Autonomous Object Handover Using Wrist Tactile Information

Chapter *in* Lecture Notes in Computer Science · July 2017

DOI: 10.1007/978-3-319-64107-2_35

5 authors, including:


Jelizaveta Konstantinova
Queen Mary, University of London


Senka Krivić
University of Innsbruck


Justus H. Piater
University of Innsbruck


Kaspar Althoefer
King's College London

Autonomous Object Handover using Wrist Tactile Information

Jelizaveta Konstantinova[1], Senka Krivic[2] Agostino Stilli[3], Justus Piater[2], and Kaspar Althoefer[1]

[1] School of Engineering and Material Science, Queen Mary University of London, U.K.,
[2] Department of Computer Science, University of Innsbruck, Austria,
[3] Department of Informatics, King's College London, U.K.
j.konstantinova@qmul.ac.uk

Abstract. Grasping in an uncertain environment is a topic of great interest in robotics. In this paper we focus on the challenge of object handover capable of coping with a wide range of different and unspecified objects. Handover is the action of object passing an object from one agent to another. In this work handover is performed from human to robot. We present a robust method that relies only on the force information from the wrist and does not use any vision and tactile information from the fingers. By analyzing readings from a wrist force sensor, models of tactile response for receiving and releasing an object were identified and tested during validation experiments.

1 Introduction

Fully autonomous grasping and manipulation of objects is a topic of great importance in robotics. One of the main challenges is stable grasping of an undefined object in uncertain environments [1]. To successfully grasp an object, the robot is required to appropriately time the motion of the fingers. Enveloping the fingers around the object too early or too late might lead to a weak grip or a complete miss [2]. Often, the capability of grasping an object fully autonomously is not required as the robot is collaborating with a human when performing a task. Robotic systems are becoming safer and are entering the living or work space of people [3]. This is important for scenarios such as household assistance and elderly care, hospital nursing or assistance during rehabilitation or disabilities. In such contexts close interaction between the human and the robot is essential. Safety is an issue, as the robot might inadvertently endanger or harm the human; hence, the timing of object grasping and releasing actions is an important aspect in this context.

Handover of an object from human to robot is one of the most common tasks where human-robot interaction is required. Handover simplifies grasp planning and implementation [4] as the object is given to the hand directly. However, it requires an accurate detection mechanism to discriminate stable grasps.

The following studies addressed the problem of robotic object handover. Generally, handover is performed based on human motion patterns that are studied and implemented on the robot [5], or they are used as input to a learning-by-demonstration system [6]. Whether the human action is learned or used as a reference, the existing approaches are computationally complex, require online robotic learning or a large data set of demonstrations.

A common problem between fully autonomous grasping and collaborative grasping is the ability to understand whether an object is safely grasped or not. It is possible to formally discriminate whether an object is successfully gripped. For example, Nagata et al. [7] presented a grasping system based on force and torque feedback that senses when the human has a stable grasp on the object, after which the robot can release the object. Such techniques are computationally intensive or require too detailed information regarding the placement of the fingers on the object. It is possible to detect a good grasp by relying on a tactile sensor or a multi-modal sensory system. In [8] authors use the wrist's current to discriminate a stable grasp. This is a simplistic approach, and does not scale well to objects with different geometries, friction and material properties. Work in [9] presented a robotic grasping controller inspired by human trials to grasp an object with minimal normal forces while ensuring the object does not slip. Such approach, however, requires a good estimate or prior knowledge of the friction of the objects to be successful. Multi-modal sensory systems increase the information available to the robot to take decisions such as detecting the contacts with the object [10]. However, such systems require additional computational complexity to perform sensor fusion in real time.

We describe a simple controller that is able to cope with different objects of different mechanical properties. It was tested on a multifingered hand and is targeted at human-robot interaction. This paper presents work addressing the problem of object handover using an algorithm which relies on wrist force and torque feedback only. Both actions of handing over the object to the human and taking it back from the user are studied. This work is performed as part of the EU project SQUIRREL. The control algorithm is implemented on the SQUIRREL robot platform, which is intended to be used in domestic environments such as a nursery for children.

Section 2 describes the design of the methodology of our studies, including the design of the robotic system and the handover problem. In Section 2.3 we present the experimental studies that were conducted for data collection. Then, in Section 3 the modeling of tactile data for object reception and release is presented. Section 4 presents validation studies that were performed to evaluate the performance of the algorithm. Conclusions are drawn out in Section VI.

2 Methodology

2.1 SQUIRREL Robot

The work presented here uses a robotic platform developed for the EU-FP7 project SQUIRREL (Figure 1). It consists of a mobile base (FESTO Robotino),

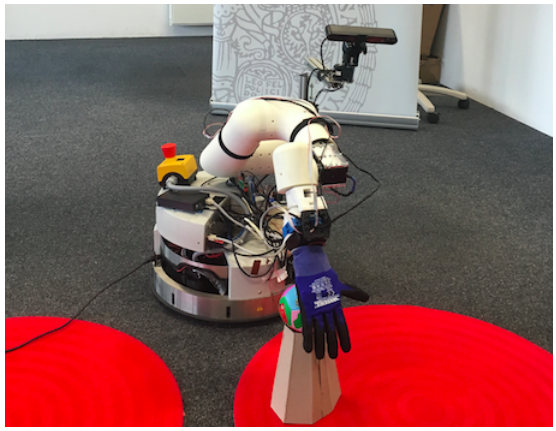


Fig. 1: SQUIRREL robot with the SoftHand as an end effector.

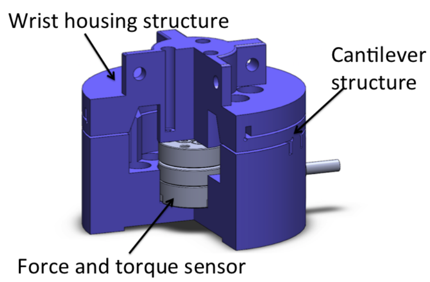


Fig. 2: Wrist sensor and wrist housing structure.

a custom-made 5 degree-of-freedom lightweight robotic arm (FESTO) and the end effector. In this version of the robot system the Pisa/IIT SoftHand [11] is used. It is an underactuated multifingered robotic hand with a single actuated degree of freedom. The hand pose is not predetermined; it adapts depending on the physical interaction of its body with the environment. Therefore, this brings more challenges for the design of the handover detection algorithm, as the pose of the hand cannot be taken into account. The second version of the SQUIRREL robot is equipped with a KCL metamorphic hand [12] (Figure 3). This hand has a reconfigurable palm and is able to adopt a wide range of different grasping postures. Therefore, this paper focuses on methods to detect handover independently of the end effector, and uses force information obtained at the wrist.

The wrist of the robotic hand is equipped with a 6-axis force/torque sensor (FT17 from IIT). Apart from the detection of contact during handover, the purpose of this sensor is 1) to act as a safety switch in case of unexpected collision, 2) to detect forces applied during kinesthetic teaching, and 3) to detect the weight of an object during grasping.

Fig. 3: KCL metamorphic hand with reconfigurable palm mounted on the SQUIRREL robot.

The structure of the wrist, shown in Figure 2, is designed to fulfill the following requirements. First, it creates a mechanical limitation on the maximum deflection of the wrist to protect the sensor from overloading and to prevent damage of the structure. In addition, it expands the force range where the sensor can operate safely before saturation, acting as a spring with a large elastic constant (in comparison to the sensor alone) in parallel with the sensor itself. In order to produce a spring-like behavior using a rigid material (ABS 3D printing material), a flexible cantilever structure was integrated directly with the walls of the structure.

2.2 Object Handover

A handover action is a structured action that is composed of different intermediate steps. For instance, human-to-human handovers [13] are composed of three main stages: reaching the receiving agent, signaling the intention to do a handover, and passing the object to the receiver. In this work, we study handovers of objects between a human and a robot (object reception) and vice-versa (object releasing).

The action of handover is part of more a complex robot behavior, where the robot acts as a companion and assistant to a human. In the general system, handover is triggered by a high-level planner which defines the type of handover. The handover type is determined by the final hand pose and orientation while performing the transfer of the object. There are different types that depend on the class of the object and the subsequent robot task.

Different types of handovers are discriminated by the hand posture used to hold or receive the object, i.e., which edge of the object is grasped, whether an object has a handle or a specific grasping area such as a knife, etc. Detecting the most suitable type of handover is outside the scope of this paper. Nevertheless, in this work, the robot is required to identify the contact with an object to be

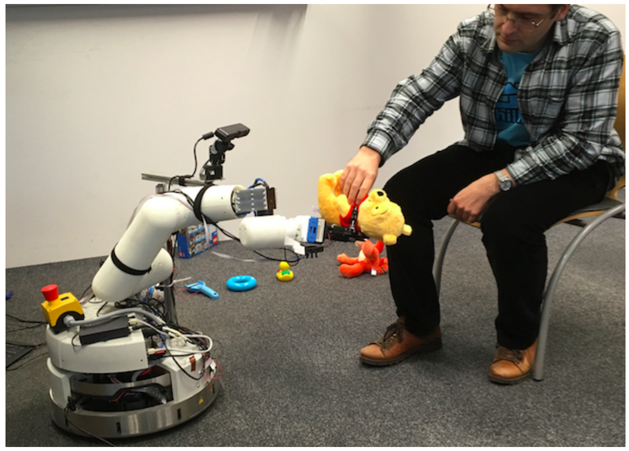


Fig. 4: Handover of an object to a human.

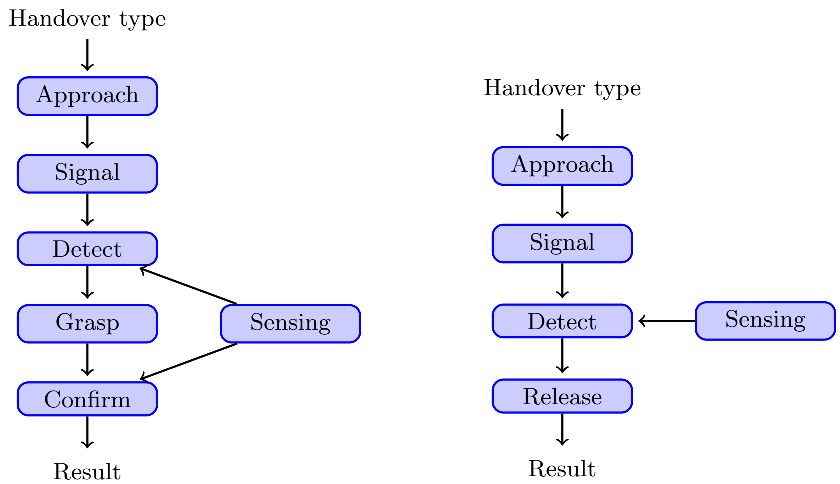
grasped or a request to release an object for different postures of an end-effector. An example of a handover is shown in Figure 4.

Our definition of handover between a human and a robot is as follows. To receive an object from a human subject, the robot is required to approach the human, to open the end effector, and to signal to the human the intention of receiving the object. Then, the robot is required to ensure that the object is in contact with the end effector in order to perform a successful grasp and to restrain the object in the robotic hand (Figure 5a). Handing over an object to a human requires approaching the subject while carrying the object in the end effector, ensuring that the object is safely restrained by the human, and releasing the object (Figure 5b). Force sensing is used to confirm that the object is in contact with the robotic hand before receiving it, then to confirm that the object is grasped successfully, and, finally, that it can be safely given to a human for a release stage.

2.3 Experimental Studies

Experimental studies were conducted, recording tactile data from the wrist for analysis and design of a handover detection algorithm. The case study presented in this work and the associated project is a kindergarten scenario, where the robot interacts with children and helps them sort and clean up toys. Such a complex scenario contains a variety of objects of different shapes, sizes and textures. The set of objects used for the handover is shown in Figure 6. Six objects, different in weight, dimension and stiffness, were selected from toy objects typically found in nurseries.

During this stage of experiments, the decision to grasp or release an object was made based on human visual observation. In all experiments for the al-



(b)

(a)

Fig. 5: (a) The handover sequence for reception an object from a human; (b) the handover sequence for releasing an object to a human.

gorithm design, the hand pose of the robot was fixed, while during validation studies (Section 4) new handover types (with different hand poses) were tested.

3 Modeling of Tactile Information

3.1 Object Reception

Algorithm Giving an object to the robot is the first stage of the handover. The orientation of the robotic hand before receiving an object is not predefined, as it depends on the previous task and can be different for each trial. However, the wrist remains at the same position during handover. Three-dimensional forces acting on the sensor by the mounted robotic hand alone change according to its orientation. To compensate for the effect of the orientation of the end effector, the magnitude F of the force vector is considered in this analysis.

The forces encountered while pushing the object into the robotic hand depend on the weight of the specific object and the strength of the subject. When the object is pushed into the robotic hand by a person, dynamic changes in the force magnitude appear. In order to understand those changes, the time derivative or rate of change of force is analyzed. Assuming constant mass, the derivative of force is the derivative of acceleration, or jerk. This value indicates how slowly or how fast the force is changing.

Fig. 6: Set of objects used in the experiments, containing six objects of various properties.

The final step of the algorithm is to assign a threshold or a classification algorithm that triggers a handover action. In order to detect those changes, an empirical approach was used. A threshold is derived from the experimental data set using the standard deviation of the derivative of force. It is described in the next section and is tested during validation studies as described in Section 4.

Analysis of Experimental Data Set This section presents the analysis of tactile data recorded during the experimental studies. The target subjects of the scenario are children of pre-school age. Therefore, the push of a child cannot be compared with the same action performed by an adult. For instance, our data show that the standard deviation of the force encountered for different subjects and trials varies from 0.24 N to 3.14 N. As a handover is characterized by a change of force, the effect of mean magnitude should be removed. The resulting, non-dimensional representation of standard deviation is the coefficient of variation, or relative standard deviation, that shows the variability of trials irrespective of the mean magnitude. It is expressed as the ratio of standard deviation over the mean. The mean value of relative standard deviation for force magnitude is just 0.03, while the same value for the derivative of force (jerk) is 17.6. This means that the use of jerk can provide a better estimate of the time instant when the contact occurs.

Figure 7 displays the derivative of force for four randomly-selected trials. It can be seen that the force exhibits sudden changes that might correspond to the instant when the object is pushed into the robotic hand.

The next step of the empirical approach is to establish a threshold to detect those changes. The grasp threshold is derived from the standard deviation across all trials. If the jerk of the force is beyond the threshold then initiating a grasp would lead to a safe grip. The threshold that identifies the contact with an object can be calculated in several ways. Figure 8 shows the distribution of standard deviation values across the experimental data set. The minimum value is $0.22\,\mathrm{m/s^3}$ and the maximum value is $1.44\,\mathrm{m/s^3}$. Thus, the variance of the distribution of standard deviation is $1.22\,\mathrm{m/s^3}$. Further on, in Section4 ten different thresholds from minimum to maximum vale with a step of 0.12 were evaluated.

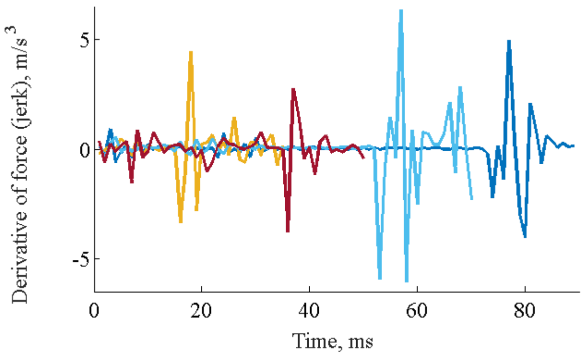


Fig. 7: Derivative of force (jerk) for four randomly-selected trials. Peaks indicate the instant of contact.

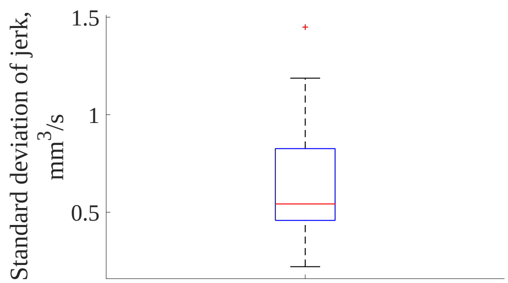


Fig. 8: Distribution of standard deviation for jerk for object reception across the validation data set.

3.2 Object Releasing

Algorithm Release of the grasped object to the human is the last stage of a handover action. During object release the robot is required to open the hand. A release is triggered when the human securely holds or pulls an object. A release request is identified by observing the force sensor at the wrist only, as it is already done for the reception stage of an object. Based on the analysis of force magnitude, it was found that the release action consists of two different force patterns. Therefore, it requires a different approach compared to the action of object reception.

For this reason, a second ad-hoc algorithm was developed and evaluated. The pseudocode of the algorithm is presented in Algorithm 1. The algorithm requires as input the force magnitude calculated from the forces of the wrist. The force magnitude was detrended by removing the mean. A release action is triggered after N consecutive samples of sign opposite to the reference are detected. In other words, detection of a steady change of the direction of force magnitude is required. The value of N was empirically set to five. In addition, the empirical algorithm based on standard deviation of force derivative as used for object reception was tested.

```
Input: F: force magnitude
Output: true if and only if release is confirmed
m ← mean(F[0], F[1], ..., F[K]);
refSign ← sign(F[K] − m);
n ← 0;
/* When countStarted is true the algorithm counts the number
   of samples with opposite sign                              */
countStarted ← false;
for i = 1; n < N; i++ do
    detectSign ← sign(F[K + i] − m);
    if detectSign != refSign then
        countStarted ← true;
        n++;
    end
    else if countStarted then
        n ← 0;
        // Swap the sign: positive to negative and vice-versa
        refSign ← invert(refSign);
        countStarted ← false;
    end
end
return true /* The loop terminates if N samples in a row with
   opposite sign to the reference are detected                */
```

Algorithm 1: Detection algorithm for releasing an object. The mean is calculated from an arbitrary number K of samples.

Analysis of Experimental Data The release-request motion patterns can be divided in two main categories as shown in Figure 9. The first strategy, shown as a red dotted line, corresponds to sharp, sudden peaks, and is more similar to the strategy that is observed for object reception. The second strategy, shown as a blue solid line, represents the scenario when the object is grasped and then pulled with a steady force. The change of force magnitude corresponds to a ramp in the recorded data.

Similarly to the stage of object reception, the empirical approach uses the distribution of standard deviation of jerk that is shown in Figure 10.The minimum value of jerk distribution is $0.26\,\mathrm{m/s^3}$, and the maximum is $1.20\,\mathrm{m/s^3}$. Therefore, the evaluation of optimal threshold for the empirical approach was performed from the minimum to the maximum value with a step of $0.09\,\mathrm{m/s^3}$.

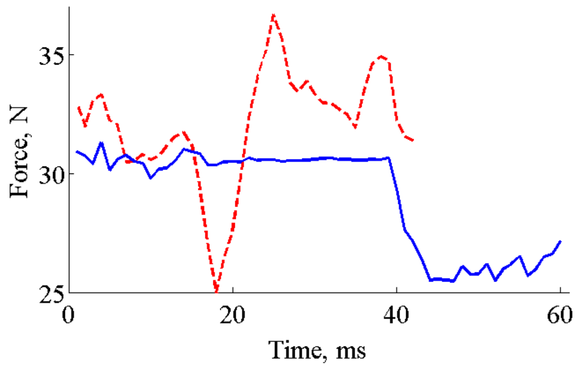


Fig. 9: Two types of strategies detected during the handover action of object release. Trials are randomly selected from two types of patterns.

4 Validation Studies

This section describes the validation studies that were carried out in order to test and to determine the best performance of the proposed handover detection methods. Five new subjects and a set of different objects was used in this section. The objects are shown in Figure 11, and each subject arbitrarily selected six objects. The subject was standing in the reachability space of the object.

To assess and compare the performance of the proposed algorithms, experimental studies were carried out on the real robot. The grasping and releasing scenarios were tested separately, and for both actions the proposed approaches were tested and compared. The success rate of the each approach was evaluated. In other words, it was studied how often a certain algorithm is able to detect a grasp or a release request correctly, as well as to estimate the number of false positives.

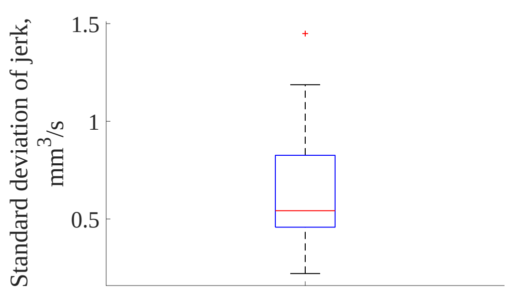


Fig. 10: Distribution of standard deviation for jerk for object releasing across experimental data set.

Fig. 11: Objects used for validation studies.

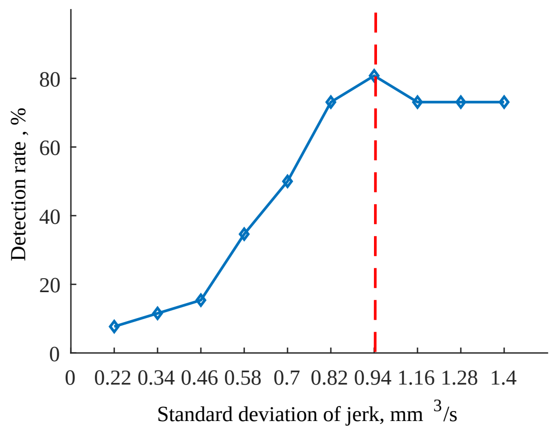


Fig. 12: Detection rate in percentages for different thresholds derived from the distribution of jerk for object reception.

4.1 Validation of Object Reception

The validation of the empirical approach for object reception is performed. The optimal threshold is calculated based on the performance of the evaluation data set to discriminate the moment of contact for approaching. Figure 12 shows the performance of the empirical algorithm for different thresholds. It can be observed that the performance of the algorithm is improving until it reaches a peak ($0.94\,mm^3/s$) and after reaching it, stays at the same level. Therefore, the thresholds that corresponds to the highest detection rate is chosen for this algorithm.

4.2 Validation of Object Releasing

Two approaches were tested for the validation of the object releasing action of handover. The empirical method used for the grasping algorithm shows poor

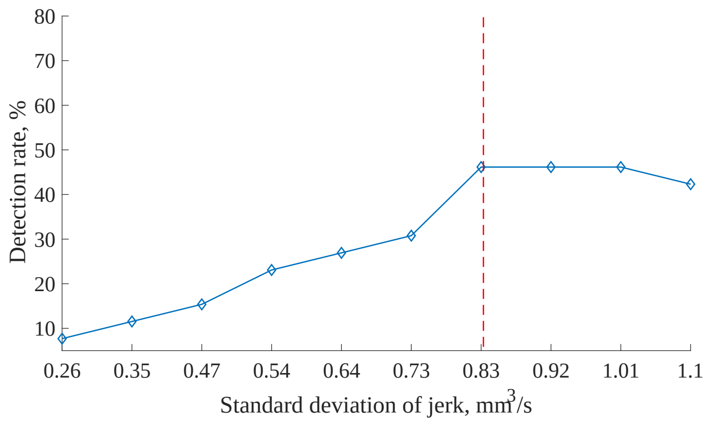


Fig. 13: Detection rate in percentages for different thresholds derived from the distribution of jerk for object releasing.

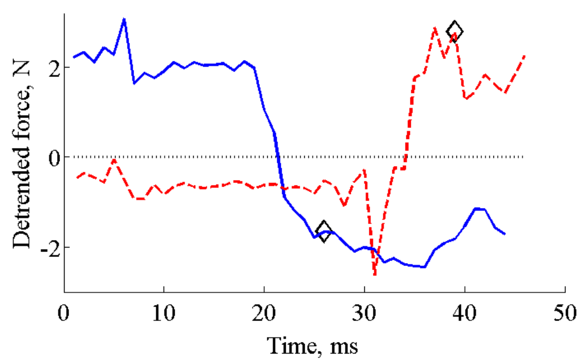


Fig. 14: The performance of the ad-hoc algorithm for both strategies, shown in different lines, of release the action; markers indicate the moment of the hand release.

performance with the maximum detection rate of 46%. The performance for the empirical method is shown in Figure 13. The ad-hoc algorithm developed for release detection, instead, had a good performance with 89% correct classification. Figure 14 shows the example cases of classification for the ad-hoc algorithm. The black dot indicates the time instant of successful release detection. It can be seen that the algorithm performs well for both release strategies. The ad-hoc algorithm is also simple to implement and fast to execute.

5 Conclusions

In this paper we present an approach of handover detection using only the information from the wrist force/torque sensor. The algorithms for object reception and release were developed based on experimentally collected data, and were validated via a separate set of experimental studies. The proposed algorithm was developed for a wide range of toy objects that is typical of objects commonly found in household environments.

In future work, it is planned to develop a learning algorithm for the ad-hoc approach. Additionally, a recurrent neural network can be tested to take into account the influence of the previous force readings when deciding whether to take an action or stay idle.

ACKNOWLEDGMENT

The research leading to these results has received funding from the European Community's Seventh Framework Programme under grant agreement no. 610532, SQUIRREL, and from the European Unions Horizon 2020 research and innovation programme under grant agreement no. 287728, FourByThree.

References

1. Dov Katz, Yuri Pyuro, and Oliver Brock. Learning to manipulate articulated objects in unstructured environments using a grounded relational representation. In *Proceedings of Robotics: Science and Systems IV*, pages 254–261, Zurich, Switzerland, June 2008.
2. G. Cotugno, V. Mohan, K. Althoefer, and T. Nanayakkara. Simplifying grasping complexity through generalization of kinaesthetically learned synergies. In *2014 IEEE International Conference on Robotics and Automation (ICRA)*, pages 5345–5351, May 2014.
3. I. Maurtua, N. Pedrocchi, A. Orlandini, J. d. G. Fernndez, C. Vogel, A. Geenen, K. Althoefer, and A. Shafti. Fourbythree: Imagine humans and robots working hand in hand. In *2016 IEEE 21st International Conference on Emerging Technologies and Factory Automation (ETFA)*, pages 1–8, Sept 2016.
4. Aaron Edsinger and Charles C Kemp. Human-robot interaction for cooperative manipulation: Handing objects to one another. In *Robot and Human interactive Communication, 2007. RO-MAN 2007. The 16th IEEE International Symposium on*, pages 1167–1172. IEEE, 2007.
5. Chien-Ming Huang, Maya Cakmak, and Bilge Mutlu. Adaptive coordination strategies for human-robot handovers. In *Robotics: Science and Systems*, 2015.
6. Andras Kupcsik, David Hsu, and Wee Sun Lee. Learning dynamic robot-to-human object handover from human feedback. *arXiv preprint arXiv:1603.06390*, 2016.
7. K. Nagata, Y. Oosaki, M. Kakikura, and H. Tsukune. Delivery by hand between human and robot based on fingertip force-torque information. In *Proceedings. 1998 IEEE/RSJ International Conference on Intelligent Robots and Systems. Innovations in Theory, Practice and Applications (Cat. No.98CH36190)*, volume 2, pages 750–757 vol.2, Oct 1998.

8. Heinrich Mellmann and Giuseppe Cotugno. Dynamic motion control: Adaptive bimanual grasping for a humanoid robot. *Fundamenta Informaticae*, 112(1):89–101, 2011.
9. M. J. Sadigh and H. Ahmadi. Robust control algorithm for safe grasping based on force sensing. In *2008 IEEE International Conference on Robotics and Biomimetics*, pages 1279–1284, Feb 2009.
10. Javier Felip, Antonio Morales, and Tamim Asfour. Multi-sensor and prediction fusion for contact detection and localization. In *Humanoid Robots (Humanoids), 2014 14th IEEE-RAS International Conference on*, pages 601–607. IEEE, 2014.
11. Manuel G. Catalano, Giorgio Grioli, Alessandro Serio, Edoardo Farnioli, Cristina Piazza, and Antonio Bicchi. Adaptive synergies for a humanoid robot hand. In *12th IEEE-RAS International Conference on Humanoid Robots (Humanoids 2012), Osaka, Japan, November 29 - Dec. 1, 2012*, pages 7–14, 2012.
12. Jian S. Dai, Delun Wang, and Lei Cui. Orientation and workspace analysis of the multifingered metamorphic hand-metahand. *IEEE Transactions on Robotics*, 25(4):942–947, 2009.
13. Kyle Strabala, Min Kyung Lee, Anca Dragan, Jodi Forlizzi, Siddhartha Srinivasa, Maya Cakmak, and Vincenzo Micelli. Towards seamless human-robot handovers. *Journal of Human-Robot Interaction*, 2013.