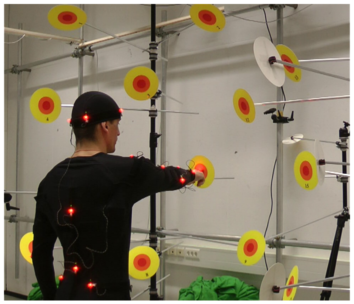
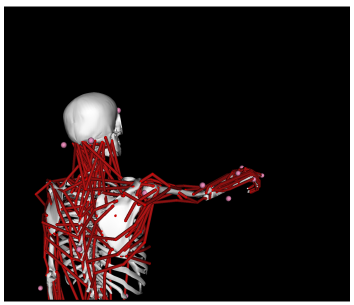


Motion capture



Biomechanical simulation

Figure 1: Our approach uses biomechanical simulation to augment captured performance data with an index of fatigue. We exploit the power of commodity motion capture hardware and circumvent difficult and expensive measurements e.g. EMG, while still being able to jointly analyze performance and fatigue characteristics of movements.

Biomechanical Simulation in the Analysis of Aimed Movements

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Abstract
For efficient design of gestural user interfaces both performance and fatigue characteristics of movements must be understood. We are developing a novel method that allows for biomechanical analysis in conjunction with performance analysis. We capture motion data using optical tracking from which we can compute performance measures such as speed and accuracy. The measured motion data also serves as input for a biomechanical simulation using inverse dynamics and static optimization on a full-body skeletal model. The simulation augments the data by biomechanical quantities from which we derive an index of fatigue. We are working on an interactive analysis tool that allows practitioners to identify and compare movements with desirable performance and fatigue properties. We show the applicability of our methodology using a case study of rapid aimed movements to targets covering the 3D movement space uniformly.

Author Keywords
Biomechanics; Fitts' law; aimed movements; fatigue

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous.

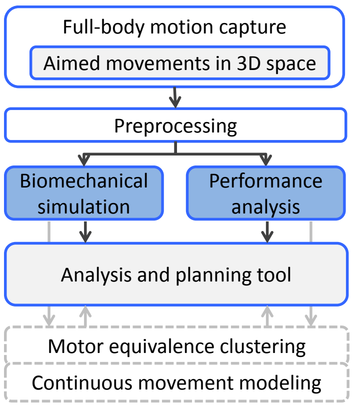

Figure 2: Method overview. The gray boxes denote our ongoing work.

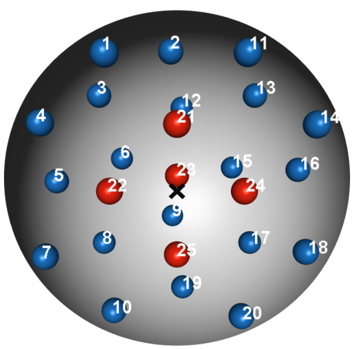

Figure 3: Setup of targets in our case study. They are uniformly covering the movement space.

Introduction

This paper describes ongoing work contributing to the analysis of user interfaces based on aimed movements, such as many gestural interfaces. We address the following design problem: human movement can be mapped to virtual movement in multiple ways and each mapping has unique effects on performance and fatigue. Some applications require fast and accurate responses, whereas others demand stable performance over longer time periods. In drawing, action gaming, and text entry, for example, fatigue may limit use. In exergames, on the other hand, fatigue is desirable, but if it overly compromises performance, gamer experience suffers.

We present a novel method that integrates biomechanical simulation into the standard analysis of user performance in pointing. Data is captured in a task where users perform *aimed movements* at physical targets in 3D space in an optical tracking laboratory (Figure 1). Movement trajectories are captured with optical motion tracking and analyzed for speed and accuracy. However, biomechanical aspects of the movements, in particular fatigue of specific muscles, are difficult to obtain in a lab experiment.

The novel aspect of our methodology is the inclusion of biomechanical simulation to obtain the biomechanical aspects of the movements. To do so, we apply inverse dynamics and static optimization in a biomechanical simulator with an anatomically accurate model of bones, joints and muscles (Figure 1). This allows estimating moments and forces at joints, muscle activations, and the total energy consumption of muscles during a movement. These can be used as indices of fatigue.

Our ongoing work will contribute to efforts at understanding aimed movements in HCI by: 1) allowing the analysis of both fatigue and performance from data collected in a single experiment, 2) informing interface design by charting the upper limits in "pure" movement performance that assumes no external forces nor latencies caused by an intermediary like an input device, and 3) offering an analysis and planning tool that allows exploring the performance–fatigue space with designer-relevant constraints. Previous studies of aimed movements in HCI have looked at limited movement ranges and user performance has been constrained by the input device (e.g., [8]). Studies of 3D pointing have examined only parts of the movement space and assumed uniform performance that is independent of the movement location relative to human(e.g., [4]). Human factors studies have looked at fatigue during work with self-reports and biomechanical analysis of postures [3]. To the best of our knowledge, the presented method is the first combining biomechanical simulation with performance analysis to inform design.

After describing our approach, we present a case study exemplifying the applicability of our method. The goal of the case study is to understand the upper limits of user performance in 3D gestural input scenarios. An athlete (Figure 1) carried out 72,000 reciprocal aiming movements covering the whole reachable space of his dominant arm. We will report on our first results that we obtained using our method and discuss future work.

Biomechanics in Aimed Movements Analysis

Our goal is to inform the design of gestural interfaces by allowing biomechanical analysis of aimed movements in 3D space. Figure 2 shows a high-level overview of our method. We introduce a novel combination of performance *measurements* and *biomechanical simulations* to create a high-dimensional data set describing aimed movements for a specific task. We

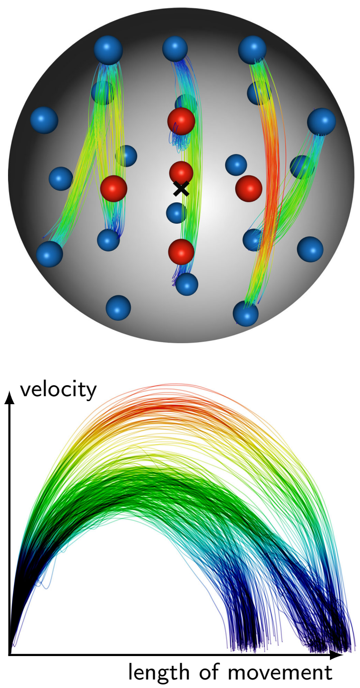

Figure 4: Motion data from our case study. (top) Motion trajectories for selected targets. (bottom) The velocity profiles of the selected movements confirm differences in peak velocity for longer movements. Color coding here refers to temporal velocity.

analyze this data using interactive visualization methods and statistics. The gray boxes in Figure 2 represent ongoing work for expanding the analysis opportunities by modeling and inference from the discrete model. In the following, we will describe the individual steps.

Motion Capture and Data Preprocessing

We apply optical motion tracking to record the actual movements of a human body (or parts thereof). From this data we can easily derive performance data such as speed and accuracy, but the same data serves as input for biomechanical analysis. Optical measurement using markers has a high accuracy and resolution (in our case $1/5\,mm$ accuracy at 480 samples per second). In fact, optical tracking is well developed, relatively inexpensive, and in the process of becoming a widely available tool. We collect the motion data by tracking markers which are rigidly attached to the human body (see Figure 1). Subjects are asked to perform repeated aimed movements to targets in the 3D space. The motion capture data is cleaned and smoothed using common preprocessing methods (e.g. Kalman smoothing, interpolation to fill gaps) in order to remove artifacts and noise. Other preprocessing steps could be necessary depending on data peculiarities and the used motion capture system. Figure 4 shows selected examples of motion data in 3D space and their corresponding velocity profiles.

Biomechanical Simulation

Using simulation we augment our data by variables which will be too difficult to measure in a lab. This includes muscle activations, moments and forces at joints, and forces at tendons, from which we can derive an index of fatigue, or muscle synergies for clustering.

We use the SIMM Full Body Musculoskeletal model and the OpenSim biomechanical simulation software [2, 5], which represent the state of the art in modeling anatomy and dynamics of the human body. Musculoskeletal model is based on previous studies of separate body segments and combines multiple earlier models of skeleton, joints and muscles. It represents average adult male and for better performance can be tuned to parameters of a particular subject.

In order to derive an index of fatigue we compute the following steps using OpenSim:

1. First, we *scale* the musculoskeletal model to the dimensions and weight of the subject.
2. *Inverse kinematics* gives the generalized positions of all joints for all time steps, from which we can infer angular velocities and accelerations at these joints.
3. *Inverse dynamics* is used to derive total moments at joints from accelerations and inertial properties of body segments.
4. Using the total moments at joints, *static optimization* solves for the moments produced by particular muscles as well as forces and activations of those muscles. The method relies on the assumption that opposite muscles are not activated simultaneously (otherwise causing cancellation of moments), and that human motor control is optimal in terms of total muscle activation.

We derive an *index of fatigue* by integrating the muscle activations over a complete movement and normalizing by movement amplitude. This correlates with the total energy expenditure of unit movement [6]. We are still in the process of fully validating this measure against electromyography (EMG). We also compute *total moments* by integration of moments at joints over complete movement and normalizing them over

Study variables: 25 target IDs and 3 target sizes (mm).
Performance variables: speed (m/s), duration (ms) and offset (mm).
Biomechanical variables: a moment (with 1 to 3 degrees of freedom) for 22 joints (163 total variables). A force and an activation for 51 muscles (102 total variables).

Table 1: Variables in our data.

amplitude. Total moments have correlation with the energy expenditure and joint stress.

Interactive Analysis and Planning Tool

Motion capture and biomechanical simulation create a high-dimensional data set (see Table 1) describing complex interrelations between performance, fatigue, spatial locations, and other variables. We are developing an analysis tool for this kind of data that serves three main purposes: validation, exploration and planning. The *validity* of the data can be checked in all stages of the pipeline, particularly during motion capture to detect

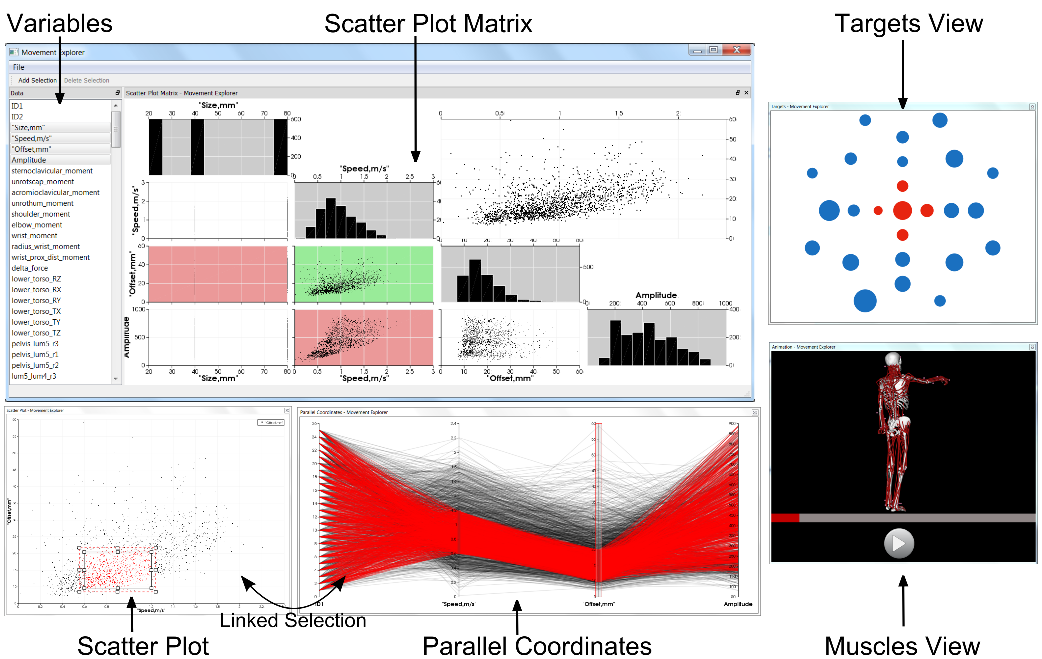

Figure 5: Our analysis tool features several interactive visualization methods that are linked with each other such that a selection in one window shows up in all other windows. In this example, the selection from the scatter plot is also shown as red lines in the parallel coordinates plot.

learning effects, outliers in the measurement, or tiredness of the performer. One example is given in Figure 4: the bell-shaped velocity curves match the expected shape of aimed movements in motor control literature. We want to *explore* the high-dimensional data set to get a better understanding of three-dimensional movements in general. Designers can *plan* new gestural user interfaces by defining constraints regarding e.g. performance or fatigue to narrow the huge design space of gestures.

Our tool (Figure 5) goes beyond classic statistical analysis by incorporating *interactive* visualization methods. This includes scatter plots, histograms, parallel coordinates as well as representations of the aiming targets and the muscles and joints. All visualizations are linked with each other – in the sense that a user selection in one of them is reflected in all other visualizations. This well-established approach in visualization called *Linking & Brushing* [1] deals effectively with high-dimensional data.

Ongoing Work

We are presently working on two data modeling tasks. First, in what we call *motor equivalence clustering*, we cluster movements to *equivalence classes* based on the involved muscle groups. According to previous literature, this can be done using factor analysis or principal component analysis. However, according to the kinematic theory [7], the muscular synergy pattern of a movement also defines its performance parameters. Thus, if the clustering is reliable, it can be used as a compact representation of whole performance+fatigue data. Second, we are working on *continuous movement modeling*, where we interpolate Fitts' law models to areas in the 3D space uncovered by the targets in the data collection phase. We will examine if a Fitts' law model can be inferred for arbitrary points in space based on the

Participant: The subject is a 27 years old male (right-handed, 180 cm, 72.5 kg) with no known disorders. He placed 1st in the French and three times 2nd in the French and German amateur kickboxing competitions, respectively.

Movement targets: Figure 3 shows the 3D coordinates of aiming targets. The reachable space is a half-sphere with radius equal to the subject's arm length and centered at the right shoulder's pivot point. Aims were created from round cartons of 3 colors: yellow, orange, and red, that correspond to three target width conditions with radii of 8 cm, 4 cm, and 2 cm, respectively.These were attached to the ends of aluminium pipes. To ensure that the shoulder stays at the center of the sphere, we prevented leaning with a horizontal obstacle placed about 2 cm in front of the chest.

Experimental design: The experiment consists of 80-85 aiming movements carried for all pairs of the 25 targets, each with three target width conditions (2, 4, and 8 cm). This yields a total of 72,000 pointing acts. The order of trials was randomized in the experiment.

Procedure: Thirty sessions of 90-120 minutes were carried out. Study leader tells subject IDs and size of next target pair, and when to start and when to stop movements. The subject stands in a position marked on the floor and repetitively moves between two given targets as accurately and quickly as possible. Ends of single aimed movement are derived in postprocessing using local minima of absolute velocity. Before each target-pair, the subject can find the best manner to aim at the targets. Timing starts with index finger on a target. After a trial, if self-reported fatigue level is high, five minutes of rest are required. In this study, all movements were done with the subject's dominant hand. We imposed a minimum recovery interval of 6 hours between sessions to allow fast twitch muscle fibers to restore their potential energy.

Apparatus: The PhaseSpace motion capture system with 12 Impulse cameras at 480 fps was used to record the movement of 38 active markers (Figure 1b). Marker placement was done with care to minimize drift during a session. Tracking accuracy is approx. $1/5\,mm$.

Table 2: Pointing experiment

known similar Fitts' law models derived from the data. This is necessary to work with movements with arbitrary origin and target in the space.

Case Study: Pointing with the Arm

We are studying the applicability of the method through a case study of rapid aimed movements with the arm. We cover the whole reachable space of the arm in a *reciprocal tapping task* [8] with physical targets in 3D space.

Data Collection using Motion Capture and Preprocessing
We collect extensive data on the movement of the right arm of a single subject: an amateur kickboxer. Because kickboxing emphasizes stamina and hand-eye coordination, this data provides an estimate of the upper boundary of performance reachable by regular users. A detailed experiment description is given in Table 2. The data set contains more than 72,000 individual aimed movements. One aimed movement is represented in our data as a 3D trajectory of the tip of the index finger from one target to another. Preprocessing is done as in the general case by removing occlusions and outliers, interpolation to fill gaps and Kalman filtering.

Performance
From the curated motion data, we derive an *index of accuracy*, or rather inaccuracy, by defining the *offset* of the aimed movement: following the computation of effective target width [8], we define the offset as the distance of end-points to their centroid in a trial. The finger tip was never to touch the target center and using the center of the physical target would have inflated the offset. Furthermore, we define an *index of speed* as average velocity of aimed movement.

Biomechanical Simulation
Our main goal is to augment the performance data with an *index of fatigue*. As described earlier, we perform a biomechanical simulation using OpenSim, where the curated motion data serves as input. The computations are performed on a workstation with 24GB of memory and 10 parallel processes. The inverse kinematics simulation took 5 days for all data and the inverse dynamics 1 day. We are currently in the process of implementing and running the static optimization. It is likely to require about a week of computation time. Fatigue can then be computed based on muscle activations as described in the previous section. However, in our preliminary results we use total moments at joints as an index of fatigue since the static optimization is not yet completed.

Preliminary Results
We manually divided the 3D space into *segments*, emulating those of an interface tracking the arm. Figure 6 shows a horizontal segmentation (left, center, right) and associated performance and biomechanics data. Large differences among segments are visible. First, the moments for most joints *decrease* from left to right. Only for the sternoclavicular joint the situation is the opposite. Clearly, arm movements in the left part need more force than those in the right part. Second, the fastest movements are in the right segment. These movements also have smaller total moments, than movements in the central and left segments. Third, accuracy in all segments is very similar, in the right segment it is 4% higher but in the left segment only 1% higher than in the central segment. The conclusion from this analysis is that movements in the right segment (of a user using the right hand) are preferable, because they have the highest performance - yet smallest total moments. The central segment has only slightly higher moments, but lower

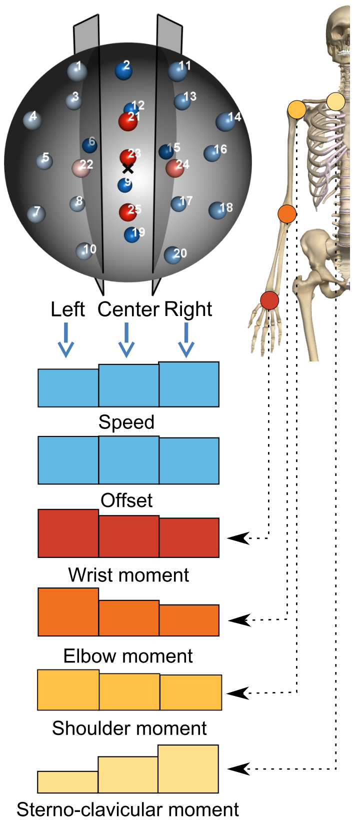

Figure 6: Performance and fatigue in *segmented* movement space. (top) Vertical movement space segmentation and legend for mapping the variables: speed, accuracy, and moment in four joints. Image of skeleton from `http://www.zygotebody.com/`

accuracy and speed than the right one. When compared to left segment the center segment has lower accuracy and significantly lower moments and higher speed.

Conclusion

Load and fatiguability of the musculoskeletal system involved in interaction is a major concern for HCI, but previous methods did not seamlessly incorporate the empirical analysis of aimed movement performance. We presented our ongoing efforts to integrate biomechanical simulation as part of the process. Motion capture equipment is becoming a commodity, and biomechanical simulation is reaching maturity. The method allows collecting data as part of aimed movement studies and our tool-chain will support all subsequent steps. In principle, any HCI situation that involves aimed movements can be incorporated, with limitations posed by optical tracking and the availability of valid musculoskeletal models. Our tool will allow practitioners with motion capture equipment to identify pointing movements with needed performance and fatiguability properties. For example, a painting application should allow long-term use with high precision and minimum fatiguability, but puts less emphasis on speed. A golf game, by contrast, will place directional and positional constraints on possible movements like swings, and our analysis tool allows finding which allow highest speed and precision and make predictions on biomechanical factors like extraneous loading on muscles or joints.

The case we presented is a proof-of-concept study showing that optical tracking data can be used for such purposes, but we are expanding to other domains such as rotation gestures on surfaces. We are working on our tool-chain to create templates for validation, hypothesis-testing, and exploration. Our future work will seek to rigorously validate the predictions of biomechanical models with subjective and physiological measures. We also plan to implement a predictive model of fatigue that takes into account the duration of movement and the number of repetition.

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