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Let's Handshake and I'll Know who You Are: Gender and Personality Discrimination in Human-Human and Human-Robot Handshaking Interaction

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Abstract—**In order to appear as natural as possible during social interaction, robots need either the ability to express or to measure emotions. Touch can be a very powerful communication modality but is very little exploited. Our paper aims to create a model of the tactile features activated during a handshake act, that can discriminate intrinsic characteristics of a person such as gender or extroversion. First, we construct a model of handshaking based on the human-human styles of handshaking. This model is thereafter compared with a human-robot handshaking interaction. The Meka robot is used in our experiments. A method is proposed to manage the modeling using feature selection with ANOVA and linear discriminant analysis (LDA). The first preliminary results show that it is possible to recognize gender and extroversion personality trait based on the firmness and movement of the style of handshaking. For instance, smaller pressure and frequency were found to describe female handshakes and higher speed amplitude describe introverted handshakes. Consistency was also found when comparing human-human handshaking with human-robot ones. These are encouraging results that will allow us to develop personalized interactions.**

I. Introduction

The new generation of robots must be able to socially interact with humans and exhibit emotional skills. This can be required, for instance, when robots closely collaborate or interact with humans (social interaction, collaborative manipulation, etc.). To make the interaction more natural, it is necessary to understand the mechanism of interpersonal social interaction and more specifically emotional communication to create models that can be implemented in Human-Robot Interaction (HRI) systems. As an interaction is bi-directional, emotion has either to be expressed or measured. Emotion can also be transfered through several channels. Research in mediated communication largely tackled facial expression [1], prosody [2], gesture, posture [3], and physiological data [4] to see how emotion is expressed. Many robots are able to express emotions using facial expression [5], voice and gesture like the robot Nao [6], or simply colors like the Nabaztag rabbit [7]. Several affective robots have been made like Probo [8], an elephant-like robot with an expressive face and gesture abilities, or the Haptic Creature, a small animal developed by Yohanan et al. [9]. The Haptic Creature's breathing rate and ear stiffness are used to convey its state of arousal and it is used to study human-robot affective touch.

Surprisingly, touch modality has received less attention than the other modalities. This is due to the limit of current tactile stimulation technologies (intrusiveness, lack of transparency, limits of tactile stimulation, etc.) [10], but also to the lack of research in touch communication compared to other nonverbal channels.

Some works highlighted the effectiveness of this channel to communicate several dimensions of emotions. In [11], it was shown that tactile stimulation plays a strong role in children development based on cultural studies and monkey experiments. Moreover, Hertenstein et al. [12] [13] highlighted that humans are able to distinguish different emotions during the interpersonal touch on the arm and also on any body part (with stroke, tapping, etc.). The results showed that people use touch to communicate effectively at least six different types of emotions (i.e., anger, fear, disgust, love, gratitude, and sympathy). The emotion recognition rates are comparable to those obtained through voice and facial expressions. Moreover, this work identified specific touch patterns and physical features for the communication of the different emotions. Based on these results, several works studied the haptic communication with virtual agents. For instance, Bickmore et al. [14], designed a virtual agent with a face displayed on a monitor and an air bladder that squeezes a user's hand. The results showed that touch leads to better perception of the relationship with the agent. Similarly, Gaffary et al. [15] studied the combination of force feedback, conveyed through a haptic arm, and a virtual agent displayed on a screen to communicate a series of emotions. It was shown that the force feedback effectively supports the arousal and dominance dimensions. The authors in [16] also used the haptic modality to transfer emotion from a person to another through an interface.

Given the importance of touch modality in emotional interaction and the key role played by emotion recognition in human-robot social interaction, the final goal of our work is the enhancement of the emotional discrimination ability of humanoid robots using touch.

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This paper focuses on a generic method capable of discriminating gender and extroversion characteristics by using the handshaking interaction.

Indeed, the extroversion personality trait is seen as a facilitator of more social interaction and hence is the only trait used in our study. Greeting is a social interaction context interesting to choose as it is a crucial time of social acceptance. By this exchange several information are provided: personality, mood, emotion, and the level of consideration of the partner. Therefore, greeting could be physically altered by emotion and personality. Moreover greeting is almost systematic when meeting someone, this facilitates participant's acting during experiments. Thus this context is often used in human interaction studies. Greeting has several forms of expression (handshake, kiss, hug, hand wave, simple speech, etc) which depends on the general context of interaction (professional, friendly, information request) and the cultural aspect. Handshaking is commonly used in European countries, in professional context but also between acquaintances. The rest of this paper is limited to the handshake form of greeting and the experiments are carried out with European people in acquaintance context.

A psychological study [17] showed that people (in Alabama) handshake differently depending on their gender: male individuals handshake stronger than female individuals. That indicates gender could be a good characteristic to be discriminated during handshaking.

Several studies tested dynamic models for handshaking implemented on robots to make it as human-like as possible [18], [19], and [20]. They usually simulated two behaviors (leader or follower) and base their models on human styles of handshaking. Then, they evaluated the models through subjective scores of the participants. In [21], the authors studied the perception of the bi-modality haptic-facial expression during a greeting handshaking between a human and a humanoid robot. They highlighted different fusion rules that enable people to combine touch and vision to perceive emotions.

In this context, we designed a glove that can be worn by a person or a humanoid robot. The glove embedded a series of sensors that enable the measurement and the analysis of the hand-to-hand contact features. This paper is structured as follows: in Section II the concept and the choices that have been made are defined, in Section III the human-human style of handshaking modeling is detailed, Section IV describes the human-robot experiment and some discussions, and finally Section V concludes our paper.

II. General Overview of the Concept

In this study, we want to extract physical and measurable features of a handshake that can convey intrinsic information about an individual. This information is intended to be integrated in a robotic system for a more natural interaction. In [17], the author shows consistency in the handshaking of an individual depending on time, on the partner, and his/her gender. It is assumed that in general the handshake manner would differ depending on the partner (human or robot). That is why instead of using a specific robot to measure the handshake parameters, we choose first to study directly the interpersonal human-human handshakes, and then to compare the results obtained with those obtained from a human-robot handshake experiment. In both cases, one of the partner wears the glove and is called the receiver. The second partner is the participant that initiates the handshake and is defined as the sender.

A. Points of interest touched during a handshake

In our case, the handshake is characterized by the pressure applied on different areas of the hand but also by the movement of the hand. The areas where the sensors are placed have been determined by the most often touched points during an experiment in which ink was printed from a sender glove to a receiver white glove during handshake. The data was acquired from 8 participants of different combination of gender (male, female), extroversion personality trait (introverted, extroverted), and hand size (small, large) handshaking a small handed woman and a large handed man. Figure 1 shows the positions touched during these handshakes. The same kind of experiment was carried out on the humanoid robot. The points are divided in two groups: the ones that are touched by the sender (*group s)* and the ones from the receiver (*group r)*. We decided to put sensors in zones belonging to both groups because it enables to differentiate the pressure applied by each partner (sender and receiver). Indeed, as we want to detect intrinsic information from the sender, it will be interesting to study how its response depends on the receiver's action.

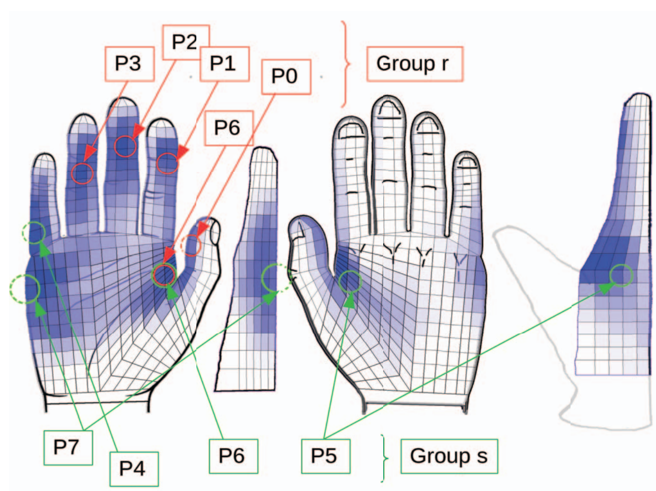

Figure 1. Sum of areas touched by the inked handshakes (blue) drawn on a standard right hand. The selected points are rounded and associated to sensors for the glove design. They are divided between group r (receiver) in red and group s (sender) in green

B. Hypotheses

Our hypotheses are as follows: Our first hypothesis (H1) is that the mean pressure for the *group r* will increase as the handshake is firmer. Our second hypothesis (H2), based on the results of [17] and [22] studies, is that gender is easy to discriminate in normal firmness handshakes : women handshake softer than men. Our third hypothesis (H3), also based on [17] and [22], is that introverted persons handshake softer than extroverted persons.

III. Human-Human style of handshaking

The first experiment consists in measuring the pressure exerted and the movement during a handshake depending on the firmness of the receiver. Based on the acquired data, we investigate if we can discriminate gender and extroversion of the sender.

A. Experimental Device and Data Acquisition

The experimental device (see Figure 2) is a fully embedded glove equipped with 8 piezoresistive sensors, 7 sensors of 8 mm diameter, and one of 12 mm diameter, corresponding to P_7 as the touched zone is larger (see Figure 1). The sensors were embedded and covered by a clean elastic fabric to make the interaction more natural (mobility, hide the electronics, and comfortable contact). Four of the sensors are on the thumb (P_0), index finger (P_1), middle finger (P_2), and ring finger (P_3) of the receiver, they belong to the *group r*, and three are on the little finger (P_4), the top (P_5), and the bottom (P_7) of the sender belonging to the *group s*, and one is present in both groups: the palm (P_6).

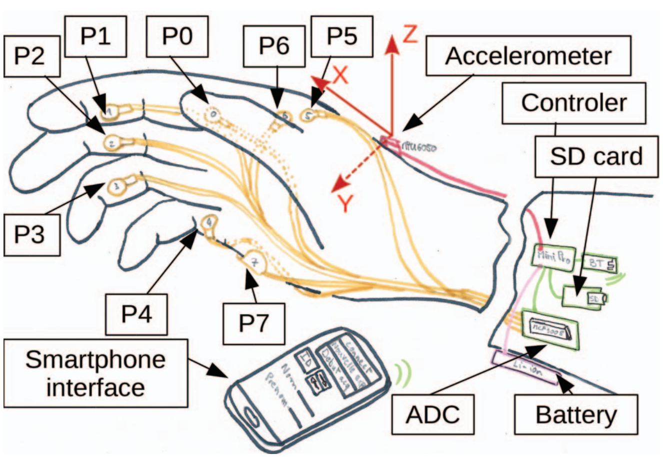

Figure 2. Glove schematic

All these sensors are read by a MCP3008 analogical to digital converter. An accelerometer/gyrometer MPU-6050 is fixed on the back of the hand and data is transmitted to an Arduino recording the points on a SD card. A Bluetooth module enables to remotely control the system using a smartphone.

Before the experiment, a step of calibration is required either to detect the gyrometer bias or to detect the initial orientation of the hand by the accelerometer. During this step of 2 seconds the arm is static and perpendicular to the body. Afterwards, the data of the gyrometer is integrated to calculate the orientation of the hand as a function of the time during post-treatment. The feature extraction detects a threshold of movement, which indicates the start of the handshake. The end of it is chosen when there is no more pressure. The duration of the handshake (TP) is given by the time when pressure differs from zero. We select the maximum variation of hand orientation from the initial time as two global angles ($\delta\theta X$ and $\delta\theta Y$), where the X *axis* is in the receiver hand direction and the Z *axis* is vertical. This means that for the receiver, a positive $\delta\theta X$ indicates a supination movement (pronation for negative) and a positive $\delta\theta Y$ represents adduction (abduction for negative). The 3-axis acceleration signal is projected on the principal axis of movement, which is defined by two global angles (αY and αZ). αY implies that the movement is out of the frontal plan and αZ indicates it is out of the sagital plan. The frequencies of the acceleration signal are calculated from a Fast Fourier Transform (FFT). The non-zero peak of maximum energy ($EPeak$) is chosen as the fundamental frequency ($FreqPeak$). We also calculate the mean of the signal because there is a strong continuous component called acceleration offset ($AOff$) in addition to other acceleration and speed features. Then we get the maximum (P_iMax), mean ($\overline{P_i}$) and maximum derivative (dP_iMax) of pressure signals for each 8 sensors, and global maximum ($PMaxMax$) and mean $\overline{\overline{P}}$. All the features are summarized in Table I.

Table I
Notation of the study features

Duration	TP
Oscillations number	$OscNb$
Peaks number	$PeakNb$
Acceleration peak frequency	$FreqPeak$
Acceleration peak energy	$EPeak$
Acceleration total energy	$ETot$
Acceleration offset	$AOff$
Maximum acceleration amplitude	$AAmp$
Maximum speed amplitude	$SAmp$
Maximum speed	$SMax$
Supination angle	$\delta\theta X$
Adduction angle	$\delta\theta Y$
Movement direction (non frontal)	αY
Movement direction (non sagital)	αZ
Maximum pressure on sensor i	P_iMax
Mean pressure on sensor i	$\overline{P_i}$
Maximum pressure derivate for sensor i	dP_iMax
Global maximum pressure	$PMaxMax$
Global mean pressure	$\overline{\overline{P}}$
Max or mean pressure for group j	PG_jMax ; $\overline{PG_i}$

B. Human-Human Handshaking - Experimental protocol

The experiment has been carried out with 36 participants (11 females (**F**) and 25 males (**M**)) and an experimenter. All participants answered a questionnaire in which they were asked to fill-in their age, their width and length of the hand, and filled-in a Big Five Personality test [23] that determines the five personality traits (extroversion, agreeableness, conscientiousness, neuroticism, and openness). [24] shows in a study of 2 499 French students, the mean score for the extroversion criteria is 3.2 either for males or females and it follows a normal law. As a result, we classified the participants in two categories concerning the extroversion personality trait: introverts (**I**), whose score is below 3.2 and extroverts (**E**), whose score is higher or equal to 3.2. We got 19 **E** and 17 **I**. We used a linear combination of the hand's width and length to associate a hand size category to the participants: small hand (**S**) or large hand (**L**). The correlation link between width (**W**) and length (**Le**) of the hand size is found as:

$$W = b + a * Le \tag{1}$$

where $a = 0.42mm$, and $b = 7.2mm$. The separation is set to the mean value for European people:

$$\frac{Le}{\sqrt{1+a^2}} + \frac{W * a}{\sqrt{1+a^2}} = 189mm \tag{2}$$

where $Le = 173.5mm$, and $W = 83mm$. This is calculated independently of the gender despite the correlation between the hand size and the gender. We choose this because it is the geometrical aspect that interest us for the pressure distribution. That makes 9 **S** and 27 **L**, with only 3 **LF** (Large handed Female) and 1 **SM** (Small handed Male). The characteristics of the experimenter are as follow: male, introvert, large handed.

We tried to make this experiment as ecological as possible. The experiment took place in the participants' environment (their office), the experimental setup was hidden to them and the handshake context was an usual greeting between acquaintances, as handshake is their habitual form of greeting. Despite this wish of natural interaction, some rules had to be expressed: the participant has to initiate the handshake, he/she can begin when the experimenter looks at him/her (because of the calibration phase), the context is to handshake the experimenter like they do in every other day and several handshakes will be made. The experimenter handshakes normally four times (it is the normal firmness: **N**), then twice softly (**so**), twice firmly (**fi**), once softly, and a last time firmly. It makes a total of 10 handshakes. During (**so**) the experimenter has an almost passive hand and during (**fi**) he closes harder and try to lead the movement. During **N** the pressure exerted by the experimenter has a mean of 67.7 kPa and an standard deviation of 16.2 kPa. This has been measured squeezing a passive object with the gloved hand.

C. Human-Human Handshaking - Experimental results

After recording the signals and extracting the features we used ANOVA so as to determine if, for each feature, the difference of mean between subgroups of categories of the variables "gender", "extroversion" or "firmness", is significant. This difference divided by the mean of a reference category is noted $\delta\mu$. The significance is determined using the post-hoc test of Tukey and we note the resulting Q-statistics as q. This analysis allows us to indicate if a feature is able to discriminate a category and hence select it for the next analysis. The feature selection is used to prevent from overfitting. We choose as learning algorithm the LDA (Linear Discriminant Analysis) that finds a new space of representation of the data that maximizes the inter-class variance and minimizes intra-class variance for a given category variable. The new components created allow to discriminate more easily the categories.

This subsection will try to address the following questions:

- Is it possible to recognize the receiver's firmness and is it linked to the *group r* sensors?
- Is it possible to recognize the sender's gender and what are the important features for that? Can the receiver's firmness change help in the discrimination? What is the influence of hand size in these results?
- Is it possible to recognize the sender's extroversion and what are the important features for that? Can the receiver's firmness change help in the discrimination?

Our corpus is composed of two datasets: one homogeneous in terms of experimenter firmness (2 times x 3 types of handshaking: softly, normal, firmly) with 216 points of 36 participants called "dataFirmness"; and another one with only normal handshaking (4 per participant), it has 132 points of 33 participants called "dataNormal".

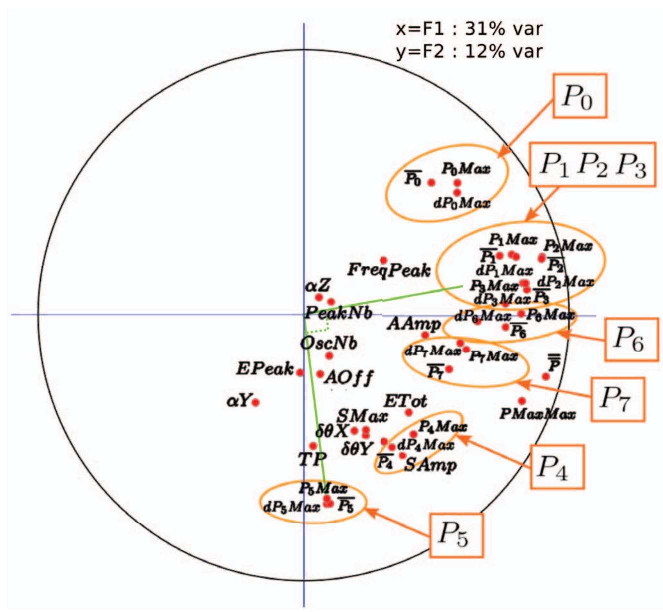

Figure 3. Correlation circle of the features

The first step in the analysis corresponds to finding the correlations between the features. Figure 3 shows the correlation circle of the features, which converts the correlation matrix in distances between features and projects it in the 2D space, which preserves the largest variance of the data. As the feature is close to the periphery, the interpretation of its distance with other features is more reliable. We see that for each pressure sensor, the mean, maximum, and maximum derivative of the signal are strongly correlated. This suggests that when someone presses harder, it is the whole pressure signal that is scaled, the signal profile is kept. Pressure sensors can be grouped in this way: $\{P_0\}$, PG_1=$\{P_1$, P_2, $P_3\}$, $\{P_4\}$, $\{P_5\}$, $\{P_6\}$, $\{P_7\}$. PG_1 represents the sensors from *group r*. What is interesting is that P_0 is totally uncorrelated with P_5 and P_4 (form a $90°$ angle with them) and is closer to PG_1 than to other sensors from *group s*. This tends to confirm that the action of the receiver (experimenter) does not depend on the sender's action. P_6, which belongs to both groups (*group r* and *group s*) is between them.

1) Firmness recognition: For the receiver's firmness study, the ANOVA is applied on "dataFirmness" for each feature and using the "firmness" variable. We qualify a result as significant if the related p-value is lower then 0.05. The results are as follow: A soft handshake lasts longer (TP) than a normal ($\delta\mu$=11%, q=5.1, F[2,213]=7.1). The frequency of acceleration ($FreqPeak$) is higher for firm handshakes ($\delta\mu$=27%, q=4.2, F[2,213]=9.4) than normal handshakes. The direction of movement is slightly closer to the sagital plan for soft handshakes than for normal ones: the αZ angle is smaller ($\delta\mu$=-12%, q=7.9, F[2,213]=15.6). The maximum speed ($SMax$) behaves the same way: soft handshakes are slower than normal handshakes ($\delta\mu$=-29.1%, q=3.4, F[2,213]=3.6). However, the most important discrimination rates are for pressure and slightly more for maximums than for means or derivatives. The higher are the pressures the firmer are the handshakes. Strong effects are visible for sensors 0,1, and 2 ($\delta\mu$=110%, q=7.6 for sensor 2 comparing firm handshakes with normal ones; and $\delta\mu$=-65%, q=12.7 comparing soft ones with normal ones, F[2,213]=65.9), but also for the sensor 6 ($\delta\mu$=77%, q=9.2 for the firm way and $\delta\mu$=-53%, q=4.3 for the soft way, F[2,213]=74.2). Then the difference is less significant for sensors 4,5, and 7. This is consistent with the hypothesis that the sensors from *group r* can discriminate receiver's firmness but not the sensors from *group s* and that a firmer handshake is linked to higher pressure values.

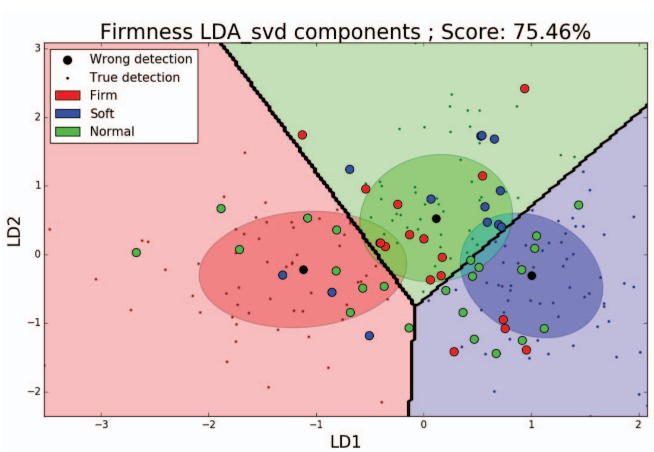

Figure 4. LDA space for firmness discrimination. The small dots represent the true detections, the large ones represent the wrong detections. The color of the dots indicates the real category of the sample. The colored areas are the calculated class attribution from the LDA model.

By selecting these features: TP, $FreqPeak$, αZ, $SMax$, P_6Max, and PG_1Max, we are able to plot the points on the firmness discriminating space calculated by LDA with SVD solver (see Figure 4). We can see the division of the plan in 3 areas corresponding to the discriminatory function, the well classified samples by the small points and the misclassified by the large points. The success rate (score) reaches 75.5%. The two component LD1 and LD2 are a linear combination of the selected features and their weight are shown in Figure 5. The most discriminatory feature is PG_1Max, which is consistent.

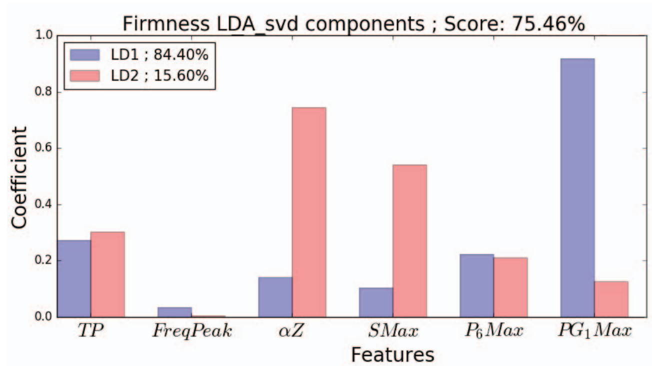

Figure 5. LDA components for firmness discrimination.

The success rate is high but we can tackle the overfit situation. We used feature selection to prevent this phenomena. Nonetheless, we checked if the score is not too different between learning samples and evaluation samples using the "testset" method. We split the dataset in two same-sized subsets, and we learned on the first and evaluated on the second, the split was done randomly. We did 2000 LDA calculations recording either the learning scores and evaluation scores. The histogram is shown in Figure 6, the learning tests scores are (μ=75.3%, σ=3.2%) and for the evaluation the scores are (μ=71.6%, σ=3.5%). Based on this data, we can say there is no overfit for this analysis.

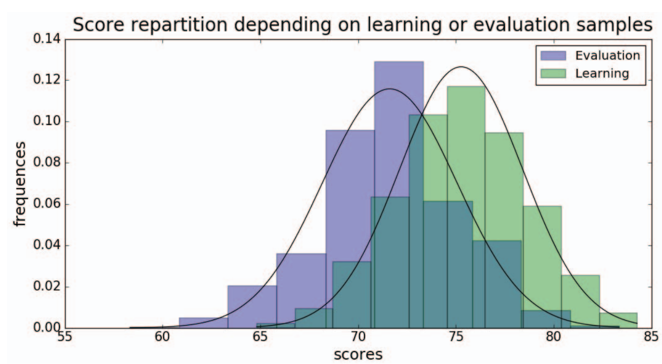

Figure 6. Histograms of LDA scores depending on the learning and evaluation datasets

The results show that our first hypothesis (H1) is validated.

2) Gender recognition: To study the gender handshake dependency, we used the dataset "dataNormal". The ANOVA analysis showed that handshakes differ in term of strength mainly because of the sensors P_1, P_2, and P_4 meaning that the receiver is influenced by the gender of its partner. Indeed the difference for $\overline{P_1}$ is ($\delta\mu$=-79.6%, q=4.1, F[1,130]=11.9) and for $\overline{P_4}$ it is ($\delta\mu$=-60.4%, q=4.3, F[1,130]=13.1) showing that during a female to male handshake both participants apply less pressure than for a male to male handshake. The other features show that female handshakes are longer (TP) ($\delta\mu$=15.2%, q=3.4, F[1,130]=8.1), and have a lower frequency ($FreqPeak$) ($\delta\mu$=-23.8%, q=3.1, F[1,130]=6.7). However, the speed maximum amplitude ($SAmp$) is higher for female interaction ($\delta\mu$=24.2%, q=3.1, F[1,130]=6.9). What is also notable is that the slope of the hands $\delta\theta Y$ differs a lot ($\delta\mu$=26.7%, q=4.8, F[1,130]=16.2), meaning that the hand of the male receiver is pointing down when he handshakes a female participant. This actually can be due to the fact that female participants are on average smaller. Given the ANOVA results we choose the features for the LDA calculation whose weight in the component is plotted in Figure 7. The model score is 76.5% and after overfit evaluation it drops to (μ=72.8%, σ=4.6%). This demonstrates that it is possible to discriminate gender by handshake, mainly by received pressure at the bottom of the hand P_4, speed, and acceleration amplitude, and hand inclination. This is in favor to our second hypothesis (H2).

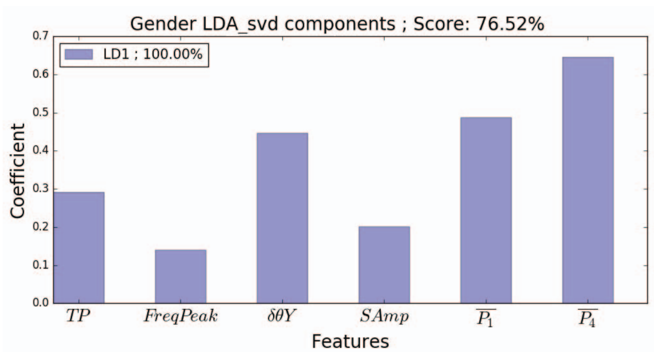

Figure 7. LDA component for gender discrimination

Given these results, it can be assumed that the styles of handshaking are due to hand size rather than gender. Indeed, female participants are more likely to have smaller hands and this geometrical aspect could change the probability to touch a sensor and give a smaller inertia to the hands. In our "dataNormal" dataset, we only have two females out of 10 female participants with large hands and one male with small hand making 12 samples of exception. It can nonetheless be noted that only 3 points out of these 12 samples are misclassified and 2 from the same person, which tends to confirm that the gender discrimination is made from behavioral components rather than geometrical.

We used the "dataFirmness" dataset composed of the three kinds of firmness to know if by changing the handshake firmness a receiver can detect more easily the gender of its partner. We applied the LDA model calculated above on subsets depending on the firmness. The results are depicted in Table II and show that having a soft handshake makes easier gender recognition.

3) Extroversion recognition: We use the same method as for gender to study extroversion. The ANOVA on "dataNormal", which is homogeneous in terms of extroversion, gives that the inclination of the hand ($\delta\theta Y$) is higher if the receiver handshakes an introverted person ($\delta\mu$=16.2%, q=3.6, F[1,130]=6.6), the movement axis is further from the frontal plan (αY). Speed maximum amplitude ($SAmp$) is also a discriminatory element, introverts reach higher speed ($\delta\mu$=20.2%, q=3.2, F[1,130]=5.3). Surprisingly there is no significant difference on sensors from *group s*. This results is against our third hypothesis (H3). However the mean pressure on sensors P_1 and P_2 has a strong difference and this is reported on the feature $\overline{PG_1}$, the receiver handshake stronger introverts ($\delta\mu$=28.9%, q=4.4, F[1,130]=10.1). This means that the experimenter has a way to detect extroversion and its behavior is unconsciously altered. The fact that he handshakes harder may have modified the perception of firmness of raters in psychological studies.

Table II
GENDER DISCRIMINATION SCORES DEPENDING ON RECEIVER FIRMNESS

Firmness	LDA Score
Soft	80.5%
Normal	68.1%
Firm	72.2%

The LDA component ploted Figure 8 enables to reach 62.1% of true detections. After overfit evaluation it drops from 67.2% (the model seams to be more precise with less samples) to 61.2%. This value begins to be close to the 50% random choice, this is due to the fact fewer features are extroversion discriminative, but this still indicates it is possible to discriminate extroversion by interpersonal handshake. The relevant features are receiver pressure, speed amplitude, orientation of the hand, and direction of the movement.

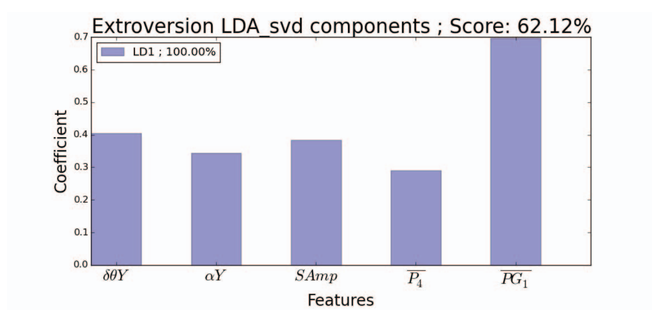

Figure 8. LDA component for extroversion discrimination

We did not see any significant difference in the classification scores depending on the firmness of the receiver.

IV. Human-Robot Interaction

A. Human-Robot Interaction - Experimental design

The experiments presented in this section were conducted with the Meka humanoid robot pictured Figure 9. This compliant robot has been designed for human-robot social interaction studies. Its joins are intrinsically safe and the actuators are able to simulate customized stiffness. It has a moving head, is able to simulate facial expression, has an omnidirectional base, a customized body height and two 7 DOF arms. Its hands have 5 cable driven DOF: a 2 DOF thumb and 3 fingers. We can adjust the close ratio (**cr**), stiffness (**kh** for the hand and **ka** for the arm), and speed. Its hands are slightly larger than a human hand and is designed for dexterous manipulation.

The glove we designed for the robot has one layer of fabric on which we embedded 8 pressure sensors in most touched areas found by the ink experiment (see Section II). However, because the hand is large, participants did not touch the same areas and it was difficult to instrument the whole surface. An accelerometer is also sewed on the back of the robotic hand. Then the glove is covered by another fabric layer. The acquisition was done using and Arduino transferring data through USB and commands were sent using ROS.

After having filled the same questionnaire as in the previous experiment, participants were introduced to the robot. They had five minutes to perform handshake training with the the robot exerting various closing ratios and strength. During a handshake the participant starts the move and when he/she is close to the robot hand, the experimenter sends the closing command. The closing duration is about one second. After a few seconds of interaction, if the participant did not start to remove his/her hand, the experimenter sends the open request. 9 measures were made: 3 soft (**cr**=50%, **kh**=50%, **ka**=30%), 3 normal (**cr**=70%, **kh**=70%, **ka**=60%), and 3 firm (**cr**=80%, **kh**=85%, **ka**=90%). Then, we extracted the same features as in the human-human experiment.

The experiment was carried out with 8 participants (7 **M** and 1 **F**, 4 **E** and 4 **I**) making a 72 samples dataset.

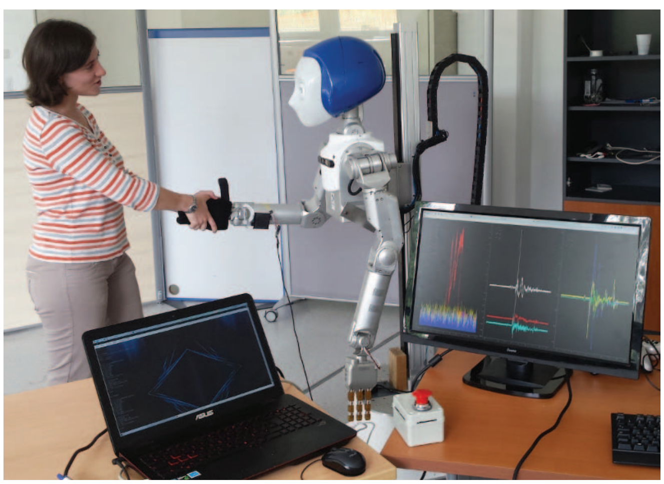

Figure 9. Human-Robot handshake using Meka humanoid robot

B. Experimental results and comparison

The first thing we can notice is that some sensors are never or hardly touched but the touched sensors are consistent depending on the participant. For instance P_0 is never touched, P_7 is touched by one person, P_6 by two, P_1 by three, P_2, P_3, P_4, P_5 by five. No correlation can be made between the fact a sensor is touched and the extroversion value. We decided to take into account only the touched sensors and calculate the mean and maximum values of this selection.

We first checked if a firmer robot handshake produces higher sensor responses. We did an ANOVA on firmness category and we found that only discrimination between firm and soft handshakes is significant and it is using the $PMaxMax$ feature. $PMaxMax$ is higher for firm handshakes than for soft ones ($\delta\mu$=87.1%, q=3.8, F[2,69]=4.1), $\overline{\overline{P}}$ behaves the same way but less significantly. This result is consistent with the previous experiment and the order of magnitude of this pressure gap is similar ($\delta\mu$=99.3%, q=12.3, F[2,213]=38.7). Unfortunately, we cannot determine which sensor belonging to *group r* or *group s* is responsible for this difference.

Given the fact our number of participants is very small we only can do a qualitative comparison between the two experiments. We can say that the only female of our robot experiment handshaked slightly softer than males (μ=25.8 kPa, σ=22.3 versus μ=29.4 kPa, σ=16), the maximum acceleration amplitude is also lower, the maximum speed higher and the frequency lower. So apart from the inclination of hand feature, this is consistent with the human to human results. Similarly, for the extroversion study we found that the two out of three main features selected in the previous study ($\delta\theta Y$, $SAmp$, but not $\overline{\overline{P}}$) behave the same way: $\delta\theta Y$ is higher for introverts (μ=11.8°, σ=6.8 (**I**) versus μ=9.8°, σ=6.6 (**E**), $SAmp$ is higher (μ=0.21$m.s^{-1}$, σ=0.12 (**I**) versus μ=0.18$m.s^{-1}$, σ=0.12 (**E**), and $\overline{\overline{P}}$ is equal. This last information is still against of our third hypothesis (H3). Indeed in the previous experiment, the sensors with a stronger response belonged to the *group r*. As the robot has the same behavior whatever the participant personality, it shows that there is no link between the extroversion of the participant and the pressure he applies.

This experiment is a first exploratory study that gives an idea of the consistency of our model but many other samples have to be measured to make it relevant. More control of the conditions have also to be managed and a more sophisticated movement model has to be implemented. The non anthropomorphic shape of the hand seems to have disturbed participants, which goes against our wish to have a natural greeting interaction.

V. Conclusions

This paper focuses on modeling the handshake interaction, starting from human-human handshake study, in order to discriminate gender and personality of a participant. A glove was designed to measure pressure exchanged and movement features. It has been checked that depending on the handshake firmness of the individual that wears the glove, the analysis method is able to recognize the firmness condition with a success rate of 75%. The main features for this are the handshake duration, frequency, direction of movement, maximum speed, and the pressure of the individual that wears the glove. The results are consistent with the first hypothesis (H1) as the pressure is higher and the glove pressure is discriminative.

The experiments results are also in favor of the second hypothesis (H2): it is easy to recognize gender through handshake as the success rate is 77%. An important feature is the hand inclination and also the participant's pressure. This means that there is a real behavioral effect of the participants depending on their gender. It has also been found that using a softer handshake it is easier to recognize gender.

The extroversion discrimination is more difficult as the success rate is around 62%. If some important features are movement characteristics, the relevant pressure information is linked to the behavior of the individual that wears the glove. This means that detecting extroversion through contact pressure might not be relevant. This goes against the third hypothesis (H3) but further studies need to be carried out (like taking into account physiological data: hand temperature and dermal conductivity).

The comparison with the human-robot handshakes showed some consistency with respect to the human-human interaction. To the best of our knowledge, no other study focused on modeling human-human handshake behavior in order to discriminate gender and personality and used it in a human-robot interaction. This is an exploratory but promising study. Further work will focus on the development of a more sophisticated and controlled interaction so as to make the experiment more natural and evaluate the differences between human-human handshake and human-robot handshake. The number of participants involved in the human-robot interaction experiment was too small. More experiments will be run. We will also investigate if the fact that we used a specific robot would prevent from designing a valid general model as it would depend on the robot's shape. However we will move towards an anthropomorphic hand as it is not the practical grasping technique we want to study but if the general appearance of the robot changes the way of handshaking. It would also be interesting to evaluate the influence of other variables like eye gaze, smile, head motion, and distance between partners; and in a further step investigate the multi-modal features (haptic, physiologic, face expression, etc).

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