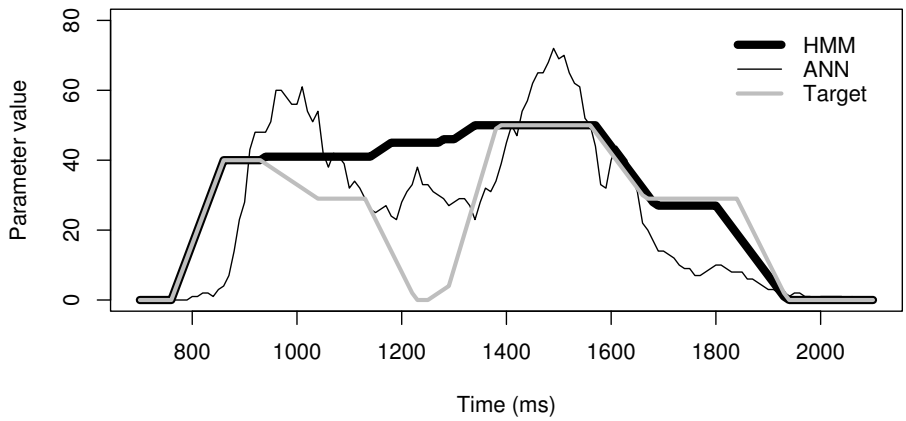

Figure A.3: Trajectories for the lip rounding parameter. The thick gray curve is the target trajectory obtained from the forced alignment.

A.3 Evaluation

Recognition accuracy of viseme classification was computed for different types of models (monophones, triphones and visemes). In the case of monophones and triphones, the clustering into visemes was done after recognition (post-clustering).

Results have shown that the pre-clustering method, in which models for visemes are employed, never performs as good as the post-clustering solution. The accuracy for monophones with eight mixtures is 47.0%, while visemes with sixteen mixtures obtain only 42.4% accuracy. The best results were obtained with triphones, modelled by eight mixtures (56.2%).

For the ANNs, accuracy scoring is not possible because there is a direct mapping of the audio to the face-synthesis parameters, and no classification is done.

When evaluating the results, we are not primarily interested in the classification of linguistic units. Rather we want to know how well the methods produce the articulations of the synthetic face, i.e. how well they produce the parameter trajectories. The evaluation is therefore done by referring to the target trajectories used as target values for the ANNs.

It is important to keep in mind that, in our study, those target trajectories were generated by applying the same synthesis rules as in the HMM method. These rules are not necessarily optimal for the application. Therefore, trajectories obtained from a perfectly recognized utterance, even if optimal (according to our evaluation method), may not be so regarding the end result, since they keep the limitations

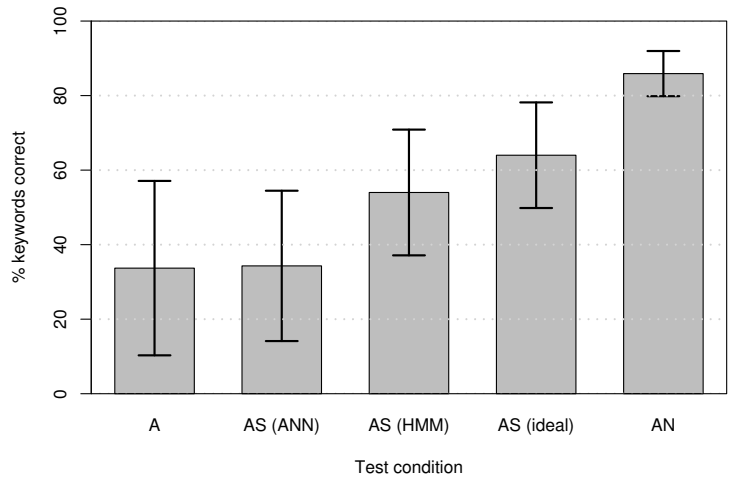

Figure A.4: Results of the intelligibility tests for the audio only condition, A, the audio presented together with the natural face, AN, and together with the synthetic face, AS, for which the parameter trajectories were ANN-generated, HMM-generated, or ideal. The bars show one standard deviation above and below the mean values.

which are intrinsic in the rule-based synthesizer. This is not the case for the ANN method, since the target trajectories may be obtained in any way, e.g. by manually adjustments or by re-synthesis from measurements of human speakers.

The differences between the methods can be visualized in Figure A.3, where the ideal trajectory for the lip rounding parameter is shown together with the trajectories obtained by the HMM method and the ANN method. For the HMM method, the result is perfect if the phonemes are recognized into the correct viseme classes (before 900 ms and after 1400 ms in Figure A.3).

However, when the recognition fails, the generated movements may be completely misleading (between 900 and 1400 ms in Figure A.3). The results from the ANN, on the other hand, are usually neither perfect nor completely wrong. The articulation is most of the time carried out in the right direction, but seldom all the way. For example, bilabial occlusion (one of the synthesis parameters) is often near, but never exactly, 100% for bilabials (which it should be). Since speech readers are sensitive even for small deviations in, e.g. bilabial occlusion, this is a serious drawback. Another characteristic feature for the ANN method is that, since it works on a frame by frame basis, the trajectories tend to become jerky, as can be seen in the figure.

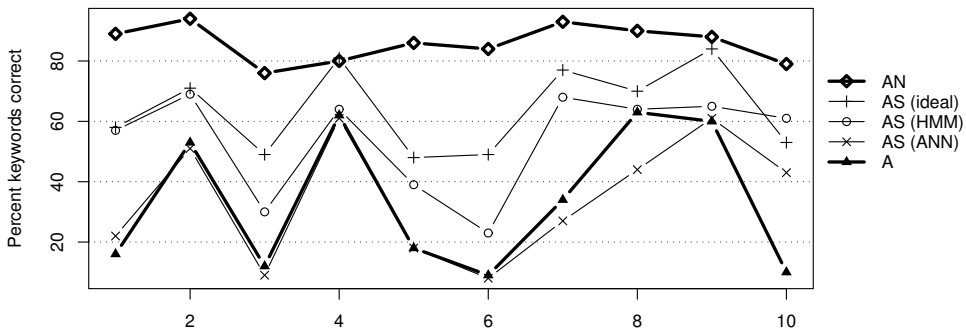

Figure A.5: Individual results for the audio only condition, A, the audio presented together with the natural face, AN, and together with the synthetic face, AS, for which the parameter trajectories were ANN-generated, HMM-generated, or ideal.

Intelligibility tests

The ultimate test of the two methods is to evaluate how they affect the audio-visual perception. For that reason, we have performed intelligibility tests to see how the end result is perceived and subjectively evaluated by humans. The subjects were ten hearing-impaired persons with a high motivation for using the synthetic face. All but one of the subjects have been active in previous tests. The visual stimuli were presented on a computer screen and the auditive stimuli were presented using a separate loudspeaker with the volume set to a comfortable level. During a few training sentences the subjects were allowed to adjust their hearing aid to obtain as good hearing as possible. The test material consisted of short everyday sentences (Öhman, 1998), specially developed for audio-visual tests by Öhngren at TMH based on MacLeod and Summerfield (1990). The sentences were presented without any information about the context. The subjects' task was to verbally repeat the perceived sentence. The number of correctly repeated keywords (three per sentence) were counted and expressed as the percent keywords correct.

Stimuli were presented in three basic modes: natural voice and no face (the audio only test condition, labeled A), natural voice and synthetic face (AS), and natural voice and video recordings of a natural face (AN). The natural voice used in all modes, and for the recognition, was filtered to a bandwidth of 3.7 kHz to simulate the audio quality of an ordinary telephone.

For the test condition with natural voice and synthetic face (AS), articulation for the synthetic face was prepared in three different ways. In the first method, the ideal rule-based trajectories were used. This is the way the articulation of the synthetic face has been created for our previous intelligibility tests. In the other two cases, the trajectories were obtained by the HMM and ANN method,

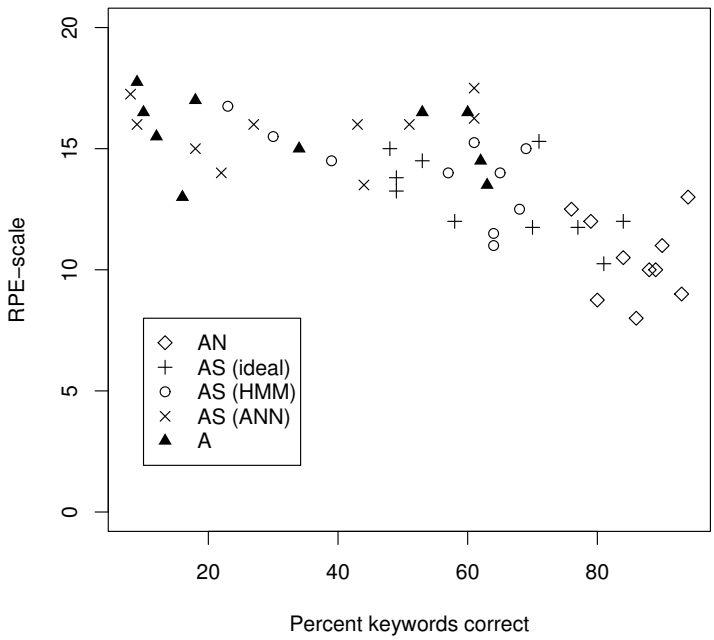

Figure A.6: Scatter plot of RPE values and intelligibility scores for the audio only condition, A, the audio presented together with the natural face, AN, and together with the synthetic face, AS, for which the parameter trajectories were ANNgenerated, HMM-generated, or ideal. The samples show a negative correlation ($|r| > 0.7$)

respectively. For the HMM method, we chose to use the triphone models, trained on both males and females. The ANN was a speaker independent net, trained on male speakers. Figure A.4 shows the result of the intelligibility test. Mean values from ten hearing-impaired subjects are presented, and the standard deviation (one above and one below the mean) is shown as vertical bars. The HMM method improved the intelligibility over the audio alone condition (54.0% keywords correct compared to 33.7%), and approaches the ideal rule-based condition (64.0%). The ANN method did not improve intelligibility significantly (34.3%). The audio-visual intelligibility with the natural face was nearly the same for all the subjects (85.9%), whereas it varied considerably for the other test conditions.

If we take a closer look at individual results for the ten subjects (Figure A.5), we see that in most cases the ANN method did not improve intelligibility over the audio alone condition, whereas the HMM method improved the intelligibility for

all but two subjects. We have performed binomial significant tests to see whether the difference is significant, rather than being a result of random variation. We found only two subjects for which the intelligibility of the ANN method differed significantly from the audio alone condition. For subject number ten, the ANN method was better (significance level < 0.01), and for subject eight, it was worse (significance level < 0.05). The HMM method was significantly better than the audio alone in six cases (significance level < 0.05).

The subjects were asked to complete a form regarding the subjective mental effort they experience when lipreading the different faces. The result of this form was transformed into the RPE-scale (Rating of Perceived Exertion), proposed by Borg (1982), and we found a negative correlation ($r < -0.7$) between the PRE value and the percent of correctly perceived keywords. Figure A.6 shows a scatter plot of this relation. In general the subjects experienced a high subjective mental effort for the audio alone condition and for the synthetic face when the movements were generated by the ANN or the HMMs. For the natural face, and to some extent for the synthetic face driven by ideal parameter trajectories, the effort was lower.

A.4 Discussion

In this paper we have presented two methods for generating the movements of an artificial face with telephone speech as input. In intelligibility tests, we have seen that the HMM method increases the percentage of correctly perceived keywords considerably compared to the audio alone condition. For the ANN method, the improvement compared to the audio only was not significant.

In this study, we did not process the output of the ANNs in any way. In future work, we will experiment with different filtering of the trajectories to smooth the movements of the synthetic face. Another possible way to improve the ANN method is to divide the parameters into smaller groups and train separate nets for each group. Current nets are trained for all eight parameters, including the parameters controlling the length and elevation of the tongue. These parameters are probably not as important as e.g. the parameters for rounding and bilabial occlusion. Since the ANN generated parameters are often not reaching its extreme values, a further possible improvement might be to expand the amplitude of the parameter trajectories.

Apart from improving details, the next important issue for our project is to implement the algorithms in real time.

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Paper B

Dynamic Behaviour of Connectionist Speech Recognition with Strong Latency Constraints

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Dynamic Behaviour of Connectionist Speech Recognition with Strong Latency Constraints

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Abstract

This paper describes the use of connectionist techniques in phonetic speech recognition with strong latency constraints. The constraints are imposed by the task of deriving the lip movements of a synthetic face in real time from the speech signal, by feeding the phonetic string into an articulatory synthesiser. Particular attention has been paid to analysing the interaction between the time evolution model learnt by the multi-layer perceptrons and the transition model imposed by the Viterbi decoder, in different latency conditions. Two experiments were conducted in which the time dependencies in the language model (LM) were controlled by a parameter. The results show a strong interaction between the three factors involved, namely the neural network topology, the length of time dependencies in the LM and the decoder latency.

B.1 Introduction

This paper describes the use of a hybrid of artificial neural networks/hidden Markov models (ANNs/HMMs) in a speech recognition system with strong latency constraints. The need for such a system arises from the task of classifying speech into a sequence of phonetic/visemic units that can be fed into a rule system to generate synchronised lip movements in a synthetic talking face or avatar (Beskow, 2004). As the aim is to enhance telephone conversation for hearing-impaired people (Karlsson et al., 2003), the round-trip transmission delay should be less than 500 ms to avoid problems with the turn taking mechanism (Kitawaki and Itoh, 1991). In our experience, to prevent this kind of difficulties, the total latency allowed between incoming speech and facial animation is limited to less than 200 ms. This includes the latency in capturing the sound and generating and animating the facial movements. The constraints imposed on the recogniser are thus especially demanding if compared to other applications of speech recognition.

In such conditions, and more in general in real-time applications, conventional decoders based on different flavors of the Viterbi algorithm (Viterbi, 1967), can only be used in an approximate fashion. This is because the need for incremental results requires the best-path solution to be based on partial decisions, with limited look-ahead in time. The difference between the standard Viterbi solution and the approximated solution is often called "truncation error". Truncation error in the Viterbi algorithm has been extensively studied for convolutional codes in the

area of speech coding (Kwan and Kallel, 1998; Weathers, 1999). There, given the relatively simple nature of the problem, error bounds could be found analytically and confirmed empirically.

In speech recognition, a few empirical studies dealing with this problem can be found in the area of broadcast news recognition/transcription (e.g. Imai et al., 2000; Ljolje et al., 2000). In Ljolje et al. (2000) a system based on incremental hypothesis correction was shown to asymptotically reach the optimal MAP solution. In Robinson et al. (2002) connectionist techniques are employed in the same task. These studies are concerned with large vocabulary word recognition, and have less stringent latency constraints.

The aim of the current study is to analyse the effect of truncation errors at very low latencies (look-ahead < 100 ms) in different set-ups of the language model, while keeping phonetic recognition as the main focus for the application we have in mind. In connectionist speech recognition it is of particular interest to study the interaction between the time evolution model learnt by the time delayed or recurrent neural networks and the transition model imposed by the Markov chain, with varying look-ahead lengths.

The first experiment in this study does this by gradually changing the recognition network from a free loop of phones (short time dependencies) to a loop of words with increasing lengths. In the second experiment the language model (LM) is composed of a scaled mixture of a free loop of phones and a forced alignment topology where the time dependencies are as long as the utterance. The gradual modification of the LM is achieved in this second case by changing the mixing parameter. In addition, a confidence measure particularly suitable for connectionist models (Williams and Renals, 1999) is discussed. The reader also is referred to Salvi (2003) for an evaluation of the Synface recogniser in more realistic conditions.

The paper is organised as follows: a formal definition of the problem is given in Section B.2, Section B.3 introduces the method, Section B.4 the data and experimental settings. Results are described in Section B.5 and discussed in Section B.6. Section B.7 concludes the paper.

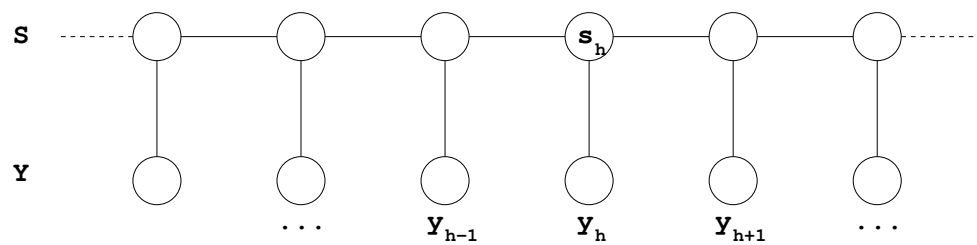

Figure B.1: Dependencies in a first order HMM represented as a *Bayesian network* graph

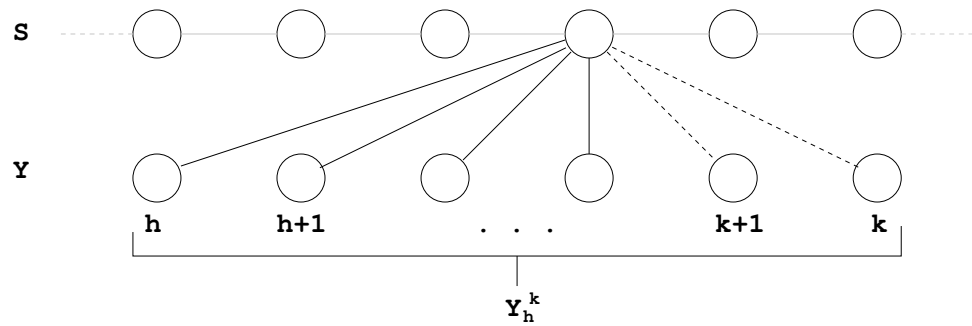

Figure B.2: Dependencies introduced by time dependent MLPs.

B.2 Problem Definition and Notation

Speech production in formulae

The process of speech production could be seen as one of encoding a sequence of symbols $X_1^M = (x_1, \cdots, x_M)$ into a sequence of states $S_1^N = (s_1, \cdots, s_N)$ with an associated output sequence $U_1^T = (u_1, \cdots, u_T)$. In our oversimplified description, X_1^M could represent phonetic classes, S_1^N are motivated by the dynamics introduced by articulatory gestures that in turn generate the speech signal U_1^T. Phonetic speech recognition is therefore the process of recovering the original sequence X_1^M on the base of some features $Y_1^N = (y_1, \cdots, y_N)$ extracted from U_1^T. When the feature extraction procedure is assumed to be given, as in the current study, the distinction between U and Y is not essential. Speech production is then a (stochastic) function of the kind: $P : X \rightarrow Y$. The natural choice for characterising this function is a Markov model Θ where the states s_i are assumed to vary synchronously with the features y_j, which explains why we indicated the length of S and Y with the same symbol N. Besides an *a priori* term, Θ is then fully specified by the distribution of state transition probabilities $a_{ij} = P(s_j|s_i)$ and the likelihood of the data generation given a certain state $b_i(Y_h^k) = P(Y_h^k|s_i)$. The usual assumption is to consider the latter as local models, in the sense that the state s_i at a particular time h influences the observation only at that time h: $P(Y_h^k|s_i) = P(y_h|s_i)$, as illustrated in Figure B.1. In this case, all the information about the dynamic evolution of the process under study is coded in the transition model a_{ij}.

State-to-output probability estimators

Robinson (1994) has shown how multi layer perceptrons (MLPs) can be efficient estimators for the *a posteriori* probabilities $P(x_i|Y_1^n)$ of a certain state x_i given an observation Y_1^n. A particularly efficient training scheme uses back propagation through time (Werbos, 1990) with a cross entropy error measure (Bourlard and

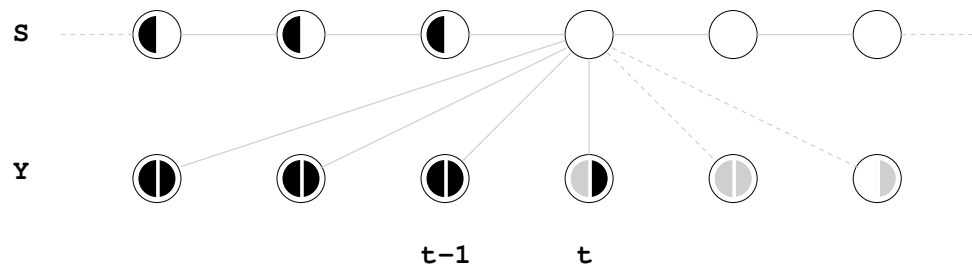

Figure B.3: Interaction between the δ and b terms in Viterbi decoding.

Morgan, 1993). If the nonlinearity in the units is in the tanh form, we can write for the state to output probabilities:

$$P(Y_h^k|x_j) = \frac{P(x_j|Y_h^k)P(Y_h^k)}{P(x_j)} \simeq \frac{o_j + 1}{2} \frac{P(Y_h^k)}{P(x_j)} \tag{1}$$

Where x_j is a phonetic class and o_j the activity at the output node corresponding to that class. The linear transformation in the formula $((o_j + 1)/2)$ is necessary to transform the tanh values, that span from -1 to 1, into probabilities. In the following we will refer to output activities of the MLP as the linearly transformed outputs that assume values in the range $[0, 1]$. Y_h^k is the sequence of feature vectors spanning a window of time steps that depends on the dynamic properties of the MLP. In the case of simple feed-forward nets, Y_h^k reduces to the current frame vector y_k, while for strict recurrent topologies (RNN), $h = 1$ and k is the current frame. This is illustrated in Figure B.2 that shows how the dynamic properties of the neural network can introduce dependencies between states and observations that span over a number of time steps. In Ström (1992) a mixture of time delayed and recurrent connections was proposed. In this model the input layer received contributions both from the past and the future frames thanks to time delayed connections with possibly negative delays (represented in the Figure by dashed lines). In this study, only positively delayed connections are considered, in order to reduce the total latency of the system.

Interaction between HMM topology and ANN dynamic properties

Given the probabilistic model Θ, the *maximum a posteriori* (MAP) solution to the speech recognition problem is the sequence X_1^M that maximises

$$P(X_1^M|Y_1^N, \Theta) = P(x_1, \cdots, x_M|y_1, \cdots, y_N, \Theta) \tag{2}$$

A more pragmatic solution, provided by the Viterbi algorithm, approximates the sum over all possible state sequences, implicit in Equation 2, with a maximum op-

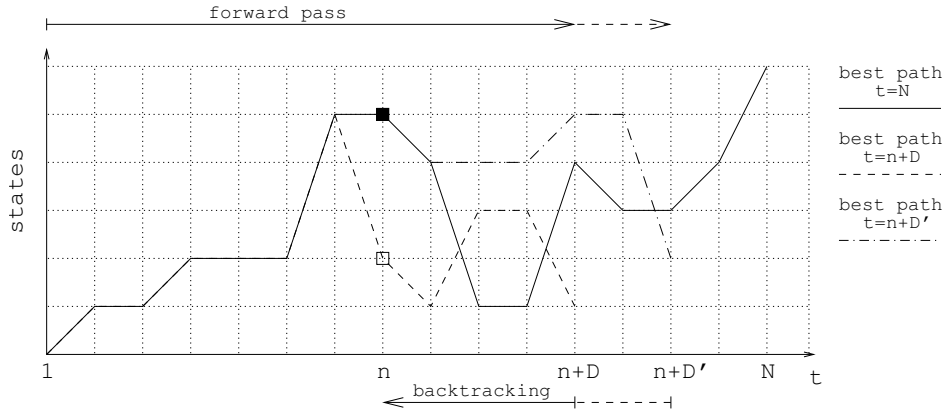

Figure B.4: Trellis plot in with three Viterbi paths (varying look-ahead length)

eration. Since in our model X_1^M is fully determined by S_1^N, the recognition problem is equivalent to finding the sequence S_1^N for which $P(S_1^N|Y_1^N, \Theta)$ is maximum. This can be done iteratively according to the Viterbi recursion formula:

$$\delta_t(j) = \max_i[\delta_{t-1}(i)a_{ij}]b_j(y_t)$$

Where $b_j(y_t) = P(y_t|x_j)$ is the likelihood of the current observation given the state and $\delta_t(j)$ is the Viterbi accumulator. In practice we substitute to $b_j(y_t)$ the estimate of $P(Y_h^k|x_j)$ given by Equation 1. In the case of recurrent MLPs, $P(Y_h^k|x_j)$ equals $P(Y_1^t|x_j)$ and the information contained by $\delta_{t-1}(i)$ and $b_j(Y_1^t)$ in the Viterbi recursion formula becomes widely overlapping. Figure B.3 illustrates this by indicating which states and observations the two terms in the Viterbi recursion formula depend on. Left semicircles refer to the term $\delta_{t-1}(i)$ and right semicircles to the term $b_j(Y_1^t)$. Grey semicircles are included if the MLP has negatively delayed connections.

As the two sources of information in the Viterbi recursion are strongly dependent, we expect the evidence brought by their joint contribution to be lower than the sum of each single contribution, as if they were independent.

Interaction between HMM topology and look-ahead length

When truncation is considered, the optimal solution at time step n is the state s_n extracted from the sequence $S_1^{n+D} = (s_1, \cdots, s_n, \cdots, s_{n+D})$ that maximises $P(S_1^{n+D}|Y_1^{n+D}, \Theta)$, where D denotes the look-ahead length in time steps. The difference between the two approaches is exemplified in Figure B.4. The grid displays the states as a function of time (trellis). The continuous line shows the Viterbi solution, while the dashed and dashed-dotted lines refer to the best path obtained using the partial information up to $t = n + D$ and $t = n + D'$, respectively. The figure

also illustrates a phenomenon that is common in practice: the influence of an observation at time t_1 over the result at time t_2 decays with the distance $D = |t_1 - t_2|$. In the example the observations in the interval $[n+D+1, n+D']$ influence the result at time n, as prolonging the look-ahead from D to D' leads to different results (open and filled squares). With respect to the solution at time n, however, adding the observations in $[n+D'+1, N]$ to the search mechanism does not change the response. As a result the truncated solution will in general asymptotically approach the standard Viterbi solution (filled square in this case) as D increases. The value D^* at which the two solutions become indistinguishable depends on the dynamic characteristics of the problem at hand, i.e. on the time correlations in Y and on those imposed by the transition model Θ.

B.3 Method

To evaluate the interaction between the language model, the properties of the probability estimators, and truncation in the Viterbi decoder, three-factor experiments were designed. The factors involved are: the length of time dependencies in the recognition network (*language model*), the dynamical properties of the *probability estimators* and the *look-ahead length*.

Language model

Varying the length of time dependencies in the language model (LM) was simulated in two different ways. In both cases, a different LM is used for each utterance, based on information contained in its transcription.

The first method consists of constructing the recognition network as the union of two topologies with transition weights scaled by a factor α:

$$\mathrm{LM}(\alpha) = \alpha \ \mathrm{AL} \ \cup \ (1 - \alpha) \ \mathrm{PL} \tag{3}$$

PL specifies a free loop of the phones included in the transcription for each utterance, while AL is the LM obtained by connecting in a sequence the phones specified by the transcription of each utterance. When $\alpha \to 0$ the grammar has the short time dependencies of a phone loop, when $\alpha \to 1$ the time dependencies are as long as the utterance, and the recogniser performs forced alignment. The parameter α assumes seven values in the experiments: $0, 0.1, 0.3, 0.5, 0.7, 0.9, 1$. This design will be referred to as the "alpha test".

In the second method, the LM defines a loop of words, where a word is defined by successively extracting N phones from the transcription of each utterance (see Figure B.5). For $N = 1$ the LM is again a loop of phones. The parameter N assumes the values from 1 to 7. To be noted here is that, since each phone is modelled by a three state Markov model, the lower bound to the time dependencies induced by this LM ranges from 3 to 21 frames in the experiments. This design will be referred to as the "wordlen test".

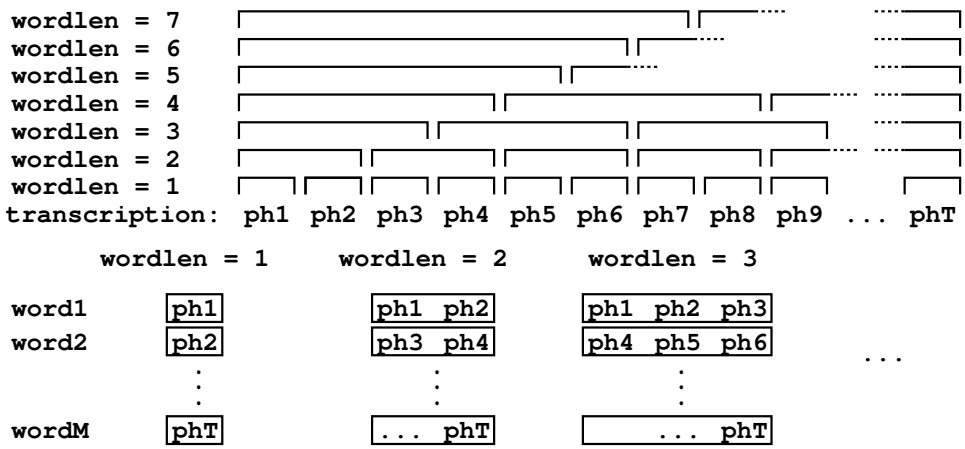

Figure B.5: Illustration of the "wordlen test" design: the transcription of each test utterance is spit into words of increasing lengths, that are used in the recognition network.

As already noted, the phone-loop condition ($\alpha = 0$ or $N = 1$) is obtained in the alpha and wordlen tests by selecting for each test utterance only those phones contained in its transcription. This was necessary to guarantee homogeneity with the other conditions ($\alpha \neq 0$ or $N \neq 1$), as the main objective of the experiment is to compare the different conditions, rather than computing an absolute performance score. When evaluating the recogniser from the perspective of the application, a loop of all phones should be used. This condition is analysed in Section B.5 as a reference.

A factor that turned out to be important in the evaluation of the different LMs, especially in the low-latency condition, is the phone-to-phone transition probability. In the phone-loop condition the transition probability from phone i to phone j is $1/N$ (the uniform case) where N is the number of phones. In the other conditions, the within-word phone-to-phone transition probability should in principle be 1, as each phone can only be followed by the next in the pronunciation model. This introduces terms that turned out to strongly affect the search mechanism, especially for low-latency conditions. The solution was to keep the same transition probabilities in both cases ($1/N$), releasing the constraint of a stochastic grammar (outgoing transition probabilities that sum to 1). This is a common practice in speech recognition where multiplicative and additive terms are usually applied to a subset of the transition probabilities, often corresponding to the language model. The aim is however different, as we are not directly interested in tuning the performance of the decoder, but rather in ruling out from the comparison factors that do not depend on the dynamic properties of the LM.

Probability estimators

The second experimental factor is the ability of the state-to-output probability models to express time variations. In this case, similarly to Salvi (2003), three multi layer perceptrons (MLPs) were used with different complexities and dynamic properties. One feed-forward MLP is considered as a static model, while two recurrent MLPs represent models capable of learning the time evolution of the problem (details in Section B.4).

Look-ahead length

The third experimental factor is the look-ahead length L that can be varied in our decoder. One problem is how to decode the last L frames at the end of each utterance. As every utterance begins and ends with silence, it was suggested in Salvi (2003) to decode the whole test set in a continuous stream, limiting the boundary problem only to the last file. Here, in contrast, each utterance is analysed separately and the result for the last L frames is assumed equal to the best path obtained when the forward phase has reached the end of the utterance. This is a somewhat more standard way of computing the Viterbi solution and was necessary to enable the use of a different language model for each utterance. Five values of the look-ahead length (in frames) were used in the experiments: 1, 3, 5, 10, 20.

Scoring method

The scoring method chosen for this study is frame-by-frame correct classification rate simply computed as the ratio between the number of correctly classified frames and the total number of frames. A correct classification occurs when a frame has been assigned the same phonetic class as in the transcription. This method was preferred to the more common minimum edit distance at the symbolic level, because the application we have in mind requires not only correct classification of the speech sounds, but also correct segment alignment. In Section B.5, phone-loop results are reported in terms of frame-by-frame correct classification rate, as well as accuracy and percent of correct symbols (Young et al., 2002) in order to compare these scoring methods.

Confidence measure

As noted in Williams and Renals (1999) the property of multi-layer perceptrons to estimate posterior probabilities, as opposed to likelihoods, is advantageous when computing confidence measures of the acoustic models. A simple measure of the acoustic confidence is the per-frame entropy of the k phone class posterior probabilities. Although the entropy measure, in Williams and Renals (1999), is averaged over a number of frames, we will consider a frame-by-frame measure. A factor that strongly influences the entropy measure is the choice of the target values during training of the networks. A common practice is to use $0+\epsilon$ and $1-\epsilon$, with small ϵ, as

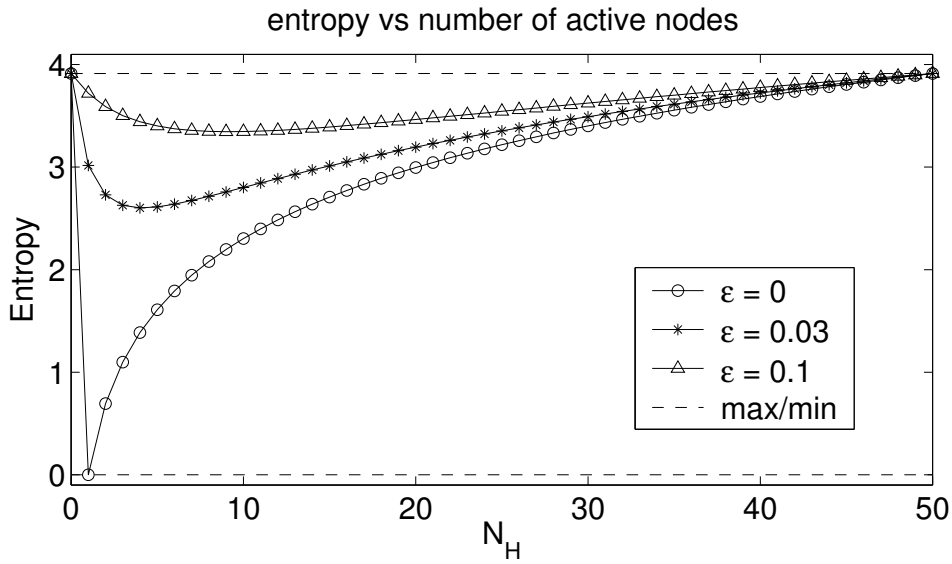

Figure B.6: Simulation of entropy of a distribution with N_H high levels

target values, in order to speed up the convergence in the standard back propagation algorithm (Note that when using tanh squashing functions, the limits are internally -1 and 1, and the above discussion refers to the linearly transformed outputs of the network, see also Equation 1). As a consequence, the networks trained this way are more noisy in the sense that the activities of the inactive output nodes seldom fall below $0 + \epsilon$. Strictly speaking, this also gives incorrect posterior probabilities estimates.

To show the effect of the target values on the entropy measure we consider a simplified example. We assume that the activities of the output nodes of the network trained with target values o_H (active) and o_L (inactive), can only assume those values when the network is excited by new input. In reality the activities take any value in between and sometimes even outside the range $[o_H, o_L]$. Even if the network is trained with only one active output node per time step, there will be, during excitation, a number N_H of simultaneously active nodes. If we call N_L the number of inactive nodes ($N_H + N_L = N$ is the total number of output nodes), then, from the definition of the entropy:

$$H = -N_H b_H \log b_H - N_L b_L \log b_L \tag{4}$$

where b_H and b_L are the normalised activities obtained imposing that the sum of probabilities be 1:

$$b_H = \frac{o_H}{N_H o_H + N_L o_L}, \quad b_L = \frac{o_L}{N_H o_H + N_L o_L}$$

In the case of symmetrical values, i.e. $(o_L, o_H) = (\epsilon, 1-\epsilon)$, Equation 4 assumes the form:

$$H = \log(N_H(1-\epsilon) + N_L\epsilon) - \frac{N_H(1-\epsilon)\log(1-\epsilon) + N_L\epsilon\log\epsilon}{N_H(1-\epsilon) + N_L\epsilon}$$

When $\epsilon \to 0$ ($o_H \to 1$ and $o_L \to 0$), the entropy H tends to $\log(N_H)$, as easily seen in the formula. In Figure B.6 the entropy is plotted as a function of the number of active nodes N_H, for the cases $\epsilon = 0, 0.03, 0.1$, and for $N = N_H + N_L = 50$ as in our networks. The figure shows how the entropy of the output of a network trained between 0 and 1, given our assumptions, spans the whole range from 0 to $\log N$, while the network trained between ϵ and $1-\epsilon$ has a more limited range in the high entropy region. The range strongly depends on ϵ. In our experiments one network was trained with $[0, 1]$ targets and the other two with $[0.1, 0.9]$ targets ($\epsilon = 0.1$).

In Section B.5 the impact of ϵ on the entropy based confidence measure is discussed with examples on the test data.

B.4 Data

The experiments were performed on the Swedish SpeechDat corpus (Elenius, 2000), containing recordings of 5000 speakers over the telephone. The official training and test sets defined in SpeechDat and containing respectively 4500 and 500 speakers, were used in the experiments. Mel frequency cepstrum features were extracted at 10 ms spaced frames.

The training material for the neural networks, and the test material were restricted to the phonetically rich sentences. The training material was further divided into training and validation sets of 33062 and 500 utterances respectively. The test set contains 4150 utterances with an average length of 40.9 phonemes per utterance. Figure B.7 shows the distribution of the length of the test utterances in terms of number of phonemes.

One problem with the SpeechDat database, that is important when training the MLPs and for testing at the frame level, is the unbalanced amount of silence frames compared to the amount of material for any phonetic class. Part of the silence frames that were concentrated at the beginning and at the end of each utterance, was removed.

Since the dataset lacks phonetic transcriptions, some pre-processing was necessary. The time-aligned reference, used for both training and testing the MLP models, was obtained with forced alignment employing the word level transcriptions, the official SpeechDat lexicon and triphonic HMMs based on Gaussian models. The HMMs were trained with the procedure defined in the RefRec scripts (Lindberg et al., 2000). The alignment lattice allowed non speech sounds to be inserted between words. The method proved to be reasonably accurate for our purposes.

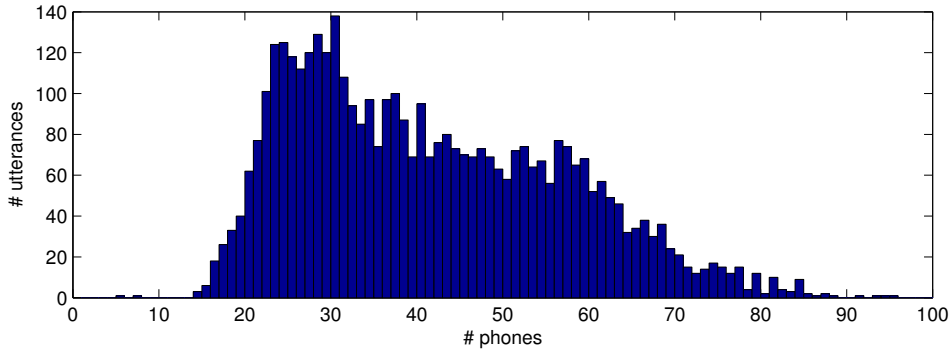

Figure B.7: Distribution of the length of the test utterances in terms of number of phonemes.

Table B.1: Details on the Acoustic Models and Frame-by-frame MAP results

model	# params	# hidd.units	# hidd.layers	recurrent	% correct frame
`GMM`	379050	-	-	-	35.4%
`ANN`	186050	800	2	no	31.5%
`RNN1`	185650	400	1	yes	49.6%
`RNN2`	541250	400	1	yes	54.2%

Acoustic Models

Three multi-layer perceptrons were used in this study. The first (`ANN`) is a feed-forward network with two hidden layers of 400 fully connected units each. `RNN1` and `RNN2` are recurrent networks with one hidden layer of 400 units and a varying number of time delayed connections. The choice of topology in `ANN` aimed at ensuring a comparable complexity (in number of free parameters) between `ANN` and `RNN1`.

As a reference, results obtained with a set of Gaussian mixture models (`GMM`), are reported together with the multi-layer perceptrons results. The `GMM` results show the discriminative power of the set of Gaussian models, when the phonetic class with the maximum *a posteriori* probability (MAP) is selected for each frame. The Gaussian mixture parameters where estimated using the HMM training with 32 Gaussian terms per state.

Details on the acoustic models are reported in Table B.1. The table shows the overall number of parameters, and, in the case of the perceptrons, the number of hidden layers and hidden units and the dynamic characteristics. The last column reports the correct frame classification rate when the maximum *a posteriori* class was selected frame-by-frame.

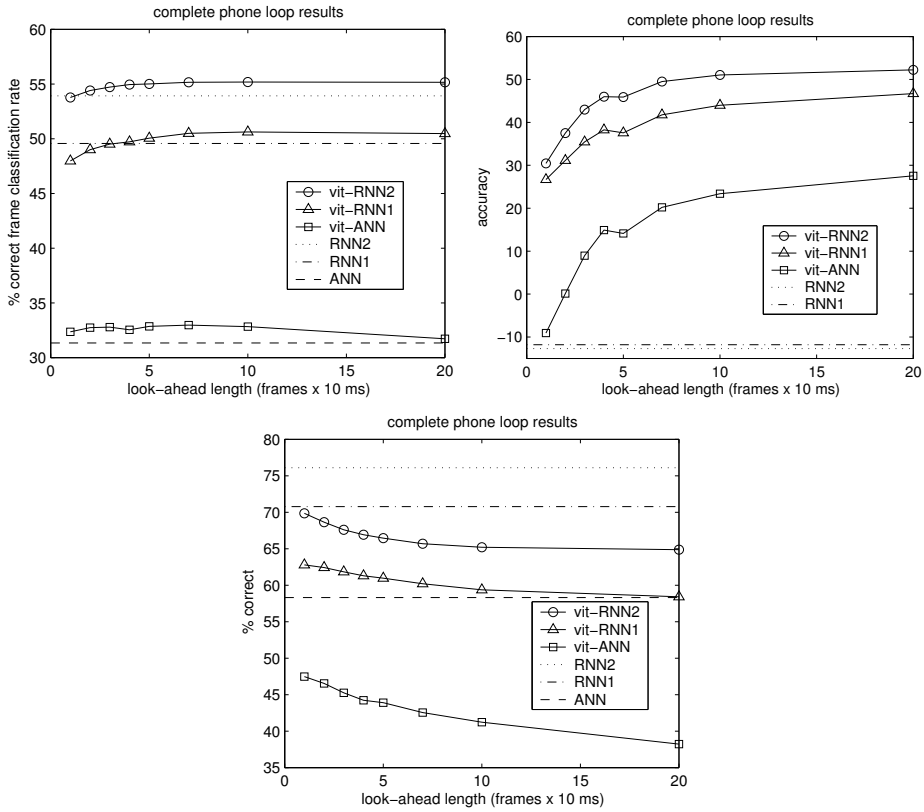

Figure B.8: Phone loop results

Implementation note

The HMM training was performed using the HTK Toolkit (Young et al., 2002). The MLP training algorithm was implemented in the NICO Toolkit (Ström, 1996). The modified Viterbi algorithm is the decoder used in the SYNFACE project (Salvi, 2003; Karlsson et al., 2003), and, together with the other tools used in the experiments, was implemented by the author. The statistical analysis was performed using the R software (R Development Core Team, 2003). All experiments were performed on a GNU-Linux platform running on standard hardware (PC).

B.5 Results

Results obtained with a normal phone loop are reported in Figure B.8 as a reference to the performance of the recogniser in the real task. The left plot in the figure

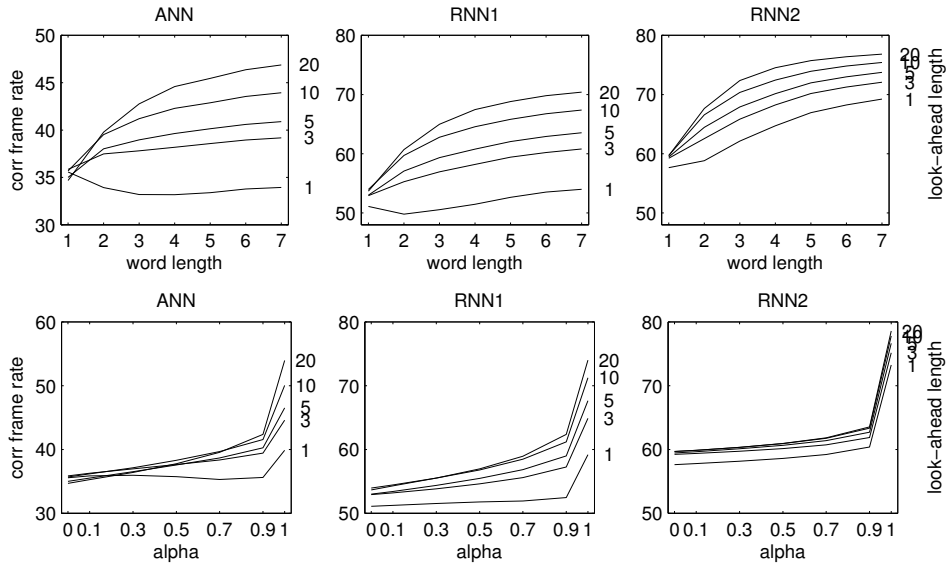

Figure B.9: Summary of "wordlen" (top) and "alpha" (bottom) results

shows the average correct frame classification rate over the 4150 test utterances for varying look-ahead length and for the three neural networks (`vit-ANN`, `vit-RNN1` and `vit-RNN2`). The horizontal lines in the figure indicate the classification rate without Viterbi decoding, i.e. selecting the highest activity output at each frame (frame-by-frame maximum a posteriori). The results are very close to the ones obtained in Salvi (2003), the differences being due to the way the boundary effects are handled (see Section B.3), and to the fact that in Salvi (2003) a global score was computed over the whole test material, while here we compute the correct frame classification rate of each utterance and then average the results.

The middle and right plots in Figure B.8 show the accuracy and percent of correct words as defined in (Young et al., 2002). These results are reported in order to compare the three scoring methods, and to mention that none of them are fully satisfying given the application. Accuracy and correct words do not take into account segment boundary alignment in time and were therefore discarded in the following evaluation. Correct frame classification rate, in contrast, does not indicate how stable the result is (number of symbol insertions).

The "wordlen" and "alpha" tests results are summarised in Figure B.9. In the first case (top) the average correct frame rate is plotted as a function of the word length in the "wordlen" test for different values of the look-ahead length and for the three multi-layer perceptrons. In the second case (bottom) the x-axis indicates the α parameter in the "alpha" test. Note that the range of the y-axis in the `ANN` case is different from the other two.

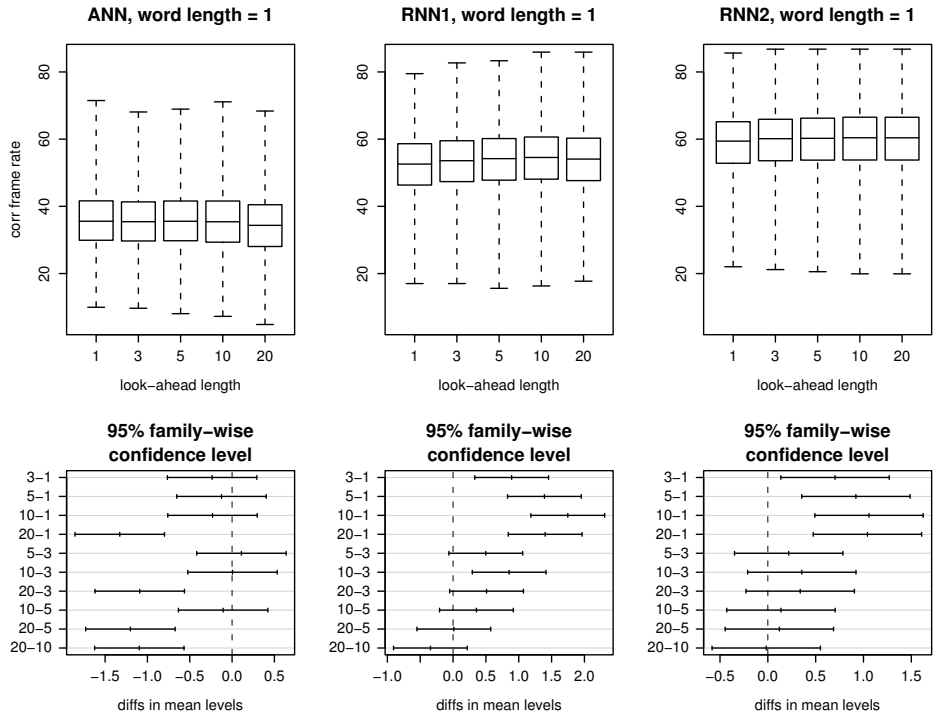

Figure B.10: Box-plots (top) and 95% family-wise Tukey confidence intervals (bottom), word length = 1

Longer time dependencies in the language model (LM) and longer look-ahead lengths are beneficial in most conditions, as most of the curves increase monotonically and do not overlap. Exceptions to this are the conditions in which the static model `ANN` is used in conjunction with either a short time LM or a short look-ahead length. In those cases, more irregular results can be found (see left plots in the Figure). Examples are the fluctuating results corresponding to different look-ahead lengths when wordlen = 1 or $\alpha = 0$ (top-left and bottom-left plots) and the non-monotonic variation of the score with respect to the word length and α when the look-ahead length is one frame (top-left and bottom-left plots). The last phenomenon can be found also in the `RNN1` case (top-middle plot).

In the following, these results will be analysed in details with statistical means.

Wordlen test: short to long time dependencies

Figure B.10 (top) shows box plots for the phone-loop case (word length = 1) for different look-ahead lengths. The middle line in the box displays the median, while

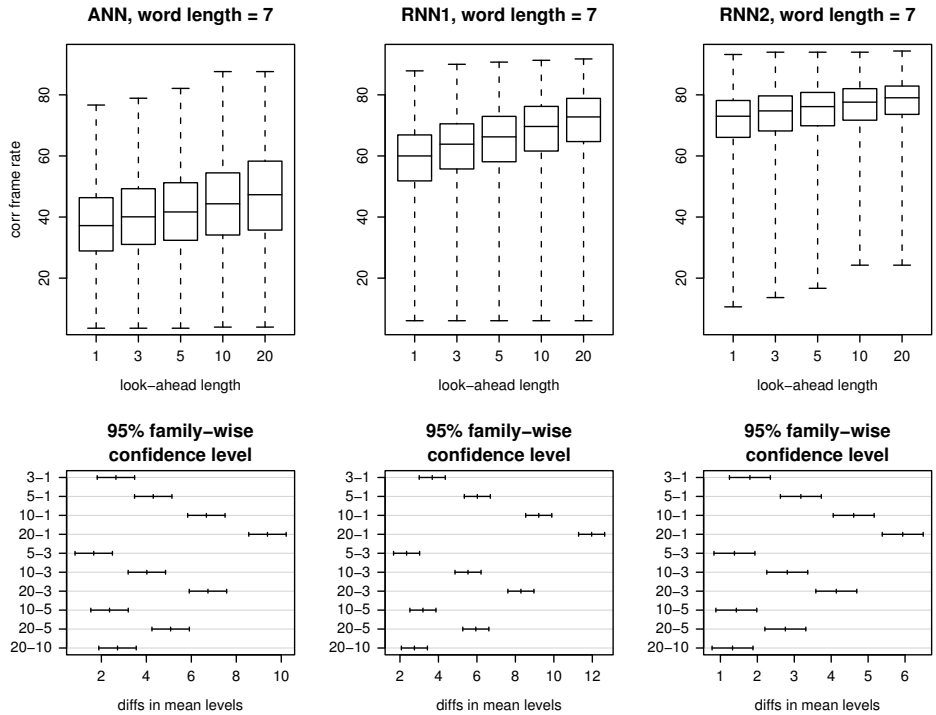

Figure B.11: Box-plots (top) and 95% family-wise Tukey confidence intervals (bottom), word length = 7

the lower and higher lines, called lower and higher hinges, display respectively the first and third quartiles. The lower and higher whiskers show the full range of the data. It is not clear in the `ANN` case, whether the use of longer look-ahead is beneficial to the recognition score. In `RNN1` and `RNN2` there is a slight improvement along increasing look-ahead lengths. Applying an ANOVA to the data returns significant differences in all the three cases (respectively for `ANN`, `RNN1` and `RNN2`: F(4,20745) = 15.31, 21.79, 8.96; p = $1.65\text{x}10^{-12}$, $<2.2\text{x}10^{-16}$, $<3.1\text{x}10^{-7}$). A successive Tukey multiple comparison test is visualised in Figure B.10 (bottom). The figure indicates the 95% family-wise intervals for all possible combination of the values of the look-ahead factor. The difference between condition x and y is indicated by $x - y$ that is the increase in correct frame rate going from look-ahead length y to x. If an interval crosses the zero line, the differences between the two conditions are not significant.

There are significant differences in `ANN` but with negative signs. In `RNN1` the difference $10 - 3$ and all differences between $L = 1$ and $L \neq 1$ are significant.

Table B.2: Wordlen test: Tukey HSD multiple comparison results

ANN										
wordlen	3-1	5-1	10-1	20-1	5-3	10-3	20-3	10-5	20-5	20-10
1	n	n	n	-	n	n	-	n	-	-
2	+	+	+	+	+	+	+	+	+	n
3	+	+	+	+	+	+	+	+	+	+
4 to 7 equal to 3										
RNN1										
wordlen	3-1	5-1	10-1	20-1	5-3	10-3	20-3	10-5	20-5	20-10
1	+	+	+	+	n	+	n	n	n	n
2	+	+	+	+	+	+	+	+	+	+
3 to 7 equal to 2										
RNN2										
wordlen	3-1	5-1	10-1	20-1	5-3	10-3	20-3	10-5	20-5	20-10
1	+	+	+	+	n	n	n	n	n	n
2	+	+	+	+	+	+	+	+	+	+
3 to 7 equal to 2										

Finally in RNN2 only the $L = 1$ condition seems to be distinguishable from the others.

On the other end of the word length parameter values (wordlen = 7), the information carried by the transition model, and the Viterbi processing has a stronger effect on the feed-forward perceptron. Figure B.11 (top) shows the corresponding box plot. The differences are significant in all cases (respectively for ANN, RNN1 and RNN2: $F(4,20745) = 281.32, 707.16, 262.17$; $p = <2.2\text{x}10^{-16}$). Multiple comparison leads to significance in every difference as illustrated by Figure B.11 (bottom). Of the consecutive distances, $3-1$ is always the greatest. In ANN and RNN1, $10-5$ is greater than $5-3$.

Table B.2 summarises the results for intermediate word lengths. A plus sign in a x-y column indicates a positive significant difference between the latency conditions y and x, a minus sign indicates a significant negative difference and, finally, "n" no significant difference.

Alpha test: short to long time dependencies

Experiments carried out with the "alpha" test show similar results to the "wordlen" test. In the phone loop condition ($\alpha = 0.0$) the language model is equivalent to the one in the "wordlen" test with word length 1 (see previous section). Figure B.12 shows the intermediate condition $\alpha = 0.5$. In the ANN case the $3-1$, $5-1$ and $10-1$ differences are significant and positive, while the $20-10$ difference is significant but negative. RNN2 shows clear significant differences when changing from 1 frame to

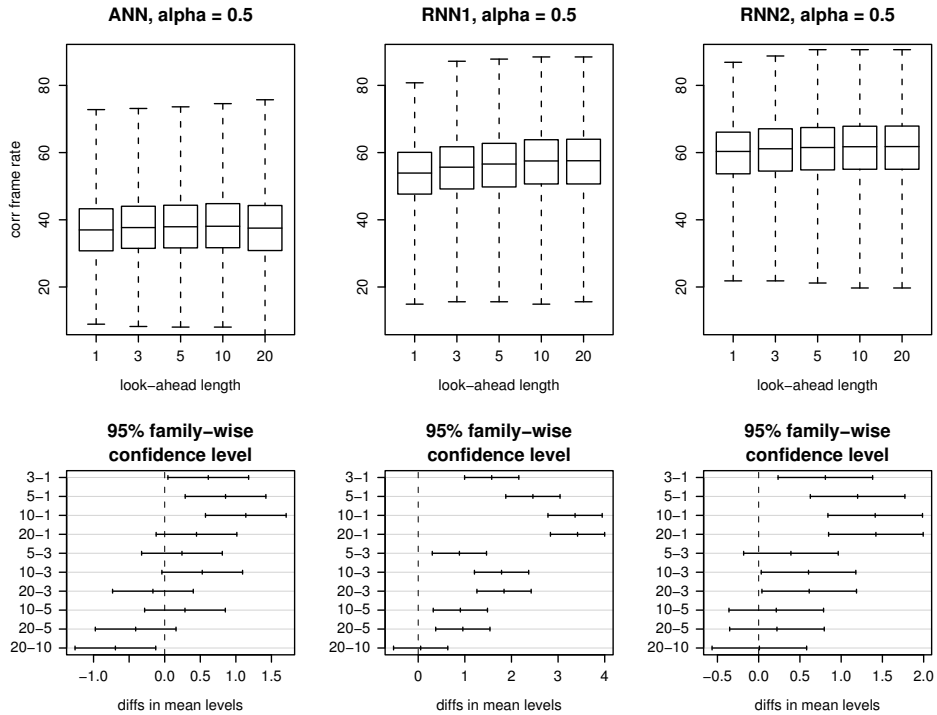

Figure B.12: Box-plots (top) and 95% family-wise Tukey confidence intervals (bottom), alpha = 0.5

longer look-ahead. The $5-3$ and $10-3$ differences are also significant but less evidently. With `RNN1` all differences are significant except $20-10$.

For $\alpha = 1$, the LM specifies forced alignment. The results in Figure B.13 indicate significant increase of the correct frame classification rate with respect to the look-ahead length, in all cases. Finally, Table B.3 shows the Tukey results in all intermediate cases. These are not as regular as the "wordlen" results, revealing differences between the neural networks.

Summary

In both the "wordlen" and "alpha" tests, the statistic analysis shows significant differences. A successive Tukey multiple comparison test shows which couples of values of the look-ahead parameter correspond to significant differences in the correct frame rate. The results strongly depend on the MLP for short time dependences in the recognition network (towards the phone loop condition). This dependency fades when the condition is shifted towards the forced alignment case.

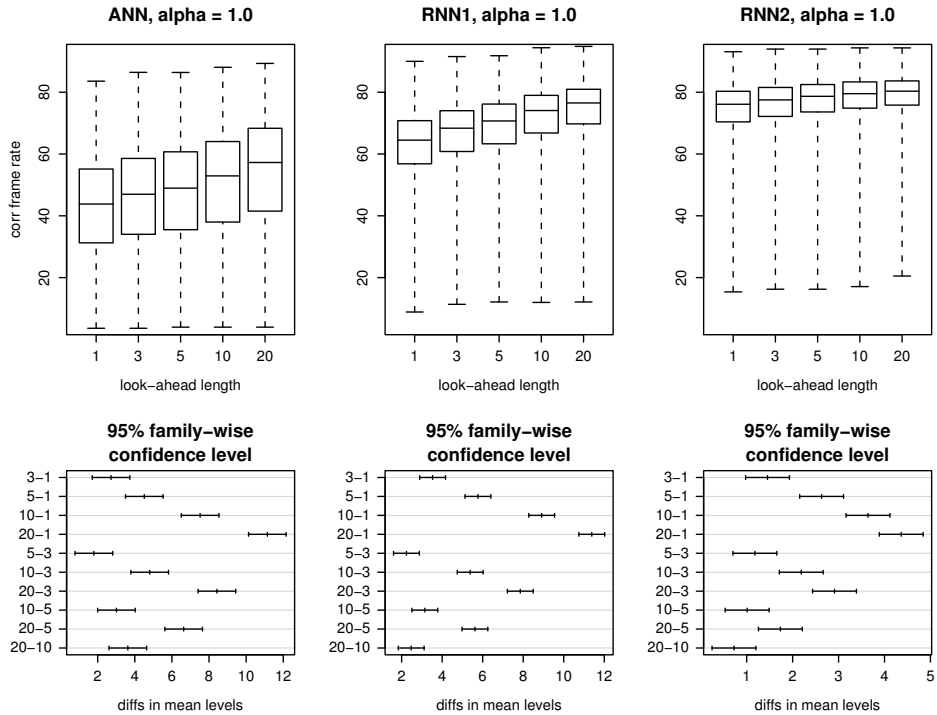

Figure B.13: Box-plots (top) and 95% family-wise Tukey confidence intervals (bottom), alpha = 1.0

Confidence measure

Figure B.14 shows the distribution of the entropy for correct (continuous line) and incorrect (dashed line) classification, and for the networks `ANN` (left), `RNN1` (centre), and `RNN2` (right). The vertical dashed-dotted lines indicate the maximum entropy ($\log N$). In the rightmost plot, the shaded area corresponds to the range chosen in the other two plots, and is used to facilitate the comparison between the two conditions. For the networks trained with $[0.1, 0.9]$ targets (`ANN` and `RNN1`) the entropy is concentrated in the high range, as explained in Section B.3. For `RNN2` the entropy range is larger (the network was trained with $[0, 1]$ targets).

The prediction capabilities of the entropy as confidence measure are however very similar for the recurrent networks. If we consider a Maximum Likelihood decision, based on the conditional entropy distributions, that leads to the minimum total error in case of equal *a priori* probabilities, we obtain the results shown in Table B.4. Note that the distributions shown in Figure B.14 and the results in Table B.4 are obtained on two independent data sets created by splitting the test

Table B.3: Alpha test: Tukey HSD multiple comparison results

ANN										
alpha	3-1	5-1	10-1	20-1	5-3	10-3	20-3	10-5	20-5	20-10
0.0	n	-	n	-	-	n	-	+	n	-
0.1	n	n	n	-	n	n	-	n	-	-
0.3	n	n	n	n	n	n	-	n	-	-
0.5	+	+	+	n	n	n	n	n	n	-
0.7	+	+	+	+	n	+	+	+	n	n
0.9	+	+	+	+	n	+	+	+	+	n
1.0	+	+	+	+	+	+	+	+	+	+
RNN1										
alpha	3-1	5-1	10-1	20-1	5-3	10-3	20-3	10-5	20-5	20-10
0.0	+	+	+	+	n	+	+	+	+	n
0.1	+	+	+	+	n	+	+	n	n	n
0.3	+	+	+	+	+	+	+	+	+	n
0.5	+	+	+	+	+	+	+	+	+	n
0.7	+	+	+	+	+	+	+	+	+	n
0.9	+	+	+	+	+	+	+	+	+	+
1.0	+	+	+	+	+	+	+	+	+	+
RNN2										
alpha	3-1	5-1	10-1	20-1	5-3	10-3	20-3	10-5	20-5	20-10
0.0	+	+	+	+	n	n	n	n	n	n
0.1	+	+	+	+	n	n	n	n	n	n
0.3	+	+	+	+	n	n	n	n	n	n
0.5	+	+	+	+	n	+	+	n	n	n
0.7	+	+	+	+	n	+	+	n	n	n
0.9	+	+	+	+	+	+	+	n	+	n
1.0	+	+	+	+	+	+	+	+	+	+

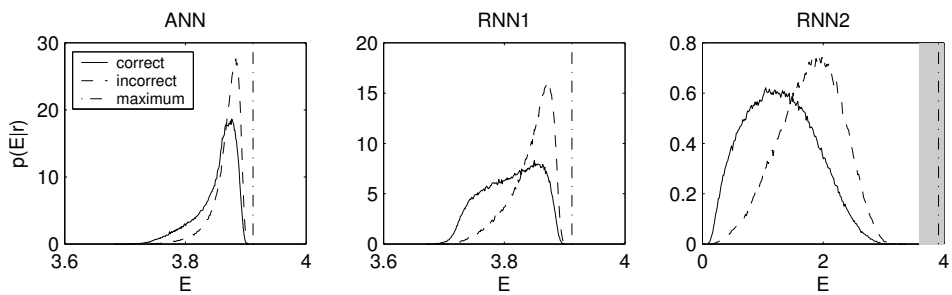

Figure B.14: Entropy distribution for correct and incorrect classification

Table B.4: Prediction capabilities of the entropy as confidence measure (ML decision)

net	corr. accept	corr. reject	false accept	false reject	tot. error
ANN	21.5%	37.2%	10.2%	31.1%	41.3%
RNN1	32.1%	34.2%	17.7%	16.0%	33.8%
RNN2	32.4%	33.9%	21.8%	11.9%	33.7%

data into two subsets of equal size.

B.6 Discussion

The three factors considered in the experiments seem to strongly interact in the decoding process. When the language model (LM) is similar to a phone loop, most of the information on the time evolution is provided by the multi-layer perceptron. In this case differences emerge on the latency behaviour of different neural network topologies. The static network (ANN) produces irregular results when the look-ahead length L is varied. The dynamic models (RNN1 and RNN2) show a slight improvement with increasing L, that fades for higher values of L. The look-ahead length for which no further improvement is achieved seems to be lower for RNN2 than for RNN1.

When the LM contains longer time dependencies, all acoustic models benefit (to different extents) of longer look-ahead lengths. This can be explained by noting that

- the Viterbi decoding makes use of time dependent information regardless of its source (transition model or dynamic neural network),
- the information provided by the transition model and the dynamic neural network might overlap/conflict,
- the look-ahead length needed to take full advantage of the Viterbi decoding is closely related to the length of the time correlations contained in the hybrid model (transition model or dynamic neural network).

Given these remarks, the results obtained here can be interpreted in the following way. The static model ANN, providing no time dependent information, takes advantage of the Viterbi decoding only for long time transition models and long look-ahead. The more complex recurrent perceptron (RNN2) provides information that partly overlaps with the transition model, causing only limited improvements when the look-ahead is increased (especially in the "alpha" test). The simpler recurrent perceptron (RNN1) provides more limited time dependent information and takes more advantage of the Viterbi decoding.

However, more specific tests should be designed to support this interpretation, using, for example, techniques from non-linear dynamics to analyse the dynamical behaviour of the recurrent networks in details. Factors such as the target values during training should also be excluded from the tests. The scoring method used rises also questions on the kind of errors the system is affected by in different conditions. It would be important, for example, to investigate to which extent the errors are due to misclassification of isolated frames or longer sequences, or to misalignment of the segment boundaries.

B.7 Conclusions

The interaction of transition model, dynamic probability estimators and look-ahead length in the decoding phase of a speech recognition system has been analysed in this paper. The results show how the dynamic information provided by the recurrent multi-layer perceptrons does not always interact in a constructive way with the transition model in Viterbi decoding. With static MLPs, the use of longer look-ahead lengths is not beneficial when the time dependencies in the language model are limited as in the phone loop condition. With recurrent MLPs, the benefit depends on the complexity of the network.

The frame-by-frame entropy proved to be a reasonably accurate confidence measure. This measure is not strongly affected by the use of target values in training other than [0,1].

Acknowledgements

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Paper C

Segment Boundaries in Low-Latency Phonetic Recognition

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Segment Boundaries in Low-Latency Phonetic Recognition

Giampiero Salvi

Abstract

The segment boundaries produced by the Synface low latency phoneme recogniser are analysed. The precision in placing the boundaries is an important factor in the Synface system as the aim is to drive the lip movements of a synthetic face for lip-reading support. The recogniser is based on a hybrid of recurrent neural networks and hidden Markov models. In this paper we analyse how the look-ahead length in the Viterbi-like decoder affects the precision of boundary placement. The properties of the entropy of the posterior probabilities estimated by the neural network are also investigated in relation to the distance of the frame from a phonetic transition.

C.1 Introduction

The Synface system Karlsson et al. (2003) uses automatic speech recognition (ASR) to derive the lip movements of an avatar Beskow (2004) from the speech signal in order to improve the communication over the telephone for hearing-impaired people.

The recogniser, based on a hybrid of artificial neural networks (ANN) and hidden Markov models (HMM), has been optimised for low latency processing (look-ahead lengths in the order of tens of milliseconds). The effect of limiting the look-ahead length has been investigated in Salvi (2003, 2006) by means of standard evaluation criteria, such as recognition accuracy, number of correct symbols and percent correct frame rate. However, in applications such as this, where the alignment of the segment boundaries is essential, standard evaluation criteria hide important information.

In this study the recognition results from the Synface recogniser are analysed in more detail showing how the boundary placement in some cases is dependent on the look-ahead length.

The use of neural networks allows the estimation of the posterior probabilities of a class given an observation. The entropy of those probabilities is shown to assume local maxima close to phonetic transitions, which makes it a good candidate for a predictor of phonetic boundaries.

The rest of the paper is organised as follows: Section C.2 describes the recogniser and the data used in the experiments. Section C.3 displays examples extracted from the sentence material in the test set. Section C.4 explains the method and the measures analysed in the experiments. Finally Section C.5 presents the results of the analysis and Section C.6 concludes the paper.

original	}	2	{	9	@
modified	uh	ox	ae	oe	eh

Table C.1: Modification of the SAMPA phonetic symbols

C.2 The Framework

The Recogniser

The Synface recogniser is a hybrid of recurrent neural networks (RNNs), and hidden Markov models (HMMs). The input layer of the RNN contains thirteen units that represent the Mel frequency cepstral coefficients $C_0, ..., C_{12}$.

The single hidden layer contains 400 units and is fully connected with the input and output layers with direct and time delayed connections. Moreover, the hidden layer is connected to itself with time delayed connections.

The activities of the output layer represent the posterior probability $P(x_i|O)$ of each of the $N = N_\mathrm{p} + N_\mathrm{n}$ acoustic classes x_i, given the observation O. The acoustic classes include N_p phonetic classes and N_n noise and silence classes. The total number N of output units depends on the language, see the following section.

The posterior probabilities are fed into a Viterbi-like decoder where the look-ahead length can be varied. The recognition network specified by a Markov chain defines a loop of phonemes, where every phoneme is represented by a three state left-to-right HMM.

Data

The recognizer was trained on the SpeechDat database Elenius (2000) independently on three languages (Swedish, English and Flemish). The experiments in this paper refer to Swedish. The Swedish database has been divided into a training, a validation and a test set, with 33062, 500 and 4150 utterances, respectively. The Mel frequency cepstral coefficients were computed at every 10 msec.

Phonetic transcriptions have been obtained with forced alignment. For part of the test utterances, the transcriptions have been manually checked in order to obtain a more reliable reference of the test data.

The phonetic transcriptions used in the following use SAMPA symbols (Gibbon et al., 1997) with a few exceptions (Lindberg et al., 2000) presented in Table C.1. The total number of acoustic classes is 50 for Swedish, with 46 phonemes and 4 kinds of noise/silence.

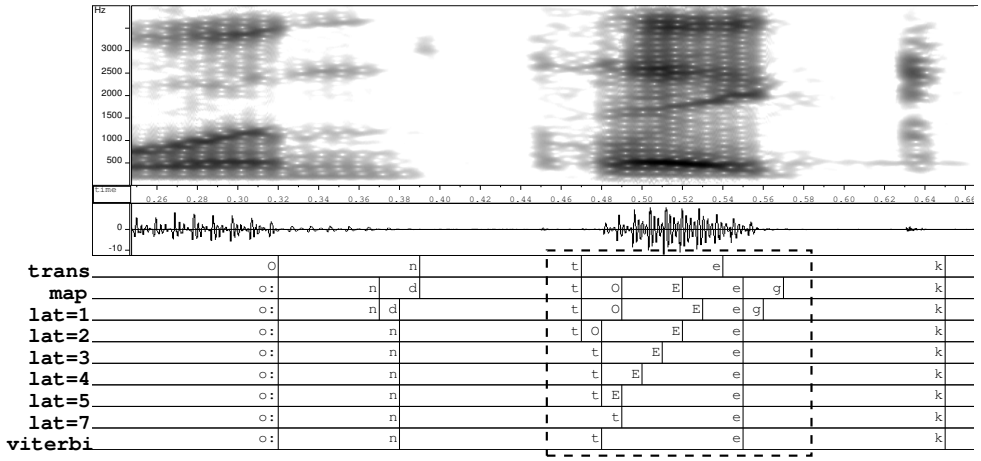

Figure C.1: Example of recognition results with varying look-ahead length. The sentence contains the phrase "Någon teknisk..." ("Some technical..."). See detailed information in the text.

C.3 Observations

Boundaries and Latency

Fig. C.1 shows an example from the phrase "Någon teknisk..." ("Some technical..."). The spectrogram and waveform are shown together with a number of transcription panes. From the top: the reference transcription (trans), the maximum a posteriori solution (map) obtained selecting for each frame the phonetic class corresponding to the neural network output node with the highest activity, the approximated Viterbi solution (lat=1,7) with look-ahead 1 to 7, and finally the standard Viterbi solution.

It can be seen from the figure that the boundary placement is strongly dependent on the look-ahead length whenever there is ambiguity in the posterior probability estimates. For example, the transitions between `O` and `n`, between `e` and `k` and between `k` and the next symbol, do not present any difficulties. The transition between `t` and `e` ($t = 0.47$ sec), on the other hand, is more problematic as the segment `e` is partly confused with `E` and `O` (see map solution). This has an effect on the final solution that strongly depends on the look-ahead length [1].

[1]Note, however, that from the application point of view, this particular case should not be considered as an error as `E` and `e` are mapped to the same visemic class (they share the same visual properties).

	map	lat=1	lat=2	lat=3	lat=4	lat=5	lat=7	viterbi
I	4	4	2	1	1	1	0	0
S	1	1	1	1	1	1	1	1
D	0	0	0	0	0	0	0	0
%Corr	80	80	80	80	80	80	80	80
Acc	0	0	40	60	60	60	80	80
%cfr	58.5	58.5	63.4	65.8	68.3	70.7	70.7	73.2

Table C.2: Insertions, Substitutions, Deletions, % Correct symbols, Accuracy and % correct frame rate for the example in Fig. C.1

Some standard evaluation criteria for speech recognition (*e.g.*, accuracy and correct symbols) compute the similarity between the recognition and the reference string of symbols by aligning the two sequences and counting the number of insertions I, deletions D, and substitutions S obtained in the process. Other measures (*e.g.*, percent correct frame rate) work with equally spaced frames in time.

In the example in Fig. C.1 there is one substitution (`O` with `o:`) in all conditions, no deletion and a number of insertions as indicated in Table C.2

The table shows how the accuracy is affected by insertions, deletions and substitutions, but not by boundary position. On the other hand, the percent correct frame rate, also shown in the table, measures the overlap in time of correctly classified segments, but does not take the boundaries explicitly into account. This motivates a more detailed study on the errors in boundary alignment.

Boundaries and Entropy

Fig. C.2 shows an example from the phrase "...lägga fram fakta..." ("...present facts..."). In this case the entropy of the posterior probabilities estimated by the output nodes of the neural network is displayed for each frame together with the reference transcription.

It is clear that at each transition from a phonetic segment to the next, the entropy assumes a local maximum. Note in particular that in the transition between `f` and `a` the maximum is shifted backward, compared to the reference transcription. In this case the position of the reference boundary is set at the onset of voicing ($t = 1.715$ sec) whereas the "entropy" boundary is more related to the onset of the articulation. The choice of one boundary or the other is questionable. From the application point of view the boundary indicated by the maximum in the entropy is more informative, as it is related to a change in articulation that is more visually relevant.

The figure indicates that the entropy may be a good predictor of phonetic transitions.

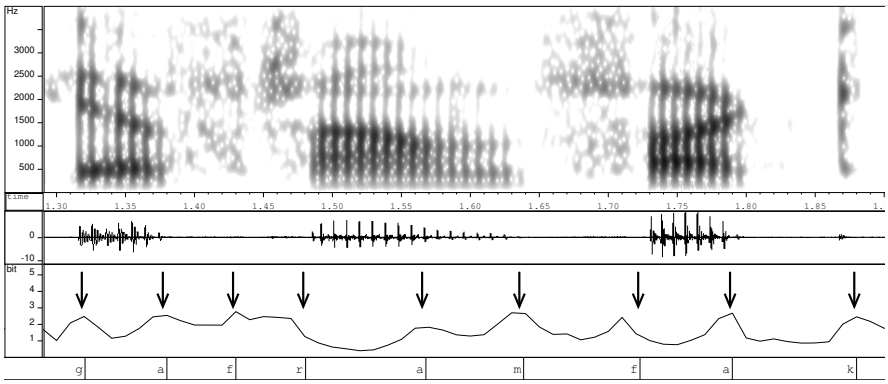

Figure C.2: Example of time evolution of the entropy. The sentence contains the phrase "...lägga fram fakta..." ("...present facts...")

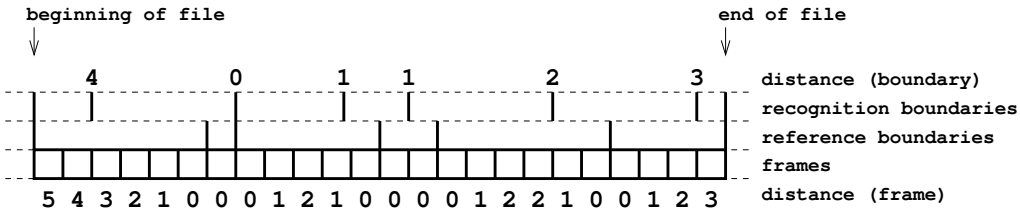

Figure C.3: Example computation of the distance between couple of boundaries and between a frame and a boundary.

C.4 Method

The experiments in this study aim at evaluating the precision of boundary placement at different latency conditions, and at investigating whether the frame-by-frame entropy of the posterior probabilities of the phonetic classes can be used as a predictor of the phonetic boundaries.

Two kinds of measures are therefore considered: the first relates the recognition boundaries to the reference boundaries. The second relates the entropy (or a quantity extracted from the entropy) measured over a frame to the position of the frame with respect to the reference boundaries.

The way the distance is measured in the two cases is exemplified in Fig. C.3. The reference boundaries are in the middle line. The line above shows the recognition boundaries with the distance from the nearest reference boundary. Note that beginning and end of the speech file are not considered as boundaries. The line below the reference shows the frames and their distance from the reference

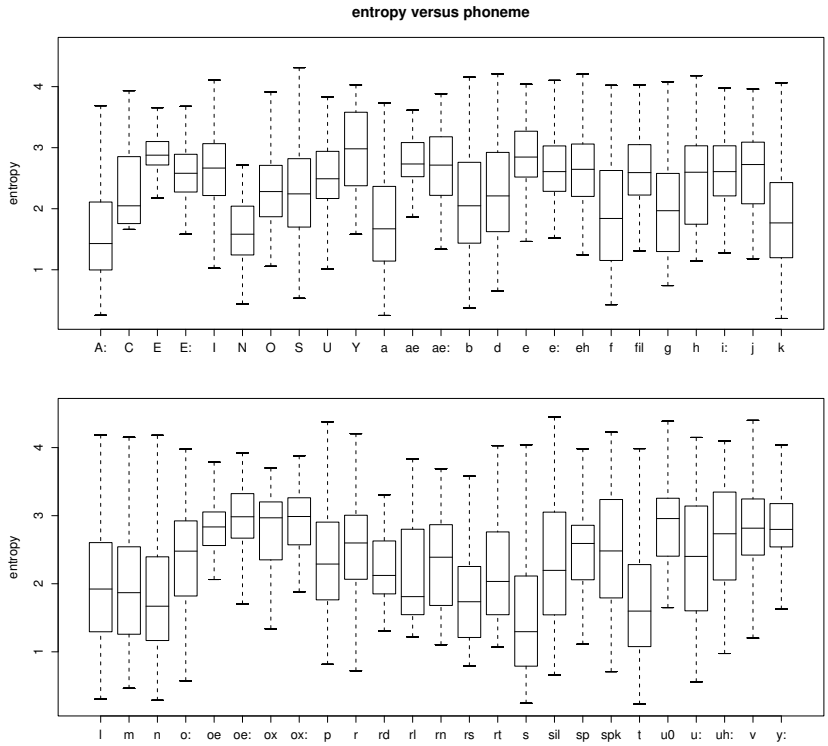

Figure C.4: Box plot of the frame entropy for each phonemic class. The maximum entropy is $\log_2 N = 5.64$ bits

boundaries: frames adjacent to a transition have distance 0.

We use the term displacement when the distance is considered with a sign (negative displacement indicates that the recognition boundary is earlier than the reference). The displacement is interesting when evaluating whether there is a bias in the position of the recognition transitions.

Entropy

Given the posterior probabilities $P(x_i|O(n)),\ i \in [1, N]$ of the acoustic class x_i given the observation $O(n)$ at frame n, the entropy of the frame is defined as

$$e(n) = -\sum_{i=1}^{N} P(x_i|O(n)) \log_2 P(x_i|O(n))$$

The entropy varies as a function of the uncertainty in the classification of each frame. As shown by the observations in the previous section, we can expect uncertainty to be higher at phonetic boundaries, but there are many sources of uncertainty that need be considered.

For example, some phonemes are intrinsically more confusable than others, some speakers are harder to recognise, or there might be noise in the recordings that increases the entropy.

In order to reduce the effect of the first of these factors, the mean entropy was computed for each phoneme and subtracted from the frame by frame entropy in some evaluations. Fig. C.4 shows the boxplot of the entropy for each of the phonemes, as a reference.

As the focus is on the evolution of the entropy in time, the first and second derivative defined as $e'(n) = e(n) - e(n-1)$ and $e''(n) = e'(n+1) - e'(n)$ have been also considered. The definition of the second derivative assures the maxima and minima of $e''(n)$ correspond to the maxima and minima of $e(n)$. Note that given the rate of variation of the entropy in function of time (frames) the first derivative $e'(n)$ should not be expected to be close to zero in correspondence of a maximum of $e(n)$. On the other hand a negative value of the second derivative $e''(n)$ is a strong indicator of a maximum in $e(n)$ for the same reason.

C.5 Analysis

Boundaries and Latency

Fig. C.5 shows the distribution of the recognition boundaries displacement (in frames) with respect to the reference for different latency conditions. The thicker line corresponds to a latency of three frames (30 msec), as used in the Synface prototype. The figure shows that there is no global bias in the position of the boundaries. More than 80% of the boundaries are within 2 frames (20 msec) from the reference.

The total number of boundaries decreases with larger latency (the number of insertions is reduced), but the distribution of the displacements from the reference is very similar. This implies that the extra transitions inserted at low latencies have the same distribution in time than the correct transitions. A better measure of correctness in the position of phoneme boundaries would disregard insertions of extra transitions. A simple way of doing this is to select from the recognition results a number of transitions equal to the reference. The drawback of such an approach, similarly to the % correct symbol measure, is that solutions with a high number of insertions are more likely to contain a higher number of correct answers. This is the reason why this approach was not considered in this study.

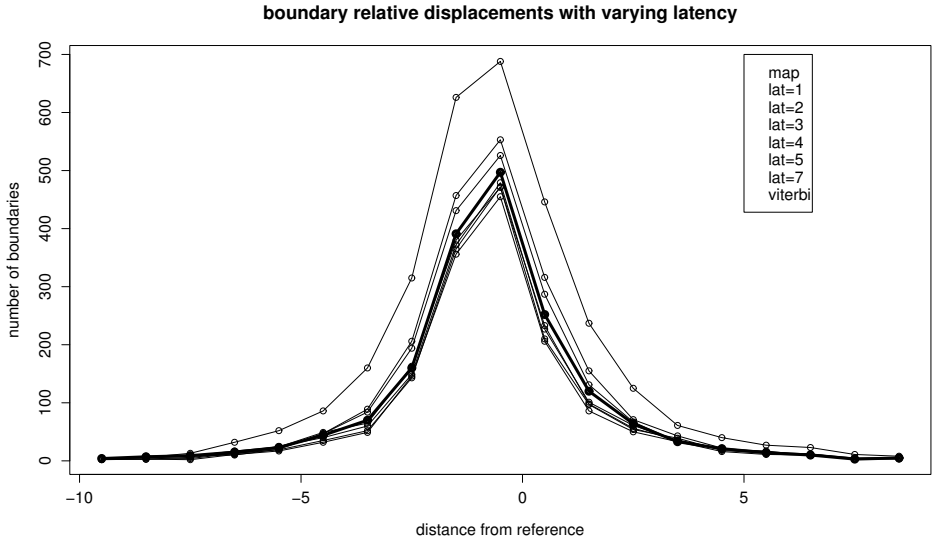

Figure C.5: Distribution of the relative displacement of the recognition boundaries to the reference for varying latency.

Boundaries and Entropy

The distribution of the entropy for different distances from the a phonetic transition are displayed in Fig. C.6 with box plots. The three figures show the unnormalised entropy, the entropy normalised with the average for every phoneme in the reference transcription and the same normalisation but referring to the recognition transcription (with three frames latency). All plots show that the entropy increases in the neighbourhood of a phonetic transition (distance from the boundary equals 0). In the normalised cases the variation around the median is reduced.

Even in the normalised cases, the large variation around the median shows that the frame-by-frame entropy needs to be improved to be a good enough predictor of phonetic boundaries.

Figure C.7 shows the distributions of the first and second derivative depending on the distance from a phonetic boundary. As explained in Section C.4 the first derivative assumes values far from zero at boundaries, which indicates that the entropy has a strong variation in time. The second derivative often assumes negative values, suggesting there might be a maximum of the entropy or at least a convex shape of the entropy curve.

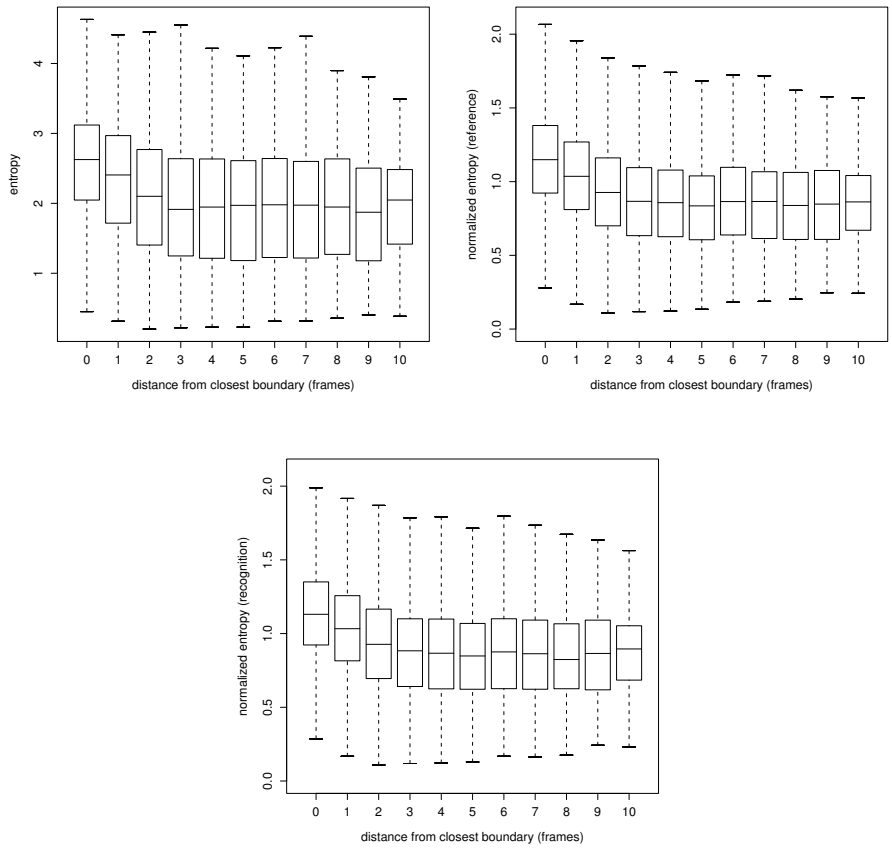

Figure C.6: Box plot of the entropy at varying distances from the nearest reference boundary. In the second and third plots the entropy is normalised to the mean for each phoneme in the reference and recognition transcription, respectively.

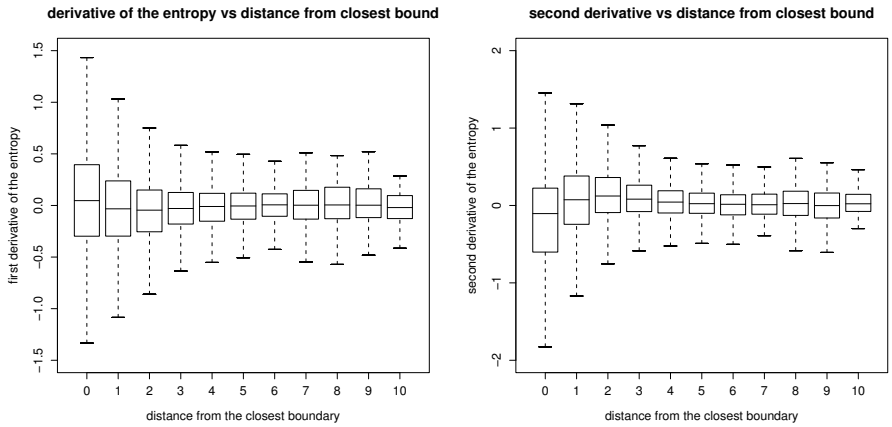

Figure C.7: Box plot of the first and second derivative in time of the entropy at varying distance from the nearest reference boundary.

C.6 Conclusions

This article analyses the phonetic transitions obtained with a low latency phoneme recogniser. It shows that the distribution of displacements of the recognition boundaries, with respect to the reference transcription, do not vary significantly with the latency, in spite of the increased number of insertions at low latency conditions.

We propose to use the entropy of the posterior probabilities estimated by a neural network in connectionist speech recognition, as a predictor of the phonetic boundaries. A dependency of the entropy with the distance from a phonetic transition has been found. However, in order to use this measure as a predictor of phonetic boundaries, a number of interfering factors should be removed. The use of dynamic features, such as the first and second derivative might serve this purpose.

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Paper D

Accent Clustering in Swedish Using the Bhattacharyya Distance

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Accent Clustering in Swedish Using the Bhattacharyya Distance

Giampiero Salvi

Abstract

In an attempt to improve automatic speech recognition (ASR) models for Swedish, accent variations were considered. These have proved to be important variables in the statistical distribution of the acoustic features usually employed in ASR. The analysis of feature variability have revealed phenomena that are consistent with what is known from phonetic investigations, suggesting that a consistent part of the information about accents could be derived form those features. A graphical interface has been developed to simplify the visualization of the geographical distributions of these phenomena.

D.1 Introduction

In automatic speech recognition (ASR), acoustic features extracted from the digitized speech signal are used to classify different phonetic or phonemic categories. This process, based on statistical methods, is made more difficult by a long list of phenomena that introduce acoustic variations in the speech signal. Among many others are *gender*, *age*, *level of education*, *anatomical characteristics*, *emotions* and *accent* of the speaker. The classic solution is to blindly increase model complexity and let some optimization procedure decide how to model each phenomenon. This approach is often successful, but has some drawbacks: the models obtained this way, given their complexity, are difficult to interpret and provide little information about the phenomena they were optimized for. Furthermore, the rising complexity sets limits to the efficiency of the optimization procedures. These can be technical, as for example the increasing amounts of data needed to adjust the model parameters, and the resulting computational load, or theoretical: models based on imprecise assumptions can be improved only to a certain extent.

Explicitly incorporating information into these models, on the other hand, requires the information to be formulated in a complete and consistent way. Dialectal and pronunciation variations in Swedish have been extensively studied by, among others, prof. Claes Christian Elert. In one of his books (Elert, 1995), that will be the main reference for this study, Elert defines areas of homogeneity as well as general descriptive rules to distinguish between them.

The aim of this study is to verify if data driven statistical models for speech recognition retain some of the accent information in a consistent way. This corresponds to verifying how accent related pronunciation variations influence the

distribution of acoustic features. Since the analysis is done for each phoneme independently, it can also provide indications on how complex models are needed to describe the pool of allophones emerging from accent variations.

D.2 Method

Models for speech recognition are a suitable tool for collecting statistics on speech material that is not annotated at the phonetic level. The standard paradigm consists of a signal processing step aimed at extracting suitable *features*, and a *statistical modeling* step that characterizes the distributions of these features for each phoneme, and the dynamics of the speech production process. While the signal processing step is somehow standardized, the statistical models can have varying complexity depending on the application. In this study we consider simple dedicated models representing the allophones for each geographical area. An acoustic similarity criterion can then show which of these areas can be merged (according to each phoneme) indicating that, from the speech recognition viewpoint these areas are homogeneous.

Features

Speech feature extraction has two main purposes in speech recognition: the first is to reduce the amount of data per time unit the classification algorithm has to work on; the second is to reduce, as much as a simple filtering method can, the amount of *spurious* information and noise that can degrade accuracy, while enhancing the phonetic related characteristics of the signal. Features used in this study, and in most speech recognition systems, are Mel scaled cepstral coefficients plus short time energy, first introduced in Davis and Mermelstein (1980). One of the properties of these features can be interesting in this context: the cepstrum is based on modeling the spectrum envelope, and thus discarding pitch information. This means that intonation and prosody will not be considered in this study.

Models

Each Mel-cepstral coefficient is described statistically by its mean and standard deviation. This is a sufficient statistic if we assume the values to be normally distributed and independent. In general this is not true and multimodal models are chosen instead. In this study, simple unimodal normal distributed models are used. Given the dynamic properties of speech, each phone is divided into an initial, intermediate and final part, resulting in three independent statistics, as usually done in ASR. Since the speech material was not phonetically annotated, the estimation process is based on the expectation maximization (EM) algorithm and relies on pronunciation rules defined in a lexicon. When computing independent statistics on different subsets of data, the resulting means and variances can be interpreted as representing each subset they were extracted from. In principle any subdivision can

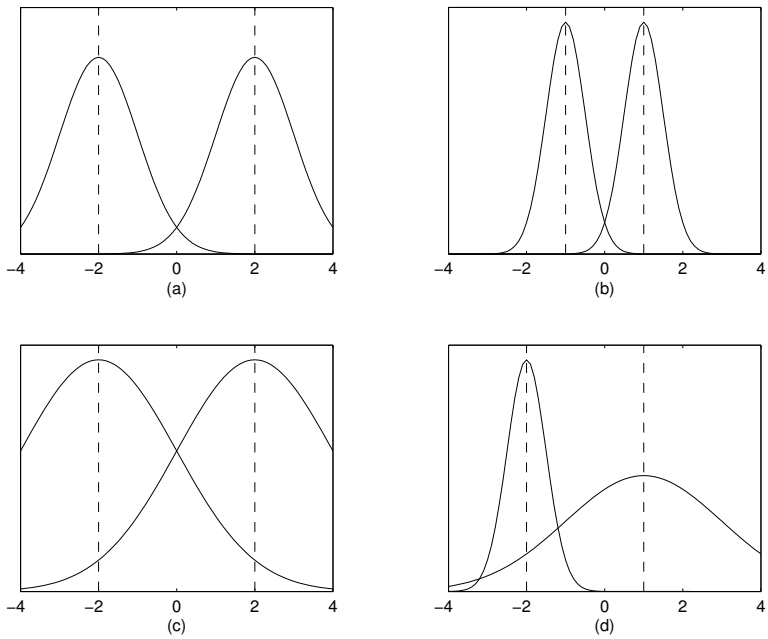

Figure D.1: One-dimensional example of pairs of Gaussian distributions. (a) and (c) show pairs with the same mean (Euclidean) distance, but different Bhattacharyya distances; (a) and (b) on the other hand have different mean distances, but similar Bhattacharyya distances. In general (d) the variances of the two distributions can be different.

be considered to the limit of individual speakers (so called *ideolects*). A limitation to this is set by the reduced amount of data that can affect the efficiency of the estimation algorithms and the significance of the result.

Clustering

If we describe the means and variances as points in a metric space, clustering methods provide means for letting natural groups emerge from the data. That is, if we start from a fine subdivision of the data, we can group the instances that, after statistical analysis are similar to each other. In the current study, for example, the fine subdivision corresponds to accent areas and each mean/variance vector describes an allophone for the corresponding area. The clustering procedure then finds which allophones, in the conditions so far described, are more similar to each other and thus can be merged.

The agglomerative hierarchical clustering method (Johnson, 1967) used in this study starts form N different elements and iteratively merges the ones that are closest according to a similarity criterion, in our case the distance between two normally distributed stochastic vectors. This can be defined by the *Bhattacharyya distance* (Mak and Barnard, 1996):

$$\begin{aligned} D_{batt} &= \frac{1}{8}(\mu_2 - \mu_1)^T \left[\frac{\Sigma_1 + \Sigma_2}{2}\right]^{-1} (\mu_2 - \mu_1) \\ &\quad + \frac{1}{2} \ln \frac{\left|\frac{\Sigma_1+\Sigma_2}{2}\right|}{\sqrt{|\Sigma_1||\Sigma_2|}} \end{aligned}$$

Where μ_i is the mean vector for class i and Σ_i its covariance matrix. Besides the mathematical formulation, it is interesting to consider some of its properties. Figure D.1 shows a one-dimensional example: considering (a) and (c) we can see that, while the euclidean distance is the same in this two cases, D_{batt} is larger in (a) than in (c). This is because the distance between the means is scaled by the variances and expresses the degree of overlapping of the two distributions. The same idea is confirmed looking at (a) and (b): here D_{batt} is approximately the same, while the distance between the means is different. Finally part (d) in the figure shows how in general the variances of the two variables may be different.

D.3 Experiments

Data

The Swedish SpeechDat FDB5000 telephone speech database (Elenius, 2000) was used for the experiments. It contains utterances spoken by 5000 speakers recorded over the fixed telephone network. All utterances were orthographically labeled and a lexicon is provided containing pronunciations in terms of sequences of 46 phonetic symbols. The database also contains information about each speaker including *gender*, *age*, *accent*, and more technical information about recordings, for example the type of telephone set used by the caller. In this study, only accent information was considered.

The accent areas defined in Elert (1994), and adopted in the SpeechDat documentation, are summarized (left) and displayed (right) in Figure D.2. The figure shows two degrees of subdivision of the population: the roman numbers (thick borders) refer to broader areas, while Arabian numbers (thin borders) to a finer subdivision. The last will be used in the rest of the study. Some of the properties described in Figure D.2 (left) refer to prosody and will be ignored as explained in Section D.2.

I (15,16,17,18) South Swedish	South Swedish diphthongization (raising of the tongue, late beset rounding of the long vowels), retracted pronunciation of /r/, no supra-dentals, retracted pronunciation [ɧ] of the fricative /ʃ/. A tense, creaky voice quality can be found in large parts of Småland.
II (10,11,12,13,14) Gothenburg, west, and middle Swedish	Open long and short /ɛ/ and (sometimes) /œ/ vowels (no extra opening before /r/), retracted pronunciation of the fricative /ʃ/, open /ɔ/ and /l/.
III (8,9) East, middle Swedish	Diphthongization into /e/ɛ/ in long vowels (possibly with a laryngeal gesture), short /e/ and /ɛ/ collapses into a single vowel, open variants of /ɛ/ and /œ/ before /r/ ([æ, œ̞]).
IV (7) as spoken in Gotland	Secondary Gotland diphthongization, long /ʊ/ pronounced as [ɔ].
V (5,6) as spoken in Bergslagen	/ɵ/ pronounced as central vowel, acute accent in many connected words.
VI (1,2,3,4) as spoken in Norrland	No diphthongization of long vowels, some parts have a short /ɵ/ pronounced with a retracted pronunciation, thick /l/, sometimes the main emphasis of connected words is moved to the right.
VII (19) as spoken in Finland	Special pronunciation of /ɵ/ and long [a], special /ʃ/ and /ç/, /r/ is pronounced before dentals, no grave accent.

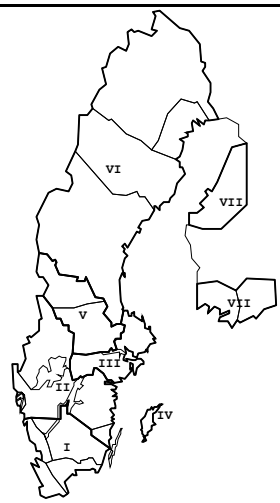

Figure D.2: Summary of pronunciation variation (left) in the seven main accent areas in Sweden and part of Finland Elert (1994) and their geographic representation (right, thick borders). Arabian numbers in parenthesis and thinner borders in the figure indicate a finer subdivision that is used in this study. Phonemes that are subjected to important variations in each area are indicated in the table with the IPA symbols corresponding to their most common pronunciation.

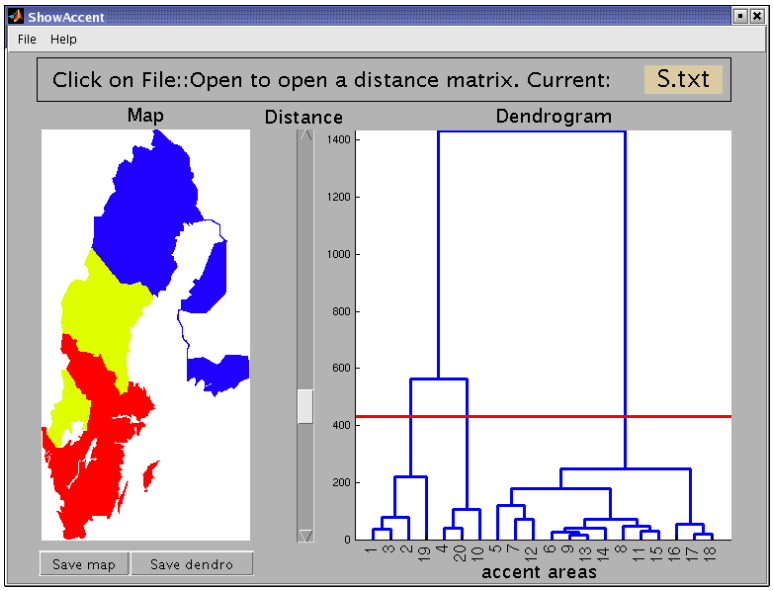

Figure D.3: The ShowAccent interface. The map on the left side displays the geographical location of the clusters for a distance level specified by the slider. On the right side the *dendrogram* is a compact representation of the clustering procedure

The ShowAccent Tool

To simplify the visual analysis, the graphical interface depicted in Figure D.3, was developed by the author. It is based on the Matlab scripting language and some of the tools in Jang (2000). The interface shows a map on the left side and a *dendrogram* on the right side. The last is a compact representation of the clustering procedure. The numbers on the x-axis correspond to the fine accent subdivision described in the previous section. The tree-like structure depicts the way those regions form clusters depending on the distance measure (y-axis). This representation is complete, but not straightforward: to understand how the clusters are distributed geographically, one needs to look up the region number on a map. To simplify this process, the map on the left is linked to the dendrogram by the slider in the central part. The user can display the clusters on the map at a certain distance level by moving the slider accordingly.

Results

Inspection of the natural clusters emerging from the data shows interesting properties. Many phonemes follow rules that resemble the ones given in Figure D.2.

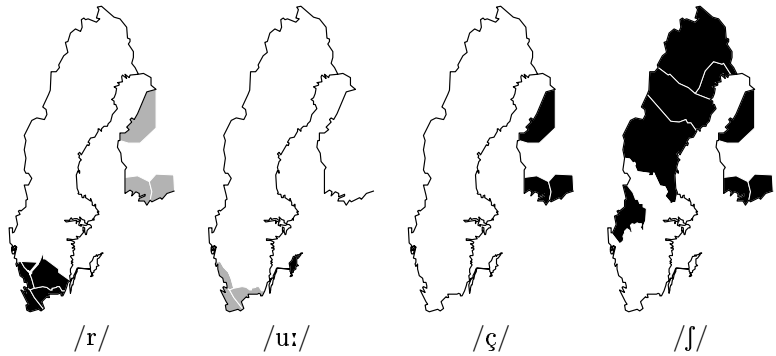

Figure D.4: Four examples of pronunciation variation across Sweden and part of Finland. White, black and gray regions represent clusters where the acoustic features are homogeneous

This in spite of the severe reduction of information caused by the telephone line and by the feature extraction procedure, that was not designed to preserve accent information. As an example the geographical distribution of allophones for four phonemes are depicted in Figure D.4. The phoneme /r/ forms three clusters clearly corresponding to the "standard" variant [ɹ] in great part of Sweden (white), to the retracted pronunciation [ʁ] in the south (black) and to the particular pronunciation in Finnish regions (gray). The vowel /uː/ forms a cluster in Gotland (black) where it is pronounced as [oː] according to Elert (1995). The gray area in part of the south indicates another allophonic variations of the phoneme /uː/. The fricative /ç/ as described in Figure D.2 is rather homogeneous in Sweden (white), but becomes an affricate in Finnish-Swedish (black). Finally an allophone of the fricative /ʃ/ (frontal pronunciation) emerges in the northern part of Sweden and in Finland (black) while the southern and central Sweden form a different cluster, most probably associated with the more retracted pronunciation [ʃ̠]. More difficult to explain is, in this case, the fact that Värmland (part of region II, see Figure D.2) clusters with the north instead of the south of Sweden.

D.4 Conclusions

This study investigated the possibility that Mel-cepstral features extracted from narrow band (telephone) speech, could retain information about accent variation in Swedish. This was done using automatic speech recognition methods to derive allophonic statistical models for accent regions and clustering methods to find natural groupings of the regions. The resulting clusters proved to be largely consistent with what is known in the phonetic literature suggesting that:

- accent information can partly be extracted from the signal processing originally developed for speech recognition,
- explicitly modeling accent variation could improve the discriminative power of speech recognition models.

Acknowledgments

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Paper E

Advances in Regional Accent Clustering in Swedish

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Advances in Regional Accent Clustering in Swedish

Giampiero Salvi

Abstract

The regional pronunciation variation in Swedish is analysed on a large database. Statistics over each phoneme and for each region of Sweden are computed using the EM algorithm in a hidden Markov model framework to overcome the difficulties of transcribing the whole set of data at the phonetic level. The model representations obtained this way are compared using a distance measure in the space spanned by the model parameters, and hierarchical clustering. The regional variants of each phoneme may group with those of any other phoneme, on the basis of their acoustic properties. The log likelihood of the data given the model is shown to display interesting properties regarding the choice of number of clusters, given a particular level of details. Discriminative analysis is used to find the parameters that most contribute to the separation between groups, adding an interpretative value to the discussion. Finally a number of examples are given on some of the phenomena that are revealed by examining the clustering tree.

E.1 Introduction

Advanced statistical methods have long been used in speech recognition for acoustic modelling. The resulting models are often of overwhelming complexity and hard to interpret. This is common for data-mining techniques where the focus is on classification performance with large amounts of data.

More traditional statistical methods, on the other hand, provide a more transparent interpretation of the phenomena under study, but are generally less appropriate for large/huge data sets. This is a particularly severe limitation in the study of language and speech, where the great amount of variables involved makes restricted collections of data poorly representative of the problem.

In Minematsu and Nakagawa (2000) it was proposed to use techniques from the data mining field, such as the ones used in speech recognition, as a tool for analysing pronunciation variants in students learning a second language. Similarly, we used related techniques to analyse regional accent variation on a large sample of the population in Sweden (Salvi, 2003a,b). Here the term *accent* is used following Crystal's acception (Crystal, 1997, ch. 8) of regional pronunciation variation as opposed to the word *dialect* which describes variations in vocabulary and grammatical rules. The same distinction is made by Elert (1996) who talks about the opposition between the regional variants of the standard language ("regionala rikssprĺksvarianter") and genuine dialects ("genuina dialekter").

The EM algorithm (Dempster et al., 1977) was used to collect statistics over phonemic units, using only partially labelled material, and a canonical pronunciation dictionary, thus overcoming the problem of creating hand made detailed transcriptions of such a large corpus. Clustering techniques were used to visualise and interpret the results.

This study is an evolution of the previous investigations (Salvi, 2003a,b) in two main aspects. Firstly we overcome the limitation of studying each phoneme independently of the others, allowing for cross-phoneme similarities to emerge. Secondly, a number of methods are explored in order to quantify the fit of the clustering models to the data and to interpret their nature.

E.2 Method

Parameter estimation

The EM algorithm (Dempster et al., 1977) is a well known method in the speech community that allows estimating a set of unknown parameters Θ given some measured data X when we lack information on some hidden variable, whose effect needs to be integrated out.

If we model continuous speech as a Markov chain, the hidden variable is the assignment of each data point (frame) to each state of the model. Representing the observations as Mel-frequency cepstral coefficients and selecting Gaussian distributions as "state-to-output" probability models, gives us a probabilistic framework to model the pronunciation of each phonemic unit. A common practice, also adopted in this study, is to separately model the initial, middle and final part of each phoneme. I the following we will refer to those as *segments* of each phoneme.

In this framework we can introduce a number of sources of contextual information that are known to affect speech production. A common practice in speech recognition is, e.g., to model co-articulation effects by splitting each phoneme into context dependent units. The regional accent information investigated in this study can be interpreted as contextual information in the same manner, resulting in phonemic units that represent the characteristics of pronunciation patterns in specific geographical areas.

Clustering

Given our framework, a dissimilarity measure defined between distributions (states) together with agglomerative hierarchical clustering can be used to evaluate pronunciation differences and similarities. As in Salvi (2003a,b) the metric used in this study is the Bhattacharyya distance. Differently from Salvi (2003a,b), we do not make here the restriction of analysing each phoneme separately. Furthermore any segment (initial, middle and final) is free to cluster with any other. This gives us a large number of units that can freely form groups of similar pronunciation models. The exact number is $R \times P \times S$ where R is the number of homogeneous regions

defined in the database, P the number of phonemes in the canonical pronunciation model, and S the number of segments for each phonemes (3 in our case).

Hierarchical clustering was chosen over partitional or density-based clustering because of its inherent property of displaying relational features at different levels of details. As will be clarified in the following, this is the main focus of this study, as opposed to finding the model that best fits the data in an absolute sense. The practical limitations with hierarchical procedures, e.g. the memory requirements for large datasets, are intrinsically avoided in this framework as the "objects" to be clustered are not single data points, but rather models representing (large) subsets of data points.

Cluster validation

A number of methods exist that evaluate the fit of the clustering model to the data. Milligan (Milligan and Cooper, 1985; Milligan, 1981) evaluates thirty cluster validation indexes with artificially generated data. Most of these methods try to evaluate the spread of points within and across clusters. Some relay on the pairwise dissimilarity measure alone, others on the relation between data points in each cluster and the corresponding cluster centroids in the space spanned by the data; finally some methods such as the log likelihood and the Bayes information criterion (BIC, Fraley and Raftery, 1998) use a parametrised probabilistic framework.

In our case, clustering is applied to model parameters (means and covariances of the Gaussian distributions) rather than to single data points. Thus indexes of the first kind, such as the Ball (Ball and Hall, 1965) or Calinski (Caliński and Corsten, 1985) are not easily interpretable. On the other hand methods based on dissimilarities e.g. the C-index (Hubert and Levin, 1976) are directly applicable to our case. Methods based on the likelihood of the data given the model such as the BIC, can also be applied as the log likelihood can be easily computed with some simplifying assumptions.

The log-likelihood of the data given a Gaussian model whose parameters are estimated according to the maximum likelihood criterion is:

$$L = \frac{1}{2} nD[\ln 2\pi + 1] - n \sum_{j=1}^{D} \ln \sigma_j$$

where D is the dimensionality of the data and n is the number of data points. Note that we do not need to refer to the actual data points to compute this quantity.

When the EM algorithm is used, the number of data points per Gaussian model (state) is unknown, but can be approximated by the so called *state occupation count* (Young and Woodland, 1993).

Making common assumptions on the effect of clustering on the state assignment, and on the possibility to approximate the total log likelihood with an average of the log likelihoods for each state, weighted by the probability of state occupancy, we can write the total log likelihood as a function of the means, covariances and

occupation counts of the original states, for each cluster configuration along the clustering tree, without referring to the original data.

The BIC (Fraley and Raftery, 1998) is an approximation of the Bayes factor that tries to find a trade-off between the complexity of a model (number of free parameters m_M), the model fit to the data (log likelihood l_M) and the number of data points available for model parameter estimation (n). Its definition is

$$BIC \equiv 2l_M(x, \theta) - m_M \log(n)$$

and it is used for example in model-based clustering to select the best model according to the above criteria.

As we will see later, given the amount of data we are dealing with, the best possible model, includes a much larger number of parameters than those used in this study. As a consequence the above methods give monotonically increasing indexes, as our models are always under-dimensioned given the amount of data.

An alternative way to interpret these indexes, that will be used in this study, is to select among several models at different levels of details.

Cluster interpretation

When we select a merging (or splitting) point for each level of details of interest, we might want to know which acoustic parameters are more important to discriminate between the newly formed clusters. The way we do this is to apply discriminant analysis to the members of the two most recent clusters, and order the parameters according to the scaling factors in the resulting linear model (normalised by the variance of each parameter). We can then compute how much of the discrimination between the two groups is accounted for by one, two or more parameters, by running a prediction on the same cluster members with a linear model of the corresponding order. This gives us insights on the contribution of each coefficient to the global distance.

E.3 Data

The Swedish SpeechDat FDB5000 telephone speech database (Elenius, 2000) was used for the experiments. It contains utterances spoken by 5000 speakers recorded over the fixed telephone network. All utterances were labelled at the lexical level and a lexicon is provided containing pronunciations in terms of 46 phonetic symbols. The database also contains information about each speaker including *gender*, *age*, *accent*, and more technical information about recordings, for example the type of telephone set used by the caller. In this study, only accent information was considered.

Figure E.1 shows a subdivision of Sweden into a number of areas as defined by Elert (1994). Seven broad and twenty finer areas are defined according to dialectal

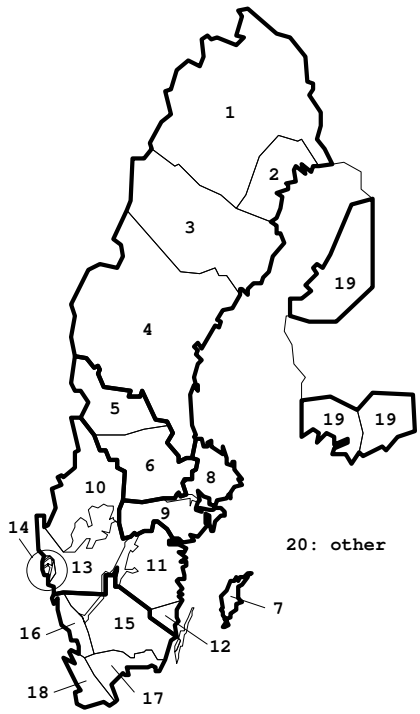

Figure E.1: A map of Sweden and part of Finland with broad and finer dialect region definition. Number 20 is assigned to people with a language other than Swedish as mother tongue

homogeneity. The same areas were considered in this study to represent regions of uniform pronunciation (regional accents). They will be referred to as $\{r_1$–$r_{20}\}$.

The official SpeechDat training set was used for a total of 4500 speakers, 270 hours of speech. Ten milliseconds spaced frames were extracted for a total of circa 97 millions frames, containing 13 Mel cepstrum coefficients $\{c_0$–$c_{12}\}$, and the first and second order differences $\{d_0$–d_{12}, a_0–$a_{12}\}$. As already mentioned three states $\{s_1$–$s_3\}$ were used for each phoneme resulting in 2940 states (20 accent regions times 46 phonemes plus 1 silence and 2 noise models times 3 segments). Of these the two noise models and the retroflex allophone [t̢] were removed (the last for lack of data points in certain regions). Thus a total of 2760 states (distributions) were used in the clustering procedure.

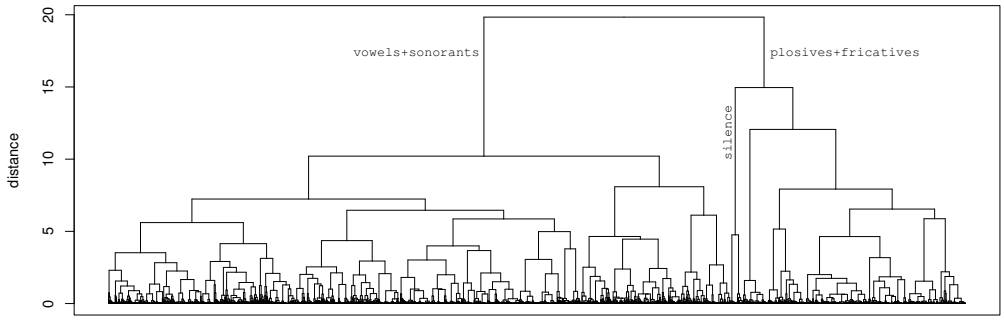

Figure E.2: Dendrogram of the full clustering tree. The y-axis shows the dissimilarity level, on the x-axis are the states in the form phoneme-segment-region. Given the number of states it is not possible to display each label, Figure E.4 shows three blow-ups for phoneme [ɹ]. Broad classes are also shown in the picture.

E.4 Results

Figure E.2 shows the full clustering tree for the 2760 distributions used in this study. The figure is shown to give a general idea of the clustering process and is not intended as a complete representation of the results.

Figure E.3 shows the corresponding log likelihood computed as described in Section E.2. The values for number of clusters close to 1 have been truncated in the figure to better display the evolution for large number of clusters. The function is monotone and presents jumps at particular numbers of clusters. The corresponding BIC values have a very similar shape, meaning that, given the enormous amount of training data, the number of parameters in the model has a negligible effect compared to the log likelihood.

Starting from the top of the tree, the first split divides essentially vowels and sonorants from non-sonorants. The discriminant analysis predicts this classification with 0.5% error. The most important cepstrum coefficients are, in decreasing order, c_0 (energy), d_0 (derivative of the energy), c_1 (related to the spectral slope) and it's derivative d_1. Truncating the discriminant function to 1,2,3 and 4 variables, the prediction error is respectively 20%, 10%, 9% and 8%, meaning that the first four of the 39 coefficients account for 92% of the discrimination.

The second split divides the initial and final part (s_1 and s_3) of the silence model (for every accent region) from the rest of the states in group two from the previous split. Note that the middle state of silence clusters with the middle states of the voiceless plosives at a lower distance level. Successive splits divide, for example, sonorants from vowels and fricatives from plosives.

An interesting phenomenon is that the first and last segments (s_1,s_3) of the vowels tend to be separated from the middle part (s_2). This is possibly due to the

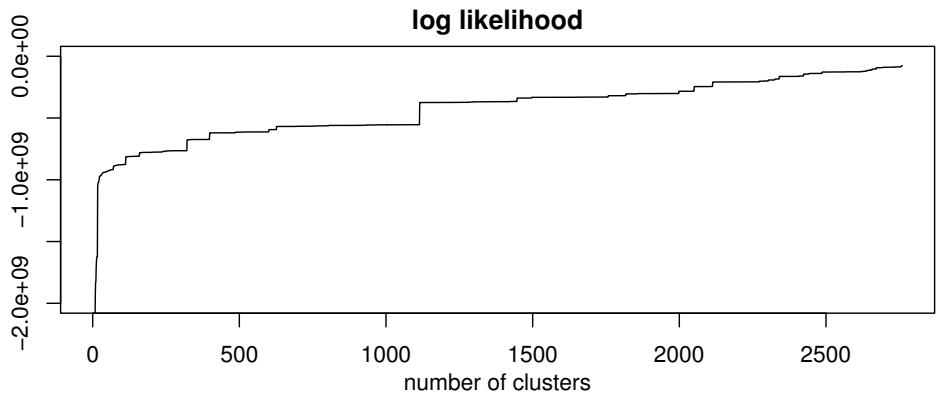

Figure E.3: Log-likelihood versus number of clusters. Clear jumps can be seen when certain "merges" take place.

latter being more stable in time (lower derivatives).

A general trend is that, in most cases, the splitting process separates states (distributions) belonging to different segments (initial, middle and final) and phonemes, while the effect of the accent region comes last in the process.

The exceptions to this are particularly interesting because they show the cases in which the pronunciation of one phoneme in the language is changed into the pronunciation of another phoneme that is also part of the phonetic inventory of that language. For example, [ʂ] (retroflex allophone of /s/) in the south of Sweden (r_{15}–r_{18}) clusters always with the main pronunciation of /s/. Similarly /ʃ/ in Norrland and Finland (r_1–r_4, r_{19}) is more similar to /ç/ and /ʂ/ in the rest of the country. The vowel /ɵ/ in Gotland (r_7) groups with the cluster including all variants of /ʊ/, and /ɛː/ in south-west Skåne (r_{18}) groups with /æː/, to give some examples with vowels.

In other cases, although the pronunciation varies greatly across regions, there is no corresponding sound in the standard pronunciation that can be confused with the regional variants. One example is /r/ that in the south (r_{15}–r_{18}) is retracted to [ʁ] while it is pronounced as [ɹ] in the rest of the country. In this case both [ɹ] and [ʁ] group together, but the dendrogram (Figure E.4) clearly shows a subgrouping that corresponds to this difference. Note that the figure shows three subtrees extracted from the complete tree in Figure E.2.

E.5 Conclusions

This study proposes the use of methods from the data mining field to analyse pronunciation variation in a language using huge amounts of data. The intension is to grasp phenomena that may be missed with more restricted data sets.

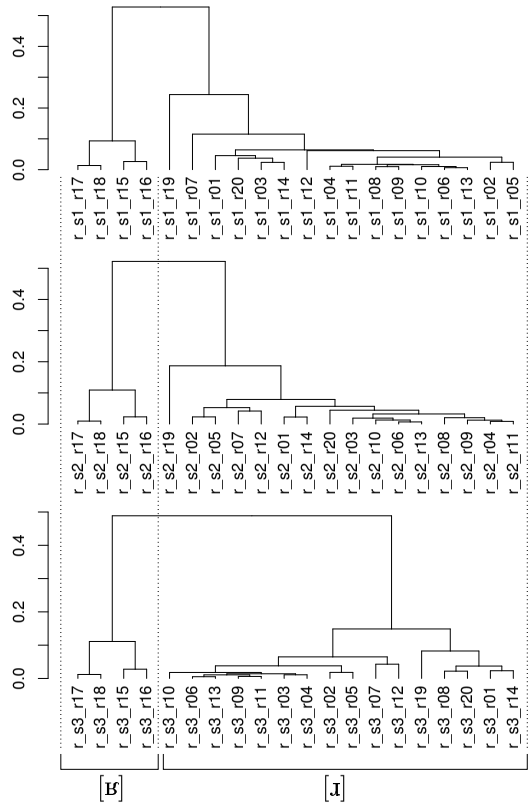

Figure E.4: Subtrees for the phoneme /r/, states s_1, s_2, s_3 and regions r_1–r_{20}

The combination of the EM algorithm and clustering methods permits to find similarities and differences in the segments of each phoneme as pronounced in different regions in Sweden.

Discriminative analysis was used to interpret the results as it gives an indication of the importance of each cepstrum coefficient in discriminating between two groups of states.

The clustering tree was interpreted both at the minimum and maximum level of details (from top and bottom). In the second case two kinds of examples were shown: in the first case a regional variant of a phoneme is found to be closer to the average pronunciation of another phoneme. In the second case, this "merge" does not happen, but plotting the corresponding subtree(s) clearly displays the regional pronunciation variation.

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Paper F

Ecological Language Acquisition via Incremental Model-Based Clustering

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Ecological Language Acquisition via Incremental Model-Based Clustering

Giampiero Salvi

Abstract

We analyse the behaviour of Incremental Model-Based Clustering on child-directed speech data, and suggest a possible use of this method to describe the acquisition of phonetic classes by an infant. The effects of two factors are analysed, namely the number of coefficients describing the speech signal, and the frame length of the incremental clustering procedure. The results show that, although the number of predicted clusters vary in different conditions, the classifications obtained are essentially consistent. Different classifications were compared using the *variation of information* measure.

F.1 Introduction

One of the aims of the project MILLE (Lacerda et al., 2004c) is to analyse the interaction between infants and their linguistic environment in order to model the language acquisition process.

According to the ecological theory of language acquisition (Lacerda et al., 2004a), the infant is phonetically and linguistically naïve. One of the challenges is therefore the analysis of emergency of phonetic classes in the presence of linguistic stimuli.

As well known by the speech signal processing and automatic speech recognition communities, modelling speech may be seen as a two-fold problem, as not only the acoustic characteristics of speech sounds are of interest, but also their evolution and interaction in time.

Semi-supervised learning techniques (Deligne and Bimbot, 1997; Holter and Svendsen, 1997) have been employed in the past in the attempt to optimise acoustic units and lexica for automatic speech recognition (ASR) tasks, or to find the best acoustic model topology (Watanabe et al., 2004). In the study of time series, clustering techniques have been used in the context of Markov chains in order to classify fixed (Li and Biswas, 1999; Oates et al., 1999) or variable (Watanabe et al., 2003; Porikli, 2004) length sequences.

In this study we focus on the static problem; the un-supervised classification of speech sounds according to their spectral characteristics, using clustering methods. The problem of integrating the sounds into longer sequences, such as syllables or words, is left for future research. Note however, that the two problems are strongly interconnected.

The aim of this study is not to model the psycholinguistic processes taking place during learning in details, but rather to explore the linguistically relevant acoustic environment the infant is exposed to with un-supervised learning techniques.

One of our concerns was modelling the phonetic acquisition process *incrementally* both in the attempt to mimic the intrinsic incremental nature of learning and because of the clustering methods limitations with large datasets. This is in agreement with studies on perception that investigate the properties of acoustic memory and of the stores we can rely on in order to analyse and recognise sounds Cowan (1984).

F.2 Method

Clustering and parameter estimation

Model-based clustering (McLachlan and Basford, 1988; Banfield and Raftery, 1993; Fraley and Raftery, 1998) is among the most successful and better understood clustering methods. This is a parametric procedure that assumes that the data points are generated by a mixture model with density

$$\prod_{i=1}^{n} \sum_{k=1}^{G} \tau_k f_k(x_i|\theta_k)$$

Where τ_k and θ_k are the model parameters and $f(x_i|\theta_k)$ is a probability distribution. In our case the shape of each distribution is assumed to be Normal and its parameters are the means μ_k and covariances Σ_k. Furthermore we assume the covariance matrices to be diagonal, with ellipsoidal shape and varying volume across Gaussian components.

A common procedure for finding the model that best fits the data is to use model based hierarchical clustering (Banfield and Raftery, 1993; Dasgupta and Raftery, 1998; Fraley, 1999) as an initialisation procedure. The EM algorithm (Dempster et al., 1977) is then used to fit the mixture model parameters with a fixed number of components G. Both the distribution form and the value of G can be varied in order to obtain models of different complexity. The Bayes information criterion (Fraley and Raftery, 1998), defined as

$$BIC \equiv 2l_M(x, \theta) - m_M \log(n)$$

is finally used to select between different models, in the attempt to find a trade-off between the model fit to the data (likelihood $l_M(x, \theta)$), the model complexity in terms of number of independent parameters m_M and the amount of available data points n to estimate the model parameters.

With our choice of distribution form, the complexity of the model is controlled exclusively by the parameter G, that corresponds to the number of classes.

Recently Fraley et al. (2003) introduced an incremental procedure to overcome the problem of model initialisation with large datasets. The procedure obtains an

initial mixture model on a subset of the data. New data is matched against the current model and the data points are divided into two groups, A and B, depending on how well they fit the current representation. A new model is initialised using the current classification for the points in group A and a new class for the ones in group B. Eventually the procedure is iterated to find the best number of mixture components. The BIC is used at each step to select the most parsimonious model that best fits the data. In Fraley's examples the data points have no specific order, and the data subsets are sampled randomly.

In this study we employ a similar procedure, where the new data is fed into the system in successive time ordered frames. One difference with Fraley's study is that, given the sequential nature of our problem, we can expect the new data points to follow a regular evolution in time. We are thus interested not only in the final model, but also in the way this model evolves in time.

A limitation with this method is that the number of classes can only increase during the process, while it is possible that a more complete sample of the data would reveal a simpler structure. This problem is somewhat more evident in our case as the subsets of data are not randomly chosen.

The incremental model based clustering procedure was implemented by the author in the `R` language (Ihaka and Gentleman, 1996) relying on the implementation of the EM and the model-based hierarchical clustering algorithms from the `MCLUST` (Fraley and Raftery, 2002) package.

Evaluation

Given the task of this investigation, it is not easy to establish a procedure to evaluate the results. The first difficulty is defining what should the target classes be, as it is not known how these classes evolve in time in the infant.

Secondly, the optimal choice for acoustic classes is strongly dependent on the task of discriminating meanings, which involves higher level processing and time integration that are not considered in this study.

Moreover, from an information theoretical point of view, it is not clear that a model that optimally represents the acoustic properties of speech sounds should correspond to a phonetic classification. In ASR for example, each phoneme is modelled by a large number of distributions to represent its variation with contextual variables.

In the absence of a good reference, we concentrate at this stage on evaluating the consistency across classifications in different conditions, in an attempt to highlight possible sources of errors due to limitations of the methods.

A measure of consistency is given in Meilă (2002) and relies on information theoretical concepts. The so called *variation of information* defined as the sum of the conditional entropies of clustering C given clustering C' (and vice-versa), forms a metric in the space of possible clusterings, and assumes the value 0 for identical classifications. This was taken as a measure of disagreement between C and C'.

Finally some examples on how the clusters evolve in time are given together with a spectrogram in order to compare the emergent classes with acoustical features.

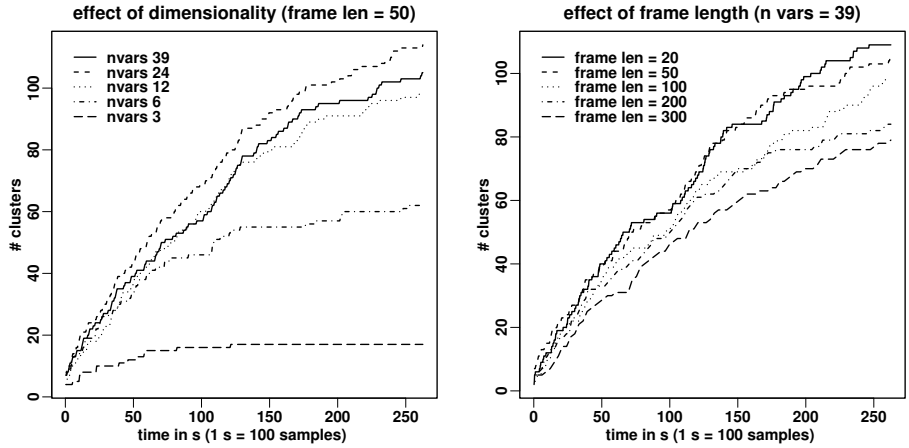

Figure F.1: Number of clusters for each iteration and for varying number of coefficients (left) and frame lengths (right)

F.3 Experiments

Data

The data used in this study is an excerpt from the recordings made at the Department of Linguistics at Stockholm University (Lacerda et al., 2004a,b; Gustavsson et al., 2004). The interactions between mothers and children are recorded with microphones and video cameras. Most of the acoustic data consists of child-directed speech by the mother. As a reference, the mothers are also recorded when speaking with an adult.

A twelve minutes recording of the interaction between a mother and her child was selected. Only the child directed acoustic data was used. Pauses and segments with the infant's voice were removed before processing. From the sound, thirteen Mel frequency cepstral coefficients (including the zeroth) were extracted at 10 msec spaced frames, and their differences were computed up to the second order, for a total of 26254 vectors with 39 coefficients. The total set of parameters is $\{c_0 - c_{12}, d_0 - d_{12}, a_0 - a_{12}\}$ where c are the static coefficients, d the differences and a the second order differences.

Experimental settings

Two of the factors involved in the process have been investigated in the experiments.

The dimensionality of the data has an interesting interpretative value in this context as the classification obtained can be interpreted in the light of the discriminative features that the infant can rely on. This factor has also a technical

frame len (sec)	# of coefficients	# clusters	final BIC
50 (0.5)	3	17	-446426.7
"	6	62	-870400.2
"	12	98	-1451219
"	24	114	-2896358
"	39	105	-4127347

frame len (sec)	# of coefficients	# clusters	final BIC
20 (0.2)	39	109	-4123062
50 (0.5)	"	105	-4127347
100 (1)	"	98	-4116574
200 (2)	"	84	-4120498
300 (3)	"	79	-4107472

Table F.1: Number of clusters and BIC value for the final models with varying number of coefficients (left) and frame lengths (right)

importance as all statistical and machine learning methods are known to suffer from the fact that high dimensional spaces are sparsely populated by data points. The number of parameters is varied from 3, 6, 12, 24, to 39, including respectively: $\{c_0, c_1, d_0\}$, $\{c_0 - c_3, d_0, d_1\}$, $\{c_0 - c_5, d_0 - d_3, a_0, a_1\}$, $\{c_0 - c_{11}, d_0 - d_6, a_0 - a_4\}$ and $\{c_0 - c_{12}, d_0 - d_{12}, a_0 - a_{12}\}$, where we tried to mix static and dynamic coefficients.

The second factor is the frame length in the incremental procedure. This can also affect the results as, at each time step, the model is presented with possibly more or less homogeneous data. The frame length was varied from 20 samples (0.2 sec) to 50, 100, 200 and 300 samples.

F.4 Results

Figure F.1 shows the evolution in time of the mixture model for different dimensionalities on the left and for different frame lengths on the right. Table F.1 summarises the results for the final models.

As expected the number of clusters increases in time, i.e. when the model is presented with more data. The asymptotic value of the number of clusters depends on the number of variables used. Interestingly, even though this dependency is mostly ascending monotone, the number of clusters obtained with 39 parameters, is lower than with 24. This can be explained noting that the discriminative power added by the last 15 coefficients and contributing to the likelihood of the data given the model is small compared to the negative effect on the Bayes information criterion of adding more model parameters. This effect could be dependent on the amount of data in use.

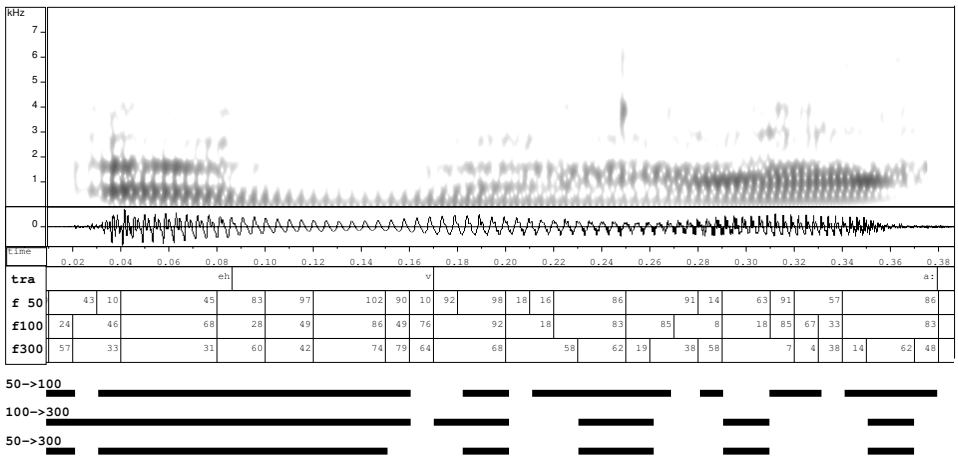

Figure F.2: Example of classifications with different frame lengths. The phrase contains "eh, vad" (eh, what). The transcriptions are respectively a reference, the classification with frame length 50, 100 and 300 samples. Note that the class numbers are mere labels and are randomly assigned by the clustering procedure. The thick line represent the agreement between classifications pairwise.

Regarding the effect of the frame length, the number of clusters increases faster with short frames. This can be considered as a limitation of the procedure, and may be caused by the fact that the number of clusters can only increase, as already mentioned in Sec. F.2. Another explanation could involve the way, at each time step, the new data is split into subsets depending on how well it is predicted by the current model.

Figure F.2 gives an example of the effect of the frame length on the classification. The example contains the phrase "eh, vad" (Swedish for "eh, what"). The segmentations represent the reference phonetic transcription, and the classifications with frame lengths 50, 100 and 300. The thick lines at the bottom represent the agreement respectively between the pairs of frame length conditions {50,100}, {100,300} and {50,300}, when the randomly assigned class numbers are mapped according to the best match over the whole material. It can be seen that, in spite of the number of clusters being different, there is a good agreement between the different classifications. The effect of frame length needs however to be further investigated.

Finally, as discussed in Sec. F.2, a measure of consistency between the classifications is given in Table F.2, in the form of the variation of information. The high values obtained when changing the number of coefficients (dimensionality) are probably due to the large difference in number of clusters predicted by the different models.

# coefficients	3	6	12	24	39
3	0	0.358	0.435	0.471	0.488
6		0	0.376	0.428	0.460
12			0	0.366	0.407
24				0	0.320
39	(frame length = 50)				0
frame length	20	50	100	200	300
20	0	0.215	0.228	0.253	0.252
50		0	0.195	0.241	0.238
100			0	0.236	0.219
200				0	0.222
300	(# coefficients = 39)				0

Table F.2: Variation of information of the classifications obtained with different number of coefficients and frame lengths

F.5 Conclusions

This study investigates the behaviour of incremental model based clustering on a set of child-directed speech data. It suggests that the method can be used to simulate the incremental nature of learning, as well as solving the technical problems arising with large data sets. The effects of two factors, namely the dimensionality of the data and the frame length, are also investigated.

The number of clusters predicted by the method increases with the dimensionality up to 24 coefficients. For higher number of dimensions, the number of parameters seems to penalise the introduction of more classes, according to the BIC criterion.

The method predicts higher number of clusters when shorter frames are used. This probably depends on the fact that the number of clusters can only increase for each time step. This could perhaps be avoided if the way the new data at each time step is partitioned into two subsets was adjusted to the frame length.

Finally the agreement between partitions was evaluated with the variation of information method, showing similar distances when the frame length is varied, and distances that increase with the difference in number of clusters when the dimensionality is varied. Classifications with varying frame lengths seem to be in reasonable agreement.

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