# Human-aware natural handshaking using tactile sensors for Vizzy, a social robot

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*Abstract*— **Handshaking is a fundamental part of human physical interaction that is transversal to various cultural backgrounds. It is also a very challenging task in the field of Physical Human-Robot Interaction (pHRI), requiring compliant force control in order to plan for the arm's motion and a confident but at the same time pleasant grasp of the human user's hand based on tactile sensing. In this paper we focus on the second challenge and perform a set of physical interaction experiments between twenty human subjects and Vizzy, a social robot whose hands are instrumented with tactile sensors that provide skin-like sensation. From these experiments, we (i) learn the preferred grip closure according to each user group (ii) analyze the tactile feedback provided by the sensors for each closure. In addition to the robot-human interactions, Vizzy executed handshake interactions with inanimate objects in order to (iii) detect if it is handshaking with a human or with an inanimate object. This work adds physical human-robot interaction to the repertory of social skills of Vizzy, fulfilling a demand previously identified by many users of the robot.**

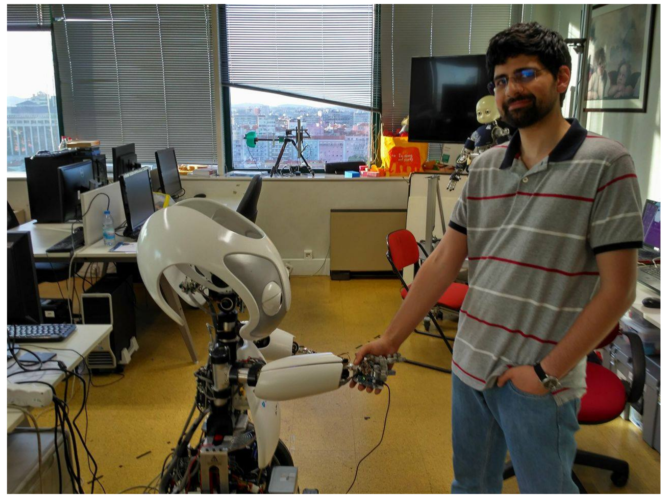

Fig. 1. Vizzy robot performing a handshake

## I. Introduction

The handshake between humans is a social ritual that has various connotations according to the cultural background and can convey trust, recognition, and equality. The initial steps of social interactions between humans usually include handshaking, so in humanoid robots the capability of performing handshaking actions and the ability detect them properly may help interaction in certain Human-robot scenarios. Handshaking is a very complex interaction that includes complex sensorimotor skills such as force-compliance, tactile feedback, and gaze synchronization. Force compliance provides the skills for the correct motion of the wrist for leading and following the human handshake movement. Tactile feedback can provide the skills for the correct motion of the finger limbs for an adequate pressure value of the handshake. Gaze synchronization is a clue that conveys the signal for starting/ending the handshake. Providing the skills above to a humanoid robot is a very complex task that is currently limited mainly by the development of tactile sensing, where the development of materials that can sense properly and provide comfort is one of the main problems. In this work we address tactile sensing problems in the context of handshaking between a person and a humanoid robot, considering two scientific questions: (i) Does the hand-shaped end-effector of the humanoid robot Vizzy [1] provide a comfortable sensation in terms of force and touch interaction during the handshake? and (ii) Is the robot capable of detecting if it is grasping a hand or another inanimate object during handshake interactions? Vizzy's four fingers are instrumented with a total of 15 tactile sensors. These sensors have two main functions (i) measure the forces being exerted at the points of contact and (ii) provide compliance and a more human-like touch feedback to the user. In this work we study the forces exerted by Vizzy's thumb, index and middle finger.

Recent developments on tactile sensors that provide both a comfortable contact for handshaking and an accurate measurement of the force [2]. The sensors provide an estimation of the force from the changes in the magnetic field, considering three main elements: (i) A 3 dimensional hall effect sensor, (ii) A magnet and (iii) a silicon cover for the magnet. The changes in magnetic field due to the deformation of the silicon part are mapped onto 3 dimensional forces, which provide the tactile perception to the silicon cover. Since silicon is one of the materials that are being studied for providing a skin-like sensation [3], we expect that people will feel comfortable during handshaking from the touch interaction point of view. However, the force exerted by the robot will play a fundamental role. Thus, to answer question one we study three different finger configurations, which correspond to a weak, medium and high strength of the handshake. Then we ask several persons to rank the handshakes by their preference, in order to find the preferred grip strength and evaluate qualitatively the handshakes.

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In addition to the quality of the handshake, the basic perceptual skill of a robotic handshake is to distinguish between grasping an object and a human hand from tactile feedback. This skill is the basic building component of totally autonomous handshaking, allowing to take corrective actions in case of disengagement and deceiving interactions. We gather the magnetic field and force data from the sensors during handshaking interactions with persons and inanimate objects, feeding the data to a supervised machine learning binary classifier. On subsequent interactions with objects, the classifier is able to detect if the interaction was with a hand or with an inanimate object.

## II. Related work

Physical Human-Robot Interaction (pHRI) is a field whose origins date back to the 90s and 2000s [4]. It is nowadays receiving increased attention due to recent developments on haptic sensors [2] as well as applications in either social robotics [5] or industrial environments [6]. Handshaking is one of the subjects studied on pHRI and is starting to receive some interest by several authors. The majority of works on Human-Robot handshakes focus on the planning and the shake motion [7] [8] of the robotic arm or mimicking a human's grasp [9] [10].

Several works study Human-Human handshakes as a basis for Human-Robot handshaking. In [11] a handshaking approaching model is proposed based on the analysis of the position of the wrists and hands of the participants. This motion model is further expanded in [12] to take the start time of a handshake request into consideration. Similarly, [13] also studies gaze when requesting for a handshake in addition to the previous motion model. The lag between the start of the request of a handshake and the start of a response, as well as the motion model of the response preferred by humans, are discussed in [14] and [15]. [16] also studies the duration, strength of grip, vigor, and rhythmicity of handshakes between humans. They make use of six force sensors to study the strength of grip.

On [17] a handshaking reactive robotic interface was developed. The designers of this solution took haptics into consideration for both the mechanical design as well as the controller design of the interface. To comfortably close the hand of the robot, the authors of this work measured the grasping force of humans, which was discovered to have a median value of 25N and a maximum value of 50N. The resulting interface consists of a four finger hand. It is also worth noting that during the user studies with the final interface, the authors noted that grasping forces applied by the subjects on the robot were different that those of Human-Human interaction. However, given the fact that a robotic hand has different pressure points than a human hand using the overall grasping force as a control reference might pose some comfort problems. This issue is covered in [18], showing that even with a lower overall grasping force, there are points in the robotic grasp where the pressure is way higher (and possibly more uncomfortable) than the one produced by a human hand.

Another interesting work [19] intends to create a model of tactile features to discriminate intrinsic characteristics of a person. They are able to recognize the gender of a person with a success rate of 77% and the extroversion with 62% success rate. For female participants, the mean sensor pressure on the sensors was of 25.8 kPa, with a standard deviation of 22.3kPa. For males, it was of 29.4 kPa and 16 kPa, respectively.

None of the above works, however, seem to employ a user-centered approach, where the handshake grasping is designed directly with user feedback.

To our knowledge, no attempts were made to discriminate between a fake and a real handshake. However, works like [20], where the system is able to classify between several materials with tactile sensors, or [21] [22] that focus on object recognition make us believe that tactile features are rich enough for this matter.

## III. Vizzy's hand design

The Robotic platform used in this work is the robot Vizzy [1], designed as a human assitant for social interaction tasks. Vizzy has an anthropomorphic upper body with similar degrees of freedom and motion execution skills of a human. Regarding its hands, the palm and finger sizes and number of limbs are also similar to an adult person, but having only four fingers capable of grasping objects. The thumb and index fingers are actuated each one by a single motor, while the middle and ring fingers are coupled to one motor. The motor of a finger is coupled to a pulley, that pulls a fishing line string. The fishing line string is attached from the pulley to the last limb of the finger, such that the motion of one motor moves in an underactuaded manner the three limbs of each finger. Regarding the sensors, the thumb has three sensors and the rest of the fingers have four sensors each. The sensors are distributed as shown in Fig. 2.

These tactile sensors [2] are composed by a soft elastomer body with a small permanent magnet inside. Below the magnet there is a magnetic field sensing element (i.e. Hall-effect sensor). When an external force is applied on the elastomer the relative magnet position changes and the Hall-effect sensor detects the magnetic field variation, that can be converted in a measurement of the applied force. An air gap is left between the elastomer and the magnetic sensor in order to increase the sensitivity for small forces. The use of a 3-axis Hall-effect sensor allows the detection of the magnetic field variations in the 3 axis, meaning the sensor is capable of measuring the force magnitude and direction in 3D. On this preliminary work we only used three fingers: thumb, pointer, and middle. The hand designed criteria included: (i) Similarity to human's hand size and (ii) the execution of two types of object grasping: cylindrical and power grasp. Since the design did not consider handshake actions, we performed an user human-robot handshake study for evaluating the plausibility of that kind of interaction.


Fig. 2. Indexes of the force sensors in Vizzy's hand

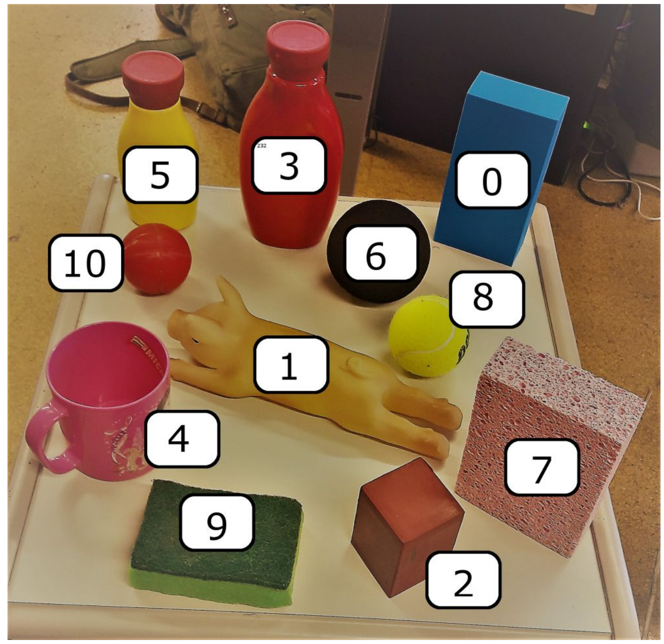


Fig. 3. Objects used as the "no hand" class.

## IV. Human-Robot Handshake Study

In order to assess user preferences regarding handshake grip strength, we conducted a series of experiments with users and our robot Vizzy [1].

These experiments consisted in asking people to handshake with the robot three times. The handshake starts with an initial position of finger joints (which corresponds to three motors), followed by a timely closing of the fingers to the final position. The final motor positions are associated to the handshake strength label, having the largest motor positions with the label "strong", the lowest motor positions as "weak" and the intermediate motor positions as "medium". After the execution of the three handshakes by the robot, we ask the participants to sort the handshake by their preference. The users are asked to rank the handshakes by considering mainly the strength that conveys an adequate handshake interaction. This means that the strength should be high enough to be engaged in the handshake, and at the same time low enough that does not make the person feel uncomfortable nor causes an injury. This means that handshakes with very low strength are ranked low as well as handshakes with very high strength. To avoid biased opinions due to eventual meetings between participants or their expectancy regarding the sequence of handshakes, the order of the three handshakes was random.

Given the fact the different persons have different hand sizes, analysis of handshake preferences based just on the final position of the fingers of the robot may not be meaningful. Since the same finger position would have a very large variability across different hand sizes, we analyzed the mean and variance of the forces measured by each sensor using two different ways of grouping: (i) The strength label from the final finger position and (ii) the preference level provided by the users. We collect the temporal sequence of the magnetic flux and force data from each tactile sensor during the handshake interactions, which will be utilized in the hand detection study.

## V. Hand detection study

In this section we tackle the problem of detecting whether the robot has performed a handshake on a human hand or on an other type of (inanimate) object. In order to do so we exploit the information gathered by force sensors and employ a supervised machine learning approach, the K-Nearest Neighbors algorithm.

We utilize the human-robot handshake data of the study described in the previous section, and collect the temporal sequences of tactile sensing readings from 11 (non-hand) objects during handshake execution, storing both the raw value of the magnetic flux (Oersted, Oe) and the force (N) estimated from the magnetic flux. On each object Vizzy executed the three handshake primitives (resulting in 3 grasps per object) as well as three empty grasps. These grasps form the "no hand" class. The selected objects are shown in Fig. 3, which cover both rigid (0,4) and deformable objects (1,2,3,5,6,7,8,9). Data is then split into training and test sets. We randomly sample 49 handshakes and 26 object grasps for training (80% of the initial dataset) and 11 handshakes and 8 object grasps for testing (remaining 20% of the dataset). Additionally, we included the weak and strong empty handshakes in the training set and the medium empty handshake in the test set. The reason for this is to have training data for the special case where the sensors are not in contact with anything.

## VI. Experimental Setup

### A. User information from the robot-human handshake study

The experiments were performed on a population of 20 subjects, 13 male and 7 female, with ages comprising of 20 to 51 years old. Each subject was briefly introduced to the experiment. The robot performed always the same movements, however, the way of placing the hand for the handshake was left free to be chosen by each subject.

After the performance of the 3 different handshakes we asked each subject to classify the handshakes from the most liked to the least, and also some overall opinion about the experiment.

### B. Hand detection study

The number of handshake samples gathered is not large enough to estimate properly the parameters of complex learning algorithms such as deep neural network. For this reason, we used a K-Nearest Neighbors approach with Dynamic Time Warping [23] as the distance measure, a method that achieves state-of-the-art results on the classification of time series in small datasets [24].

*1) Hyper-parameter tuning and cross-validation:* To tune the hyper-parameter $K$, we use 10 iterations of 7-fold cross-validation and choose the $K$ that yields the lowest average miss-classification error. For each iteration the 7 folds are randomly sampled from the training set using a uniform distribution. We use 7 folds because it is the greatest common divisor of the number of handshakes (49) and the number of "no hand" events (28) for training, allowing us to have easy splits.

*2) Features and metric:* During our experiments we used two different classifiers: one based on Forces (N) and one based on Fields (Oe). For both classifiers the features are the time series of the three $X$, $Y$, $Z$, Cartesian components of the force or magnetic flux, on each of the eleven sensors.

Since each experiment had a different duration, which is not controlled, we used the Dynamic Time Warping [25] algorithm to compute a comparison metric between samples.

## VII. Results

### A. User preferable grip strength

The 3 predefined handshake movements were called of "Weak", "Medium" and "Strong", due to the different finger joint references for each one associated to handshake strength. To visualize the magnitude of the forces applied on the sensors for each movement, we plot in Fig.4 the means and variances of the sensor readings. As we can see, sensors number 3 and 11 (fingertips), and sensors 9, 10 (middle finger) make almost no contact with the human's hand. This is to be expected since Vizzy's hand is larger than the average human's hand and the under-actuated finger limbs move to

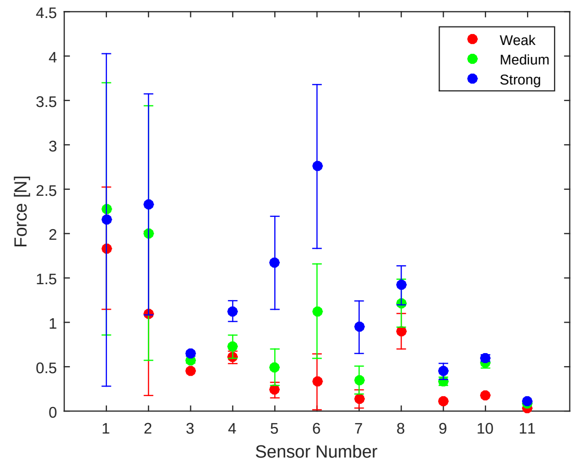


Fig. 4. Average and variance of the force measured on each sensor for each handshake action

different final configurations depending on the initial contact points. As expected the variance on the most active sensors for each closing is large due to the different sizes of human hands.

The total force magnitudes presented correspond to the sum of forces in the contact points between the human hand and the tactile sensors. There is a high area of contact (mainly in the palm of the robot hand) where the force is not measured, reason why the obtained values (Table I) are under the expected total force of a human handshake. The calculation of the handshake force, however, was never the objective of the experiment since what we wished to study was the most comfortable force distribution along the available sensors. Statistical information regarding this distribution is presented in Fig. 5. We note that people preferred similar forces on sensors 1, 2, and 6 that represent the main contact points of the thumb and pointer fingers. These preliminary results give us an idea of force distributions that can be used as feedback for a handshake grip strength controller.

From the data collected we can observe that female subjects preferred a slightly larger grip force than the male subjects (see table I and table II). This can be explained by our methodology, because the 3 different grips are defined only by the final angular position of the encoders in the motors. The resulting force that is applied by the robot and felt by the human subject is produced by the elasticity and compliance of the artificial tendons and sensors in the robot hand. Consequently, the force felt by the human is highly dependent on the shape and size of the human hand. We note that for smaller hands two of the handshakes have very low contact forces leading people to prefer to the third handshake, since there were no more options skewing the data.

### B. User experience qualitative feedback

The feedback given by the human subjects shows that despite the metallic hand, the silicon sensors give a very comfortable touch and grip. Many were surprised with a much

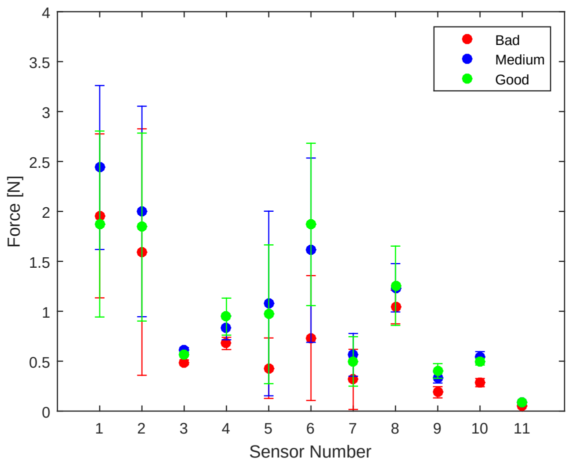


Fig. 5. Average and variance of the force measured on each sensor according to the user preference

TABLE I
AVERAGE SUM OF SENSOR FORCES BY USER FEEDBACK

| | Average Force (N) | | |
|---|---|---|---|
| **Grade** | Bad | Medium | Good |
| **Female** | 6.79 | 7.96 | 11.41 |
| **Male** | 8.63 | 13.22 | 10.50 |
| **Total** | 7.76 | 11.33 | 10.81 |

more comfortable handshake in opposition to the initial expectations due to the robotic looks of Vizzy's hand. However, they had some constructive criticism regarding the thumb contacts. These were perceived as slightly stronger than the remaining fingers, thus needing adjustment. Regarding the execution of the handshake, people suggested that all the fingers should close at the same time and that the arm should execute the oscillatory motion of a handshake. Concerning the aesthetics and design of the hand, our subjects reported that the hand was larger than expected, and that the palm of the robot should have the same tactile feeling as the material of the sensors. Including tactile sensors in the palm would increase the comfort of the handshake and simultaneously provide added perceptual information to exploit.

### C. *Handshake classifier*

We now evaluate the performance of the magnetic flux and Force based classifiers. The results of the 7 fold cross-validation step for the force-based features classifier are shown in Fig. 6. We have two minimum values for the miss-classification error at $K = 3$ and at $K = 11$. Choosing 11 as the final value for $K$ we proceeded to test this

TABLE II
PREFERRED HANDSHAKE ACTION

| | Preferred handshake (%) | | |
|---|---|---|---|
| | Soft | Medium | Strong |
| **Female** | 0.0 | 14.3 | 85.7 |
| **Male** | 15.4 | 46.1 | 38.5 |
| **Total** | 10.0 | 35.0 | 55.0 |

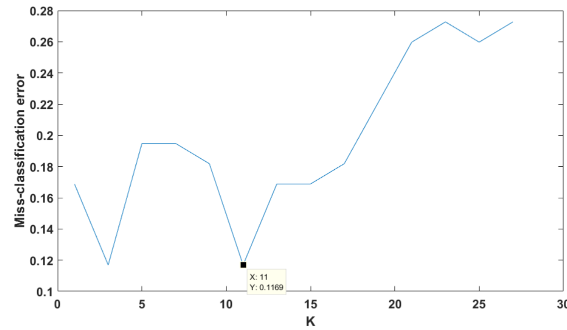


Fig. 6. Miss-classification error as a function of the K hyper-parameter for the Force (N) based classifier

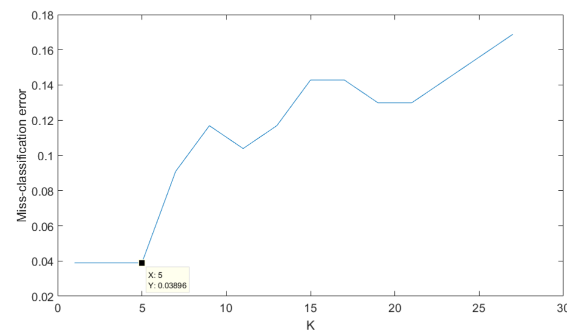


Fig. 7. Miss-classification error as a function of the K hyper-parameter for the magnetic flux (Oe) based classifier

classifier on the test set obtaining a miss-classification error of $0.15794$. The number of "no hand" events incorrectly classified was of 1 in a total of 8. The algorithm miss-classified the medium handshake on the unanimated object 5 as a human handshake. The number of "handshake" incorrect classifications was of 2 in a total of 11. The algorithm miss-classified two "Weak" handshakes.

The results of the cross-validation procedure for the magnetic flux (Oersted, Oe) based classifier are shown in Fig. 7. The minimum miss-classification error was obtained for $K = 1, 3, 5$. With $K = 5$ the miss-classification error on the test set was of 0 due to the relatively small size of the dataset.

## VIII. CONCLUSIONS AND FUTURE WORK

We developed a platform for exploring human-robot handshaking. By using a novel and state-of-the-art tactile sensor we can accurately measure in real-time the force vector at each contact point. This work can be divided into two parts i) a human subject research of the preferable handshake grip force and ii) training a classifier to detect if the handshake was successful.

From the examination of the human subject data we realize that by using fixed grip motions, the actual contact forces perceived by the users will depend highly on the size and shape of the hand of the human subject. Also, the limited number of grip trajectories limits the analysis of the user's preferred grip force. To address these issues, in our future work we will change the reference signal to be a set of contact forces, instead of fixed joint positions, taking advantage of the real-time feedback given by the tactile sensors. We will further apply Reinforcement Learning methods to make the robot autonomously explore and adapt the contact forces, without restricting to a set of predefined handshakes, to give the most natural and comfortable handshake for humans according to the user feedback.

In the second part of our work, we achieved 100% classification on our test dataset. This happens due to the small size of the dataset and the nonexistence of objects with a shape similar to a human hand. Nevertheless, the classifier is fit to our purpose of automatic detection of a successful handshake.

Our work so far has only focused on the force applied to the contacts during the handshake. In order to obtain a natural interaction, we will need to make the robot's arm move in a human-like way.

Previous work cannot be applied in a straightforward way to our platform since it makes use of the forces measured in each robot joint to synchronize with the human motion, i.e. Neural Oscillators of Kasuga et al. [7] and the shake-motion leading model of Yamato et al. [10]. Vizzy does not currently report the torques applied to each joint but provides very detailed information about the forces on the contacts of the hand. We are exploring other approaches to arm motion generation that may exploit the available tactile force perception, e.g. movement primitives for force interaction.

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