Vol.2022-UBI-74 No.5
2022/6/6

# A Comparative Analysis on Joint Importance to Achieve Better Performance for Future Forecasted Human Activities and Behavior Analysis for Intimate Distance Supportive HRC Sytem

Nazmun Nahid[1,a)] Sozo Inoue[1,b)]

**Abstract:**
Human Robot Collaboration (HRC) has always been a challenging field due to safety concerns as human motions are often unpredictable and susceptible to environmental and physio-psychological changes. Previous studies aimed at predicting human behavioral trajectories focused on predicting behaviors utilizing full-body data for HRC with minimal contact with the robot. In this work, we focused on the Hand over other body parts as it will be in very close and frequent contact with the robot for complex and challenging tasks that we considered for intimate distance supportive HRC. In our analysis, we found that joint reduction and the perfect joint combination lead to better performance and joint importance varies based on the task pattern. We also successfully forecasted the human motion and activity 1s ahead using LSTM with the highest RMSE error no more than 21mm which outperformed the work in [1].

**Keywords:** Human Robot Collaboration, Human Activity Recognition, Activity and Behavioral Computing, Future Forecasting

## 1. Introduction

Our work aims to study the challenges to achieving an intimate distance supportive Human Robot Collaboration (HRC) system and to explore and enhance the potential of this field by analyzing human behavioral patterns. There are 2 main research issues in this study: To forecast the human motion trajectory very precisely for a short amount of time and another is doing human behavior analysis to make the HRC system better. From our previous works we have found that not all body markers play a vital role in human behavior analysis. Even sometimes they are detrimental to the performance. So in this work, we tried to do a comparative analysis of different body markers on two different data sets.

To understand the importance and challenges of our work we need to first understand HRC and its current state-of-the-art position. A great number of survey has been done regarding the safety issues in HRC [7], [8], [9], [10], [11], [12], [13]. Based on the complexity of the system, HRC can be divided into four categories:

(1) Separate: Human and robot duties are kept separate; they do not share locations, tools, or workpieces.
(2) Sequential: Work locations, tools, and workpieces can all be shared, but the tasks are strictly serialized, so any sharing is separated in time.
(3) Simultaneous: Human and robot jobs are carried out simultaneously and may require working on various areas of the same workpiece, but they are all focused on completing independent task objectives.
(4) Supportive: The human and the robot collaborate to finish a common task at the same time and with the same workpiece.

Previously human-robot collaboration has always been restricted to ”separate” applications. Given that automation and human labor are typically considered successive links in the production chain, the current state-of-the-art in terms of human-robot teams could be classed as ”sequential.” Simultaneous collaborations are now possible, albeit not typical, thanks to the recent arrival of collaborative industrial robots on the market. Future generations of collaborative robot systems are projected to play ”supporting” roles, although existing technology cannot support such functionality. The main reason for simultaneous type not being common and supportive type not being achieved is the safety concern. As both of these requires very close interaction between human and robot which may easily lead to accidents.

Various studies are conducted in the HRI(Human Robot Interaction) domain and it has been discovered that the appearance, speed, and behavior of the robot have a significant impact on human behavior. A few motion trajectory prediction works have been done [5], [6], [14], [15], [16]where the researchers tried to utilize full-body data or some specific point data to predict human motion in the presence of robots. All of these works focused on

1 Kyushu Institute of Technology
a) nazmun@sozolab.jp
b) sozo@brain.kyutech.ac.jp

very simple tasks where zero to very minimal contact is required between the human and the robot. Our goal is a lot more challenging as in our system we need to design the model so that robots and humans can collaborate supportively. To design such a safe intimate distance supportive HRC system we need to focus more on human behavior and motion analysis. There have been various works in the larger trajectory planning domain but in the aspect of the close distance, not much work has been done. Our target is to focus on this domain. One of the previous works tried to predict human motion data in the very near future for a complex set of activity [1]. In this work, the whole body data was considered which increased the model complexity and performance was not up to the mark if we consider the supportive HRC condition. To solve these issues further analysis has been done and it is found that some of the body markers can be detrimental to the performance of the model [2]. The reason behind this is the features provided by these body markers are misleading. In this work body, joint analysis has been done in a generalized format also future forecasting is not done.

In this work, our main focus is to analyze human activity and behavioral data to achieve a supportive HRC system at an intimate distance. Here we put more emphasis on predicting hand motion data as for our considered task hands are most prone to have collision with the robot. With the continuation of our previous work [2] in this paper here we showed that by discarding unimportant joints we can achieve better performance. Also, we showed that depending on the task body marker importance can be varied. Also for the same person in the same environment setup depending on the task different body markers play a vital role. With a perfect set of body marker combinations, a higher performance is achievable.

Here we analyzed two different data set: the Bento data set and the Cooking data set. Both of them contain one common subject. Task complexity for each data set is different. In the Bento, data set it is required to put the food in a certain position precisely within a required time. In the Cooking, data set a combination of various small tasks to have to be done to complete the whole task. Due to these challenges, it is hard to integrate a robot into these tasks to build up an intimate supportive HRC system. As any false prediction in the human motion data can cost us accidents. Also, we cannot predict motion for a large amount of time as the human intention can change suddenly which might cause a collision with the robots. In this work, we successfully forecasted the human motion and activity 1s ahead. For bento data, the r squared value of the model is .935 is considered very good as it means 90% of the variance can be explained. For cooking data, the r squared value of the model is .495 which can be considered moderate. The performance of both models surpassed the previous works. The main contributions of our work are: We conducted a behavioral pattern analysis dedicated to intimate distance supportive HRC, from our achieved results it can be claimed that in different task scenarios different joints play a vital role even the same person is completing the tasks and finding out a perfect combination of joints for these specific tasks. In the later part of the paper, it has been shown clearly that only joint reduction cannot ensure better performance. Only a few joint combinations work perfectly for a very close range time forecasting. Also on macro-scale various tasks seems similar the joint signal patterns change drastically. We believe this work will provide new light in the direction of motion and behavioral pattern analysis for HRC.

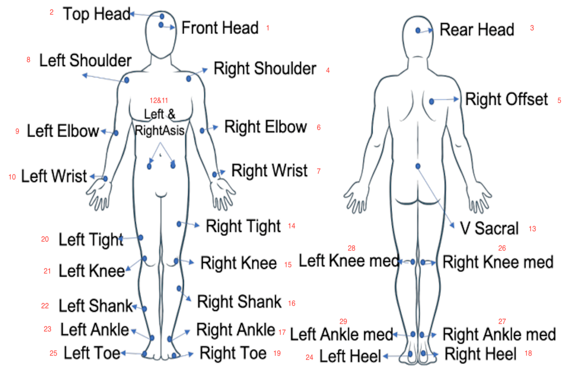



Fig. 1: Body Marker Position of 29 Markers.

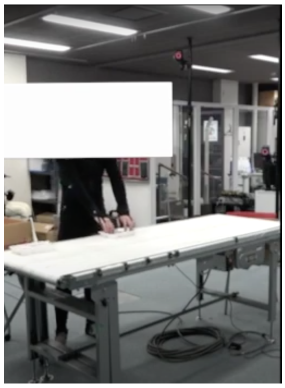


Fig. 2: Bento Data Experimental Setup.

## 2. Data Description

In this work, we used two challenging data sets to design a human motion forecast system. In both cases, body markers were placed as it is shown in Fig. 1.

### 2.1 Bento Data Set

The experiment has been carried out with the scenario in mind where humans and robots have to work in the same workspace within an intimate distance. In this condition, human lower body movement is minimized and the motion is mainly done by the upper body. Also, close observation and quick response is required as this condition is highly susceptible to the occurrence of a collision. The experiment has been carried out in the Smart Life Care Unit of the Kyushu Institute of Technology in Japan. Though the experiment has been carried out in the lab a complete imitation of the industrial work-space setup has been maintained. Due to safety concerns, no real robot has been used only the human performed the task standing within his designated place. A motion capture system from Motion Analysis Company is used for this experiment. 20 infrared cameras are used in the system to track and record the three-dimensional position of each body marker. A total of 29 body markers data has been collected. The placement of the markers is shown in Fig. 1. In this experiment 4 subjects (men) in their 20's and 30's have participated. Each

Table 1: Bento Data Description.

| Activity | Activity Description |
|---|---|
| Normal (inside) | Pick food and place it in the right place of the bento box. The bento box is placed on the belt conveyor near from human. |
| Normal (outside) | Pick food and place it in the right place of the bento box. The bento box is placed on the belt conveyor far from human. |
| Forgot to put ingredients (inside) | Pick food but forgot to place it in the right place of the bento box. The bento box is placed on the belt conveyor near from human. |
| Forgot to put ingredients (outside) | Pick food but forgot to place it in the right place of the bento box. The bento box is placed on the belt conveyor far from human. |
| Failed to put ingredients (inside) | Pick food but failed to place it in the right place of the bento box. The bento box already passed by. The bento box is placed on the belt conveyor near from human. |
| Failed to put ingredients (outside) | Pick food but failed to place it in the right place of the bento box. The bento box already passed by. The bento box is placed on the belt conveyor far from human. |
| Turn over bento-box (inside) | Pick food but failed to place it in the right place of the bento box. Turned over the bento box in a hurry while it was passing by. The bento box is placed on the belt conveyor near from human. |
| Turn over bento-box (outside) | Pick food but failed to place it in the right place of the bento box. Turned over the bento box in a hurry while it was passing by. The bento box is placed on the belt conveyor far from human. |
| Fix/rearranging ingredients(inside) | Pick food but forgot to place it in the right place of the bento box. Fix the bento box in a hurry while it was passing by. The bento box is placed on the belt conveyor near from human. |
| Fix/rearranging ingredients(outside) | Pick food but forgot to place it in the right place of the bento box. Fix the bento box in a hurry while it was passing by. The bento box is placed on the belt conveyor far from human. |

Table 2: Cooking Data Description.

| Activity | Activity Description |
|---|---|
| CEREAL | Take , Open , Cut , Peel , Other, Put |
| SANDWICH | Take , Cut , Other, Wash , Put |
| FRUITSALAD | Take , Add , Mix , Cut , Peel , Other, Put |

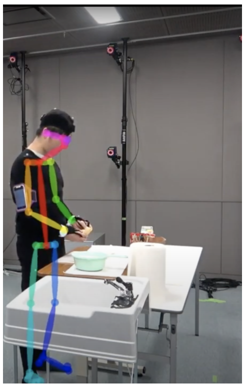


Fig. 3: Cooking Data Experimental Setup.

of the subjects was instructed to put three types of food in the bento box on a moving conveyor belt. Actions are done in two different patterns inward and outward. Participants were asked to repeat each task 5 times. An elaborate idea of this data set can be obtained from Table 1 and Fig. 2. The length of each activity segment was approximately 50 to 70 s. The data has been recorded with a frequency of 100Hz.

### 2.2 Cooking Data Set

The data collection of this experiment was conducted in the Smart Life Care Unit of the Kyushu Institute of Technology in Japan. In this experiment, 4 subjects (men) in their 20's and 30's participated and there was no overlap between the subjects. The experiment was conducted in a controlled environment where the steps are predefined for the subjects. They had to prepare three types of foods following the defined steps. The data was collected using smartphones, smartwatches, a motion capture system, and an open pose. Here we will only utilize Motion Capture data. A motion capture system from Motion Analysis Company is used for this experiment. It has 29 body markers. The places of markers in the body are shown in Fig. 1 infrared cameras are used to track the markers. The dataset used for this challenge consists of activities and actions associated with cooking. Actions are named Micro activities and activities are named Macro activities. There are three macro activities and 9 micro activities. Each macro activity consists of multiple micro activities. Details of each macro activity are given below. An elaborate idea of this data set can be obtained from Table 2 and Fig. 3. As we can see, the macro activities have many similar micro activities which are done in slightly different ways. This increases the difficulty level for correctly detecting these activities. The data has been recorded with a frequency of 100Hz.

## 3. Methodology

In this work, we utilized two different data sets which have been collected in the same laboratory environment with one subject common in both data sets. To ensure that there is enough variation between the data sets we have performed a T-test. Also, a T-test has been done among different users with different activity combinations in the case of each data set. Here we performed both activity and motion prediction for 1s ahead future with different joint combinations.

### 3.1 Data Pre-processing and Feature Extraction

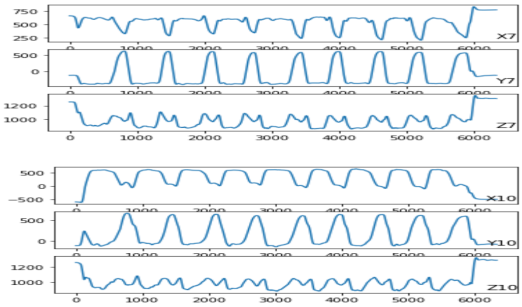
Due to various reasons, the infrared cameras failed to capture MOCAP data from the body markers in various instances. So, there were a lot of missing values present in the data. The missing values of each column have been replaced with the mean value of the respected column. The reason behind doing so is that if the missing values are replaced with zero it would provide the wrong features and if we drop rows the number of data points will decrease severely.

### 3.2 Activity Prediction

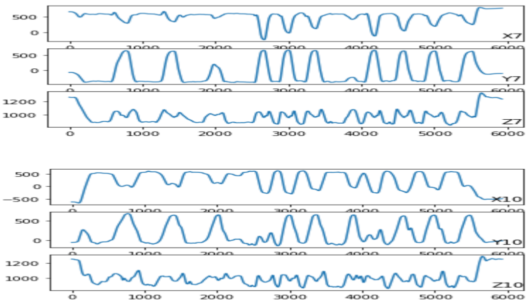
For each column of marker values, 10 statistical features are calculated. They are Standard Deviation, Average, Max, Min, Variance, Median Absolute Deviation, Kurtosis, Skew, Energy, and Interquartile Range. At first, different machine learning classifiers are tested, and Random Forest Classifier performed best in every experiment. So we considered at random seed 14. For the train-test split, we followed the leave-one-group out method where all the subjects' performances have been tested.

### 3.3 Motion Forecasting

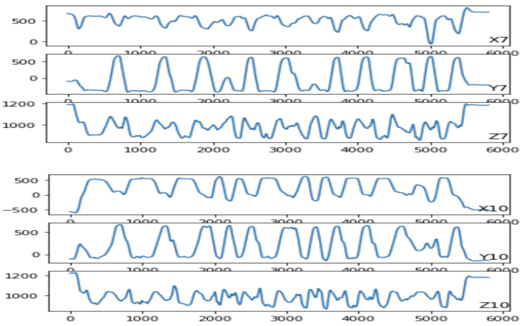
For future motion forecasting, time series features have been calculated. For forecasting, we used LSTM as it has given a better performance than other regression models. Forecasting has been done in different combinations to identify the important factors for very close time gap forecasting. For Bento data, we put the whole normal activity of 10 min in Train Set and Tested each abnormal activity of 1 min with 1s ahead future. For Cooking Data we put the combination of each micro activities for a to-



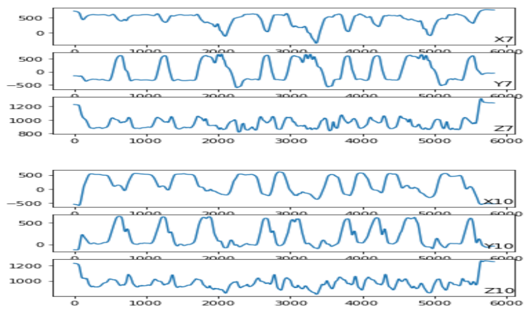
(a) Normal Activity.



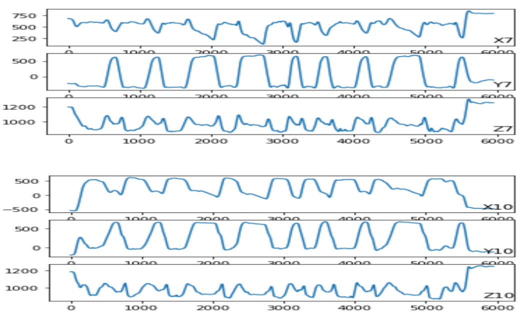
(b) Forgot to put ingredients.



(c) Failed to put ingredients.

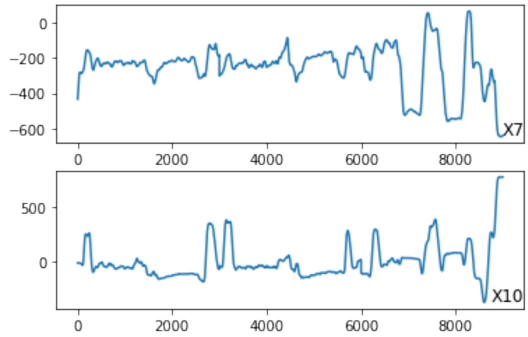


(d) Turn over bento box.

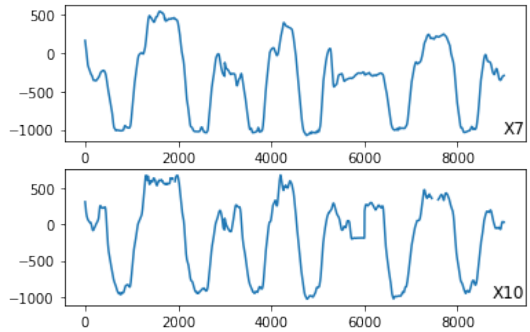


(e) Fix/rearranging ingredients.

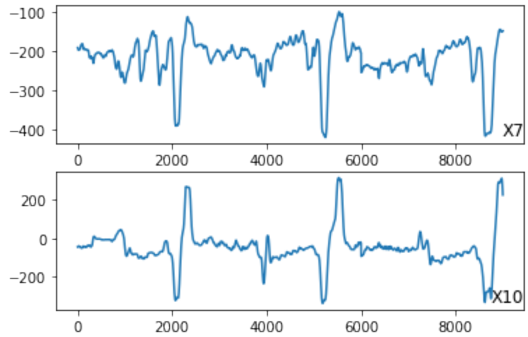
Fig. 4: Wrist position signal pattern based on differnt activites in Bento Data. (For simplicity only x coordinate position is given. X7 = Right Wrist, X10 = Left Wrist. Time stamp for each frame is 0.01s.)




(a) Making Cereal.




(b) Making Sandwich.




(c) Making Fruit Salad.

Fig. 5: Wrist position signal pattern based on different activities in Cooking Data. (For simplicity only x coordinate position is given. X7 = Right Wrist, X10 = Left Wrist. Time stamp for each frame is 0.01s.)

tal 10min and Tested the files of activities where there are done together in a 1min range for 1s ahead future. We tried different combinations of parameters for LSTM among them 50 neurons with a 20% dropout layer and a dense layer with a batch size of 72 performed best for Bento Data. For Cooking Data LSTM with 70 neurons with a 20% dropout layer and a dense layer with a batch size of 100 worked best.

## 4. Result and Analysis

Initially, Independent T-test has been done between the two data sets to check the variation among them. The mean p-value achieved is 2.05 which is higher than 0.05 and indicates strong evidence for the null hypothesis. The null hypothesis states that there is no relationship between the two samples being studied. Even for the same subject, the p-value is 0.9 which is still higher than 0.05. We also tested the T-test among the activities of the

Table 3: Performance Comparison of Different Joint Combinations for Bento Data.

| Body Markers | Subject 1 F1 Score | Subject 2 F1 Score | Subject 3 F1 Score | Subject 4 F1 Score | Balanced Accuracy Average |
|---|---|---|---|---|---|
| Head-Shoulder | 1.00 | 0.98 | 0.93 | 0.92 | 0.96 |
| Head-Elbow | 0.90 | 0.98 | 1.00 | 0.96 | 0.96 |
| Head-Wrist | 0.98 | 0.98 | 0.98 | 1.00 | 0.99 |
| Head-Shoulder-Elbow | 0.94 | 0.98 | 0.98 | 1.00 | 0.97 |
| Head-Shoulder-Wrist | 0.96 | 0.98 | 0.98 | 0.98 | 0.97 |
| Head-Elbow-Wrist | 0.88 | 0.98 | 0.98 | 1.00 | 0.96 |
| Shoulder-Elbow-Wrist | 0.90 | 0.98 | 1.00 | 0.96 | 0.96 |
| Head-Shoulder-Elbow-Wrist | 0.98 | 0.94 | 1.00 | 0.96 | 0.97 |
| Shoulder-Wrist | 1.00 | 0.98 | 1.00 | 1.00 | 0.99 |
| Shoulder-Elbow | 0.98 | 0.96 | 1.00 | 0.98 | 0.98 |
| Elbow-Wrist | 0.94 | 0.96 | 0.91 | 0.98 | 0.95 |
| Upperbody | 0.89 | 0.94 | 0.93 | 0.87 | 0.91 |
| Fullbody | 0.79 | 0.86 | 0.90 | 0.76 | 0.85 |

Table 4: Performance Comparison of Different Joint Combinations for Cooking Data.

| Body Markers | Subject 1 F1 Score | Subject 2 F1 Score | Subject 3 F1 Score | Subject 4 F1 Score | Balanced Accuracy Average |
|---|---|---|---|---|---|
| Head-Shoulder | 0.98 | 0.98 | 0.93 | 0.93 | 0.95 |
| Head-Elbow | 0.96 | 0.98 | 0.97 | 0.90 | 0.95 |
| Head-Wrist | 1.00 | 0.98 | 0.98 | 0.94 | 0.97 |
| Head-Shoulder-Elbow | 0.94 | 0.96 | 0.98 | 0.98 | 0.96 |
| Head-Shoulder-Wrist | 0.96 | 0.94 | 0.98 | 0.98 | 0.96 |
| Head-Elbow-Wrist | 0.88 | 0.98 | 0.98 | 1.00 | 0.96 |
| Shoulder-Elbow-Wrist | 0.90 | 0.98 | 1.00 | 0.96 | 0.96 |
| Head-Shoulder-Elbow-Wrist | 0.98 | 0.94 | 0.98 | 0.96 | 0.96 |
| Shoulder-Wrist | 1.00 | 0.98 | 0.98 | 0.96 | 0.97 |
| Shoulder-Elbow | 0.96 | 0.94 | 0.91 | 0.98 | 0.95 |
| Elbow-Wrist | 0.98 | 0.94 | 1.00 | 0.98 | 0.97 |
| Upperbody | 0.79 | 0.89 | 0.89 | 0.89 | 0.87 |
| Fullbody | 0.75 | 0.62 | 0.87 | 0.87 | 0.82 |

Table 5: Motion Forecasting Result of Bento Data. Soulder-Wrist combination performance is mentioned here as it achieved the best performance. The r squared value of this model is o.935. All the units are in mm range.

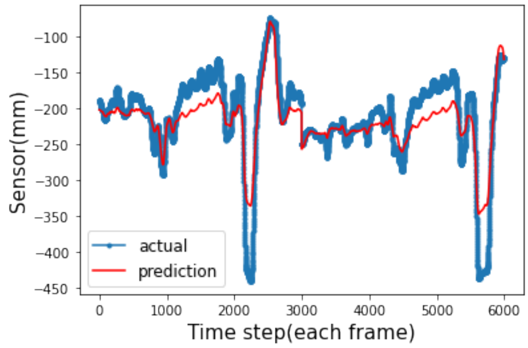
| Activity | RMSE | | STD | | MAE | |
|---|---|---|---|---|---|---|
| | X7(R) | X10(L) | X7(R) | X10(L) | X7(R) | X10(L) |
| Forgot to put ingredients (inside) | 5.55 | 7.24 | 4.68 | 6.54 | 5.19 | 6.63 |
| Forgot to put ingredients (outside) | 7.40 | 4.35 | 6.23 | 5.13 | 6.86 | 3.76 |
| Failed to put ingredients (inside) | 2.15 | 2.16 | 3.49 | 3.52 | 1.69 | 1.77 |
| Failed to put ingredients (outside) | 2.83 | 2.33 | 4.32 | 4.41 | 2.54 | 1.84 |
| Turn over bento-box (inside) | 2.66 | 3.28 | 3.46 | 6.27 | 2.33 | 2.78 |
| Turn over bento-box (outside) | 2.65 | 3.43 | 4.80 | 5.27 | 2.07 | 3.02 |
| Fix/rearranging ingredients(inside) | 6.08 | 2.74 | 6.81 | 3.64 | 5.35 | 2.36 |
| Fix/rearranging ingredients(outside) | 3.50 | 3.10 | 6.18 | 4.35 | 3.10 | 2.55 |

data sets. Even if the subjects are not the same p-value is still lower than 0.05 for Bento Data. In the case of Cooking Data, this type of occurrence could not be found. From the graphs in Fig. 4 it can be seen that most of the parts of other activities contain normal activity in Bento Data. On the other hand from Fig. 5 we can see that even though the micro activities in each macro activity are quite similar there are differences in the signal pattern.

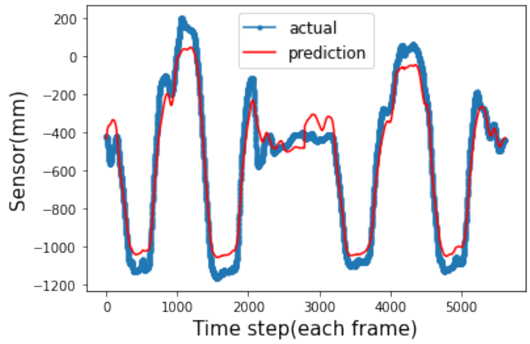
In Table 3 and Table 4, a brief performance analysis of different body markers has been done. From the tables we can see

Table 6: Motion Forecasting Result of Cooking Data. Head-Wrist combination performance is mentioned here as it achieved the best performance. The r squared value of this model is o.495. All the units are in mm range.

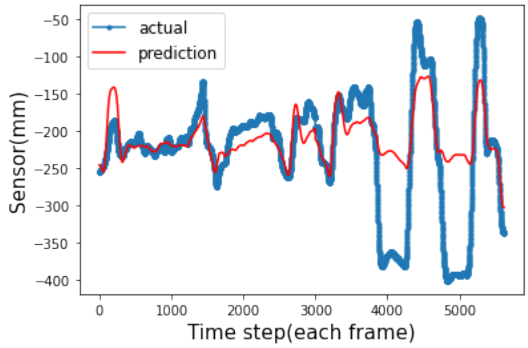
| Activity | RMSE | | STD | | MAE | |
|---|---|---|---|---|---|---|
| | X7(R) | X10(L) | X7(R) | X10(L) | X7(R) | X10(L) |
| Cereal | 20.04 | 12.17 | 14.25 | 11.64 | 20.27 | 13.23 |
| Sandwich | 9.09 | 13.32 | 4.76 | 7.13 | 10.06 | 14.64 |
| Fruit Salad | 14.81 | 15.38 | 13.25 | 13.53 | 16.50 | 17.64 |




(a) Fruit Salad making.



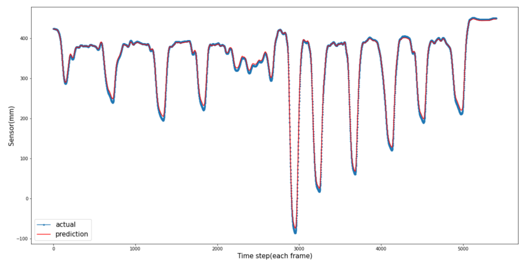

(b) Sandwich making.



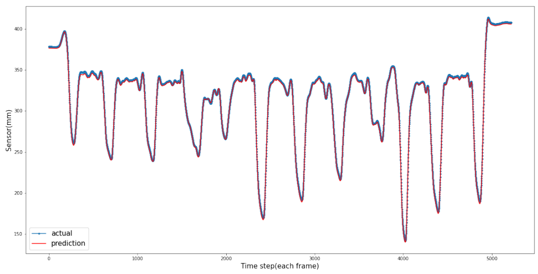

(c) Cereal making.

Fig. 6: Wrist position data predicted from head data from Cooking data set.Time stamp for each frame is 0.01s.

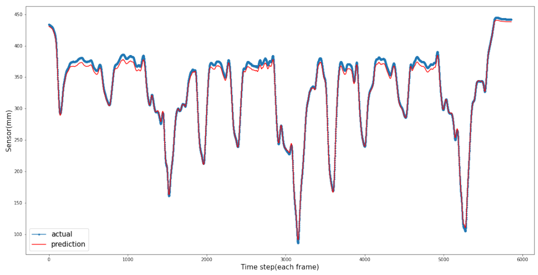
that with the reduction of markers the performance is not reduced rather it has increased a lot. Though the performance increased a lot not all reduced combinations achieved the optimal result. The highest accuracy of 99 % has been achieved from Head-Wrist and Shoulder-Wrist combination in Table 3 for Bento Data. The highest accuracy of 97 % has been achieved from Head-Wrist, Shoulder-Wrist, and Elbow-Wrist combination in Table 4 for Cooking Data. From these two results, it can be seen that



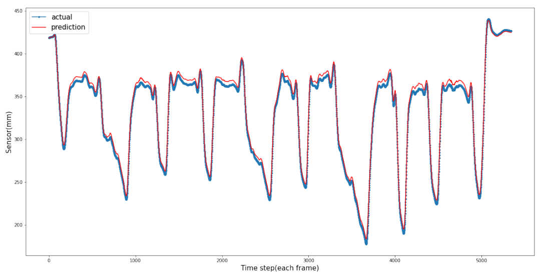

(a) Forgot to put ingredients.




(b) Failed to put ingredients.




(c) Turn over bento box.




(d) Fix/rearranging ingredients.

Fig. 7: Wrist position data predicted from shoulder data for Bento data set.Time stamp for each frame is 0.01s.

based on task the joint importance is varying as we see in 3 that Elbow-Wrist only achieved 95 % accuracy for Bento data but for Cooking data the performance changed.

For motion forecasting, we can see from Table 5 and Table 6 that the results are a lot promising. Even though the RMSE value of Table 6 is higher than Table 5 it did not cross 21mm which is a great achievement concerning the previous work [1]. The performance of Table 5 was achieved utilizing the Shoulder-Wrist combination whereas the performance of Table 6 was achieved utilizing the Head-Wrist combination. The other combinations are also tested but due to poor performance not mentioned here.

Fig. 6 and Fig. 7 are data from the same person from two different data sets. Fig. 7 is wrist position data predicted from shoulder data whereas in Fig. 6 wrist position data is predicted utilizing head data. Even for the same person depending on the task joint importance and forecasting performance can be varied a lot. Though forecasted data of Fig. 4 is not as good as Fig. 4 trend and seasonality of the signal are mostly accurate for the predicted data. So the achievement of this work is quite good.

## 5. Conclusion and Future work

Our goal is to study the challenges to achieving an intimate distance supportive HRC(Human Robot Collaboration) system by exploring human behavioral patterns. From our previous work we found that not all body markers play a vital role in Human Activity and Behavior analysis. In this work, we conducted a more detailed analysis and found that depending on the task importance of body markers changes. Also sometimes using unnecessary markers leads to poor results. The analysis has been done on two different data sets with a person in common in the same lab environment. Even though label-wise and setup wise there should be similarities in the data, we found from the T-test that they are quite different even for the same person. In keeping the intimate distance supportive HRC condition in mind we tried to design a forecasting system with important body marker combinations and it surplus the previous work performance. For future work, we will try to explore more about the parts of the signal due to which the forecasting results become poor. We will also try to analyze more challenging data sets to check for joint conditions.

### References

[1] Shotaro Yoshinaga, Yusuke Doi, and Sozo Inoue. ”Toward the near future prediction by machine learning of human behavior toward the realization of cooperative robots.” Multimedia, distributed cooperation and mobile symposium 2221 Proceedings 2020 (2020): 1409 -1415.

[2] Nazmun Nahid, Shotaro Yoshinaga and Sozo Inoue.”A Comparative Analysis on Joint’s Importance to Achieve Better Performance in Behavior Analysis in Human-Robot Collaborative Workspace.”International Conference on Activity and Behavior Computing (ABC)(WIP), online.

[3] 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. DOI: 10.1007/978-981-15-8269-1_1 (2021)

[4] 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.DOI: 10.1007/978-981-19-0361-8_17 (2022)

[5] 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

[6] P. Kratzer, M. Toussaint and J. Mainprice, ”Prediction of Human Full-Body Movements with Motion Optimization and Recurrent Neural Networks,” 2020 IEEE International Conference on Robotics and Automation (ICRA), 2020, pp. 1792-1798, doi: 10.1109/ICRA40945.2020.9197290.

[7] E. Helms, R. D. Schraft, and M. Hägele. 2002. rob@work: Robot assistant in industrial environments. In Proceedings of the 11th IEEE International Workshop on Robot and Human Communications. 399–404.

[8] Z.M. Bi, Chaomin Luo, Zhonghua Miao, Bing Zhang, W.J. Zhang, Lihui Wang, Safety assurance mechanisms of collaborative robotic systems in manufacturing, Robotics and Computer-Integrated Manufacturing, Volume 67, 2021, 102022, ISSN 0736-5845, DOI: 10.1016/j.rcim.2020.102022.

[9] Valeria Villani, Fabio Pini, Francesco Leali, Cristian Secchi, Survey on human–robot collaboration in industrial settings: Safety, intuitive interfaces and applications, Mechatronics, Volume 55, 2018,Pages 248-266, ISSN 0957-4158, DOI: 10.1016/j.mechatronics.2018.02.009.

[10] Gervasi, R., Mastrogiacomo, L. & Franceschini, F. A conceptual framework to evaluate human-robot collaboration. Int J Adv Manuf Technol 108, 841–865 (2020). DOI: 10.1007/s00170-020-05363-1

[11] S. Ehsan Hashemi-Petroodi, Simon Thevenin, Sergey Kovalev, Alexandre Dolgui,Operations management issues in design and control of hybrid human-robot collaborative manufacturing systems: a survey, Annual Reviews in Control,Volume 49,2020,Pages 264-276,ISSN 1367-5788, DOI: 10.1016/j.arcontrol.2020.04.009.

[12] Angeliki Zacharaki, Ioannis Kostavelis, Antonios Gasteratos, Ioannis Dokas,Safety bounds in human robot interaction: A survey, Safety Science,Volume 127,2020,104667,ISSN 0925-7535, DOI: 10.1016/j.ssci.2020.104667.

[13] Przemyslaw A. Lasota; Terrence Song; Julie A. Shah, A Survey of Methods for Safe Human-Robot Interaction , now, 2017.

[14] Takuma Yagi, Karttikeya Mangalam, Ryo Yonetani, Yoichi Sato: Future Person Localization in First-Person Videos, IEEE/CVF Conference on Computer Vision and Pattern, (2018).

[15] Tharindu Fernando, Simon Denman, Sridha Sridharan,Clinton Fookes: Soft + Hardwired attention: An LSTM framework for human trajectory prediction and abnormal event detection, Ne ural Networks (), Vol 108, pp.466-478 (2018).

[16] Yiwei W, Yixuan S, Ji W and Wenlong Z: Optimal Collision -Free Robot Trajectory Generation Based on Time Series Pre diction of Human Motion, IEEE ROBOTICS AND AUTOMA TION LETTERS, Vol 3, pp.226-233, (2018).