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Sensor Prediction and Grasp Stability Evaluation for In-Hand Manipulation

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Abstract— **Handling objects with a single hand without dropping the object is challenging for a robot. A possible way to aid the motion planning is the prediction of the sensory results of different motions. Sequences of different movements can be performed as an offline simulation, and using the predicted sensory results, it can be evaluated whether the desired goal is achieved. In particular, the task in this paper is to roll a sphere between the fingertips of the dexterous hand of the humanoid robot TWENDY-ONE. First, a forward model for the prediction of the touch state resulting from the in-hand manipulation is developed. As it is difficult to create such a model analytically, the model is obtained through machine learning. To get real world training data, a dataglove is used to control the robot in a master-slave way. The learned model was able to accurately predict the course of the touch state while performing successful and unsuccessful in-hand manipulations. In a second step, it is shown that this simulated sequence of sensor states can be used as input for a stability assessment model. This model can accurately predict whether a grasp is stable or whether it results in dropping the object. In a final step, a more powerful grasp stability evaluator is introduced, which works for our task regardless of the sphere diameter.**

I. Introduction

After grasping an object, often regrasping is necessary before the actual task can be performed, for example when grasping a pen for writing. Regrasping with one hand and without additional support is challenging: in order to achieve robust in-hand manipulation, the current touch state has to be taken into account, but modeling of the contact state is difficult. In particular, it is challenging to design an analytical model with multiple contacts, with complex shapes of the object or the fingertip, and with flexible materials.

It has been proposed that humans use an offline simulation to plan movements [1]. Accordingly, the task of in-hand manipulation could be split into three parts: a forward model for sensory prediction, a grasp stability assessment, and a motion sequence selection. The forward model predicts the sensory outcomes resulting from a movement. This can be done recursively for a sequence of movements. The grasp stability evaluator calculates for each step whether the grasp is stable. The motion sequence selector selects a sequence of viable movements that result in the target posture. This paper focuses on the 1st and 2nd part, namely sensor prediction and stability assessment.

A. Related Research

Analytical solutions for in-hand manipulation of a sphere are provided in [2][3][4], but simplifying assumptions are made, such as rigid bodies, known geometries, no slip, point contacts and fingertips with six degrees of freedoms (DOF). In general, motion planning in complex environments with multiple constraints is a well known problem [5][6][7], but often the current sensor state of the robot is not taken into account. Yet, the importance of tactile sensing for object manipulation is well known [8]. Realistic contact modeling for object manipulation has been attempted [9][10], yet it is still challenging to achieve. Tactile sensor prediction has for example been attempted in [11]. Tactile information has also been used for finger adjustment during in-hand object manipulation [12][13]. Others have achieved in-hand manipulation (in particular in-hand rolling and elevation) without sensors due to specialized robotic fingertips [14].

[15][16] used a data glove to train in-hand manipulation and form compact grasp representations. In [17] a dataglove and a genetic algorithm were used to learn in-hand manipulation. A Markov Decision Process for modeling and planning high-level in-hand manipulation has also been used [18]. Even though a growing number of research on in-hand manipulation is performed, it remains an open research problem.

B. Previous Work with TWENDY-ONE

Previously, already several studies about in-hand manipulation have been performed with the hand of the robot TWENDY-ONE. The hand has four fingers with 13 actuated DOF, not including the wrist (for details, please refer to Section II). [19] showed that the robot is capable of performing all the 17 different grasps that can be performed with 4 fingers according to [20]. Those grasps were defined as sets of joint angles for the 13 DOF, and some of the joint

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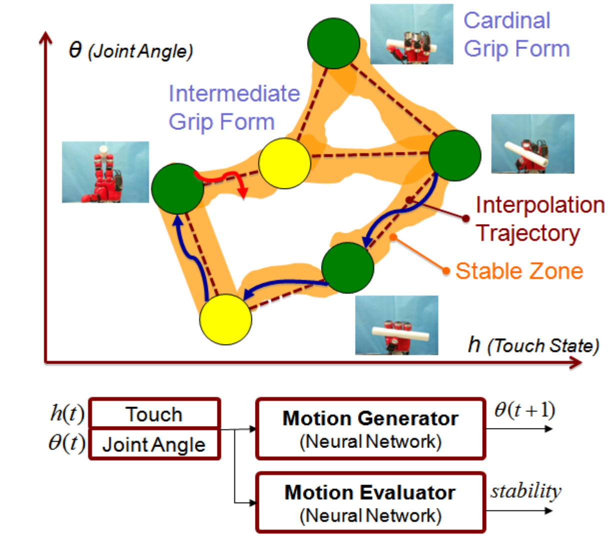

Figure 1. In-hand manipulation according to [21]. Different grasps can be shown in the state space consisting of the posture and the touch state. To move from one grasp to another, simple interpolation control can be used, but this is not robust, as it does not take the touch state into account. Therefore, a neuronal network is used to generate the next set of joint angles, depending on the current joint angles and touch state. Another neuronal network is used to calculate the stability of the grasp.

angles were defined variably to accommodate for cylindrical or spherical objects of varying diameter. In addition, by simple interpolation control between these postures and several intermediate postures, the robot was able to move from one grasp to another without dropping the object. However, the movements were unstable because the contact state between the object and the hand was not taken into consideration.

In [21] it was shown that the reason why the interpolation control is feasible is the existence of stable zones in the state space due to the hardware's flexibility. Therefore, they devised a control theory using two neuronal networks: a motion generator and a motion evaluator network (see Fig. 1). The motion generator network produced as output the joint angles for the next time-step; the motion evaluator network produced as output an estimate of the grasp stability. In the case that an unstable state was approached, alternative motions were created by adding random noise to the motion. If the resulting motion proved to be successful, it would be used for training the motion generator network. In any case, the new motion was used for training the motion evaluator network. Therefore, it was possible to detect unstable states, but alternative motions could not be planned, but only examined through trial and error.

On the other hand, the work presented in this paper makes it possible to plan alternative movements: the outcome of different motions can be simulated, in particular the touch state throughout the motion. Using the results, the grasp stability of different motions can be assessed, in order to find one that results in a stable transition to the desired grasp.

C. Overview of the rest of this paper

To perform in-hand manipulation, a robotic hand with many degrees of freedom is necessary. We use the TWENDY-ONE hand, which is described in Section II. In this section also the master-slave system used for collecting training data is introduced. Section III describes the sensor forward model and its evaluation. Section IV presents how to use the input from Section III to perform the grasp stability evaluation. Section V introduces a more powerful grasp stability evaluator. Finally, Section VI provides the overview of the achieved results and in the future work it is discussed how the results from this paper could be used for motion planning.

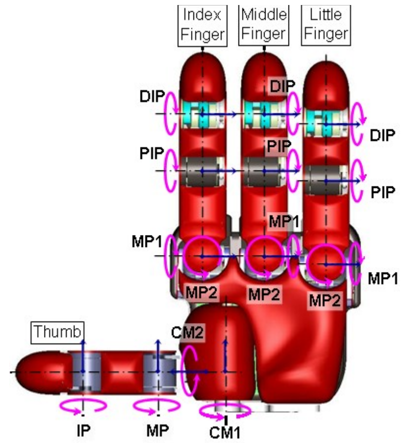

Figure 2. The hand of the human symbiotic robot TWENDY-ONE.

II. ROBOTIC SYSTEM

A. TWENDY-ONE

The hand of the human symbiotic robot TWENDY-ONE has 16 DOF, as depicted in Fig. 2. The DIP and PIP joints of the index, middle and little finger are coupled, and the hand is actuated by 13 small electric motors integrated in the joints. The DIP and MP1 joints also include springs; there are no springs for the thumb. The hand is also covered with a soft skin with 241 distributed tactile skin sensors for the whole hand [22]. In addition, 6-axis force/torque sensors are included in each fingertip. The hand is about 20 cm long and the palm is 10 cm wide.

B. Master-Slave System

In order to control the robot and provide examples of performing in-hand manipulation successfully or unsuccessfully, a CyberGlove (22-sensor model) from CyberGlove Systems was used. Amongst others, it has three flexion sensors per finger and four abduction sensors [23]. In order to map the sensor measurements to the thumb and index finger of TWENDY-ONE, the most distal index flexion measurement is ignored, and the proximal thumb flexion and thumb abduction sensor are added to move the CM2 joint of the robot. The proximal thumb flexion is also used for the robot's CM1 joint. For the other joints of the thumb and index finger there is a clear correspondence between a sensor measurement of the human hand and an actuated DOF of the robot.

III. FORWARD MODEL FOR SENSOR PREDICTION

The forward model f uses the current motor angles θ_t, the next motor angles θ_{t+1} and the current touch state h_t to predict the next touch state h_{t+1} :

$$h_{t+1} = f(\theta_t,\ \theta_{t+1},\ h_t) \qquad (1)$$

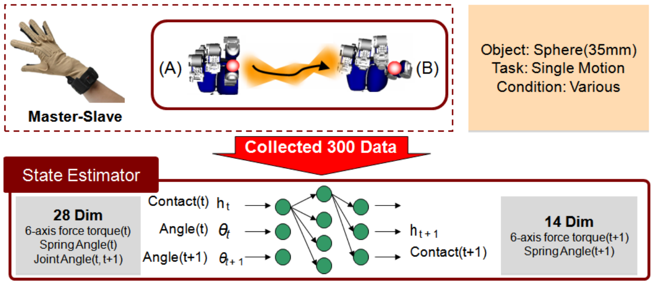

Figure 3. The neuronal network for learning the prediction of the sensory data. The task is to move a sphere from the bottom of the fingertip to its side. A dataglove is used to collect training and testing samples. The input are the current angles, the next angles, and the current touch state. The output is the next touch state.

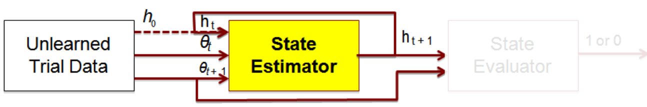

Figure 4. The sensor predictor is used recurrently.

The motor state consists of 7 parameters (3 motors for the index finger, 4 for the thumb) and the touch state includes 14 parameters: two 6-axis force/torque sensors (in the fingertips of the thumb and index finger) and the two springs in the index finger. Therefore, the input has 28 dimensions and the output 14 dimensions, overall. The hand of TWENDY-ONE also includes skin sensors, but as will be shown in Section VI, the features that can be calculated from the skin sensor are less informative for the grasp stability evaluation, and therefore the skin sensors are omitted here. The model is depicted in Fig. 3.

Because it is difficult to make an analytical model for the forward model, a simple neural network is used to learn it. In order to predict a sequence of sensor states, the output of the model is used as input in the next time-step in a recurrent fashion, see Fig. 4.

The task that we used to evaluate whether the model can learn the sensory prediction was to move a sphere (diameter 35 mm) with the thumb and index finger from the bottom of the index finger to its side, as depicted in Fig. 3. This task was chosen due to its high difficulty.

A. Evaluation

A master-slave system was used to collect the training and testing data. In total 300 time-series of θ_t and h_t were collected, out of which about 180 correspond to successful movements. Considering the failure trials, even though a data-glove was used, it proved to be difficult to successfully move the ball, and therefore some of the failure motion patterns are close to successful motion patterns. At other times, the motion was intentionally not successful, like just opening the hand.

The sampling rate is 10ms, but only a subset of the sampled time instances is used for learning and testing. If too many similar states are included in the training data, the neuronal network gets better at predicting those similar states, but worse at states that are different to the last state, yet those are the more interesting states. Therefore, only a state with an Euclidian distance of the joint angles (normalized -1 to 1) higher than 0.008, compared to the last used state, is used for learning and testing.

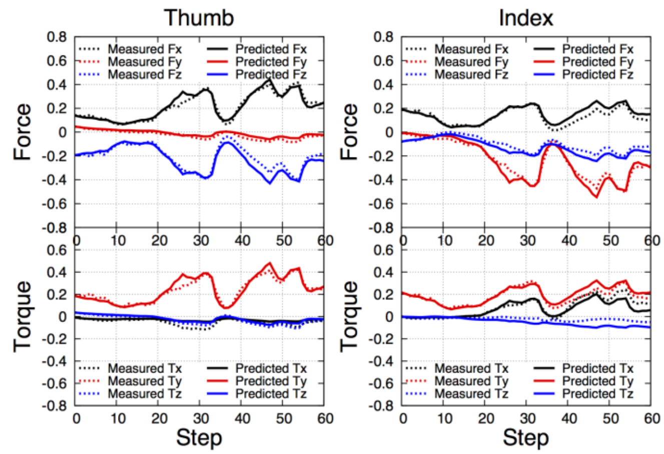

Figure 5. Success trial. The predicted and measured sensor values of the 6-axis force/torque sensor in the thumb and index fingertips are shown.

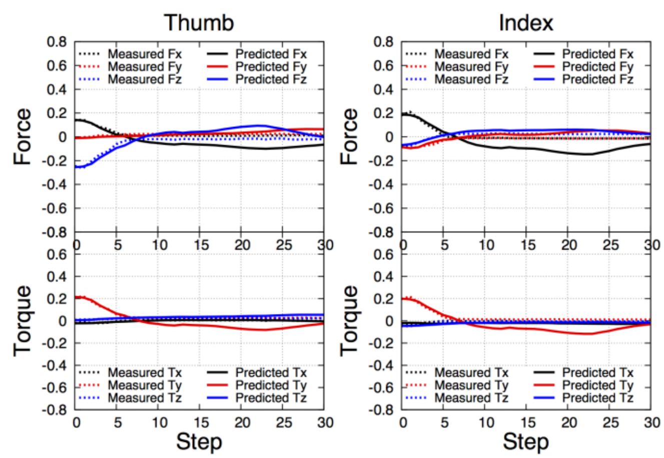

Figure 6. Failure trial. The predicted and measured sensor values of the 6-axis force/torque sensor in the thumb and index fingertips are shown.

280 time-series were used for training the artificial neuronal network, and 20 were used for testing it. 10 successful and 10 failure trials were selected randomly for testing. Typical results for a success and failure trial are shown in Fig. 5 and 6, respectively. As explained above, for the predicted sensor values, only the initial time-step was provided from the measurements, afterwards the output from one time-step was used recurrently to calculate the next time-step. Overall the results were good; even when the movement in a failure trial was similar to a success trial, the predicted sensor results corresponded to the real sensor values. Only after dropping the ball the result for the sensor prediction started to fluctuate. As will be shown in the next section, dropping the sphere could be reliably detected; therefore the sensor data after dropping the ball is not important for our purposes. For the success trials and the failure trials till the dropping time the average error of the sensor state is 0.0255 with a standard deviation of 0.0276 for all 14 dimensions (value ranges from -1 to 1) for the 20 trials for all time-steps. We concluded that the forward model worked sufficiently well for our purposes.

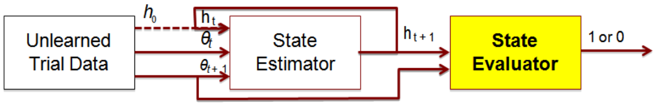

Figure 7. The grasp stability evaluator uses the input from the sensor prediction.

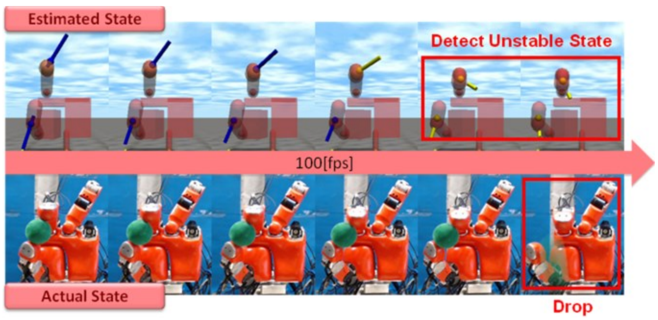

Figure 8. On top the simulation of the robotic hand is shown. The unstable state was predicted at nearly the same time instance as it was actually the case.

IV. Simple Grasp-Stability Evaluator

The grasp stability evaluator *e* uses 3 features as its input: the angle between the force vectors acting on the fingertips and the magnitude of the force on the fingertips of the thumb and index finger, respectively. A mechanical model *m* is used to calculate those features from the motor angles and the sensor state. In particular, a kinematic model uses the motor joint angles and spring angles to calculate the position and orientation of the force-torque sensors. The output of *e* is a either 1 or 0, corresponding to a stable or unstable grasp, respectively. A threshold was calculated manually for each of the three parameters and if all the values of these three features were bigger than their corresponding threshold, an unstable grasp was predicted.

$$stability\ (1\ or\ 0) = e\ (\ m\ (\theta_{t+1},\ h_{t+1})) \qquad (2)$$

A. Evaluation

To test the state evaluator we used the same data as in the last section. Moreover, the evaluator used the input from the touch prediction, as shown in Fig. 7. In all 20 cases, dropping the ball could be detected either at the correct time instance or, in the worst case, four time-steps earlier than in reality. A typical result is shown in Fig. 8.

V. Advanced Grasp-Stability Evaluator

While in the last section the features for the stability evaluator were selected by hand and the thresholds were chosen manually, in this section a support vector machine (SVM) will be used to learn the model and the features will be selected through pruning. Moreover, the goal was to find features that can be used not only for a specific object, but for objects of varying diameter, without the need to relearn the model.

The grasp stability of two different in-hand manipulation tasks had to be learned. The first task was the same as in the last two sections: rolling a sphere from the bottom of the fingertip of the index finger to its side. The motions used for training and evaluating the SVM were again created with the dataglove. In difference to the last sections, spheres of varying diameter were used: 20, 30, 40, 50 and 60 mm. The initial grasping positions were roughly controlled to 5 different positions: either in the center of the fingertip, or 6 mm to either side. The spheres were positioned with an XYZ stage, but slight variations in the initial grasping position were induced due to imprecisions while closing the fingers with the help of the master-slave control. About 250 grasping actions were recorded: 10 * each sphere size * each starting position. For each sphere size, about 30 success and 20 failure trials were recorded; in total, 146 success and 107 failure trials. All failure motions were close to successful motions; no intentionally bad motions were performed. For successful trials all time-steps were used for training (no selection like in Section III). In the case of failed attempts, only the time-steps prior to dropping the sphere, with the features being within a normalized Euclidian distance of 0.25 to the dropping instance, were used for training. In general, all features were normalized from 0 to 1. For the Euclidian distance, the joint angles, the 6-axis force/torque sensors, the spring deformations, but not the tactile sensors, were taken into consideration.

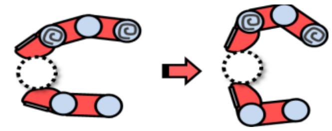

Figure 9. The pull task.

To test the generality of the approach, a second task was performed by the robot: the pull task, as depicted in Fig. 9. Again, spheres of varying diameter were used: 20, 30, 40, 50 and 60 mm. 5 different starting positions, like before, were chosen. Overall, 139 success and 111 failure trials were recorded. An independent feature selection was performed for the second task.

A SVM was used because the task at hand is basically a binary classification: stable or unstable. SVMs have a high generalization performance and a high number of input features can be used (up to 63 input parameters in our case). SVMs can deal with non-linear input and can handle a complex, non-linear state space. An RBF kernel was used.

Like in the last section, a kinematic model of the hand is used to calculate the features for the SVM. The features are listed in Table 1. Please note that the sphere size is not a feature provided to the SVM. Also the joint angles were not used as features, although they were informative. This was done to work with features that are more task independent. Moreover, the changes of features (difference to the previous time instance) proved to be not useful, and were not used.

Considering the distributed tactile skin sensors, only part of the side of the index finger includes them, and the measurements have more noise than the ones from the 6-axis force/torque sensor. Therefore, only the sum of all the tactile sensor values of each fingertip is used as a feature. Other features (contact center position, curvature of contact) were discarded early during the experiments.

TABLE I. FEATURES FOR SVM

Count	Feature description
6*2	Force/Torque sensor measurements in thumb and index fingertip (Fx,Fy,Fz,Mx,My,Mz)
2*2	Force/Torque magnitude of resultant force acting on each fingertip
2	Angle between the force/torque vectors acting on the fingertips
1	Magnitude of force facing in the MP spring direction (please see Fig. 10)
1*2	Magnitude of force facing towards the center of the other fingertip, for each fingertip
2	Spring displacement angle of MP spring and DIP spring
1*2	Contact pressure sum (sum of distributed tactile sensors), for each fingertip
1	Distance between the fingertips
7	Fingertip distance variation when simulating a joint angle error (+5 and -5 deg), for each joint (considering spring) = control error severity
1	Sum of the previous 7 features; sum of fingertip distance variation when simulating a joint angle error (+5 and -5 deg), for each joint seperately (considering spring)
7	Fingertip distance variation when simulating a joint angle error (+5 and -5 deg), for each joint (not considering spring)
1	Sum of the previous 7 features; sum of fingertip distance variation when simulating a joint angle error (+5 and -5 deg), for each joint seperately (not considering spring)
7	Effect on MP spring when simulating a joint angle error (+5 and -5 deg), for each joint
1	Sum of the previous 7 features; sum of effects on MP spring when simulating a joint angle error, for each joint seperately
7	Effect on DIP spring when simulating a joint angle error (+5 and -5 deg), for each joint
1	Sum of the previous 7 features; sum of effect on DIP spring when simulating a joint angle error, for each joint seperately

a. For details please refer to the text

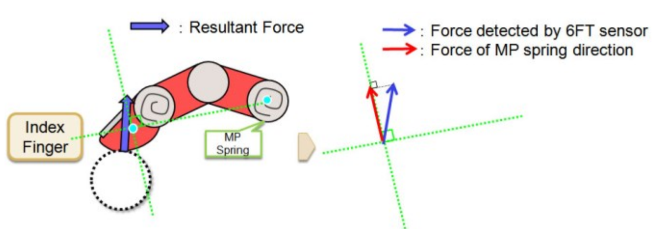

Figure 10. Magnitude of force facing in the MP spring direction.

The last 8 features listed in Table 1 were included as assessments of the severity of control errors. At each time-step, for each joint separately, a change of +5 and - 5 *deg* was simulated. The distance between the fingertips changed as a result, and the difference in distance between a change of +5 and -5 *deg* was taken as a feature: "control error severity". If the springs in the index finger were considered, changes in the fingertip distance in two dimensions (along the sagittal plane of the index finger) were compensated (as caused by changes to the MP1, PIP and DIP joint angles), as it would have happened in the real hand. But changes perpendicular to the sagittal plane, as for example caused by abduction/adduction of the index MP2 joint, resulted in a change of distance. For the thumb, if the sagittal plane of the thumb and index finger do not overlap, only part of the distance change can be compensated, accordingly.

Feature selection was used to select the most informative features. A wrapper method with backward elimination is used: The SVM was trained and tested, leaving one feature out at a time. The least informative feature (according to accuracy) was deleted, and the process was recurrently repeated with the remaining subset of features. 5-fold cross-validation was used each time.

A. Results

For the first task (moving the sphere from the bottom to the side of the index fingertip), the ten most informative features were (starting with the highest accuracy): magnitude of force measured in thumb facing towards the center of index fingertip; distance between the fingertips; control error severity of index MP2 (considering spring); effect on MP1 spring by control severity of thumb MP; effect on MP1 spring by control severity of thumb CM1; spring displacement of index MP1; control severity of all Joints (considering spring); sum of effects on DIP spring by control severity of all joints; moment angle between the fingertips; and control error severity of thumb CM2 (considering spring).

The accuracy of the stability evaluation for different numbers of features is depicted in Fig. 11. Using 10 features, an accuracy of 0.9963 was achieved. The first, second, and ninth feature are calculated directly from the kinematic and mechanical model, while the other features rely on the simulated control error severity.

For the second task (pull task), the ten most informative features were (starting with the highest accuracy): magnitude of force measured in thumb facing towards the center of index fingertip; spring displacement of index MP1; sum of control error severity of all joints (not considering spring); distance between the fingertips; effect on DIP spring by control severity of thumb MP; control error severity of index PIP (not consider spring); moment angle between the fingertips; control severity of index MP1 (not consider spring); contact pressure on index fingertip; and spring displacement of index DIP. The accuracy of the stability evaluation for different numbers of features is depicted in Fig. 12. Using 10 features, an accuracy of 0.9919 was achieved.

In both cases, a high accuracy was achieved. Moreover, features were found that could be used to evaluate grasp stability for various object sizes. It could also be observed that the stability was higher when the posture was such that the fingers were facing each other, so that the spring could absorb inaccuracies in the handling control.

VI. CONCLUSION AND FUTURE WORK

A. Conclusion

This paper presented the prediction and evaluation of the sensory outcomes of an in-hand manipulation. Real world data was gathered with the hand of the humanoid robot TWENDY-ONE and a dataglove. For the machine learning, the sensor prediction employed a neural network and the grasp stability evaluator used a SVM. Both the prediction and evaluation achieved high accuracy.

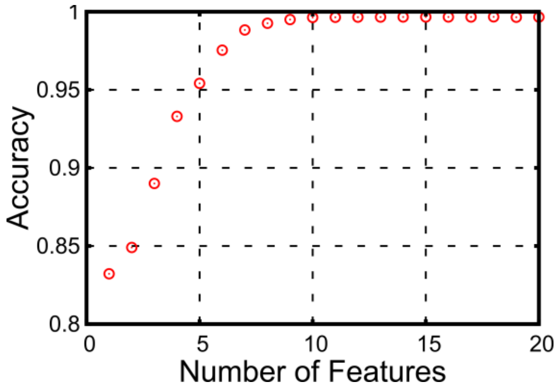

Figure 11. The accuracy for the 20 best features, for the first task (moving the ball from the bottom to the side of the index finger).

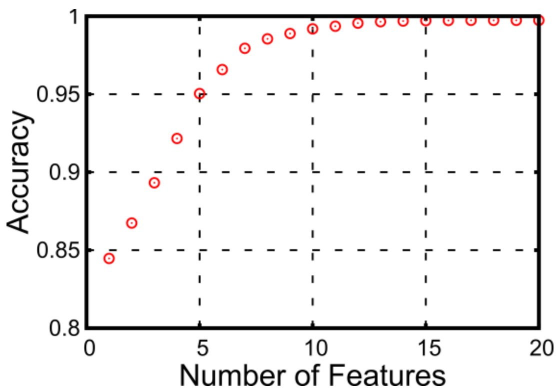

Figure 12. The accuracy for the 20 best features, for the second task (pull task).

B. Future Work

The sensor prediction and stability assessment presented in this paper would make it possible to build a graph that can be used for motion planning, but this has not been done yet. One issue that has to be dealt with is that, even if only 2 fingers are used, each node has 3^7 possible followers: increasing, keeping or decreasing joint angle for 7 joints. Therefore, heuristics like greedy search have to employed, or the motions could be expressed through less dimensions with the help of synergies, or other dimension compression techniques such as principle component analysis could be used.

The advanced grasp stability evaluator worked for objects of varying diameter; enabling the sensor predictor to work similarly for objects of varying diameter has not been attempted so far and could prove more difficult as in this case the actuator and sensor signals are used directly.

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