# Learning grasp stability based on haptic data

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## I. Introduction

Grasping is an essential skill for a general purpose service robot, working in an industrial or home-like environment. The classical work in robotic grasping assumes that the object parameters such as pose, shape, weight and material properties are known. If precise knowledge of these is available, grasp planning using analytical approaches, such as form or force closure, may be enough for successful grasp execution. However, in unstructured environments the information is usually uncertain, which presents a great challenge for the current state-of-the-art work in this area.

Sensors can be used to alleviate the problem of uncertainty. To determine the shape and pose of an object, vision has been commonly used. However, the accuracy of vision is limited and small errors in object pose are frequent even for known objects. It is not uncommon that even these small errors cause failures in grasping. These failures are also difficult to prevent at the grasp planning stage. This problem is magnified when also the object models are acquired on-line using vision or other similar sensors. While the tactile and finger force sensors can be used to reduce this problem, a grasp may fail even when all fingers have adequate contact forces and the hand pose is not dramatically different from the planned one.

The main contribution of this paper is to show that it is possible to infer knowledge about grasp stability using information from tactile sensors while grasping an object before being further manipulated. This is very useful, because if failures can be detected, objects can be regrasped before trying to lift them. However, the relationship between tactile measurements and grasp stability is embodiment specific and very complex. For this reason, we propose to use machine learning techniques for the inference.

We first study one-shot recognition approach using support vector machine classification: detecting grasp stability from a single tactile measurement. We also implement the time-series analysis approach using hidden Markov models based on a sequence of tactile measurements. The results show that the idea of exploiting the machine learning approach is feasible and it opens a number of interesting venues for the future research.

## II. Simulator and The database

To achieve good generalization performance, machine learning approaches typically require large amount of training data. Generating large datasets on real hardware is time consuming and in robotic grasping generating repeatable experiments is difficult due to the dynamics of the grasping actions. As a solution to the problem of acquiring enough training data, we propose to simulate the grasping process. However, we evaluate the feasibility of the approach both on simulated and real data.

The tactile database aims to include numerous stable and unstable grasps on different objects. In this work, the 3-finger Schunk Dextrous Hand (SDH) with tactile array sensors and 7 degrees of freedom is used to generate grasping data (Figure 1).

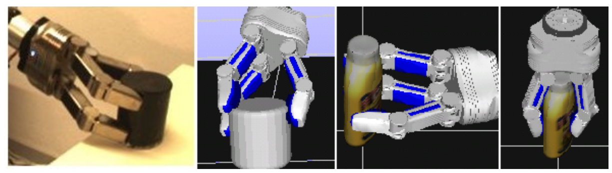

Fig. 1. Examples of real and simulated grasps

In the simulated environment, grasps are labeled as stable or unstable by calculating the quality of grasps. The tactile images from the distal sensors in Figure 2 represent a stable grasp of a cylinder. The similarity between the simulated and the real sensors can be observed in Fig. 3 which shows a visual comparison between the real and the simulated sensor output where a sharp edge was pressed against both sensors.

Fig. 2. Tactile images from the distal sensors of the SDH

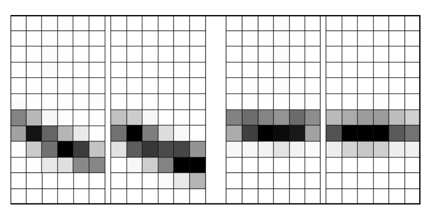


Fig. 3. Measured (a and c) versus simulated (b and d) sensor values.

Real world experiments are also performed to demonstrate that the grasp stability recognition is possible in real robots. In addition, we demonstrate that the same methods applied in simulation experiments also apply to the real world scenario. In the real setup, to generate the stable/unstable label for the grasp, the object is lifted and rotated around the approach direction. The grasps where the object dropped or moved in the hand were labeled as unstable.