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Classification of haptic handshake data for the control of human-telerobot social contact interactions

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***Abstract*—Mobile Remote Presence (MRP) robots have emerged out of the need for telepresence in various settings such as the workplace and hospitals. As with face-to-face experiences, these robot mediated encounters have social aspects that current commercially available MRP robots lack the capabilities to incorporate. In previous work, we integrated a manipulator onto a commercial telerobotic platform to enable expressive gestures and demonstrated that the gesturing capabilities enhanced the social connection between remote and local users. However, we also found that controlling the robot for complex interactions, such as a handshake, diminishes the remote user's social experience. This paper presents the discovery of models for handshakes in different social contexts, which can be used in a shared-control architecture to reduce the effort on the remote user. Using a haptic measurement glove, force and inertia data was collected for human-human handshakes in various social contexts. By applying a k-nearest neighbor algorithm in combination with dynamic time warping and a support vector machine algorithm, two classification models are derived that predict the social context and can be used in an intelligent shared-control robot architecture.**

Keywords—Telerobot, Mobile remote presence, Human-robot interaction, social robotics, Machine Learning, Robot handshaking

I. Introduction

Telerobots or mobile remote presence (MRP) robots are used for human-to-human activities that are normally conducted face-to-face, such as providing services like doctor's visits to hospitalized patients or classroom participation for homebound students. The MRP experience is characterized by (a) a *pilot*, who is a remote human user operating the robot from a distant location, (b) the MRP robot itself, and (c) a *colocated human user*, who is interacting directly with the robot to communicate with the pilot (Fig. 1).

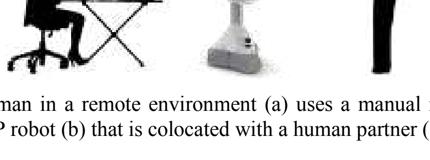

Fig. 1. A human in a remote environment (a) uses a manual interface to control a MRP robot (b) that is colocated with a human partner (c)

MRP robots have emerged out of the need for "telepresence" and to bridge the gap between audiovisual communication tools and face-to-face experiences. Currently, commercially available MRP robots lack the capabilities to incorporate human-to-human social aspects of body language, gesturing, and social contact (e.g., handshakes and fist bumps) that are part of our everyday face-to-face interactions [11]. The challenge to adding such capabilities is controlling the robot's physical actions with reasonable fidelity to the pilot's intended social and emotional expressions. Specifically, how does the pilot's actions (a) trigger their physical expressions in the MRP robot's system and how does the MRP robot's system (b) control its end effectors to express the pilot's actions in a manner that is correctly interpreted by the colocated human partner (c). The focus of this work is on MRP robot to human handshaking, as handshaking plays an important role in many cultures and is used in a variety of everyday situations [11].

Handshaking is a form of nonverbal communication that can convey trust as well as signaling a willingness to engage in conversation. Handshakes also require physical contact without violating other people's personal space. Often, first impressions are influenced by handshakes. For example, a hardy handshake can convey a person's competence and trustworthiness, while a feeble handshake can signal introversion and insecurity [2]. From a robot control perspective, whether autonomous or teleoperated, handshaking is a complex technical action requiring accurate positioning in relation to the human partner, cadence appropriate to the social context, force-compliance with respect to the human partner, and synchronization for beginning and ending the action [1].

In addressing these control complexities, we consider the cadence and grip forces. What social information is conveyed by the different types of handshakes and how might this information be used to control an MRP robot's handshaking behavior to convey the similar social information? To this end, we investigate the physical properties of a handshake between humans to enable future control and experiments with a handshake between a human and a robot.

For this purpose, we study the physical characteristics of handshakes between two humans in different social situations, such as a greeting, condolence or congratulations.

Our project aims at a quantitative analysis of the handshake, in particular the synchronization phenomenon that occurs when the hands of two people interact. The goal of this work is to gather handshake data to create classification models using Machine Learning methods that can be used to guide a robot's actions in corresponding social situations.

This paper reports on the modeling of human-to-human handshakes. We use a wearable haptic measurement glove (HMG), developed in our previous work [3], to collect force and inertia data during handshakes in human-human interactions. Two supervised machine learning methods, KNN and SVM are then used to create classification models of handshake characteristics and resulting models are evaluated.

In the following section, we present our previous work and other related works. In sections III and IV, we describe the methods used, the data collection process and share our evaluations of the algorithms and the data. Finally, in sections V and VI, we analyze the data, present our classification model, and provide an overview of future work.

II. RELATED WORK

The handshake is proven to be almost 3,000 years old when it was first illustrated in ancient Greek reliefs and on gravestones [4]. It has played an important role in human communication. People communicate with each other constantly through verbal and nonverbal forms. Over time, a simple gesture like the handshake has helped to improve interpersonal relations in almost every area of daily life, such as in negotiations and in the workplace, to convey empathy and to solve conflicts. Early etiquette books ([12], [17]) described the proper handshake and its social implications.

In general, the handshake itself is quite well studied. Hall et al. [6] was one of the first works to examine the handshake as an interaction and its history in detail. They found that the handshake is consistently accompanied by other gestures, both verbal and nonverbal, and does not occur in isolation. Katsumi et al. [8], studied the role of ethnic and gender differences in the effect of handshake on appraisals of social interactions. They found that the handshake is most commonly used in Western cultures for greeting, especially among men. Furthermore, they confirmed that the handshake is commonly used as a nonverbal form of communication to signal approach and avoidance intentions.

In their paper, Stahl et al. [13] discuss the limitations of current video conferencing systems in replicating natural interaction and non-verbal cues, hindering effective communication and collaboration. They proposed the development of humanoid telepresence robots that can mirror human actions and gestures to overcome these limitations. The authors highlighted the importance of body posture and gesture in telepresence and called for further exploration of these elements. They also addressed the concept of "presence disparity" and emphasized the need for robots to resemble humans and exhibit positive attributes to gain acceptance in a business environment. This research aligned with the goal of facilitating natural handshakes for mobile remote presence (MRP) robots and addressed the challenges of social and non-verbal cues in telecommunication.

Despite being well studied, experiments on the handshake in different situations in the context of human-robot interactions are rare. In previous NSF-funded work, we designed, built, and integrated a modular manipulator onto a commercial telerobotic platform, the Anybots QB 2.0, to enable expressive gestures (Fig. 2) [12]. This work was inspired by prior research on robotic manipulators which span a spectrum of functionalities and realism. We demonstrated our lightweight, 5 DOF anthropomorphic arm and 5-fingered hand (OpenBionics Brunel Hand 2.0), shown in Fig. 2a, can achieve expressive gestures (waving), reference pointing, and tangible interactions such as handshakes (Fig. 2c). Control of the manipulator is achieved through the HTC Vive virtual reality (VR) tracking system and the Manus VR Prime One glove, resulting in direct mapping of the remote operator's movements to the manipulator pose (Fig. 2b). Through empirical user studies, we demonstrated that gesturing capabilities onboard the telerobot enhanced social connection for the colocated user, but not for the pilot user. With only the visual feedback from two cameras mounted on the telerobot, the control of the manipulator added to the pilot's cognitive effort, particularly for complex action that required synchronizing with the remote user.

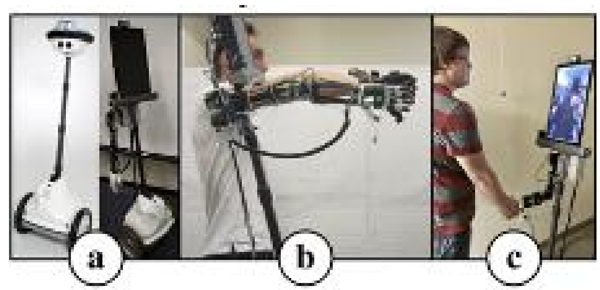

Fig. 2. (a) Anybots QB 2.0 and modified platform; (b) manipulator matching a user pose (overlaid photographs); (c) modified platform and colocated human

To study human-robot handshake interactions in detail, we developed the HMG (Fig. 3). In contrast to the four stages described in [8], we found that both the human-human handshake (HHI) and the human robot handshake (HRI) consist of five distinct phases. Phase 1 is between the start of data recording and the first contact, where interactants raise their arms from the resting position. Phase 5 is a mirror image of phase 1; it lies between the termination of physical contact at the end of the handshake and the end of the recording, during which the participants lower their arms. Phases 2, 3, and 4 characterize the contact portions of the interactions [3]. The robot system consisted of the Anybots QB 2.0 [16] equipped with our previously described robot manipulator. In summary, this work found that there are differences between HRI and HHI handshakes in terms of duration, pulses, energy, and firmness.

Tagne et al. [15] is one of the first works to study the social context of a handshake related to robotics. Similar to the work reported in this paper, they studied handshakes in different situations (i.e., hello, congratulations, sympathies). They found that context influences the strength and duration of the handshake. In Melnyk et al. [10], they developed a glove to measure the physical parameters, similar to our HMG, and found that there is a difference in the duration of the handshake in the context of the greeting handshake and the consolations handshake. Our research builds on these results by taking the step of deriving classification models of handshake data collected using our HMG [3] for the purpose of controlling robot handshakes that convey social messaging.

Fig. 3. A participant wearing the HMG and the confederate shaking hands

III. METHODS

The HMG was used to collect the data such as force, acceleration, angular rotation and orientation. As shown in Fig. 4, the HMG [3] consists of a silk glove with force sensitive resistors (FSRs), a slide switch, an LED, a built-in battery, an SD card, and an IMU on a 9-DOF Razor IMU microcontroller. It has 14 total sensing capabilities (5 FSRs + 9 degrees of freedom IMU) and can form-fit to most sized hands. The FSRs are three-layer sensors consisting of a conductive layer, a spacer, and an interdigitated electrode layer. In total, there are five FSRs placed on points of the glove determined in our previous work [3] to have concentrated contact during a handshake. These points are on (1) the tip of the index finger, (2) the heel of the ulnar side of the palm, (3) the base knuckle of the little finger on the ulnar side of the palm, (4) the middle of ulnar side of the hand between the palm and the back of the hand, and (5) the radial side of the base knuckle of the index finger.

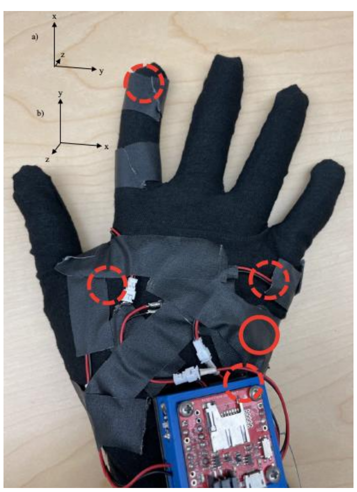

Fig. 4. The HMG components: silk glove, FSRs (locations circled with dotted lines representing a sensor on the palm side), slide switch, LED, built-in battery, SD card, 9-DoF Razor IMU microcontroller, insulated wires, conductive thread. The orientation of the IMU axes is different for the (a) accelerometer/gyroscope and the (b) magnetometer. In (a), the positive z-axis is in the palm direction. In (b), the positive z-axis points in the dorsal direction [2]

To collect handshake data in different situations, a three-part experiment was conducted. We collected force and inertial data on handshakes in between two people in situations such as a greeting, sympathy or congratulation in order to identify quantitative and qualitative characteristics of each and to compare the execution of handshakes in between the three scenarios. A total of 15 subjects participated in this study, 10 of whom were male students. The mean age of the participants was 24. Each subject was asked to shake hands two times per situation. In total, each subject shook hands 7 times, one handshake for testing purposes and to get familiar with the study procedure and 6 situational handshakes.

During the study, a subject, wearing the HMG, shook hands with a confederate. The confederate, a student from SIUE, and the participant were instructed to stand at arm's length. The participant was told a short story by the experimenter, depending on the situation, to better empathize with the situational action. For the greeting handshake, the participant was told they would meet an old friend. Then the confederate said: “"Hey [participant], how are you? It's good to see you again." and the handshake was initiated. All handshakes were performed with the right hand.

TABLE I. EXAMPLE OF THE STORIES FOR THE DIFFERENT HANDSHAKING SITUATIONS

Handshake Situation	Story
Greeting	Meeting with an old friend
Congratulatory	Congratulations on graduation
Sympathy	Loss of a beloved pet

After starting the data collection, both subjects hold their arms in idle position, carry out a handshake and return their arm to idle. This was repeated three times for each of the four situations per pair of subjects to record 180 total handshakes. The study was approved by the SIUE's Institutional Review Board. The duration of each study session was around 20 minutes and the subjects received a $10 gift card for their participation.

A. Analysis Metrics

According to [4], handshakes can be quantitatively categorized by the following factors: Vigor, duration, number of up and down movements, firmness, and completeness of grip. Vigor, duration and the number of up and downs can be measured by the accelerometer, gyroscope, and magnetometer. The completeness of grip, firmness and duration can be computed from the FSR data.

With the collected data, a profile of each handshake was created. Data on handshake duration, waveform amplitude, number of waveform peaks, number of sensors activated, and force magnitude of activated sensors are recorded for each trial (see Fig. 5).

Preprocessing the dataset is vital before training the machine learning model, as it prepares the data for analysis.

One important preprocessing step is the data selection. The analysis is based on handshake stages 2, 3, and 4 as they characterize the handshake the most. All these stages describe the contact interaction and can be extracted by filtering the data by force. Since no contact is made in phases 1 and 5, the force values for the FSR are at 0. The handshake stages are described in more detail in the Results section.

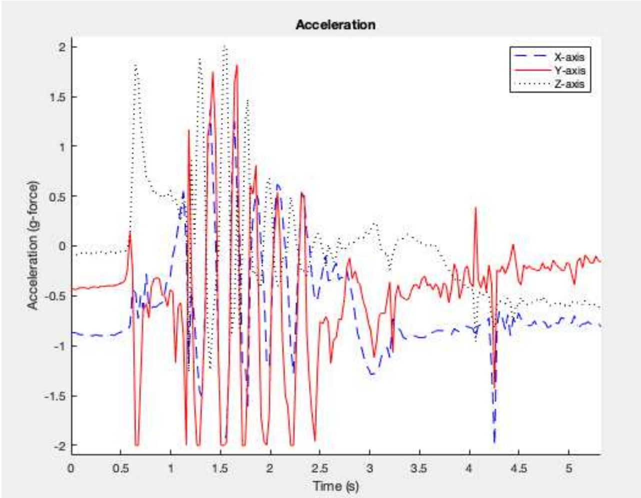

Fig. 5. Representative time plots of 3-axis linear acceleration for a greeting handshake

Two algorithms are used to derive classification models: 1) k-nearest neighbor (KNN) in combination with a Dynamic Time Warping (DTW) algorithm and 2) Support Vector Machine (SVM) algorithm.

DTW is a mathematical method for comparing two time series sequences that do not perfectly match by computing the distance of similar elements [5]. DTW includes the following steps: (1) compute a distance matrix between the two sequences, where each cell in the matrix represents the distance between two points in the sequences, (2) compute the cumulative distance matrix by summing the distances along a path through the distance matrix and (3) find the path with the lowest cumulative distance, using dynamic programming [9]. With the DTW technique, we are able to detect similarities in the handshakes even if one person was shaking hands faster than the other. This can mitigate the emphasis on individual idiosyncrasies in classification that could lead to overfitting.

The KNN algorithm is used because of its simplicity and wide usage in applications. Given a new observation, KNN finds the k-nearest points to that observation in the training dataset and assigns the class of the majority of the k-nearest points to the new observation. The KNN algorithm includes the following steps: (1) choose the k number of expected classes, (2) calculate the distance between the new observation and each point in the training dataset using the DTW distance, (3) select the k-nearest points to the new observation based on the smallest distance, and (4) assign the class of the majority of the k-nearest points to the new observation [7].

A SVM algorithm is a supervised machine learning algorithm used for classification and regression tasks. It works by finding an optimal hyperplane that separates different classes in the input data [14]. The SVM aims to maximize the margin, which is the distance between the hyperplane and the nearest data points of each class. This allows the SVM to create a decision boundary that generalizes well to new, unseen data. SVM can handle high-dimensional data efficiently and is effective in cases where the data is not linearly separable by transforming the input space using kernel functions. By mapping the data into a higher-dimensional space, SVM can find a nonlinear decision boundary.

Both the KNN with DTW and the SVM algorithm split the dataset containing the handshake time series data for each category into 80% for training and 20% for testing.

IV. RESULTS

In this section, we present our results from the classification study and describe outcomes regarding the characteristics of handshakes in different situations. As described in [3], when interpreting the data, the positive Y-axes for the accelerometer and gyroscope points down when the arm is extended parallel to the ground with the palm of the hand perpendicular to the ground during a normal handshake. The axis orientation is provided in Fig. 4.

A. Handshake Stages

Representative time plots are shown in Fig. 6 for context. Similar to our previous work [3], all handshakes consist of 5 different phases.

Stage 1 describes the part between the start of the data recording after switching the slide and the first contact. While doing this, the participants rotate their hands around the Z-axis and, as shown in Fig. 6, the hands experience relatively constant acceleration. In stage 1, there is no FSR data as there is no physical contact between the confederate and participant. Stage 5 mirrors stage 1, i.e., it is the phase between the end of the contact interaction and the participant switching the slide again to end the recording. The stages 2, 3, and 4 describe the contact interaction. In stage 2, the participants make contact and start their handshake movement. During this stage, the participant subconsciously determines how the handshake will proceed. Stage 3 is the main stage and shows the typical up and down motion (see Fig. 6). Stage 4 is the phase when one or both participants want to terminate the handshake and the physical contact ends.

For all different handshake situations, stages 1 and 5 are relatively similar with constant acceleration. Stages 2 and 4 consist of more unstable data and vary from participant to participant. Stage 3, the main stage, shows a steady waveform. As shown in Fig. 6, the greeting and congratulation handshakes have relatively high amplitudes and are pretty similar in terms of acceleration. In comparison, the sympathy handshake has less up and down movements, and the amplitude is lower. The similarities and differences observed in each stage are discussed in more detail in Section V.

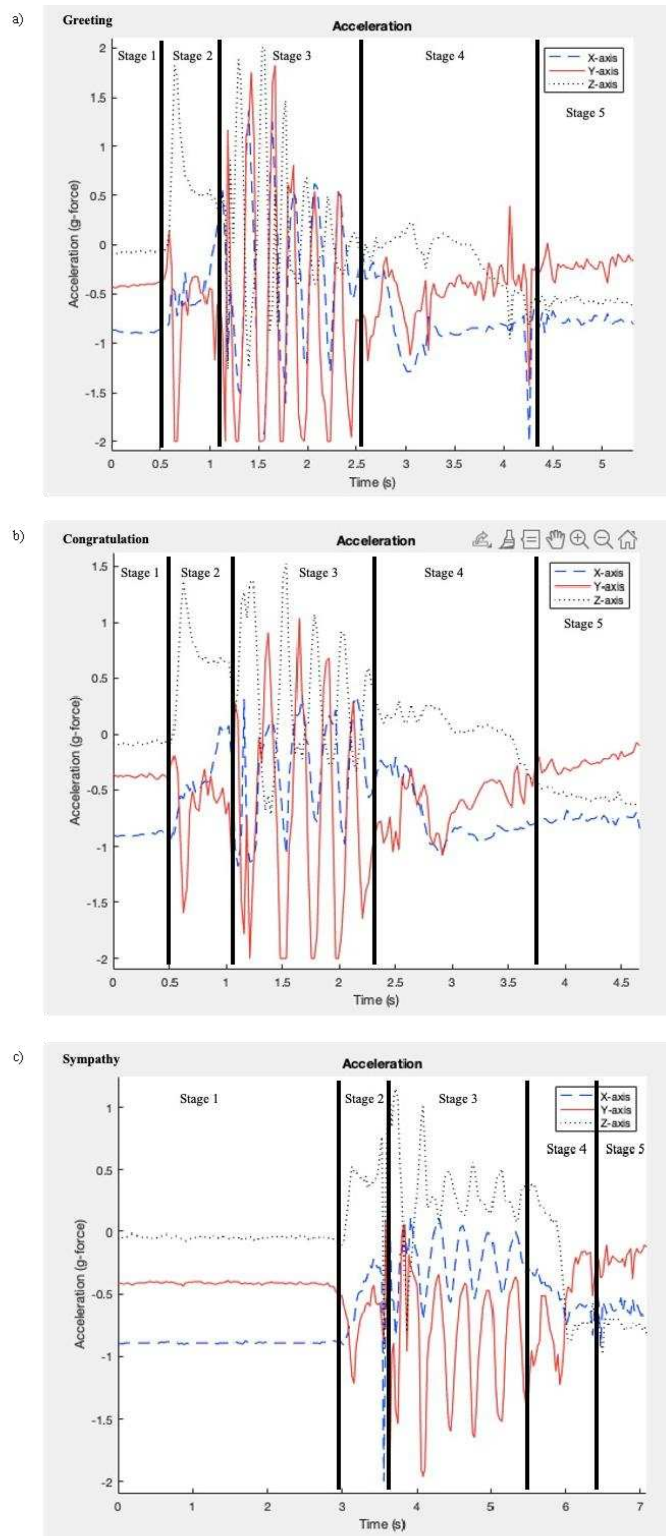

Fig. 6. Time plots of 3-linear acceleration for (a) a greeting handshake, (b) a congratulation handshake, and (c) a sympathy handshake. The handshakes are divided into five stages

B. Handshake Metrics

We now further analyze stages 2, 3, and 4 in the context of the 5 characteristics of handshakes.

Duration: The greeting handshake duration is *1.7 ± 0.41seconds*, the congratulation handshake duration is *1.6 ± 0.36seconds* and the sympathy handshake duration is *1.3 ± 0.39seconds.*

Vigor: Sympathy handshakes have lower acceleration waveform amplitudes compared to greeting and congratulation handshakes. The waveform amplitude is measured from the y-axis waveform because the amplitude of the y-axis waveform is the most prominent and consistent of the three axes. The sympathy handshake acceleration amplitude is *3.8 ± 0.49g*, the congratulation handshake acceleration amplitude is *3.9 ± 0.18g*, the sympathy handshake acceleration amplitude is *2.3 ± 0.43g*.

Pulses: Greeting and congratulating handshakes have more pulses than sympathy handshakes. The highest amplitudes are seen in stage 3 of the handshakes. The average number of waveform peaks for greeting handshakes is *4.0 ± 1.9peaks*, the average number of peaks for congratulation handshakes is *4.3 ± 1.7peaks* and the average number of peaks for congratulation handshakes is *3.7 ± 1.8peaks*.

Firmness: Sympathy handshakes have lower firmness compared to congratulation and greeting handshakes. Similar to [3], firmness is determined by taking the mean of the magnitude of force (N) applied to the sensors that are activated in each trial. The sensors that are not activated are ignored so as not to bias analysis by differences in grip completeness. The mean force exerted on FSRs during sympathy handshakes is *8.1 ± 5.4N,* the mean force for greeting handshakes is *8.8 ± 7.69N* and the mean force for congratulating handshakes is *9.1 ± 8.12N*.

Completeness of Grip: The number of activated FSR is lower for Sympathy handshakes than for the other handshakes. As in [3], the number of activated sensors for each trial is counted to determine completeness. The average sensor activation per congratulation handshake (out of 5 sensors in total) is *2.8 ± 0.89sensors*, the average per congratulation handshake is *2.9 ± 1.12sensors*, and the average per sympathy handshake is *2.1 ± 1.01sensors*.

C. Classification Results

We now discuss the data classification results. We applied DTW to solve the problem of time warping between time series data. In this way, we were able to align time series data across participants and compute a distance that accounted for differences in temporal alignment between two given series. For example, by comparing the DTW distance between two handshake signals, we can determine how similar their waveforms are, which is essential for analyzing and characterizing handshakes in different situations. Fig. 7 shows representatively how two greeting handshakes are aligned, although the second greeting handshake (blue) has a longer duration and shows two additional up and down movements. It becomes clear that the length of the handshake has no influence on this time series and that the waveforms are well matched by the application of the algorithm and thus made comparable.

Using a k-nearest neighbors algorithm with a k value of 2 and Dynamic Time Warping, the implemented model achieved an accuracy of 0.85 on the test set. This means that 85% of the test set samples were correctly classified based on their handshaking patterns, demonstrating promising results.

Using a Support Vector Machine (SVM) algorithm, the implemented model achieved an overall accuracy of 0.89, which means that 89% of the test samples were classified correctly.

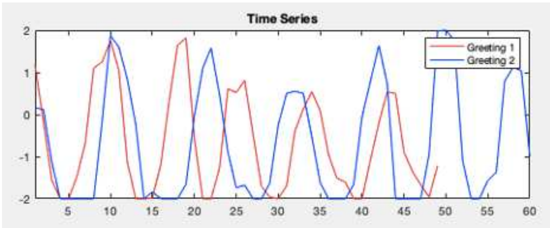

Fig. 7. Representative DTW results for 2 greeting handshakes

V. DISCUSSION

A. Handshake Stages Discussion

Similar to [3], phases 2, 3, and 4 represent the core function of the handshake and contain most of the information about a handshake. Phases 2 and 4 are contradictory because each person has their own expectation of the handshake. These phases differ from participant to participant and are therefore very different. We observed that some participants are very insecure in phase 2 because this is the phase in which first contact with the confederate is established. Similarly in Phase 4, where the handshake ends and some participants seemed to be waiting for a sign from the confederate to end the handshake.

In Phase 3, the phase in which individuals move their hands up and down, force and momentum are periodic, while completeness and firmness are constant. As can be seen from the results, handshaking in sympathy is slower and has fewer waveform periods compared to the other situations. For example, in Fig. 6 (b) for the congratulatory handshake, the participant slowed down the movement and decided that the handshake was complete, but received additional feedback from his counterpart and started the up-and-down movement again.

B. Handshake Metrics Discussion

In almost every category, the sympathy handshake was significantly different from the greeting and congratulatory handshakes, while the greeting and congratulatory handshakes were similar in terms of duration, force, frequency, firmness, and completeness of grip.

During the study, it was also noticed that people shake hands differently, everyone has their own handshake style. Also, as expected, there were significant differences between female and male participants. Most male participants shook hands more vigorously and with fewer up-and-down motions, while most female participants shook hands more slowly and made more up-and-down motions. In addition, participants reported that they had never thought about shaking hands differently in different situations; after the study, some of them asked how to perform a particular handshake. This shows that shaking hands is something natural, people do it without thinking about it, and yet people unconsciously shake hands in different ways.

The data shows that there are differences in various handshake situations.

C. Handshake Classification Discussion

In the following, the results for the KNN and SVM algorithms are presented.

KNN with DTW

Fig. 8 presents the confusion matrix that shows the classification results of the KNN model using DTW with a k of 2 for the handshake situation recognition. The rows represent the true labels, while the columns represent the predicted labels.

The values in the confusion matrix in Fig. 8 represent the proportion of samples that are classified into each label. For example, the value at row 1, column 1 (0.85) indicates that 85% of samples with the true label greeting are correctly classified as greeting. Similarly, the value at row 2, column 1 (0.16) indicates that 16% of samples with the true label congratulations are incorrectly classified as greeting.

Overall, the confusion matrix suggests that the KNN model performs reasonably well on the three classes, with highest accuracy on the sympathy class and lowest accuracy on the congratulations class. However, there were also some misclassifications. Specifically, 8% of the greeting handshakes were misclassified as congratulations handshakes, 8% of the greeting handshakes were misclassified as sympathy handshakes, 16% of the congratulation handshakes were misclassified as greeting handshakes, 9% of the congratulation handshakes were misclassified as sympathy handshakes, 5% of the sympathy handshakes were misclassified as greeting handshakes, and 4% of the sympathy handshakes were misclassified as congratulations handshakes.

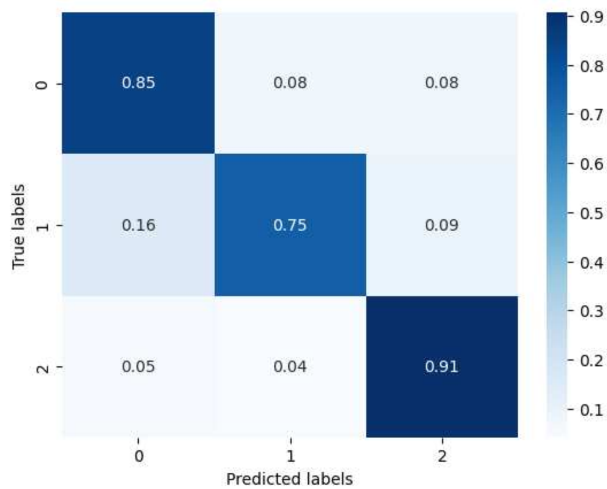

Fig. 8. Confusion matrix showing the performance of the KNN-DTW model on the handshake recognition task, with class labels of 0 (greeting), 1 (congratulations), and 2 (sympathy)

SVM

The confusion matrix of the SVM algorithm shows that the model performed well overall with an accuracy of 0.91 for greeting, 0.85 for congratulations, and 0.89 for sympathy (Fig. 9). The model has the lowest precision for congratulations, with 12% of greeting being classified as congratulations and 3% of sympathy being classified as congratulations. The training accuracy, validation accuracy, and test accuracy are 94%, 88%, and 89%, respectively. These results indicate that the model is not overfitting and has a good generalization performance. The mean cross-validation score is 86%, indicating that the model performed consistently across different training and validation sets.

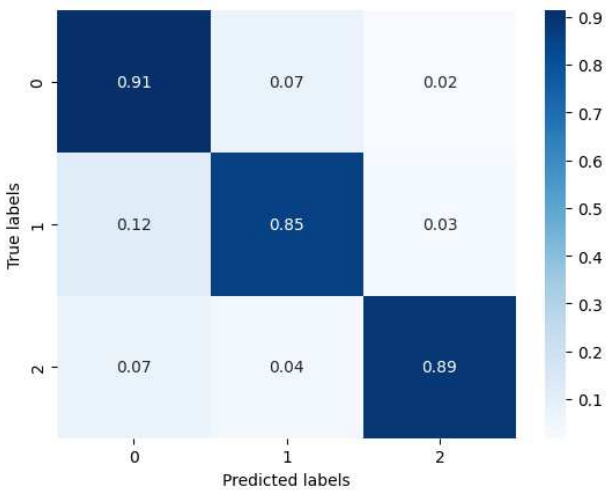

Fig. 9. Confusion matrix showing the performance of the SVM model on the handshake recognition task, with class labels of 0 (greeting), 1 (congratulations), and 2 (sympathy)

VI. CONCLUSION

We showed that handshakes have distinct characteristics that vary depending on the situation. Handshakes consist of five stages, and the main stage (stage 3) shows a steady waveform with a typical up and down motion. The greeting and congratulation handshakes have higher acceleration waveform amplitudes and more pulses compared to sympathy handshakes. Sympathy handshakes have lower acceleration waveform amplitudes, lower firmness, and lower completeness of grip compared to greeting and congratulation handshakes. The duration of greeting and congratulation handshakes is longer than that of sympathy handshakes.

Furthermore, the results show that it is possible to classify different types of handshakes using KNN with DTW and SVM, and the classification results were highly accurate. Another approach of classifying the data would be the combination of SVM with DTW. Overall, the study provides insight into the characteristics of handshakes in different situations, which can be used to model handshakes for specific social situations and to control robot actions for more human-like social interactions.

Future work will focus on utilizing the derived handshake models to implement robot handshake control, ensuring appropriate handshakes in social contexts. This requires designing a shared control architecture that integrates the classification models with the robot's motor control system. In an MRP robot system, the pilot would trigger the appropriate type of handshake. The telepresence robot would then navigate through phase 1 and 2. Then an exemplar from the corresponding derived handshake class would guide the motor controls with the appropriate social characteristics of vigor, pulse, firmness and completeness of grip.

Evaluating the performance of the models in situated human-robot interaction (HRI) and telerobot HRI, considering factors like communication delay and limited sensory feedback, is essential. Enhancing telepresence and user experience in telerobot-assisted handshakes is crucial to bridge the physical gap between the operator and the remote environment. Adapting and optimizing the classification models for telerobot HRI scenarios, including investigating methods for triggering handshakes based on social context, would contribute to real-world applications. Expanding the dataset, mitigating ordering effects, and considering gender-based differences are important for a comprehensive understanding of handshakes.

Overall, addressing these aspects would advance handshakes classification, foster socially intelligent robots, and improve human-robot interactions.

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