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Development of A Multimodal Trust Database in Human-Robot Collaborative Contexts

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***Abstract*—Robots are gradually being incorporated into the workforce to assist with labor-intensive and repetitive tasks, especially in smart manufacturing contexts. This leads to increased human-robot collaboration, which may be an unfamiliar, distrustful, and uncomfortable situation for inexperienced people to navigate. Motivated by these issues and aiming to have a comprehensive understanding of the factors that affect people's trust in robots, we developed a new trust database by investigating the trust between human collaborators wearing four biological sensors and a robot performing collaborative tasks. Using these sensors, we collected trust-related physiological human factors from the brain (EEG), heart (ECG), forearm (EMG), and eyes during human-robot collaborative tasks. As well as a trust rating through a questionnaire, this allows for the creation of a multimodal human-robot trust database (TrustBase). TrustBase provides insightful guidance to optimize and improve the environment deployment and robot configuration in human-robot partnerships within smart manufacturing contexts.**

Keywords—Trust, robotics, human factors, physiological signals, database.

I. Introduction

The rapid development of technology and the exponential growth of data in recent years has led to monumental breakthroughs in manufacturing, robotics, and artificial intelligence. Robotics is a rapidly expanding field that is on the horizon of being incorporated into more common workspaces for various applications. Grau et al. and Garcia et al. both conducted studies indicating the progression of robotic evolution into new industries and its incorporation into numerous fields. They have also pioneered and pushed the boundaries of Human-Robot Interaction (HRI) [1, 2]. In the past, robots were primarily utilized in the military, large-scale manufacturing plants, healthcare, and various other industries. In the military, robots were deployed with tactical approaches and advancements in tasks like bomb diffusion, reconnaissance, and air defense [3], with the aim of preventing casualties and providing assistance in these areas. Manufacturing, a vast industry offering many physically demanding jobs, has seen a transformation with the introduction of robotic assistance. These robots help alleviate monotonous tasks, and grueling work hours by utilizing the proficient assistance of artificial intelligence [4, 5]. According to Sherwani et al., collaborative robots can perform a wide range of tasks such as "picking, packing and palletizing, welding, assembling items, handling materials, product inspection, and much more" [6]. These robots have the ability to increase the production of these tasks by working alongside their human counterparts.

As artificial intelligence and technology continue to evolve, it is becoming increasingly likely that robots will become more commonplace in daily life. The advancing involvement in robotics leads to an increase in human-robot collaboration (HRC) [7]. HRC is a conjoined effort between humans and robots working together efficiently to complete tasks. To successfully integrate human-robot collaboration into everyday life, it is crucial to establish a substantial level of trust in robots among people. People often feel comfortable working alongside others because they can build a foundation of trust by observing each other's character and capabilities. However, the new introduction of robots in the workspace may lead to skepticism due to the absence of a biological and physiological connection, making it challenging to gauge their trust when working with a robot. On the other hand, robots must assess their human coworkers' capabilities to determine if they can establish trust and successfully perform tasks. Trust is a fundamental aspect of human-robot collaboration [8]. Studying people's trust levels when they work with robots can provide valuable insight into how we can integrate robotics into new settings, optimize workplace deployment, and improve robot configuration.

In this study we employed a collaborative robot, with 7 degrees of freedom, to conduct user studies in which subjects collaborated with the robot in a manufacturing task. The subjects wore four types of sensors to track and detect various physiological information during the human-robot collaboration process. These sensors tracked electroencephalography (EEG), electromyography (EMG), electrocardiography (ECG), and ocular data. While wearing these sensors, the robot would pick a part of the product and hand it to the human subject. The participant would then retrieve the part from the robot and rate their trust on a Likert scale questionnaire placed beside them. All multimodal physiological data and ratings were collected to develop our TrustBase. The physiological data allows us to visualize fluctuations in human trust towards the robot and any patterns, anomalies, or distinctions between participants and the robot throughout the collaboration process.

II. The TrustBase

In this study, we refer to our database management system (DBMS) as TrustBase, which is structured with a three-tier DBMS architecture comprising the User Layer, the Trust Logical Layer, and the Trust Physical Layer. As shown in Fig. 1.

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The User Layer in TrustBase allows users to access information about HRC participants, questionnaire responses, and the collected physiological data. This layer is also essential during HRC sessions, both for users to submit their trust ratings on the questionnaire and for sensors to acquire the physiological data. Next, we have the Trust Logical Layer, which ensures that all collected data is appropriately organized within the database's corresponding tables. Lastly, TrustBase also features a Trust Physical Layer where questionnaire responses are stored as integers in the QuestResponse table. For each set of data collected from the sensors, they are stored as BLOBs within each of their respective tables. Currently, TrustBase includes data from 65 user studies involving HRC trust. These studies encompass participants of different ages, genders, and education levels, and the number of participants continues to grow.

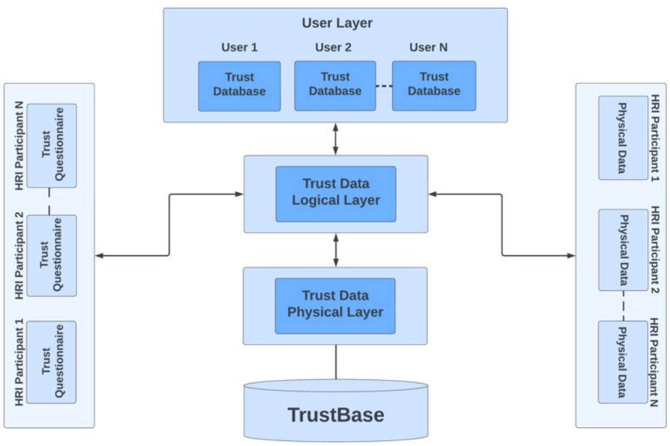

Fig. 1. The Architecture of TrustBase.

III. Human-Robot Collaboration Experiments

A. Experimental Platform

In this work, the Franka Emika collaborative robot is utilized through user studies as one of the main components of the HRC. As shown in Fig. 2, the robot has 7 degrees of freedom, which gives the arm the freedom to move more fluidly compared to arms with fewer degrees of freedom. The robot is designed to collaborate safely and seamlessly with humans in various tasks, akin to human-human collaboration [9]. During the user studies, a human-robot collaborative task was employed to examine the interaction between a human subject and the robot. More specifically, the task involved the robotic arm retrieving a segment of a model car and handing it to the human subject, who would then retrieve it from the parallel grippers. This task was iterated 27 times, with each iteration featuring variations of the robot performance factors such as velocity and position during the HRC. The positioning of the robot arm encompassed a range of heights including low, medium, and high. Furthermore, different distances — close, medium, and far — were incorporated into the task. The robot's speed was also manipulated during the experiment, with three different settings: slow, medium, and fast.

B. Sensors for TrustBase Data Collection

The human-robot collaboration experiment involves a participant wearing four physiological sensors and answering a seven-point Likert scale questionnaire that ranks trustworthiness on a scale from very untrustworthy to very trustworthy during the interactive task. All physiological data is recorded during each interaction. Between interactions, the robot returns to its home position for four seconds while the user rates their trust level on the questionnaire. The robot then proceeds to its next sequence of joint states for another handoff. The data collected from the sensors includes Electroencephalography (EEG), which records electrical activity within the brain; Electromyography (EMG), which records electrical activity from muscles in the dominant arm used during the interaction; Electrocardiography (ECG), which records electrical activity produced by the heart (heartbeat); and ocular senses data.

We utilized the Emotiv Epoc+ EEG helmet to collect electrical activity data from 14 regions of the brain. Additionally, we employed the MYO armband, equipped with 8 metal plates to capture EMG data from the user's upper forearm when activated. Along with the EMG data, we gathered the information on forearm motion using an inertial measurement unit (IMU). To collect ECG data, we implemented a wearable chest strap known as the Polar H10. We chose this heart strap due to its superior accuracy. Furthermore, we collected ocular data by deploying the Vive virtual reality headset to track users' eye data. During the study, the headset was calibrated using the eye-tracking API and then switched to augmented reality mode. Participants wore the headset while performing the collaborative tasks in augmented reality, allowing us to collect nine distinct types of eye-related data, including gaze origin left eye, gaze origin right eye, left gaze, right gaze, eye openness, left eye pupil diameter, right eye pupil diameter, left eye pupil position, and right eye pupil position. An example of a configured participant can be seen in Fig. 2.

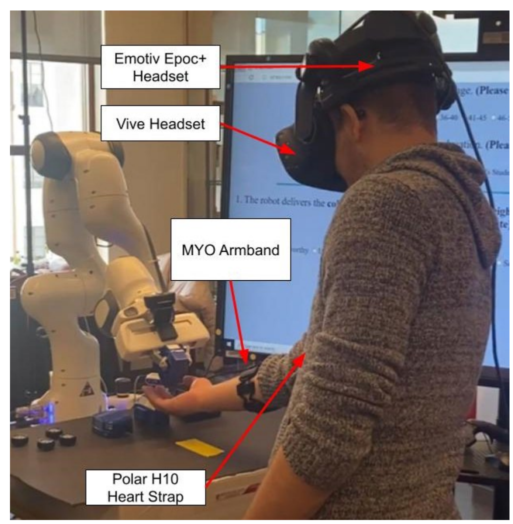

Fig. 2. Experimental platform and subject configuration.

IV. TrustBase Data Collection

A. Ocular Senses Data Collection

The Vive headset is a virtual reality (VR) headset with the capability to track a user's eyes when worn, allowing us to. utilize this feature and transform the virtual reality world into augmented reality (AR). In this context, we use augmented reality to track and store information of where the user is looking in the real world during the experiment. The headset requires a program called SteamVR to create the virtual reality world. Using an API called Super Reality Runtime (SR_Runtime), the headset can calibrate and track eye information. We developed a program to parse the information from the SR_Runtime API to store all eye information related to the subject. During the hand-over interactivity, the augmented Vive headset tracks nine data points: time, gaze origin left eye (X, Y, Z), gaze origin right eye (X, Y, Z), gaze normalized direction left (X, Y, Z), gaze normalized direction right (X, Y, Z), eye openness left and right, left eye pupil diameter, right eye pupil diameter, left eye pupil position (X and Y), and right eye pupil position (X and Y).

B. Human Operation Motion Data Collection

The MYO EMG armband utilizes eight metal plates, which read electrical impulse data from a user's muscle contractions in the upper forearm. As a user performs the car-building tasks with the collaborative robot, the armband will record data as the user contracts their muscles, including the brachioradialis, flexor carpi radialis, palmaris longus, flexor carpi ulnaris, flexor digitorum superficialis, and pronator teres. Additionally, the MYO armband contains an inertial measurement unit (IMU). The IMU consists of an accelerometer, gyroscope, and magnetometer [10, 11]. This allows for the collection of the roll, pitch, and yaw of the user's arm when moving around in free space.

C. Electroencephalography Data Collection

The Emotiv Epoc+ headset, an electroencephalography (EEG) helmet, utilizes fourteen nodes that are to be placed on corresponding regions of a subject's scalp as shown in Fig. 3, to collect electrical impulses from the brain. These electrical impulses collect data from regions: AF3, AF4, F7, F8, F3, F4, FC5, FC6, T7, T8, P7, P8, O1, and O2, as depicted in Fig. 3.

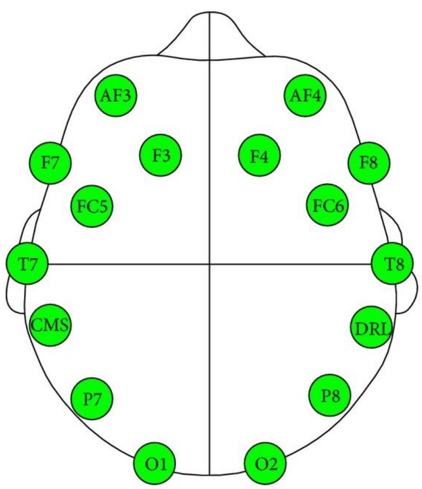

Fig. 3. Emotiv Epoc+ headset markings [12].

D. Heartbeat Data Collection

To collect electrocardiograms, we used the Polar H10 heart strap (Fig. 4). Users wear the strap around their chest snugly to maintain consistent skin contact with the electrodes. This ensures the collection and transmission of electrical activity from the heart to the H10 node on the front of the strap.

Fig. 4. Polar H10 strap and node reference model.

E. Trust Rating Questionnaire

To facilitate the acquisition of participants' responses during the human-robot collaborative task, we implemented a locally hosted questionnaire. The questionnaire solicited information such as compliance, gender, age range, education level, and trust level for each task with the robot. Collecting these demographics allows us to categorize and conduct further analysis, potentially revealing trends or distinctions between these categories. During the human-robot collaborative task, after receiving the part of the car model from the robot users rate their trust level utilizing a Likert scale, as shown in Fig. 5. After completing the human-robot interaction, participants submit the questionnaire and demographic information to the database. Within the database, a participant's responses would be recorded between 0 to 6, where 0 being very untrustworthy and 6 being very trustworthy.

Fig. 5. The Likert scale for trust level rating.

V. DATA ANALYSIS

To present this data in a concise and meaningful manner, we grouped the data points about time. We chose to use 5-second intervals for grouping since each interaction occurred at different times during the experiment. However, each group still consisted of hundreds to thousands of lines of data, which made it challenging to visualize the data effectively. To address this issue, we calculated the mean of the data for each group. This consolidation allows us to create meaningful plots that depict the physiological features throughout the experimental process. All the data visualized and explained in the following sections is from one of our 65 participants.

A. Human Eye Data Analysis

Fig. 6. displays the degree of eye openness during the HRC. In this visualization, a closed eye is represented by a value of 0, while an open eye is represented by a value of 1, with any value in between indicating partial eye openness. According to a study conducted by Urasaki et al., "the frequency of blinking is not only due to dryness of the eyes but also due to several other factors, including mental fatigue" [13]. This indicates that the user's blink rate has a potential connection into a theory known as cognitive load theory (CLT). To better comprehend the user's eye data, we resampled the data into 3-second intervals and used an aggregation mode, which refers to the most frequently occurring values in a dataset. Since we resampled our dataset into subsets, this aggregation technique was applied to each, helping us to identify the most frequent variables. Upon reviewing the data, we observed a higher rate of the eye(s) being slightly, or fully closed at the beginning of the interaction. This may indicate an increased trust-related cognitive load, as users engage in cognitive functions such as memory processing.

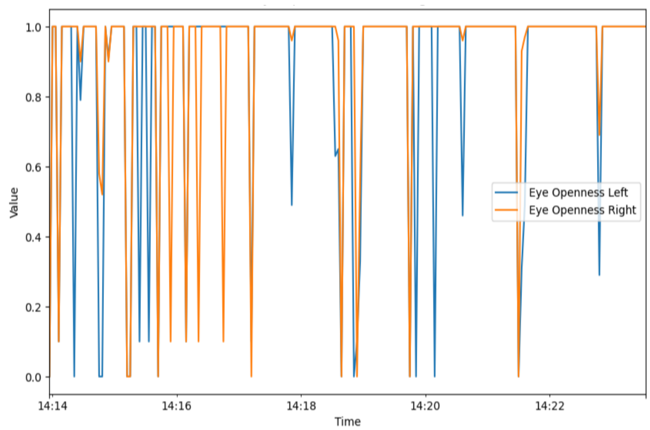

Fig. 6. The subject's eye openness for left and right eyes.

B. Human Operation Motion Data Analysis

The MYO armband has the capability to record 8 channels of EMG information in a person's upper forearm. To visualize the data, we resampled the data into subsets, by grouping the data in relation to a 5-second time interval. We then calculated the mean of each group as shown in Fig. 7. Upon examining the data, it becomes evident that EMG 4 consistently exhibits the most spikes. This particular node is positioned near the flexor digitorum superficialis on the participant's arm. These findings suggest that the user primarily engages the flexor digitorum superficialis and profundus when performing the human-robot collaborative task, indicating significant muscular activity when receiving the car model part. Additionally, we observed that the muscle activation increases as the user receives the part, with only three instances approaching a value of 600. These occurrences may represent higher-stress tasks, resulting in increased muscle usage.

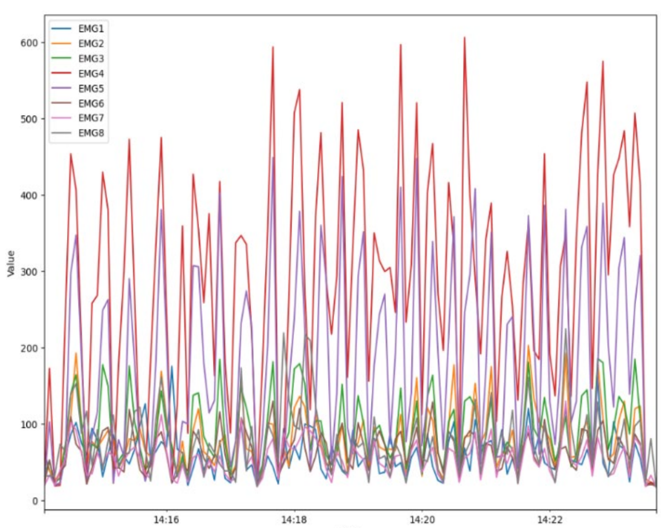

Fig. 7. The subject's EMG signals in HRC.

C. EEG Data Analysis

The Emotiv Epoc+ headset collects EEG information from the subject, which is crucial for understanding brain activity in various regions during the HRC. Since the Epoc+ headset collected approximately 73,000 lines of data for each user, we resampled the data by grouping it into 5-second intervals and calculated the mean of each group. This analysis resulted in Fig. 8, which illustrated six significant spikes in data during the first three minutes of the experiment. These spikes could be attributed to the user's lack of trust and discomfort with the robot's action, triggering a cognitive response and creating these spikes. This interpretation is supported by a comparison with the user's questionnaire responses in Fig. 10. During the initial nine interactions that span approximately five minutes, questions four, five, and eight received significantly lower ratings compared to the others.

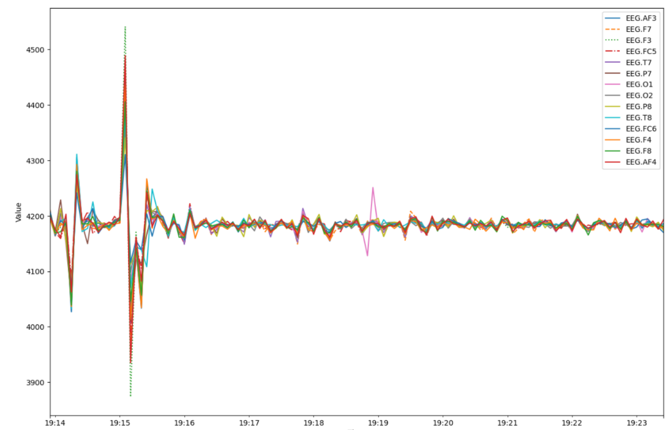

Fig. 8. The subject's EEG information in HRC.

D. Heartbeat Data Analysis

After visualizing the user's heartbeat data collected from the Polar H10 Heartbeat monitor, we observe that initially, the user experienced a higher heart rate, peaking at around 108 beats per minute. This increase in heart rate may be attributed to the novel experience of working with their new robot partner. As shown in Fig. 9, the user's heart rate occasionally dropped to as low as 76 beats per minute, possibly during moments when the robot was returning to its home position, and the participant was responding to the questionnaire. Subsequently, the heart rate would rise again. Notably, the user's heart rate got progressively calmer during the second half of the experiment, which occurred after the four-minute mark. During this period, the heart rate consistently remained below 100 beats per minute anymore. This could indicate an increase in trust and a reduction in participant anxiety.

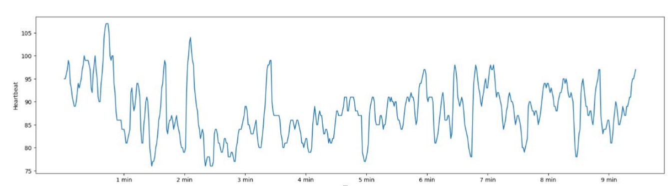

Fig. 9. The subject's heartbeat information in HRC.

E. Trust Ratings

To identify factors contributing to low levels of human trust during the HRC, in Fig. 10, we can see that the first instance was the first interaction where the speed increased. This potentially made the user feel uneasy, as the robot suddenly shifted from a slow speed to a medium speed. The user may not have been expecting the transition, therefore producing a lower trust level.

Furthermore, the subsequent interaction was also a continuation of the medium-speed interactions, where the user was still potentially uneasy from the previous interaction. We can see the user regains some trust, but not as much as when the robot was interacting at a slower speed. As the user advances through the HRC, we can see around question 18 the user starts to lose a bit of trust, as the robot progresses at a faster speed. Although the user gained a bit of trust from the lower height interactions, the user again may have felt uneasy as it increased in height and had a far distance. Afterwards, the user gained more trust as the robot gained distance and was closer, and the height was easier for the user to adjust to.

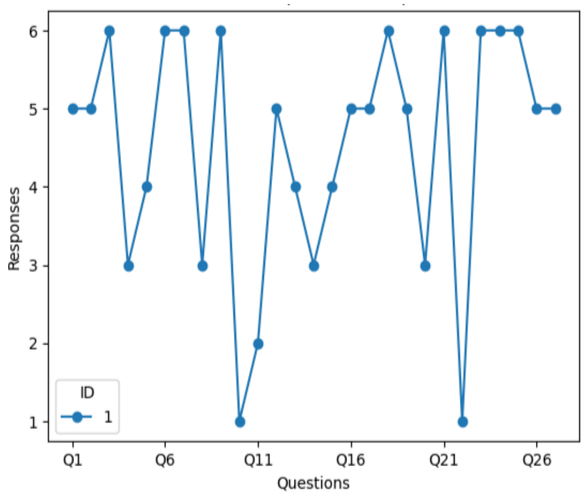

Fig. 10. The subject's trust levels for 27 robot performance factors in HRC.

VI. Conclusions and Future Work

In this work, we have created a multimodal TrustBase through user studies in human-robot real-world collaborative contexts. This database will help both researchers and industrial workers have a comprehensive understanding of what factors may affect people's trust in robots during collaborative tasks. The data of the TrustBase includes EEG, EMG, ECG, and ocular senses are collected from four types of physiological sensors. As a user performs the human-robot collaborative task, the user's physical information is recorded, as well as the completion of a seven-point trust rating Likert scale. With this information, we were able to visualize the user's physical and cognitive intentions and correlate them to their trust rating. This information gave further insight into whether the participants were truthful in their trust rating or were pressured by social constructs around them. Future work would involve a dynamic approach to our human-robot collaboration experiments, allowing for new motions and a different experience for every user. In addition, more participants will be recruited to enrich the data of our TrustBase. To view the data in a better way for TrustBase users, we will investigate and develop new metrics, data features, and visualization methods.

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