Learning Continuous Grasp Stability for a Humanoid Robot Hand Based on Tactile Sensing

J. Schill and J. Laaksonen and M. Przybylski and V. Kyrki and T. Asfour and R. Dillmann

Abstract— **Grasp stability estimation with complex robots in environments with uncertainty is a major research challenge. Analytical measures such as force closure based grasp quality metrics are often impractical because tactile sensors are unable to measure contacts accurately enough especially in soft contact cases. Recently, an alternative approach of learning the stability based on examples has been proposed. Current approaches of stability learning analyze the tactile sensor readings only at the end of the grasp attempt, which makes them somewhat time consuming, because the grasp can be stable already earlier.**

In this paper, we propose an approach for grasp stability learning, which estimates the stability continuously during the grasp attempt. The approach is based on temporal filtering of a support vector machine classifier output. Experimental evaluation is performed on an anthropomorphic ARMAR-IIIb. The results demonstrate that the continuous estimation provides equal performance to the earlier approaches while reducing the time to reach a stable grasp significantly. Moreover, the results demonstrate for the first time that the learning based stability estimation can be used with a flexible, pneumatically actuated hand, in contrast to the rigid hands used in earlier works.

I. INTRODUCTION

The sense of touch is essential to human grasping. The work described in this paper considers robotic tactile sense as a biomimetic replacement for the sense of touch, especially when estimating grasp stability. Grasp stability in analytical sense is well defined and can be readily computed in simulation where enough data of the grasp is available, i.e. all contacts between the robotic hand and the object that is grasped. Additionally, using a force closure metric for grasp stability, one can compute a grasp that sufficiently resists outside forces, such as gravity, thus allowing the robot to manipulate the object, for example by lifting the object. However, when using real hardware, the tactile sensor data is imperfect, both in the sense of detecting contacts and in the sense of determining the actual contact forces. In some cases the proprioceptive information, i.e. joint configuration, is also difficult to determine accurately, thus, causing uncertainty in ascertaining the kinematic configuration of the hand. All these described phenomena pave a difficult road for computing the grasp stability analytically with real hands.

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In this paper, we focus on learning the grasp stability instead of analytically solving it. Compared to the analytical methods, learning requires training data, which needs to be collected beforehand. As the training data, we can use any pertinent data that can be collected from robotic hand, in our case we use input from all tactile sensors and the hand finger configuration. It is also important to notice that the raw sensor data can be used in the learning, for example, there is no need to know the kinematic configuration of the hand to compute the true locations of the contacts when analytically solving the grasp stability. This feature allows grasp stability to be learned for many different robotic hands with only minimum changes.

There has been a number of publications on learning the grasp stability [1], [2]. These approaches evaluate the stability after the hand finished closing around an object. We extend the work presented in previous papers, so that the decision on the grasp stability can be achieved during the grasping instead of at the end of the grasp. We also demonstrate that the learning of the grasp stability is possible with the ARMAR-IIIb hand [3], [4], a flexible anthropomorphic hand operating on pneumatics.

The rest of the paper is divided into four sections. Section II gives an overview on learning grasp stability as well as other learning approaches that are grasp and manipulation related. Section III introduces a theoretical background on machine learning methods and how they can be applied to the grasp stability problem. Section IV contains the experiments made on data collected using the ARMAR-IIIb hand. We conclude with discussion of the results in Section V.

II. RELATED WORK

Grasp stability analysis by analytical means is a well established field. However, to analytically determine the grasp stability, the kinematic configuration of the hand and the contacts between the hand and the object must be perfectly known. This subject has been well studied and [5] gives a detailed review on the subject. However, the references are useful only in cases when conditions described above are true. When this is the case, it is possible to determine if the grasp is either force or form closure grasp [6], which ensures the stability. Compared to this body of work, we wish to learn the stability from existing data, i.e. the tactile data.

The research on use of tactile and other sensors in a grasping context has increased in last few years. Felip and Morales [7] developed a robust grasp primitive, which tries to find a suitable grasp for an unknown object after a few initial grasp attempts. However, only finger force sensors were used in the study.

Apart from using tactile information as a feedback for low level control [8], tactile sensors can be used to detect or identify object properties. Jiméneza et al. [9] use the tactile sensor feedback to determine what kind of a surface the object has, which is then used to determine a suitable grasp for an object. Petrovskaya et al. [10] on the other hand use tactile information to reduce the uncertainty of the object pose, upon an initial contact with the object. In their work, a particle filter is used to estimate object's pose, but the tactile sensor used to detect contact with the object is not embedded in the gripper performing the grasping.

Object identification has been studied by Schneider et al. [11] and Schöpfer et al. [12]. Schneider et al. show that it is possible to identify an object using tactile sensors on a parallel jaw gripper. The approach is similar to object recognition from images and the object must be grasped several times before accurate recognition is achieved. Schöpfer et al. use a tactile sensor pad fixed to a probe instead of a gripper or a hand. They also study on different temporal features which can be used to recognize objects. Similar object recognition systems have been presented in [13], [14].

The approach used and extended here has been published in [1]. Similar approach was used in [2]. However, in this paper we show that we can use the described methods with a more complex hand, the ARMAR-IIIb humanoid hand, and that we can extend the single time instance classifier by means of filtering.

III. Supervised Learning of Grasp Stability

A. Learning Grasp Stability

Our notation of observations follows [1]:

- $D = [o_i], i = 1, \ldots, N$ denotes a data set with N observation sequences.
- $o_i = [x_t^i], t = 1, \ldots, T_i$ is an observation sequence with T_i samples.
- $x_t^i = [\mathbf{f}_t^i \ \mathbf{j}_t^i]$, each sample consists of $\mathbf{f}$, the features extracted from tactile sensors and $\mathbf{j}$, the joint configuration.

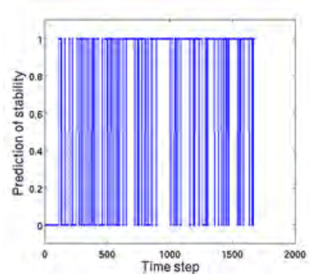
To learn grasp stability, the training data is collected from series of grasps, noted by the observation sequences o_i. Each recorded observation sequence is labeled with a label indicating either a stable or unstable grasp. Then, from each observation sequence the last sample, $x_{T_i}^i$, is used for the training. This captures the time instant on which the decision of stable or unstable grasp is based on. Both unstable and stable grasp must be included in the training data so that sufficient data is available to discern the stable grasps from the unstable grasps.

We use a Support Vector Machine (SVM) [15] to classify the grasp as either stable or unstable. Compared to force closure metric from the analytical methods for computing the grasp stability, the binary classification is not as informative as the continuous value given by the force closure metric, however the classification result reflects the stability criteria in the training data directly. Another benefit of SVM is that it is computationally efficient, so that it can be used on-line during grasping. To train the SVM, the sample $x_{T_i}^i$ from each training observation sequence is given as an input vector and the corresponding label as the desired output.

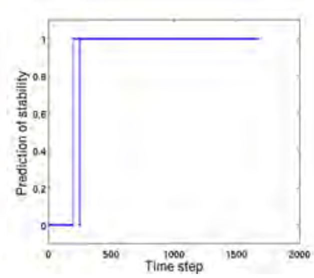
B. Learning Temporal Changes in Grasp Stability

In [1], the temporal information collected during a grasp is used in conjunction with a hidden Markov model (HMM) to decide whether the grasp is stable or not. But for the method to be able to decide, the grasp must be completed. The second method presented in [1] was based on the idea depicted in III-A. We propose to extend the instantaneous SVM-based method by applying the learned stability model on-line to each sample $x_1, \ldots, x_T$ we obtain during the grasp, contrary to the previous approach, where only the final sample, x_T, is is used to determine the stability of the grasp. This extension allows quicker decision making on the grasp quality in the case of a stable grasp.

As the method described in III-A does not remember any of the previous time instances and does not consider the whole grasp sequence from $t = 1, \ldots, T$, the classification result over time may oscillate. One pathological example is shown Figure 1. Through the use of filtering and thresholding, the oscillations can be effectively removed.



(a)



(b)

Fig. 1: (a): Each time instance of a stable grasp classified with a SVM classifier; (b): The classification result filtered with an exponential filter and thresholded.

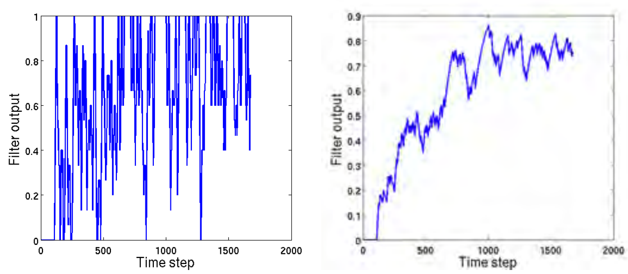
We study two different filter types: a mean filter and an exponential filter. The results of the experiments with the filters are shown in Section IV. The input for the filters are the results from the classifier, either 0 or 1. The mean filter can be defined as a sliding window, with window size w. The mean of the data in the window is then calculated, and this result is the output of the filter. Exponential filter is described by

$$y(t) \ = \ (1 - \alpha) \cdot y(t-1) + \alpha \cdot x(t) \ . \tag{1}$$

Equation 1 consists of $y(t)$ and $y(t-1)$, filter output at time instances t and $t-1$, of $x(t)$ the binary stability at time t and of α which a weighting factor. Examples of both filters are shown in Figure 2 which depicts the same sequence as in Figure 1.

Introducing the filters requires setting more parameters in addition to the parameters for SVM. These include w for the mean filter window width, and α for the exponential filter. In addition both require the threshold, thr, for the binary decision of stability. After the threshold has been crossed, the grasp is deemed stable. Close to optimal parameters can be found experimentally and we have done that for the datasets used in this paper.

In addition to the filters, we ran experiments without using any filters, thus, the output from the classifier is taken directly. This approach provides a quicker response to stable grasps but can also misclassify unstable grasps as stable grasps more frequently than the filter based approach.



(a) (b)

Fig. 2: (a): Filter output of mean filter; (b): Filter output of exponential filter.

C. Feature Extraction

Each of the tactile sensors on the ARMAR-IIIb platform produces a tactile image. An example image showing all six tactile images is shown in Figure 3. This imaging property of the sensors allows us to use image feature extraction techniques. In this case we have chosen the image moments as our feature extractor, which have been shown to perform well in this task [16]. The hand comprises of two different sizes of tactile sensors which contain 4x7 or 4x6 tactile elements or taxels.

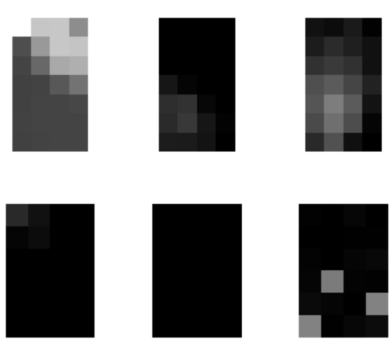


Fig. 3: Tactile images from ARMAR-IIIb.

Raw image moments are defined as

$$m_{p,q} = \sum_x \sum_y x^p y^q I(x,y) \;, \qquad (2)$$

where $I(x,y)$ is the force measured by the taxel. The moments are computed up to order two, that is $(p+q) = o,\ \ o = \{0,1,2\}$. These are related to the total pressure, the mean of the contact area, and the shape of the contact area, indicated by the variance in x- and y-axes. Moments are computed for all tactile sensors individually, thus $\mathbf{f} \in \mathbb{R}^{36}$.

In addition to the tactile images, the joint angle sensors provide a source of information relevant to the stability of the grasp. However as the number of fingers and joints is usually much less than the number taxels (tactile sensing elements) in tactile sensors, it is reasonable to use the data from the joints directly. In this case, 8 joint angle sensors are available, thus $\mathbf{j} \in \mathbb{R}^8$. All feature vectors, x_t^i, were normalized to zero mean and unit standard deviation.

IV. EXPERIMENTS

A. Hardware Platform

We used the humanoid robot ARMAR-IIIb as a test platform for the experiments with our stability classifier. ARMAR-IIIb consists of several kinematic subsystems: The head, the torso, two arms, two hands, and the platform. The head has seven degrees of freedom (DoF) and contains four cameras, i.e. two cameras per eye. The torso has 1 DoF in the hip, allowing the robot to turn its upper body. Each of the two 7 DoF arms consists of a 3 DoF shoulder, a 2 DoF elbow and a 2 DoF wrist. At the tool center point (TCP) of each arm a FRH-4 Hand [17] is mounted. The hands are pneumatically actuated using fluidic actuators. For the experiments in this paper, we used ARMAR-IIIb's right hand, (see Fig. 4), which is equipped with joint encoders and pressure sensors. This allows a force position control of each DoF [18]. The hand has 1 DoF in the palm, and 2 DoF in the thumb, the index and the middle finger, respectively. Apart from that, there is 1 DoF for combined flexion of the pinky and ring finger. Furthermore the hand contains 6 tactile sensors from Weiss Robotics [19]. One tactile sensor is mounted on the distal phalanges of the thumb, the index and the middle finger, respectively. Three tactile sensors are mounted at the palm, in the area between the thumb and the index and middle fingers. The tactile sensors have a resolution of 4×7 taxel (phalanges) and 4×6 taxel (palm). They use a resisitive working principle to measure the pressure applied to the sensor. Therefore an array of electrodes is covered with a layer of conductive foam. When a pressure is applied to the sensor the resistance between the electrodes decreases, which is measured by an microcontroller. Further information can be found in [20], [21], [22].

B. Data Collection

In order to provide sensor input for the training and the validation of the classifier, we needed to treat two distinct cases:

- Collect data for successful, stable grasps.

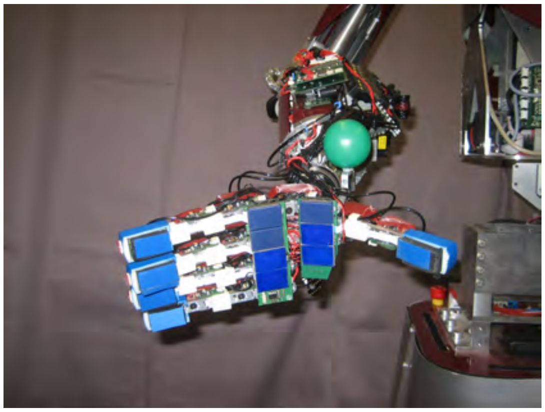


Fig. 4: ARMAR's right hand. Tactile sensors are mounted on the palm and the distal phalanges of the thumb, the index and the middle finger.

- Collect data for unstable grasps.

The second case also includes data for the cases where the hand cannot close completely or not at all, due to obstacles, and cases where the hand closes emptily, i.e. it does not experience contact to any object at all. Yet in all these cases one gets sensor readings that have to be considered for training and validating the classifier. We collected data from the following two types of sensors:

- Tactile sensor data
- Joint angle data of the hand joints

Fig. 5: The basket with our test objects.

For data collection, we executed grasps on a set of household items located in a box (see Fig. 5). The configuration of the objects in the box was modified between the individual test runs in order to allow the hand to reach a large variety of different end configurations. We used the following data collection procecure: First, we placed the box with the objects in front of the robot. Then we moved ARMAR's right hand to a pre-grasp pose near the target object. Different possible pre-grasp poses included the following:

- Grasps from the top where the hand would move vertically down.
- Grasps from the top, but with tilted approach directions.
- Grasps from the side.
- Varying roll angles of the hand with respect to the approach direction, for each of the three cases above.

After moving the hand to the pre-grasp pose, we started the data recording which means we began to read and store the tactile sensor data and joint angle data once during every pass of ARMAR's control loop. All data was labeled with a time stamp. In the next step, we moved the hand towards the object until the tactile sensors in the palm reported contact with the object. Then we closed the hand and waited until the pressure on the hand's actuator stabilized and would not grow anymore. The finger forces are set to the maximum to create a strong tactile image on the sensors. Due to the compliant characteristic of the hand, the hand adapts to the shape of the object. In this context we point out that we considered only three-fingered grasps, i.e. we only closed the thumb, the index and the middle finger during grasping. We did not close the ring and small finger, as they are not equipped with tactile sensors and thus they would not contribute to the tactile sensor input of the classifier. After closing the hand, we stopped the recording of the sensor data. Finally, we tried to lift the object by moving ARMAR's hand up. Then, we reported the result of the experiment, i.e. whether the grasp was successful or not. We repeated the above procedure until enough samples had been collected. We collected two separate sets, D_1 and D_2. D_1 contained 71 stable grasps and 94 unstable grasps. D_2 comprised of 82 stable grasps and 76 unstable grasps. By collecting two separate sets with different grasps, we can get an idea of the generalization capability of the classifier which was tested in the validation tests. Figures 6 and 7 show some successful grasps from the validation tests. The left column shows the situation after closing the hand. The right column shows the grasps after lifting the respective object.

C. Experimental Results

We have divided the experiments into two parts. The first part consists of synthetic tests, which presents the reliability and accuracy of the classification of the grasp stability and comparisons between different filter types. The second part is validation test, using a learned stability model with the real ARMAR-IIIb platform.

1) Synthetic tests: In the synthetic tests, we used both datasets D_1 and D_2. For most experiments, the confusion matrix is presented, showing how the classifier performs in terms of true positives (stable, predicted stable), false positives (unstable, p. stab.), true negatives (unstable, p. unstab.) and false negatives (stable, p. unstab.).

In Table I, the SVM was trained with data from a corresponding dataset, only the last sample from each observation sequence was classified to enable comparison to earlier works. The reported results are averages from 10-fold cross validation. The results show that the performance across datasets is similar. These results can be compared with reported results in [1], [2], showing that the ARMAR-IIIb hardware is able to reach similar performance as the Schunk Dextrous Hand (SDH) or the Barrett hand in this task.

Fig. 6: Some example grasps. Left column: situation immediately after closing the hand. Right column: After lifting the object.

TABLE I: Confusion matrix for classification rates of grasps when classifying only the last sample, for datasets D_1 and D_2.

D_1	P. Stab.	P. Unstab.	D_2	P. Stab.	P. Unstab.
Stable	0.79	0.21	Stable	0.72	0.28
Unstable	0.28	0.72	Unstable	0.26	0.74

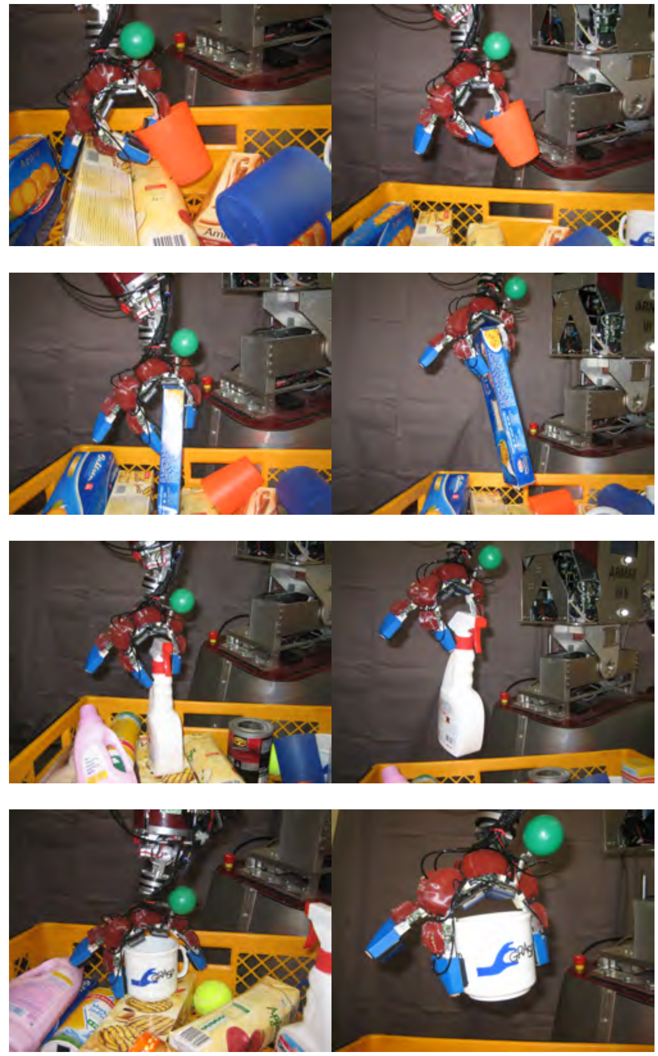


Fig. 7: Some example grasps. Left column: situation immediately after closing the hand. Right column: After lifting the object.

Contrary to the results in Table I, in Tables II, III and IV the whole observation sequence was classified using the methodology presented in Section III-B. In Table II, the mean filter was used with a window width of 25 and with a threshold of 0.61, Table III shows the result with an exponential filter with $\alpha = 0.056$ and threshold of 0.61. These parameter values were searched using grid search and produced the best results for both datasets. The results in Table IV were obtained without using a filter.

Overall, when using a filter with the classification, the overall classification rate is similar to the last sample classification, but classification rate of the unstable grasps is better. This can be explained through the use of the filter which filters out the effect of the last sample, thus, leading to a better classification result. In the case where no filters are used, in Table IV, the stable grasps are predicted well, but this translates also to falsely predicting that unstable grasps are stable. On average, the filter based classification is better in predicting the stable and unstable grasps across the two datasets.

One interesting possibility that comes with the method described in Section III-B is that the grasp sequence can be stopped when the classifier decides that a stable grasp has been achieved. Using a mean filter, the decision time was 68.6 % of the whole grasp sequence on average, with a exponential filter, the time was 66.9 % and without a filter the time was 59.6 %. For example, if a whole grasp sequence is 1000 time steps long, the classification using a mean filter can stop the grasp at time step 686 on average, if the grasp is a stable grasp. Without a filter, the average time goes down as expected but with a cost of overall classification rate as seen in Table IV.

2) Validation tests: To mimic a real world usage scenario, the observations in dataset D_1 were used to train the SVM classifier. Then using the trained classifier, dataset D_2 was classified. Each observation sequence in the dataset was

TABLE II: Confusion matrices for classification rates of grasps using mean filter ($w = 25$, thr $= 0.61$).

D_1	P. Stab.	P. Unstab.	D_2	P. Stab.	P. Unstab.
Stable	0.77	0.23	Stable	0.74	0.26
Unstable	0.24	0.76	Unstable	0.16	0.84

TABLE III: Confusion matrices for classification rates of grasps using exponential filter ($\alpha = 0.056$, thr $= 0.61$).

D_1	P. Stab.	P. Unstab.	D_2	P. Stab.	P. Unstab.
Stable	0.79	0.21	Stable	0.73	0.27
Unstable	0.23	0.77	Unstable	0.16	0.84

classified with mean and exponential filters and without filtering. The results are show in Table V. Compared to results in Table I, the number of false positives rises. This effect might be due to tactile sensor hysteresis, i.e. the output from the sensors changes between the collection of datasets which in turn means that dataset D_1 does not represent the data in D_2 and leads to worse results.

V. CONCLUSIONS

In this paper, we focused on learning grasp stability from labeled data, similar to approaches in [1], [2]. We utilized a well-known classifier, SVM, and trained it using grasp data acquired from the sensors of the humanoid hand of ARMAR-IIIb. We showed that we are able to reach similar results with ARMAR-IIIb as previously reported on other types of hardware, such as the Schunk Dextrous Hand or the Barrett hand. We also extended the SVM based grasp stability classifier with the use of filters to classify the whole grasp sequence instead of just the end of the grasp sequence. This allows faster decisions for stable grasps.

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TABLE IV: Confusion matrices for classification rates of grasps without a filter.

D_1	P. Stab.	P. Unstab.	D_2	P. Stab.	P. Unstab.
Stable	0.90	0.10	Stable	0.87	0.13
Unstable	0.46	0.54	Unstable	0.21	0.79

TABLE V: Confusion matrices for validation tests.

Mean filt.	P. Stable	P. Unstable
Stable	0.77	0.23
Unstable	0.39	0.61
Exp. filt.	P. Stable	P. Unstable
Stable	0.76	0.24
Unstable	0.38	0.62
No filter	P. Stable	P. Unstable
Stable	0.90	0.10
Unstable	0.46	0.54

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