Integrating Human Behavioral Model for Safe Intimate-distance Human Robot Collaboration

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Abstract

In this paper, we present a method for integrating a human behavior model into robot motion control to enable safer intimate distance Human Robot Collaboration (HRC). This approach establishes safety parameters based on personality and experience, and optimizes the system through observing human reactions. It integrates a behavior pattern-based emergency shutdown. In our experiment, we tried to validate our claim that incorporating a human behavior model into the robot control will increase the safety of the system in intimate distance conditions. Validation through a mixed-reality approach demonstrates the feasibility of the framework in a simulated environment, ensuring ethical considerations and safety. Notably, it outperforms traditional benchmarks, and other forecasting based approaches, achieving zero collisions in 100 trials and exhibiting a forecasting error rate below 10mm. Despite notable improvements, challenges persist, including residual time delays in safety compensations and potential slowdowns for introverted, inexperienced workers. While these limitations need further refinement, the proposed approach signifies a substantial stride towards safer HRC, successfully preventing collisions in intimate distance conditions.

1 Introduction

To harness the full capabilities of both humans and robots, the concept of collaboration has emerged. ISO defines collaboration as "an operation by purposely designed robots and people working within the same

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space" [1]. The term "cobot" was coined in 1996 by Colgate & Peshkin, with the conceptualization attributed to Brent Gillespie [2]. However, it wasn't until 2008 that the first commercially available cobot, the UR5 by Universal Robots, entered the market [3]. Human-Robot Collaboration (HRC) aims to establish an optimal level of collaboration to efficiently accomplish a task [4], [5], [6]. In collaborative scenarios, humans and robots share the same workspace, working hours, and task objectives, with direct communication for successful task completion [7]. The levels of HRC evolve with increased interaction [8], as illustrated in Figure 1:

- Coexistence: Only the workspace is shared, and the robot and human engage in separate tasks and workpieces.
- Sequential: The robot and human perform distinct tasks in the shared workspace, sequentially sharing the workpiece.
- Simultaneous: The robot and human undertake separate tasks in the shared workspace, but the work is performed on the same workpiece simultaneously.
- Supportive: The robot and human collaboratively participate in the same task within the shared workspace, working on the same workpiece.

The predominant category of applications in Human-Robot Collaboration (HRC) within the industrial context is identified as coexistence applications. In a survey conducted by Bauer et al. [9] examining industrial applications, 60% of HRC installations were categorized as coexistence. While it is feasible to implement other collaboration levels in academic research, achieving the "supportive" level, which represents the ultimate goal of HRC, has encountered challenges. Safety concerns pose a significant obstacle, as this level necessitates close human-robot interaction, carrying an elevated risk of accidents [10]. Consequently, despite the considerable potential, the realization of the benefits of supportive human-robot collaboration remains elusive due to safety considerations.

In this study, we tackle this challenge by developing a Human Robot Collaboration (HRC) system centered on close-distance collaboration. Our proposed approach incorporates a human behavior model into robot motion control, enabling the robot to be cognizant of human situations. A scrutiny of review studies conducted over the last two decades reveals a limited number of articles explicitly concentrating on human-related factors in human-robot collaboration [11]. Based on their claim, earlier years predominantly emphasized robot factors, but in 2022, there is a discernible shift towards the increasing significance of human factors. Given the integral role of humans in the HRC system, prioritizing an elevated level of interaction necessitates a thoughtful consideration of the human condition. Consequently, recent research efforts have been directed towards addressing this crucial aspect.

To attain the objective of achieving intimate distance supportive Human-Robot Collaboration (HRC), safety emerges as the paramount concern [12]. The incorporation of human-based observation into the system becomes imperative for this purpose, serving as the primary motivation for

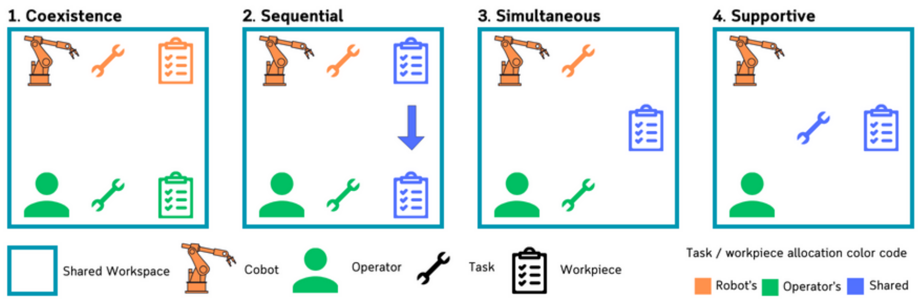


Figure 1: Various levels of HRC based on interaction pattern [8].

our research. Constrained by ethical considerations and safety imperatives, we opted for the mixed reality method. The delineated goals for our work encompass:

- Devise safety functions distinct from conventional workplace-based approaches [40–42].
- Integrate a human-oriented behavioral model into robot control.
- Monitor human reactions (both physical and psychological) in diverse scenarios and refine our system accordingly.
- Rigorously adhere to the intimate distance condition [12] throughout all phases of the system design.

By embodying these objectives, we formulated safety functions grounded in a behavioral model for intimate distance HRC. The contributions of this research are elucidated as follows:

- Analyze human body movements, predict future motion, and identify abnormalities to integrate into robot control for intimate distance conditions.
- Establish initial safety parameters based on personality and experience analyses.
- Optimize the system based on the observation of human reactions (both physical and psychological) in various scenarios.
- Integrate an emergency shutdown approach based on behavior patterns.

To authenticate our research, a case study was undertaken employing a mixed-reality approach. In the validation process of distinct components within the behavioral module, two supplementary datasets were incorporated. Subsequently, we gauged the motion planning performance through comparison with established planning approaches in a simulated environment over 100 trials. Notably, our model demonstrated superior performance, achieving zero collisions with a forecasting error of less than 10 mm.

2 Related Works

Existing research has highlighted the importance of incorporating human-related factors in the design of Human-Robot Collaboration (HRC) systems. A comprehensive survey paper [11] underscored this significance. The current landscape of research integrating human factors into HRC can be summarized as follows:

Despite the pivotal importance of understanding the human state, a majority of studies primarily rely on surveys to discern human feelings and perceptions [13], [14], [15], [16], [17], [18], [19], [20], [21], [22].

A limited number of studies incorporate physiological signals alongside surveys [23], [24], [25]. However, these investigations mainly focus on trust and human perception, neglecting the integration of behavioral cues into motion planning.

Only a small subset of studies incorporate video, motion tracking, and physiological data along with surveys [26], [27]. These integrations predominantly serve purposes such as human perception, understanding, trust generation, and certain forms of human adaptation training.

Recent research has acknowledged the significance of human behavior during collaboration, with some studies attempting to integrate human motion-based behaviors into their systems. For instance, study [28] introduces a robot-following approach based on human-intentioned directions, utilizing gaze direction and body gestures to take over the task.

An advanced approach is evident in study [29], where whole-body motion dynamics are estimated. This estimation method is applied to a humanoid, assisting the robot in motion.

Similar goals are identified in study [30], where robot motion is planned based on information learned from analyzing human motion. Notably, this study considers task variation-based time variation for prediction. It considers how variations in the tasks (complexity, difficulty) themselves can influence variations in the time it takes to complete them as features. Where as other studies simply looks at average times or total time spent, this study acknowledges the importance of task and time correlation.

Author [32] forecasts the human trajectory horizon step by step, requiring knowledge of the total time to reach the goal from the start.

In the study by author [31], the hand trajectory position is directly incorporated into the robot's planned path. Here, short-duration prediction is utilized for frequent motion path updates.

Study [31] aligns most closely with our motion planning approach. Although their focus is on forecasting human motion for robot control, our work distinguishes itself by integrating numerous safety functions rooted in behavioral models. A prior study [33] demonstrated that, despite frequent path updates, real-time synchronization delays hinder a robot's ability to promptly follow the path. Consequently, this time gap poses a risk of collision during intimate human-robot collaboration. The present study contributes several novel advancements beyond the existing research in this domain:

- We address safety concerns related to synchronization delays, a facet overlooked by other studies. Our motion forecasting accounts for delays, ensuring that the human trajectory aligns with the present, not a prior time, even if path updates take time.

- Our study pioneers the establishment of initial safety distances and robot speed parameters based on personality and experience, with the potential for system optimization in subsequent runs.
- Introducing a behavior observation-based emergency stop approach is a unique aspect of our approach not found in any other study. This function swiftly reduces the risk of collisions.

The integration of a behavioral-based approach in our study enhances safety, as evidenced by the comparative analysis of collision occurrences in the evaluation section. Our aspiration is that this research brings us closer to realizing supportive Human-Robot Collaboration (HRC) by instilling a sense of safety in intimate distance HRC scenarios.

3 Method of Behavior-based Robot Control

In this approach, we propose to develop some safety functions based on behavior. Then we integrate this behavior module into the robot control. The biggest challenge for supportive distance is operating the HRC system in intimate distance conditions [12]. The reason is that with intimate distance conditions, the risk of collision increases. So we need to provide multiple layers of safety parameters, but they can only be based on human factors or robot factors, or they can be combined, as introducing workplace related safety factors will contradict our target as supportive HRC needs to share work pieces and workplaces. Unfortunately, transition delay and asynchronization are big challenges for robot-related factors to provide enough safety. For these reasons, we opted for a human-related factor. In Figure 2, we have provided the state machine diagram of our approach which is briefly explained below:

In the initial run, we calculate the target joint based on joint importance. Based on the task pattern, different joints can give different information. Even though many HRC studies consider the head joint as the most important indicator [37–39], in our case study, we found that in the case of a repetitive sequential task, the shoulder joint plays a prominent role in trajectory estimation. Based on this finding, we have developed a target joint selection formula. Here,

$H(t)$- position of the head at time t,

$S(t)$- position of the shoulder at time t,

$G(t)$- position of the goal,

$E_H(t)$- error in predicting the wrist motion trajectory using the head,

$E_S(t)$ - error in predicting the wrist motion trajectory using the shoulder.

The errors can be defined as 1 and 2:

$$E_H(t) = \|H(t) - G(t)\| \tag{1}$$

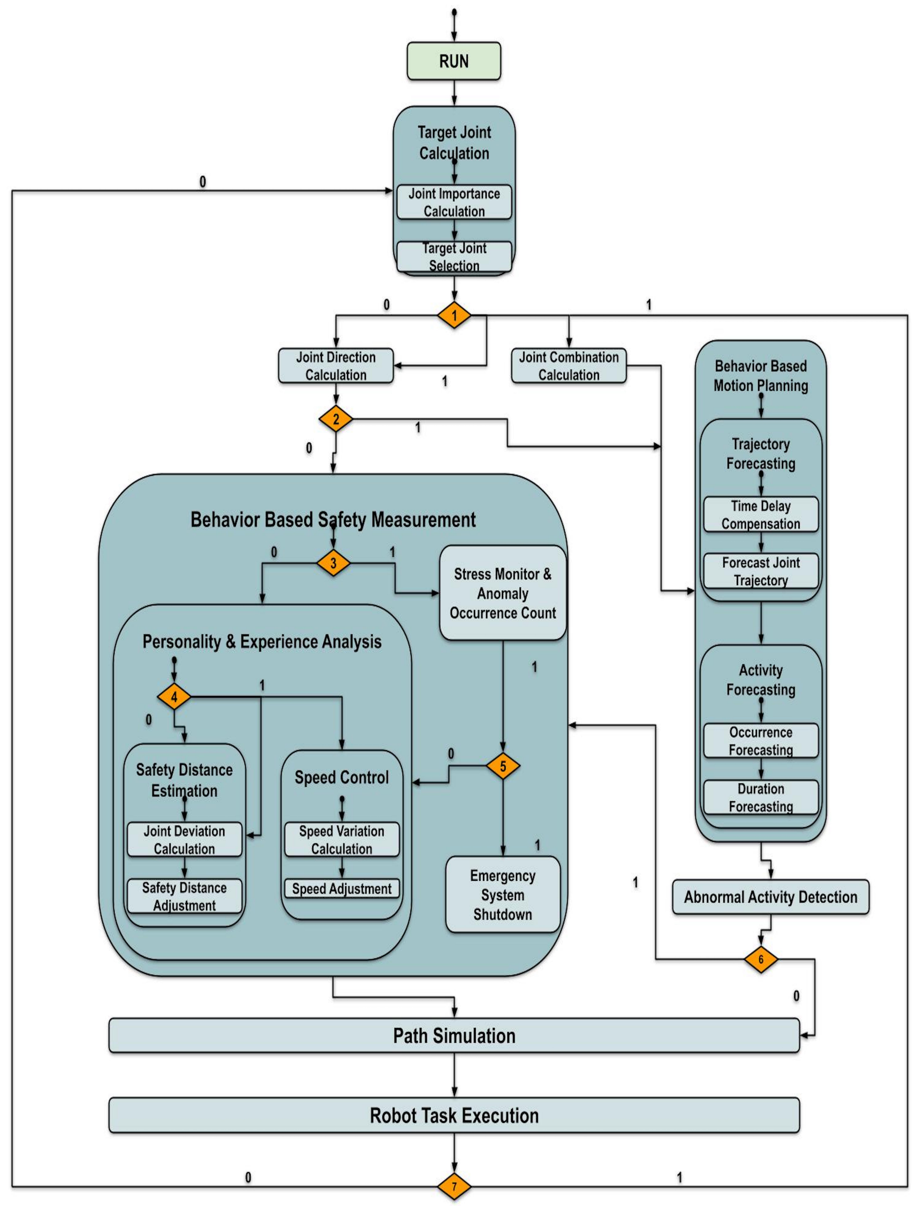


Figure 2: State machine diagram of behavior-based robot control for intimate distance HRC.

$$E_S(t) = \|S(t) - G(t)\| \tag{2}$$

The lesser the joint error the better it is for forecasting. Utilizing the error value, we determine the target joint, which subsequently feeds into two modules: behavior-based motion planning and behavior-based safety measurement. Within the safety module, scoring is determined based on personality and experience. Our investigation encompasses three experience states:

- No Experience: Individuals with no prior exposure to robots or mixed reality devices.
- Somewhat Experienced: Individuals with experience in either robots or mixed reality devices.
- Experienced: Individuals with exposure to both robots and mixed reality devices.

Simplifying matters, we restricted our consideration to Introverts and Extroverts as personality traits. Following these assessments, we assigned scores, which were validated through user surveys and performance evaluations. The scores are delineated in Table 1.

Based on this score, safety distance and initial speed are decided. Then this information, along with the forecasted results, is sent for robot control. In the next run, we just monitor stress and target joints for forecasting and error occurrence count.

In this approach, we introduce four safety functions. Below, we will elaborately explain them.

3.1 Motion Forecasting

Due to the asynchronization problem, there is always a considerable amount of delay, so instead of the current human motion path, we need information about the future human motion trajectory and the activity they will be doing. As there is a chance of abnormal activity occurring due to various environmental and physical factors, we also need to identify if the state our robot may see is normal activity or abnormal activity.

3.1.1 Joint trajectory forecasting

At first, we will discard all joint combinations that are not related to our target joint and keep only the most important ones. The input sequence is a set of joint positions leading up to the current time t. Let N be the sequence length. The input sequence can be represented as shown in equation 3:

$$x(t) = [q(t-N), q(t-N+1), \ldots, q(t-1)] \tag{3}$$

The output sequence for the forecasted joint position at $t + \Delta t$ can be represented as shown in equation 4:

$$q(t + \Delta t) = \text{Forecasting Model}(x(t)) \tag{4}$$

Our forecasting system utilizes a Long Short-Term Memory (LSTM) network specifically chosen for its effectiveness in real-time applications.

LSTMs excel at capturing temporal dependencies within data sequences, making them ideal for tasks like time series forecasting where past observations can significantly influence future values. During our performance comparison test LSTM outperformed traditional statistical methods: ARIMA and SARIMA. This is because LSTM can learn complex relationships within the data, leading to more accurate predictions. While offering better performance than statistical models, LSTM strike a balance by being less computationally demanding compared to even more complex architectures like Transformers. This translates to faster processing times and potentially less resource-intensive deployments. As they are computationally efficient and less demanding, they are well-suited for real-time implementation. This allows for near-instantaneous predictions within our system, which is crucial for our implementation.Our specific LSTM model incorporates 50 neurons in the hidden layer. This allows the network to learn a sufficient number of features from the data to make accurate predictions. Additionally, a 20% dropout layer is employed to help prevent overfitting during training. Finally, a dense layer is used to map the learned features from the LSTM to the final prediction output. The batch size of 70 defines the number of data points processed by the model at a time during training, which is a tunable hyperparameter that can be further optimized for performance.Overall, the choice of LSTM aligns perfectly with our focus on real-time forecasting, offering superior performance compared to statistical methods while maintaining computational efficiency.

3.1.2 Activity forecasting

After the future trajectory is forecasted, this data is fed to Facebook prophet to identify abnormalities before it even occurs. Abnormal behavior is identified by examining the magnitude or pattern of these residuals. Large residuals or patterns that deviate significantly from the typical behavior of residuals are considered abnormal behavior in the data. Let $y(t)$ be the observed value at time t, and $\hat{y}(t)$ be the predicted value by Prophet.The residual at time t can be represented as shown in equation 5:

$$\text{Residual}(t) = y(t) - \hat{y}(t) \tag{5}$$

Mathematically, the abnormality score is $A(t)$ for each time point t based on the residuals. It can be represented as shown in equation 6:

$$A(t) = |\text{Residual}(t)| \tag{6}$$

3.2 Speed Variation

From our case study, we found that human personality and their work experience have a great impact on their work patterns. Based on the scores calculated based on personality and experience, as shown in Table 1, we initially set a comfortable speed level for the users. In our case study, we set different levels of speed. In the evaluation part, it is explained briefly. Later, if the forecasting result shows that there is a chance of abnormal activity, we will readjust the speed of the robot.

Here, by speed variation function we refer the modification of robot speed during the operation based on user comfort. This is mainly originated from their experience level and personality trait. The speed variation or angular velocity ($\dot{\theta}$) of the robot joint can be calculated using the time derivative of the joint angle (θ) with respect to time (t). Mathematically, this can be represented as shown in equation 7:

$$\dot{\theta} = \frac{d\theta}{dt} \tag{7}$$

3.3 Safety Distance

Like speed, we also set safety distance based on the scores shown in Table 1 and Table 2 initially. Later, if the forecasting result shows that there is a chance of abnormal activity or if the users get stressed, we will readjust the safety distance by calculating the maximum joint deviation. Based on the analysis of biomechanics, the ranges of motion for each joint have a minimum and maximum deviation. We are just giving examples of shoulder, elbow, and wrist joints [43]:

- Shoulder Joint: Min Angle: 50 degrees and Max Angle: 180.
- Elbow Joint: Min Angle: 0 degrees and Max Angle: 160.
- Wrist Joint: Min Angle: 15 degrees and Max Angle: 90.

Also, these deviations are possible to calculate by using trigonometric functions and rotational matrices. Here is an example for the shoulder, elbow, and wrist joints shown in the equations 8, 9 and 10:

Shoulder Joint (θ_{shoulder}): θ_{shoulder} represents the angle of shoulder flexion/extension.

ϕ_{shoulder} represents the angle of shoulder abduction/adduction.

ψ_{shoulder} represents the angle of shoulder internal/external rotation.

$$\text{Shoulder Position: } \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} r\sin(\theta_{\text{shoulder}})\cos(\phi_{\text{shoulder}}) \\ r\sin(\theta_{\text{shoulder}})\sin(\phi_{\text{shoulder}}) \\ r\cos(\theta_{\text{shoulder}}) \end{bmatrix} \tag{8}$$

Elbow Joint (θ_{elbow}): θ_{elbow} represents the angle of elbow flexion/extension.

$$\text{Elbow Position: } \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x_{\text{shoulder}} + l_1\cos(\theta_{\text{shoulder}}) \\ y_{\text{shoulder}} + l_1\sin(\theta_{\text{shoulder}}) \\ z_{\text{shoulder}} - l_1\sin(\theta_{\text{elbow}}) \end{bmatrix} \tag{9}$$

Wrist Joint (θ_{wrist}): θ_{wrist} represents the angle of wrist flexion/extension.
ϕ_{wrist} represents the angle of wrist radial/ulnar deviation.

$$\text{Wrist Position: } \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x_{\text{elbow}} + l_2\cos(\theta_{\text{elbow}}) \\ y_{\text{elbow}} + l_2\sin(\theta_{\text{elbow}}) \\ z_{\text{elbow}} - l_2\sin(\theta_{\text{wrist}}) \end{bmatrix} \tag{10}$$

In these formulas:

- r is the distance from the shoulder joint to the elbow joint.
- l_1 is the length of the forearm (from elbow to wrist).
- l_2 is the length of the hand (from wrist to hand).

Table 1: Personality and experienced based scoring

	No Experience	Somewhat Experienced	Experienced
Introvert	1	2	3
Extrovert	1.5	2.5	3

3.4 Emergency Shutdown

In this work, we have utilized a Garmin Venu Sq watch to monitor stress and heart rate. If we find that the stress score exceeded the normal range and in our forecasted path there is a chance of abnormal activity occurring, we will do the emergency shutdown.

Let:

- S represent the current stress level,
- S_{normal} denote the normal stress level,
- A represent the occurrence of abnormal activities, and
- $A_{\text{threshold}}$ be the predefined threshold for abnormal activity occurrence.

The emergency shutdown condition can be expressed as:

$$\text{Emergency Shutdown} = \begin{cases} 1 & \text{if } S > S_{\text{normal}} \text{ and } A > A_{\text{threshold}} \\ 0 & \text{otherwise} \end{cases}$$

In this formulation, the function `Emergency Shutdown` returns 1 (indicating "True") if both conditions $S > S_{\text{normal}}$ and $A > A_{\text{threshold}}$ are met. Otherwise, it returns 0 (indicating "False").

This can be expressed more succinctly using the equation 11:

$$\text{Emergency Shutdown} = [S > S_{\text{normal}}] \cdot [A > A_{\text{threshold}}] \tag{11}$$

Here, $[S > S_{\text{normal}}]$ evaluates to 1 if $S > S_{\text{normal}}$ is true and 0 otherwise. Similarly, $[A > A_{\text{threshold}}]$ evaluates to 1 if $A > A_{\text{threshold}}$ is true and 0 otherwise. The multiplication ensures that both conditions must be true for the overall emergency shutdown condition to be true. The threshold can be set based on the task requirements and the human coworker's preference. For our study, we set the scores as stress scores above 70 and abnormal activity occurring 1 per operation.

4 Data Description

In this section, we briefly describe the datasets utilized for our study. In this paper, the main data we utilized came from our experiment. To evaluate the behavioral model, we have also utilized two supplementary data sets. The information regarding these data sets can be seen in Table 3.

Table 2: Safety distance calculation based on score

Score	Safety Distance (m)
1	0.45
1.5	0.40
2	0.35
2.5	0.30
3	0.25

Table 3: Considered tasks and their descriptions

Data Set	Task	Activity Description
Our Data	Interaction	Can do any random motion they see fit to interact with the robot.
	Moving side by side	Swing and twist one's hands side by side.
Bento [34]	Pick and place	Put food in a fixed place and put it in the bento.
	Fixing and rearranging	Fix and reorganize the bento box in a hurry while it is passing by when one forgets to put ingredients.
Cooking [35]	Washing	Wash vegetables and fruits in a bowl with water.
	Adding and mixing	Add and mix materials to prepare food.
	Cutting	Cut vegetables and fruits with a knife on a chopping board.
	Peeling	Peel vegetables and fruits using a knife or peeler held in the hand.

4.1 Our Data

The experiment has been designed based on the suggestions made in study [11]. Due to ethical committee constraints and concerns of the possible participants, the final experiment has been conducted with 10 people. All of them were healthy. The data set can be described as follows:

- Number of Participants: 10
- Age groups: (20–25), (26–30), and (31–35)
- Gender: Male (6) and Female (4)
- Country of origin: Japan, Indonesia, Vietnam, Philippines, and China
- Experience: No Experience (have never had any experience with robots or mixed reality devices), Somewhat Experience (have experience with either robots or mixed reality devices), Experienced (have experience with both robots and mixed reality devices)
- Personality trait: Extrovert and Introvert
- Survey: Pre-experiment, In-experiment, and Post-experiment
- Data type: Video (Skeleton), Survey, Heart Rate
- Utilized video amount: 200 minutes

4.2 Supplimentary Data Sets

In our study, we have also utilized two supplementary data sets for evaluation. We have utilized the data partially, as some of the activities means the same body movement pattern and are just described differently based on the requirements of the data sets.

4.2.1 Bento Data

This is a dataset utilized in ABC 2021 for Bento Challenge [34]. The experiment was conducted at the Kyushu Institute of Technology's Smart Life Care Unit in Japan. All participants were healthy. The dataset can be described as follows:

- Number of Participants: 4
- Age groups: (20–25) and (26–30)
- Gender: Male
- Country of origin: Japan
- Data type: MoCap skeleton data
- Utilized video amount: 80 minutes

4.2.2 Cooking Data

This is a dataset utilized in ABC 2020 for Cooking Challenge [35]. The experiment was conducted at the Kyushu Institute of Technology's Smart Life Care Unit in Japan. All participants were healthy. The dataset can be described as follows:

- Number of Participants: 4
- Age groups: (20–25) and (26–30)
- Gender: Male
- Country of origin: Japan
- Data type: MoCap skeleton data, accelerometer and gyroscope data from smartwatch and smartphone.
- Utilized video amount: 160 minutes

5 Evaluation

In this section, we present our evaluation methods. In our approach, we have introduced several smaller safety functions grounded in the behavioral model, and by combining all of them, the final behavioral module calculates the human condition, which is the input to the path planner so that the new path can be created. In this section, we first describe our experimental setup. Then we show validation for each small module, and finally we show the comparative analysis of our approach with other methods. Along with the results, related discussion has been given regarding why the approach is required or if there are any concerns.

5.1 Motion Forecasting

Motion forecasting is one of the most challenging parts of our behavior model. As the tasks we use cover a wider range of complexity levels compared to other case studies, it was challenging to find out the exact motion pattern.

5.1.1 Goal

The goal of this function is to forecast trajectory and predict abnormal activity occurrence.

5.1.2 Experimental Setup

For the feasibility study of our approach, we have designed a case study as shown in Figure 3. The setup can be described as follows:

- Simulation Platform: Unity 3D version 2020.3.34f1
- PC Configuration: Windows 11 with 64-bit software and an NVIDIA GeForce RTX 3050 Ti graphics card.
- Robot: Yaskawa Mottoman GP8 [44]
- Robot Control: ROS in Ubuntu 20.04.4LTS PC
- MR Device: Microsoft Hololens2
- Unity Tool for Plugin: MixedRealityFeatureTool
- Connection Protocol: TCP/IP
- Update Rate: 0.40 [s] and 0.08 [s]
- Interaction Scenario: Robot Only, AR Only and AR with Robot

Also, two supplementary data set is used.

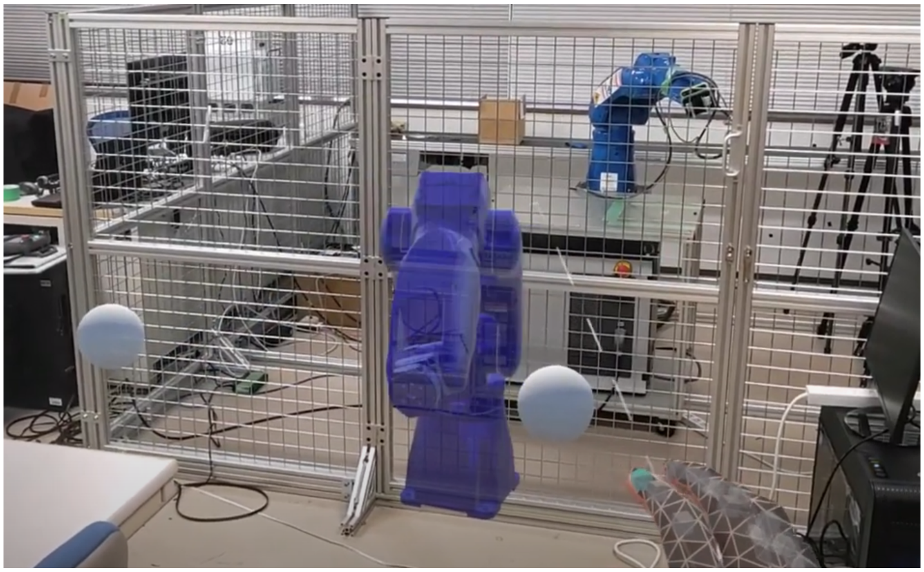


Figure 3: Experimental setup of our mixed reality based HRC system prototype.

5.1.3 Steps

The steps for this function are listed below:

- First, we need to decide the target joint.
- Then we only keep target joint-related features, which is quite different from other approaches.
- After that, a joint trajectory forecast.
- This is then used for activity forecasting, and abnormal activity occurrences are checked.
- Finally, if no abnormal activity is predicted, the generated information is sent to the path simulator for robot control.
- For evaluation metrics of the performance of the model, MAE and F1 scores are used.

5.1.4 Results

The first step of our approach is to identify the target joint. We have claimed that, based on task patterns, joint importance may vary. In Table 4, the MAE for head-based joint combinations and shoulder-based joint combinations has been calculated. We can see that, depending on the task, different joint combinations are giving less error than others.

For the evaluation of trajectory forecasting, it can be observed in Table 5. Here, we compare it with some other methods. As $DRRT^*$ [36] does not include any behavior-based approach, no scoring is made. Compared with the other two methods, our method achieved a lower error rate. Our error rate is less than 10 mm.

Table 4: Evaluation for target joint selection based on task pattern. Error is calculated in MAE

Data Set	Task	Head(m)	Shoulder(m)
Case Study	Interaction	0.02004	0.002027
	Moving side by side	0.00555	0.00215
Bento	Pick and place	0.00740	0.00265
	Fixing and rearranging	0.00266	0.00343
Cooking	Washing	0.01481	0.00909
	Adding and mixing	0.01538	0.00979
	Cutting	0.00876	0.01217
	Peeling	0.0713	0.01332

Table 5: Performance comparison of trajectory forecasting with others. Error calculated here is MAE

Task	Interaction	Moving side by side	Pick and place	Fixing and rearranging	Adding and mixing
$DRRT^*$ [36]	NA	NA	NA	NA	NA
SONIG [32]	0.1467	0.0981	0.0947	0.1043	0.0857
BP-HMT [31]	0.0978	0.0098	0.0104	0.0315	0.0097
Our proposed method	0.0204	0.0021	0.0026	0.0026	0.0097

Table 6: Performance evaluation for accurately predict abnormal activity occurence

Data Set	Task	Our Method (F1 Score)	Baseline (F1 Score)
Case Study	Interaction	0.90	0.75
	Moving side by side	0.96	0.87
Bento	Pick and place	0.96	0.87
	Fixing and rearranging	0.95	0.85
Cooking	Washing	0.94	0.83
	Adding and mixing	0.91	0.79
	Cutting	0.93	0.82
	Peeling	0.92	0.80

As for evaluating abnormal activity occurrence prediction, we have used the F1 score. Here, as a baseline approach, we used full body data like other methods. Comparing that with our method, we can see that when target joint based selection is applied, prediction model performance gets better. Especially from Table 6, we can see that for Interaction activity, the F1 score increased by 0.15.

5.2 Speed Variation

Speed variation plays an important role in ensuring user safety. As this is closely related to user preference, finding an optimal speed for each user is challenging. We found that user preferences are highly biased by personality and experience. So we defined the model accordingly.

5.2.1 Goal

Set the initial speed in such a way that human coworkers do not feel uncomfortable, and if needed in later parts of the operation, optimize it.

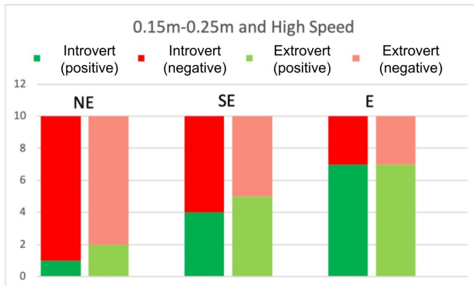
5.2.2 Experimental Setup

The same experimental setup as motion forecasting is followed here.

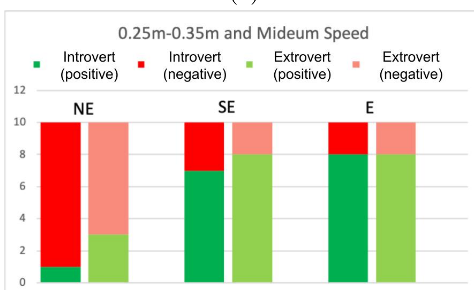
5.2.3 Steps

The steps for this function are listed below:

- Make scoring based on personality and experience analysis, as shown in Table 1.
- In the case study, we have considered the intimate distance condition.



(a)



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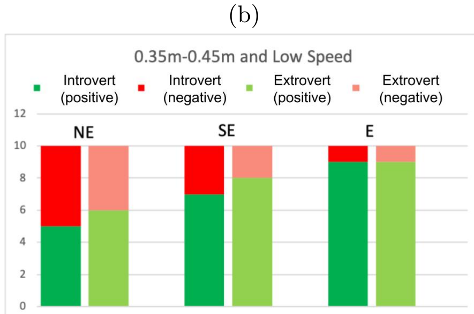


(c)

Figure 4: Human preference demographic based on personality and experience. Here, NE represents No Experience, SE represents Somewhat Experienced and E represents Experienced subjects. 0.15m-0.25m is very near to robot, 0.25m-0.35m is moderately near to robot and 0.35m-0.45m is near to robot. The range is decided based the intimate distance definition of 0.15m-0.45m. Due to ethical constraint we maintained this distance between human and virtual robot instead of the physical robot.

- Even though, due to ethical restrictions, we could not let the participants go near the real robot, the AR robot was placed in this condition.
- The operation is conducted at three speed levels.
- Speed is adjusted based on scoring level at Table 1, Table 2 and the observation at Figure 4.

5.2.4 Results

The results of our study can be seen in Figure 4 From the pre- and post-experiment questionnaires, we have found that people with Introvert personalities and No Experience have a higher negative emotional impact if they work very near the robot at a high speed. If these conditions separately happen, they still face more negative emotion compared to others. On the other hand, Experienced users are not negatively affected that much, no matter which condition is imposed. From Table 7 we can see that in this study, four subjects suffered stress. Among them are three people who are Introverts. S1 has No Experience so the occurrence of stress was frequent and longer. S2 is the only Extrovert person to feel stressed, and he also has No Experience. From these results, it can be deduced that personality and work experience have a high impact on human state and performance.

5.3 Safety Distance

To ensure user safety, distance is equally important as speed variation. Also, these two entities are complementary, as shown in Figure 4. As this is closely related to user preference, finding an optimal safety distance for each user is challenging. We found that user preferences are highly biased by personality and experience. So we defined the model accordingly.

5.3.1 Goal

Set the initial safety distance in such a way that human coworkers do not feel uncomfortable, and if needed in later parts of the operation, optimize it.

5.3.2 Experimental Setup

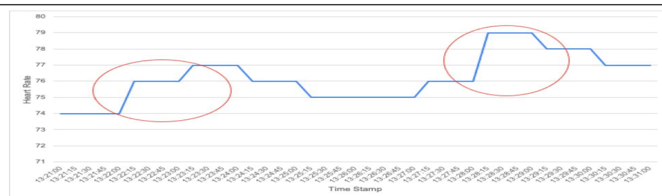
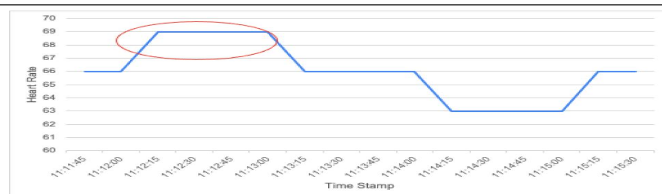
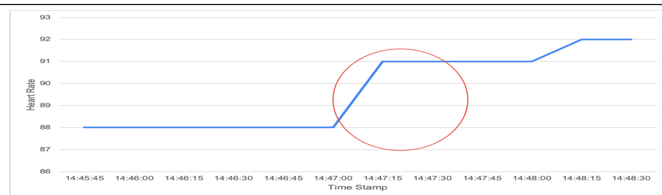
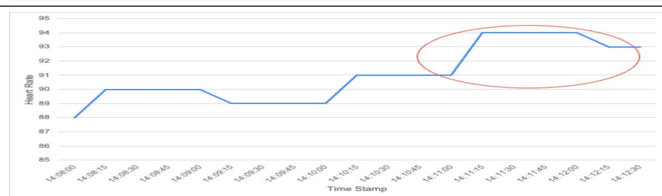
The same experimental setup as motion forecasting is followed here.

5.3.3 Steps

The steps for this function are listed below:

- Make scoring based on personality and experience analysis, as shown in Table 1.
- In the case study, we have considered the intimate distance condition. So the safety distance range we calculate is 0.15m to 0.45m.

Table 7: Proof of stress occurrence during is related to personality and experience.

Subject	Heart Rate Curve if the subject felt shock
S1 (Introvert)	
S2 (Extrovert)	
S9 (Introvert)	
S10 (Introvert)	

- Even though, due to ethical restrictions, we could not let the participants go near the real robot, the AR robot was placed in this condition.
- We set different boundaries for them while they were having the interaction.
- Safety distance is adjusted based on scoring level at Table 1, Table 2 and the observation in Figure 4.

5.3.4 Results

The results of our study can be seen in Figure 4. From the pre- and post-experiment questionnaires, we have found that people with Introvert personalities and No Experience have a higher negative emotional impact if they work very near the robot at a high speed. If these conditions separately happen, they still face more negative emotion compared to others. On the other hand, Experienced users are not negatively affected that much, no matter which condition is imposed. From these results, it can be deduced that personality and work experience have a high impact on human state and performance.

5.4 Emergency Shutdown

Behavior pattern-based emergency shutdown is a new approach. It is often impossible for the machine control operator to identify the initialization of stress. In a busy production line, this kind of manual monitoring is hard to execute perfectly, but it is closely related to author safety. So we have introduced this automated emergency shutdown approach.

5.4.1 Goal

If stress and abnormal activity occur together, immediately shutdown the robot to ensure user safety.

5.4.2 Experimental Setup

The same experimental setup as motion forecasting is followed here.

5.4.3 Steps

- Monitor stress occurrence from smart watch.
- Monitor abnormal activity occurrence.
- If both occur in the same observation cycle, instead of sending path information, send an emergency shutdown command in robot control.

5.4.4 Results

In Table 8, we show the collision occurrence comparison with other systems. Our system in 100 trials never had any collisions.

Table 8: Performance comparison for collision occurrence test

Task	$DRRT^*$ [36]	SONIG [32]	BP-HMT [31]	Our proposed method
Interaction	12	9	7	0
Moving side by side	5	2	0	0
Pick and place	5	2	0	0
Fixing and rearranging	8	4	3	0
Adding and mixing	2	1	0	0

5.5 Discussion

Here we will summarize the whole performance, achievement, and outlook:

Based on performance comparisons with other methods, our approach outperforms them all in motion forecasting and collision occurrence. Here we have compared our method with three other methods. $DRRT^*$ [36] is considered the state-of-the-art approach to traditional path planning methods. The other two methods are also well appreciated.

Our forecasting showed less error in MAE. Our approach focuses on identifying key joints, instead of using data from all body joints like other methods. This reduces the amount of potentially misleading information the model receives during abnormal situations. For example, during tasks like "moving side-by-side" and "pick and place" performed in a small workspace, the shoulder and hand movements are very similar. However, the head movement can vary significantly as the person might need to look in different directions. This variability in head movement can introduce errors because the head's gaze might not always be focused on the target direction. By focusing on key joints like the shoulder and hand, which provide more consistent information for these tasks, our model is less susceptible to errors caused by irrelevant joint movements.

The tasks considered in these studies are very simple movement tasks, whereas we considered a wide variety of tasks that contained varied movement patterns.

In comparison with our time-delay consideration and intimate distance conditions, other studies did not consider these issues. These considerations not only made our forecasting better, but also, in our 100 trials conducted in a simulated environment with various possible collision conditions, our model never had any collisions.

Another major reason for the absence of collisions is the emergency shutdown approach and personality- and experience-based safety conditions. So instead of setting similar conditions for everyone, we have proposed to modify conditions based on task patterns and people's conditions.

6 Conclusion

In conclusion, this paper addresses the critical challenge of achieving intimate human-robot collaboration while ensuring high user safety. Our method integrates human behavior analysis into robot motion control, highlighting the importance of considering human factors for improved interaction. It establishes safety parameters, optimizes system performance based on human reactions, and includes behavior pattern-based emergency shutdown, contributing to HRC technology advancement. The mixed-reality approach used for validation demonstrates the feasibility of the proposed framework in a simulated environment, ensuring ethical considerations and safety. Our method outperformed the traditional benchmarks and other studies with zero collisions and a forecasting error below 10mm in 100 trials. Despite being safer, the approach has limitations regarding potential slowness for introverted, inexperienced workers.

Overcoming these challenges requires a more detailed behavior model. Notably, the study did not modify the robot control system beyond integrating behavior model-based safety functions, leaving room for future analyses such as detailed personality checks and worker experience assessments. Ethical restrictions and subject disagreement due to safety concerns prevented us from conducting a more extensive study. Hopefully, the results contribute to dispelling safety concerns and paving the way for larger studies. Despite limitations, the approach demonstrates achieving an intimate human-robot collaboration without safety concerns, marking progress in supportive HRC.

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References

[1] Technical committee: ISO/TC 299 Robotics. Robotics — Vocabulary. ISO 8373:2021(en). Geneva, Switzerland; 2021 Nov.

[2] Colgate JE, Edward J, Peshkin MA, Wannasuphoprasit W. Cobots: Robots for collaboration with human operators. 1996;

[3] About Universal Robots [Our History] [Internet]. [cited 2021 Dec 7]. Available from: https://www.universal-robots.com/aboutuniversal-robots/our-history/

[4] Müller R, Vette M, Scholer M. Robot workmate: A trustworthy coworker for the continuous automotive assembly line and its implementation. Procedia CIRP. 2016;44:263–8.

[5] Kolbeinsson A, Lagerstedt E, Lindblom J. 151 Foundation for a classification of collaboration levels for human-robot cooperation in

manufacturing. Production and Manufacturing Research. 2019 Jan 1;7(1):448–71.

[6] Webb P, Fletcher S. Unsettled Issues on HumanRobot Collaboration and Automation in Aerospace Manufacturing. 2020 Nov.

[7] Alessandro De Luca and Fabrizio Flacco. Integrated control for phri: Collision avoid- ance, detection, reaction and collaboration. In 2012 4th IEEE RAS EMBS Inter- national Conference on Biomedical Robotics and Biomechatronics (BioRob), pages 288–295. IEEE, 2012

[8] L. McGirr, Y. Jin, M. Price, A. West, K. van Lopik and V. McKenna, "Human Robot Collaboration: Taxonomy of Interaction Levels in Manufacturing," ISR Europe 2022; 54th International Symposium on Robotics, Munich, Germany, 2022, pp. 1-8.

[9] Bauer W, Bender M, Braun M, Rally P, Scholtz O. 2016 Lightweight robots in manual assembly, start simply. 2016.

[10] Jeremy A. Marvel, Shelly Bagchi, Megan Zimmerman, and Brian Antonishek. 2020. Towards Effective Interface Designs for Collaborative HRI in Manufacturing: Metrics and Measures. Hum.-Robot Interact. 9, 4, Article 25 (October 2020), 55 pages. DOI:https://doi.org/10.1145/3385009

[11] Nazmun Nahid, XINYI MIN, Md Atiqur Rahman Ahad and Sozo Inoue,Psychological Analysis in Human-Robot Collaboration from Workplace Stress Factors: A Review, 4th International Conference on Activity and Behavior Computing (ABC 2022), October 27th - 29th, 2022, London, United Kingdom.

[12] Hall, E.: The hidden dimension. Doubleday Anchor Books, Doubleday (1966), https://books.google.de/books?id=u-wyAAAAMAAJ

[13] Lotz, V., Himmel, S., Ziefle, M. (2019, January). You're my mate–acceptance factors for human-robot collaboration in industry. In Proceedings of the International Conference on Competitive Manufacturing (COMA2019), Stellenbosch, South Africa (Vol. 30).

[14] Eimontaitre, I., Fletcher, S. (2020). Preliminary development of the Psychological Factors Assessment Framework for manufacturing human-robot collaboration.".

[15] Min Chen, Stefanos Nikolaidis, Harold Soh, David Hsu, and Siddhartha Srinivasa. 2020. Trust-Aware Decision Making for Human-Robot Collaboration: Model Learning and Planning. J.Hum.-Robot Interact. 9, 2, Article 9 (June 2020), 23 pages. https://doi.org/10.1145/3359616

[16] Alhaji, B., Prilla, M., Rausch, A. (2021). Trust Dynamics and Verbal Assurances in Human Robot Physical Collaboration. Frontiers in Artificial Intelligence, 103.

[17] Calvin KL, Vincent G. Duffy, and Chui Chui Cheung. "Perception of safe robot idle time in virtual reality and real industrial environments." International Journal of Industrial Ergonomics 39.5 (2009): 807-812.

[18] Beschi, M., Faroni, M., Copot, C., Pedrocchi, N. (2020). How motion planning affects human factors in human-robot collaboration. IFAC-PapersOnLine, 53(5), 744-749.

[19] Charalambous, G., Fletcher, S. Webb, P. Identifying the key organisational human factors for introducing human-robot collaboration in industry: an exploratory study. Int J Adv Manuf Technol 81, 2143–2155 (2015). https://doi.org/10.1007/s00170-015-7335-4

[20] Charalambous, G., Fletcher, S. Webb, P. The Development of a Scale to Evaluate Trust in Industrial Human-robot Collaboration. Int J of Soc Robotics 8, 193–209 (2016). https://doi.org/10.1007/s12369-015-0333-8

[21] Min Chen, Stefanos Nikolaidis, Harold Soh, David Hsu, and Siddhartha Srinivasa. 2018. Planning with Trust for Human-Robot Collaboration. In Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction (HRI '18). Association for Computing Machinery, New York, NY, USA, 307–315. https://doi.org/10.1145/3171221.3171264

[22] S.M. Mizanoor Rahman, Yue Wang, Mutual trust-based subtask allocation for human–robot collaboration in flexible lightweight assembly in manufacturing, Mechatronics, Volume 54, 2018, Pages 94-109, ISSN 0957-4158, https://doi.org/10.1016/j.mechatronics.2018.07.007.

[23] Dehais, F., Sisbot, E. A., Alami, R., Causse, M. (2011). Physiological and subjective evaluation of a human–robot object hand-over task. Applied ergonomics, 42(6), 785-791.

[24] Messeri, Costanza, et al. "On the effects of leader-follower roles in dyadic human-robot synchronisation." IEEE Transactions on Cognitive and Developmental Systems (2020).

[25] Lagomarsino, Marta, et al. "Pick the Right Co-Worker: Online Assessment of Cognitive Ergonomics in Human-Robot Collaborative Assembly." IEEE Transactions on Cognitive and Developmental Systems (2022).

[26] Jesper W. Henriksen, Anders S. Johansen, and Matthias Rehm. 2020. Pilot Study for Dynamic Trust Estimation in Human-Robot Collaboration. In Companion of the 2020 ACM/IEEE International Conference on Human-Robot Interaction (HRI '20 Companion),March 23–26, 2020, Cambridge, United Kingdom. ACM, New York, NY, USA, 3 pages. https://doi.org/10.1145/3371382.3378327

[27] Maurtua I, Ibarguren A, Kildal J, Susperregi L, Sierra B. Human–robot collaboration in industrial applications: Safety, interaction and trust. International Journal of Advanced Robotic Systems. July 2017. doi:10.1177/1729881417716010

[28] A. Choi, M. K. Jawed and J. Joo, "Preemptive Motion Planning for Human-to-Robot Indirect Placement Handovers," 2022 International Conference on Robotics and Automation (ICRA), Philadelphia, PA, USA, 2022, pp. 4743-4749, doi: 10.1109/ICRA46639.2022.9811558.

[29] Latella, C., Lorenzini, M., Lazzaroni, M. et al. Towards real-time whole-body human dynamics estimation through probabilistic sensor fusion algorithms. Auton Robot 43, 1591–1603 (2019). https://doi.org/10.1007/s10514-018-9808-4

[30] Kratzer, Philipp, Marc Toussaint, and Jim Mainprice. "Prediction of human full-body movements with motion optimization and recurrent neural networks." In 2020 IEEE International Conference on Robotics and Automation (ICRA), pp. 1792-1798. IEEE, 2020.

[31] Q. Li, Z. Zhang, Y. You, Y. Mu and C. Feng, "Data Driven Models for Human Motion Prediction in Human-Robot Collaboration," in IEEE Access, vol. 8, pp. 227690-227702, 2020, doi: 10.1109/ACCESS.2020.3045994.

[32] M. Wu, B. Taetz, E. Dickel Saraiva, G. Bleser, and S. Liu, "Online motionprediction and adaptive control in human-robot handover tasks," in Proc.IEEE Int. Conf. Adv. Robot. Social Impacts (ARSO), 2019, pp. 1–6.

[33] Naoya Ryoke, Nazmun Nahid and Sozo Inoue,Synchronizing an AR Robot Simulator with a Real Industrial Robot, 5th International Conference on Activity and Behavior Computing (ABC 2023), September 7th - 9th, 2023, Kaiserslautern, Germany.

[34] Adachi, K., Alia, S.S., Nahid, N., Kaneko, H., Lago, P., Inoue, S. (2022). Summary of the Bento Packaging Activity Recognition Challenge. In: Ahad, M.A.R., Inoue, S., Roggen, D., Fujinami, K. (eds) Sensor- and Video-Based Activity and Behavior Computing. Smart Innovation, Systems and Technologies, vol 291. Springer, Singapore.

[35] Alia, S.S. et al. (2021). Summary of the Cooking Activity Recognition Challenge. In: Ahad, M.A.R., Lago, P., Inoue, S. (eds) Human Activity Recognition Challenge. Smart Innovation, Systems and Technologies, vol 199. Springer, Singapore.

[36] Connell, Devin, and Hung Manh La. "Dynamic path planning and replanning for mobile robots using RRT." In 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 1429-1434. IEEE, 2017.

[37] Zhou, Tianyu, et al. "Human hand motion prediction based on feature grouping and deep learning: Pipe skid maintenance example." Automation in Construction 138 (2022): 104232.

[38] Li, Qinghua, et al. "Data driven models for human motion prediction in human-robot collaboration." IEEE Access 8 (2020): 227690-227702.

[39] Gamage, Nisal Menuka, et al. "So predictable! continuous 3D hand trajectory prediction in virtual reality." The 34th Annual ACM Symposium on User Interface Software and Technology. 2021.

[40] Khavas, Zahra Rezaei, S. Reza Ahmadzadeh, and Paul Robinette. "Modeling trust in human-robot interaction: A survey." International Conference on Social Robotics. Springer, Cham, 2020.

[41] José Saenz, Norbert Elkmann, Olivier Gibaru, and Pedro Neto. 2018. Survey of methods for design of collaborative robotics applications- Why safety is a barrier to more widespread robotics uptake. In Proceedings of the 2018 4th International Conference on Mechatronics and Robotics Engineering (ICMRE 2018¡). Association for Computing Machinery, New York, NY, USA, 95–101. DOI:https://doi.org/10.1145/3191477.3191507

[42] G. Hoffman, "Evaluating Fluency in Human–Robot Collaboration," in IEEE Transactions on Human-Machine Systems, vol. 49, no. 3, pp. 209-218, June 2019, doi: 10.1109/THMS.2019.2904558.

[43] Hanavan, Ernest P. A mathematical model of the human body. Vol. 32, no. 3. Dayton, OH, USA: Aerospace Medical Research Laboratories, Aerospace Medical Division, Air Force Systems Command, 1964.

[44] Yaskawa Motoman GP8. (n.d.). Yaskawa Motoman Robotics. https://www.motoman.com/en-us/products/robots/industrial/assembly-handling/gp-series/gp8