TUM Data Innovation Lab

Munich Data Science Institute (MDSI)

Technical University of Munich

&

Associate Professorship of Neuromuscular Diagnostics

Final report of project:

Physical Human-Robot Collaboration: Human Intent Prediction

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Abstract

The field of artificial intelligence and robotics has witnessed remarkable advancements, triggering interest in researching the potential of human-robot collaboration to enhance task performance. Although robots equipped with advanced sensors and electronics exhibit high precision and strength, they lack the ability to understand humans. This is an obstacle to improving the efficiency of human-robot collaboration. Bridging this comprehension gap poses unique challenges, as robots require explicit teaching to recognize and comprehend human actions and humans require adaptability to different robot behaviors. One way to address the challenges is to focus on human intention prediction so the robot can be aware of not only the current human behavior but also be able to understand the imminent intention.

This project builds on an experiment involving physical collaboration between humans and robots [1]. We used the data collected from this experiment and explored various algorithms (Long Short-Term Memory and Dynamic Bayesian Network) aimed at predicting the intended movement of humans in order to improve collaboration between humans and robots. The main focus reside on predicting human movements in the near future, specifically within the next 100-300 milliseconds for a better real-time anticipation and adaptation of the robot's actions and hence facilitation of synchronized collaboration between humans and robots.

Acknowledgment

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Finally, we want to thank everyone who contributed directly or indirectly to the deliverables of the project.
We hope that reading this report will retain your most distinguished review.

Contents

1 Introduction

1.1 Motivation

Over the past decades, the field of artificial intelligence and robotics has witnessed significant advancements, attracting substantial attention from researchers [2]-[3]. The interest in robotic collaboration stems from its potential to enhance task performance, leading to improved efficiency and productivity. For example, robots equipped with precise sensors and robust electronics can maintain high accuracy and exert forces beyond human limitations [4]-[5].

However, in order to achieve effective teamwork, team members should have the ability to understand one another [6]. Human-robot collaboration presents a unique challenge in this regard. Robots need to recognize and comprehend the actions of their human teammates. While humans naturally acquire this skill over time, robots need explicit teaching [5]. This recognition problem is made even more complex by the disparities present between robot and human team members, both in terms of their mental/computational capabilities and physical attributes [7]-[8]. Consequently, when faced with real-world uncertainty, robots cannot always rely on human teammates to strictly follow a well-structured algorithm, making it challenging to anticipate their reactions when things deviate from the expected path.

The field of Human-Robot Interaction (HRI) investigates the design, development, and study of interfaces and interaction modalities between humans and robots [9]. It encompasses both cognitive and physical aspects, each playing a distinct role in enhancing collaboration and optimizing performance between humans and robots [5].

To address these challenges, one of the main focuses of HRI is empowering robots to predict human intentions [10]. This means that, for a more intuitive interaction, the robot should not only be aware of the current human behavior but also be capable of annotating and predicting the human partner's imminent intentions. Essentially, the robot needs to possess high-level cognitive capacities for understanding human actions and predicting intentions, akin to a human counterpart in a human-robot interaction task.

1.2 State-of-the-art

To achieve accurate and transparent collaboration between humans and robots, cutting-edge approaches have concentrated on human intention detection [11], arbitration [12], and communication [13]. Significant research efforts have been devoted to designing robots with exceptional adaptability to humans, enabling them to seamlessly transition between various roles [12], [14] and adopt personalized strategies tailored to the unique needs and preferences of each human teammate [15].

However, this collaboration is contingent on the adaptability of humans to different robot behaviors, an aspect that remains relatively under-explored in the literature. A first step in this research direction would be human-human collaboration studies that showed the vital role of haptic communication in facilitating partner understanding and enhancing performance [16].

One recent study that delved into human adaptability to robots. This study examined how humans adapt to distinct robotic behaviors and how haptic communication influences coordination when participants assume either a leader or follower role. The participants were tasked with manipulating an object with internal degrees of freedom, requiring close collaboration between humans and artificial agents. Through this investigation, valuable insights were gained to further our understanding of human-robot adaptability and enhance collaborative interactions.

1.3 Goal of the project

This project analyzes data collected from the experiment. The goal is to explore various algorithms aimed at predicting the intended movement of humans, with the ultimate aim of fostering improved collaboration between humans and robots. During this experiment, human participants were required to generate rapid movements and execute precise adjustments. Consequently, our research focuses particularly on predicting human movements in the near future, specifically within the next 100-300 milliseconds. This time frame is of particular interest as it enables real-time anticipation and adaptation of the robot's actions, facilitating seamless and synchronized collaboration between humans and robots.
The rest of the report is structured as follows: In section 2, we introduce the background theory. Section 3 presents a literature review. Section 4 explains the experiment setup and the different algorithms used to predict the human intent. Section 5 shows the results of our models. In Section 6, we discussed the results, outlining its implications and potential directions for future research.

2 Background Theory

To ensure a comprehensive understanding of the rationale behind the method selection, we begin by providing background definitions and explanations of the algorithms employed in the project.

2.1 Human Intention Prediction

Human intention prediction is a field of research that focuses on understanding and predicting the intentions of individuals. Successful prediction of human intention can lead to more efficient, safer, and more natural human-machine interactions, fostering the integration of robots into human-centric environments such as healthcare, manufacturing, and domestic settings.
The prediction of human intention involves analyzing multimodal sensory information, such as visual and haptic feedback. Researchers employed various techniques to extract relevant features from the sensor data and model the relationship between these features and human intentions.
Numerous studies have been conducted to explore and predict human intent using a variety of methods. Machine learning techniques, such as Support Vector Machines (SVM), Hidden Markov Models (HMMs), and deep learning architectures like Long Short-Time Memory (LSTM) are applied to classify and recognize patterns in the sensory data. These models can learn the mapping between sensor inputs and corresponding human intentions

to afterward generalize and recognize specific modalities. Another approach involves using probabilistic graphical models, such as Bayesian Networks (BN) or Dynamic Bayesian Networks (DBN), to model the causal relationships between observed cues and human intentions. These models capture the uncertainties and dependencies in the data, allowing for robust inference and intention prediction. Some of these algorithms (SVM, HMM, DBN) are designed to work with categorical data and are utilized as classifiers. They aim to categorize the human movements into specific intention classes (moving up, staying still, etc.). On the other hand, some algorithms (LSTM) are capable of predicting the precise values of the movement variables such as position, velocity, and other relevant parameters. These algorithms provide a more granular understanding of the intended human movements.
In this project, our focus revolves around analyzing time series data. In 2.2 and 2.3, we identified two selected algorithms that are suited for handling such data [17].

2.2 Long Short-Term Memory

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture designed to address the vanishing gradient problem, which hampers the learning of long-term dependencies in sequential data [18]. LSTM introduces memory cells and gating mechanisms that enable the network to selectively retain or forget information over time [19]. The core element of LSTM is the memory cell, denoted by C_t, which stores and updates the memory state at each time step t in the sequence [20]. Figure 1 below illustrates the procedure at one time step. The memory cell interacts with three types of gating mechanisms: the forget gate, input gate, and output gate [19]-[20].

Forget Gate The forget gate, denoted by F_t, determines the amount of information from the previous memory cell state, C_{t-1}, that should be forgotten. It takes as input the previous cell state and the current input, denoted as X_t. The forget gate output is obtained by applying the sigmoid activation function, which restricts the values to the range of 0 to 1:

$$F_t = \sigma(w_f \cdot [H_{t-1}, X_t] + b_f)$$

where w_f and b_f represent the weights and biases associated with the forget gate.

Input Gate The input gate, denoted by I_t, determines the amount of new information to be incorporated into the memory cell state. It consists of two components: the input gate itself and the candidate cell state. The input gate controls the update of the memory cell state, while the candidate cell state, denoted by $\tilde{C}_t$, represents the new candidate values to be added to the memory cell state. The input gate output and candidate cell state are computed as follows:

$$I_t = \sigma(w_I \cdot [H_{t-1}, X_t] + b_I)$$

$$\tilde{C}_t = \tanh(W_C \cdot [H_{t-1}, X_t] + b_C)$$

Cell State As mentioned before, the network will have enough information from the forget gate and input gate to decide and store the information from the new state into the cell state $\tilde{C}_t$. For this, the previous cell state $\tilde{C}_{t-1}$ gets multiplied with forget vector F_t. If the outcome is 0, the values will be dropped from the cell state. After that, the network takes the output value of the input vector I_t and performs point-by-point addition, which updates the cell state giving the network a new cell state C_t.

Output Gate The output gate, denoted by O_t, controls the flow of information from the memory cell state to the output of the LSTM. It determines which parts of the memory cell state will be revealed as the output. The output gate output and the LSTM output, H_t, are calculated as:

$$O_t = \sigma(w_O \cdot [H_{t-1}, X_t] + b_O)$$

$$H_t = O_t \cdot \tanh(C_t)$$

In these equations, H_{t-1} represents the previous hidden state, and σ and tanh denote the sigmoid and hyperbolic tangent activation functions, respectively. w and b represent the weight matrices and bias vectors associated with the corresponding gates.
By incorporating memory cells and gating mechanisms, LSTM can effectively capture long-term dependencies in sequential data. The forget gate regulates the memory cell by determining which information to discard, while the input gate allows new information to be integrated. The output gate controls the flow of information to the final output. This architecture has proven highly successful in tasks such as natural language processing, speech recognition, and time series prediction, where long-term dependencies play a crucial role [17].

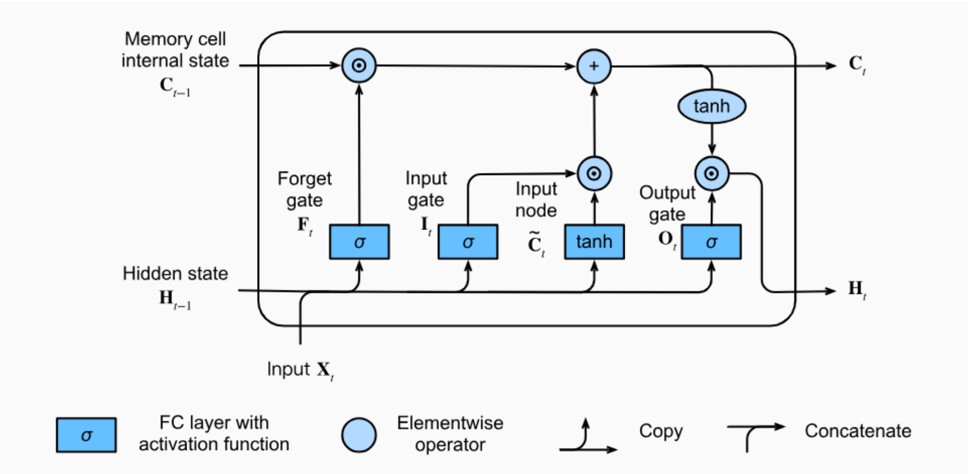

Figure 1: LSTM cell graphical illustration of data flow. [**2**]

2.3 Baysian Network and Dynamic Bayesian Network

Bayesian Networks is a powerful probabilistic model that has been widely used in various fields [21]. It is a graphical model that captures probabilistic dependencies among a set of variables through a directed acyclic graph (DAG) [17]. It is a flexible framework for representing and reasoning about uncertainty and causal relationships among variables [22]. Dynamic Bayesian Networks extend the capabilities of BNs by explicitly modeling the temporal dependencies and evolution of variables over time [23]. DBN is able to model the multivariate time series, where the relation between variables as well as the evolution over time will be both effectively captured [24].

2.3.1 Bayesian Networks

Bayesian Networks are a class of powerful tools for dealing with the uncertainty problem usually present in probabilistic models. Each node corresponds to a variable and each edge connecting two nodes represents the conditional probability for the corresponding variables [25]. The edges are directed and can only navigate in one direction.
Let $(X_1, X_2, \ldots, X_n)$ denote the nodes of the network and $\text{Parents}(X_i)$ the set of nodes that the node X_i depends on in the network. The joint probability distribution of the variables acquired by the BNs can be decomposed using the chain rule of probability as follows:

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i \,|\, \text{Parents}(X_i))$$

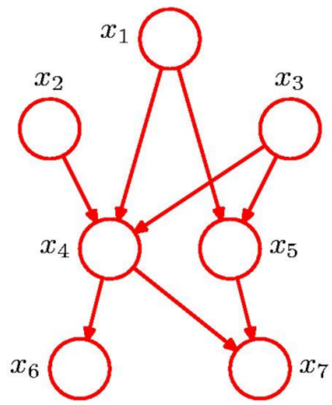

Figure 2: Bayesian Network - Directed Acyclic Graph. [26]

To quantify the dependencies between variables, conditional probability tables (CPTs) are associated with each node in the network. A CPT specifies the conditional probability distribution of a variable given its parent variables.
Inference in Bayesian Networks involves calculating probabilities of events or making predictions based on observed evidence. The posterior probability of a target variable given evidence can be calculated using Bayes' theorem:

$$P(X_i \,|\, E) = \frac{P(X_i) \cdot P(E \,|\, X_i)}{P(E)}$$

where E represents the observed evidence and $P(E)$ acts as a normalizing constant.

The strength of Bayesian Networks lies in their ability to combine prior knowledge or beliefs with observed data to update beliefs and make informed inferences. By leveraging the graphical structure and probabilistic reasoning of Bayesian Networks, researchers can gain insights into the relationships between variables, identify influential factors, estimate probabilities of different outcomes, and make informed decisions under uncertainty.

2.3.2 Dynamic Bayesian Networks

Dynamic Bayesian Networks (DBN) are usually defined as an extension of Bayesian Networks specifically aiming at time series modelling [27]. The architecture that forms the static interpretation (nodes, edges and probabilities) is identical to a BN. However, the nodes and edges in DBN include the temporal dimension [27]. DBNs allow not only connections within one time slice (intra-slice connections) but also connections between time slices. These temporal connections would incorporate condition probabilities that would be incorporated in the CPT [28].
It is worth mentioning that the states of a dynamic model do not need to be directly observable. They can be inferred from other variables that can that can be directly measured. Also, each state can be regarded as a complex structure of interacting states. In other words, each state at one time instance may depend on states at the previous time instance or/and states in the same time instance [28].

3 Literature Review

After a detailed background theory, we delve deeper in the literature to understand the state-of-the art techniques used in the field of human-robot fine movement collaboration focusing on human intent prediction.

3.1 Long Short-Term Memory Algorithm

The advances and development in the field of deep learning played a role in the prediction of intention for humans in a human-robot interaction context. Algorithms like RNN and LSTM were used to deal with time series data for the intention recognition. For example, in [29, 30], Yu et al. developed two RNN models: a supervised multiple timescale one and another object augmented-supervised multiple timescale. They were both tested and used for the understanding and detections of human intentions based on human motions in real time. The same research group also proposed an LSTM model for a better tackling of the human intention recognition task [31]. Another deep RNN was proposed in [**34**] for intention detection by using wearable IMU sensors. [32] proposes on the other hand a deep LSTM architecture for accurately recognizing the human intention in a human-robot collaborative setup based on skeleton information of human motion. The authors proposed a typically multiple stacked LSTM model combining the advantages of single LSTM layer and deep stacked network structure. We investigate the use of LSTM in a human-robot collaboration setup with new type of input data and different parameters (for example the use of haptic feedback, observations and others).

3.2 Dynamic Bayesian Network Algorithm

As discussed in Section 2.3, Dynamic Bayesian Networks are powerful and interpretable tools that capture correlations and causations between variables occurring over time. Oliver and Horvitz [33, 5] conducted a comparative study between DBN and HMM for recognizing office activity using video, audio, and computer interaction evidence. They trained separate HMMs for each data modality and also developed a DBN that integrates all three modalities simultaneously. Results showed that the DBN outperformed the ensemble of HMMs. Researchers were also interested in the modelling of robot-user actions and teaming strategies (robot-robot, human-human).

Bayesian Network has been used for human-intention detection. For example, [34] presented Bayesian Networks in a robot-grasping tasks in real-world scenarios. They showed the ability of predicting a hand grasping movement from uncertain sensory data. However there are limited literature on using DBN to predict human intent. DBN was often used in decision making and cognitive sciences researches [35], [36], [37]. [38] pioneered the use of DBN for modeling the human intention detection in a human-robot collaborative setup (called in the paper intention-action-state scenario) to facilitate for probabilistic intention inference. DBN was also used in [39] to learn interactions between assistive robotic walker and human users. The model was able to recognize a subset of possible actions of gait stability, such as standing up, sitting down or assistive strolling, and then adapt the behaviour of the device accordingly.

In this project, we explored the use of DBN to predict the human intention (velocity and hand position) in the next timestamps according to different factors and data collected (from the task, the user and the other participant). Different combinations were tried to understand the relevant dependencies for meticulous human-robot collaboration.

4 Methods

This section presents the methodology followed in this project from the data preprocessing to the description of the different models used in the project.

4.1 Setup and Data

4.1.1 Experimental Setup

The experimental setup has been designed to investigate the utilization of haptic feedback in physical human-robot collaboration. The task was to balance a ball on a board at a target area. The participants controlled the left side of the board, while the artificial agents controlled the right side. The task requires precise coordination between humans and artificial agents. The experiment was simulated using virtual reality (VR) technology. The participants interacted with each other through haptic devices (Phantom Touch; 3D SYSTEMS) that generates force feedback.
The experiment consisted of 11 participants, and each dyad performed a total of 600 trials. The duration of each trial ranged from 5 to 15 seconds. To investigate the impact of haptic feedback on intention prediction, the experiment was designed with two conditions. In half of the trials, participants received haptic feedback from the devices, while in the other half, they solely relied on visual information. There were two types of artificial agents, namely the low-gain and the high-gain agent. The high-gain agent was much more proactive compared to the low-gain agent.
During the experiment, kinematic and kinetic data were recorded at a sampling rate of 1000 Hz. The recorded data encompassed the participants' movements, haptic feedback, environment variables throughout the task. This comprehensive dataset provides valuable insights into the collaborative dynamics between humans during physically interactive tasks. The experiment aimed to better understand how humans utilize haptic feedback to predict the intentions of their partners. By analyzing the recorded data, the study intends to uncover patterns and behaviors that contribute to effective collaboration.

4.1.2 Data Preparation

In this section, we describe the preprocessing and organization of the recorded data, which was performed to facilitate further analysis and modeling.
The recorded data was loaded and organized for each participant and experiment. The data for each experiment was stored in separate folders, and the processed data was obtained by combining the data from all experiments for each participant. In this project, we only used the trials where haptic feedback was available.
For the training of DBN, we selected the following variables: the velocity of the participants, the relatve position of the ball to the target, the velocity of the ball, the orientation of the board, and the force feedback of the participant. Since DBN only works with categorical data, we grouped these variables into categories using predetermined bins. The resulting dataset was randomly split into 80% of training data and 20% of testing data. The data from each trial was organized into sequential segments of four consecutive data points.

Similarly for the LSTM model, relevant information from the dataset was extracted. This included measurements related to participant velocity, the relative position of the ball, the categorical representation of ball position, and the applied force. The dataset was downsampled to 5 Hz to reduce its size and simplify the analysis. This downsampling allowed for a more manageable dataset while retaining the essential information.
To facilitate the prediction task, a sliding window approach was adopted. Each input sequence for prediction consisted of 10 consecutive data points. The total length of the downsampled dataset was determined, and the data was split into training and testing sets using the same ratio as before.
For each data point in the downsampled dataset, starting from the 10th data point, the previous 10 data points were used as the input sequence. The corresponding target value was recorded, representing the next step to be predicted.
In summary, the data preparation step involved selecting relevant measurements, downsampling the dataset, and organizing the data into input sequences and target values for training and testing the prediction model.

4.2 Models

After data preparation, different prediction algorithms were tested to find a compromised solution for the problem at hand: human-intent prediction.

4.2.1 Long Short-Term Memory Model

For this study, we employed a LSTM neural network model to predict the trajectory of human limb dynamics in different agent gain settings. Our LSTM model consisted of two LSTM layers, each comprising 400 neurons, to facilitate a deeper understanding of the complex temporal patterns in the input data. Furthermore, we appended a fully connected Dense layer with a single output unit to produce trajectory predictions. A Batch Normalization layer was applied to normalize the input to the Dense layer, improving convergence during training.
The model was trained using the Adam optimizer with a learning rate of 0.001 and the mean squared error (MSE) loss function to quantify the discrepancy between the predicted and ground truth trajectories.

4.2.2 Dynamic Bayesian Network Model

Different DBNs network were designed during the study. We present two DBNs in this section. Both networks have the same nodes/criteria influencing the prediction of the current position or velocity of the hand : hand velocity, ball position, ball velocity, board angle. For example, the previous and current position of the ball affect the hand velocity. The previous position through affecting the previous board angle and the current position of the ball directly affecting the Hand Velocity. The exact network structures where we can see the different nodes dependencies (each for current and previous state) are shown in Fig. 3, 4.

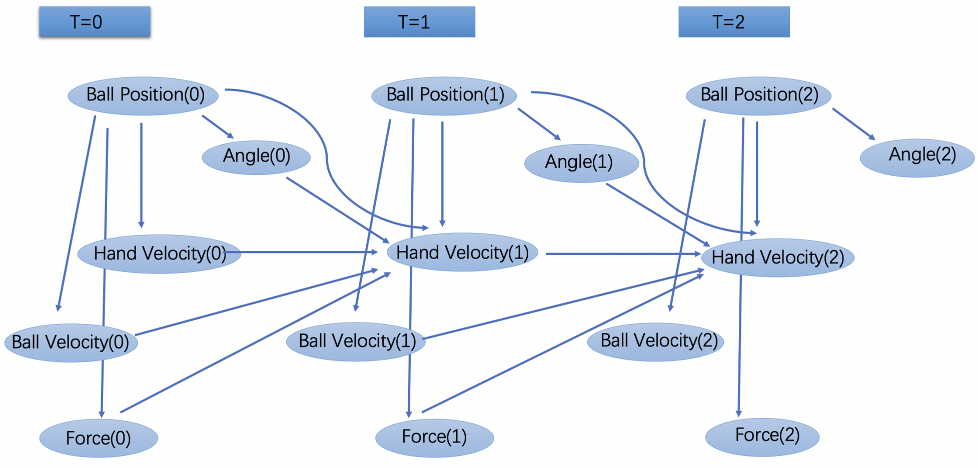

Figure 3: DBN model with haptic feedback

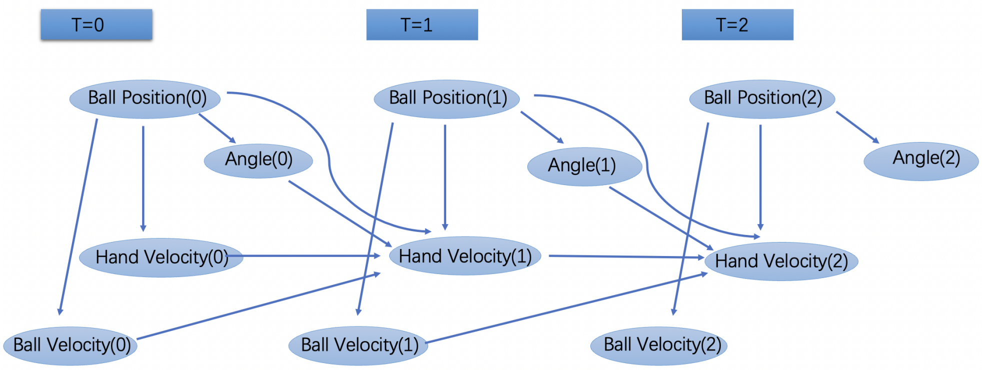

Figure 4: DBN model without haptic feedback

We used the pgmpy python package to construct, train and test the DBNs. The parameters of the DBNs are trained using Maximum Likelihood Estimator. We used the DBNs to predict the human movement in 100ms, 200ms or 300 ms.

4.2.3 Persistence Model

The limited rate of change in hand position or velocity, attributed to the inertia in the human body, often results in the hand maintaining its movement status from the previous timestep to the new timestep. Based on this idea, we constructed this simple persistence model that assumes the velocity in the previous timestep will maintain at the current timestep. Hence the equation, $Vel_t = Vel_{t-1}$.
This is a naive way of predicting the human movement. This persistence model will be used as a baseline for evaluating our models.

5 Results

5.1 Long Short-Term Memory

In the experiment with the high gain agent, which represents a relatively easier task, we observe that the LSTM model effectively predicts the trajectory of the system, as demonstrated in Figure 5. The relatively low test loss value (indicated in the plot) further substantiates the model's performance on the test data. The low test loss signifies that the model's predictions closely match the ground truth values, validating the efficacy of the LSTM architecture in capturing the dynamics of the system under the high gain setting.

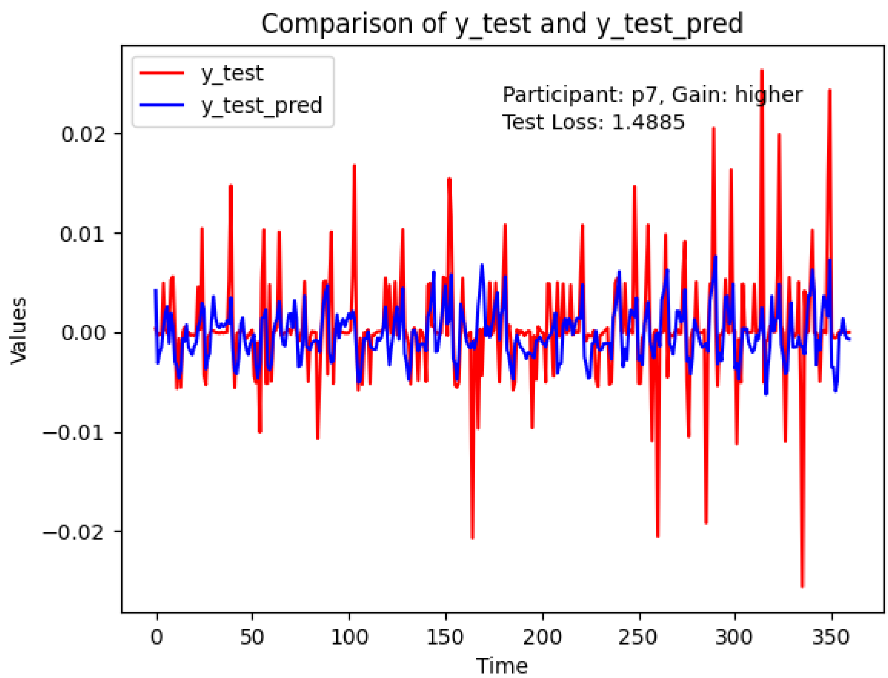

Figure 5: LSTM method with high gain agent

In contrast to the relatively easier task with the high gain agent, the experiment with the low gain agent proves to be more challenging for the LSTM model to predict the trajectory using the human limb dynamics. Figure 6 shows that the LSTM model's predictions (in blue) deviate from the ground truth data (in red). The trajectory predictions display a noticeable discrepancy from the actual values, suggesting that the model struggles to accurately represent the intricate limb dynamics under this setting. The relatively higher test loss value, which is indicated in the plot, is indicative of the model's reduced performance on the test data.

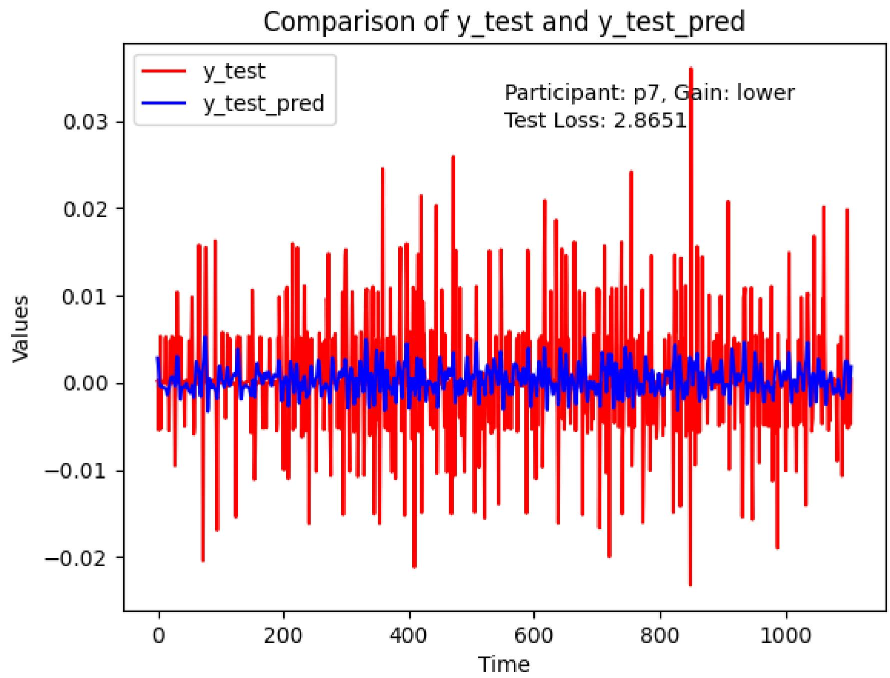

Figure 6: LSTM method with low gain agent

The x-axis of the figures represents the time steps, with each time step corresponding to a duration of 200 milliseconds. As the experiment with the low gain agent takes a longer duration to complete, the x-axis of Figure 6 is longer compared to the x-axis of Figure 5, reflecting the extended time required for the low gain agent's trajectory prediction. In summary, the LSTM model demonstrates proficient trajectory prediction capabilities for the relatively easier task with the high gain agent, while facing challenges in accurately capturing the intricacies of human limb dynamics for the low gain setting-

5.2 Dynamic Bayesian Network

The accuracy on the training data is always slightly higher than the validation data, as expected. There is a decrease in accuracy as the prediction horizon increases. This is expected, as it is more difficult to predict longer periods of time into the future. We found that in the case of higher gain, the accuracy difference between training data and verification data is larger than that of lower gain.

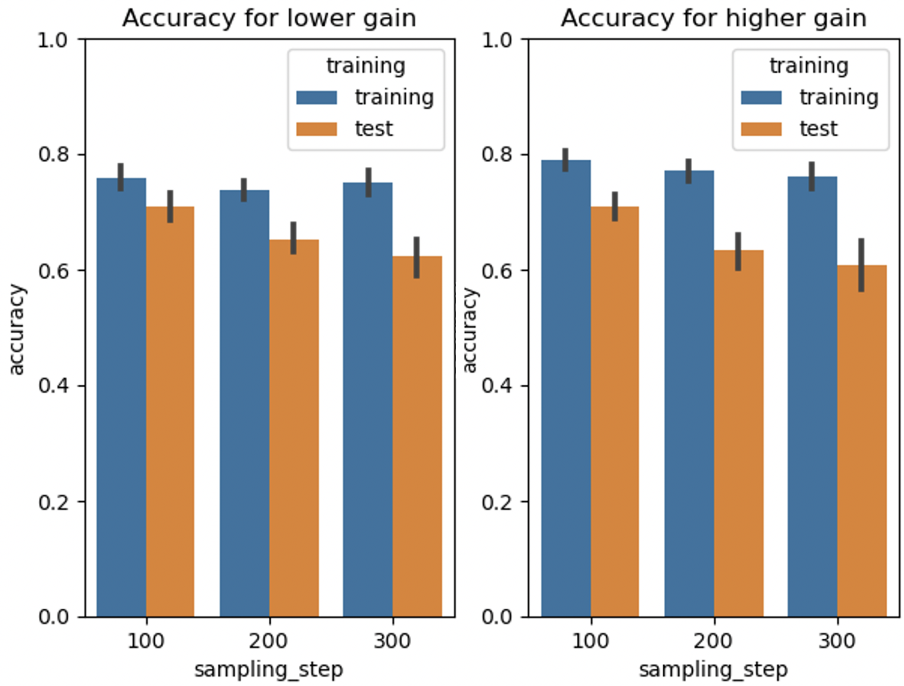

Figure 7: train data and test data comparison for DBN model

Comparing DBN model with the persistence model, it can be seen that as the prediction time step changes from 100ms to 300ms, the performance of DBN relative to the persistence model has been significantly improved showing that the network is actually learning.

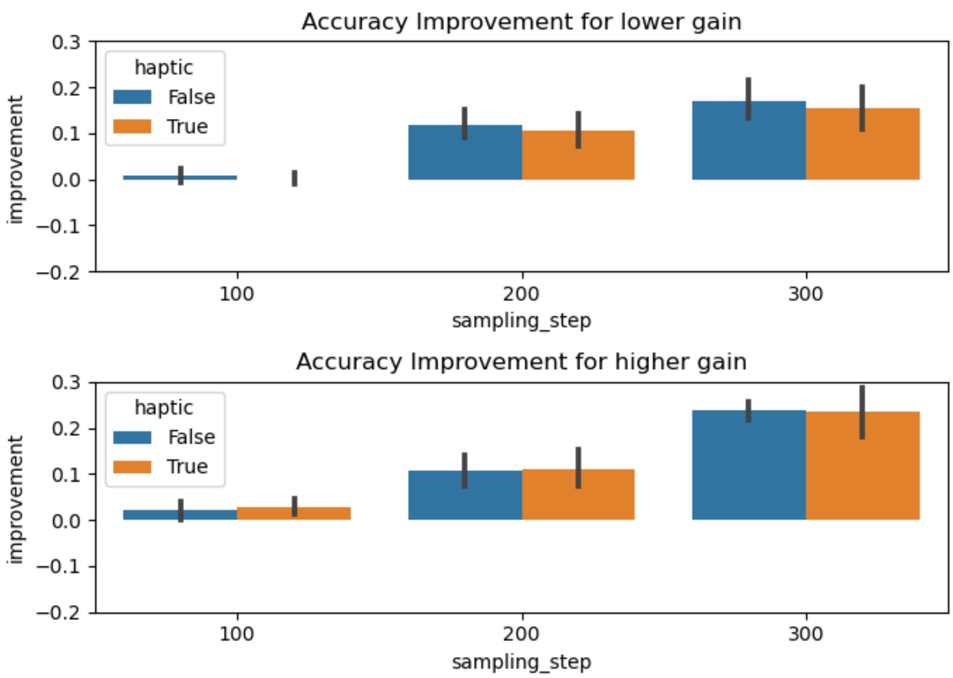

Figure 8: Accuracy improvement of DBN model over persistence model

In the confusion matrix, the x-axis is the actual state and the y-axis is the predicted state. We can see that the values on the diagonal of the matrix are significantly greater than the values on the off-diagonal positions, which means that the prediction made by the DBN model is correct most of the time. The accuracy to correctly predict still state is the highest. When humans are moving up or down, DBN often mis-classifies the movement to be still. However, the accuracy is still more than 50%.

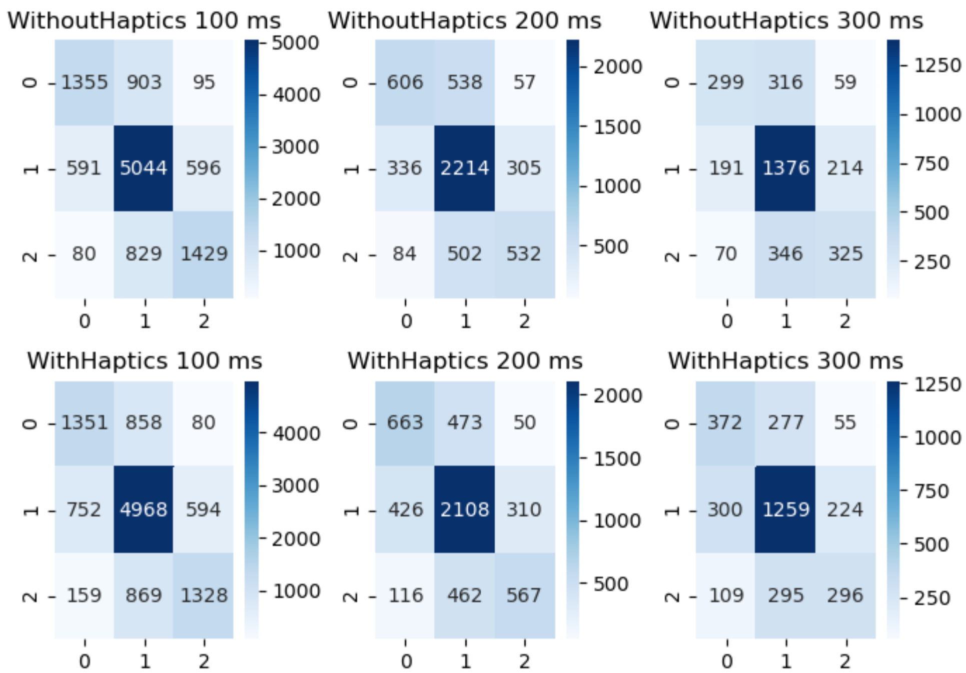

Figure 9: Confusion matrix for DBN model. Here the x-axis is the actual state and the y-axis is the predicted state. 0 means down, 1 means still, 2 means up

In the comparison chart with and without haptic feedback, we found that the prediction accuracy is always higher with haptic feedback. However, this difference is very subtle.

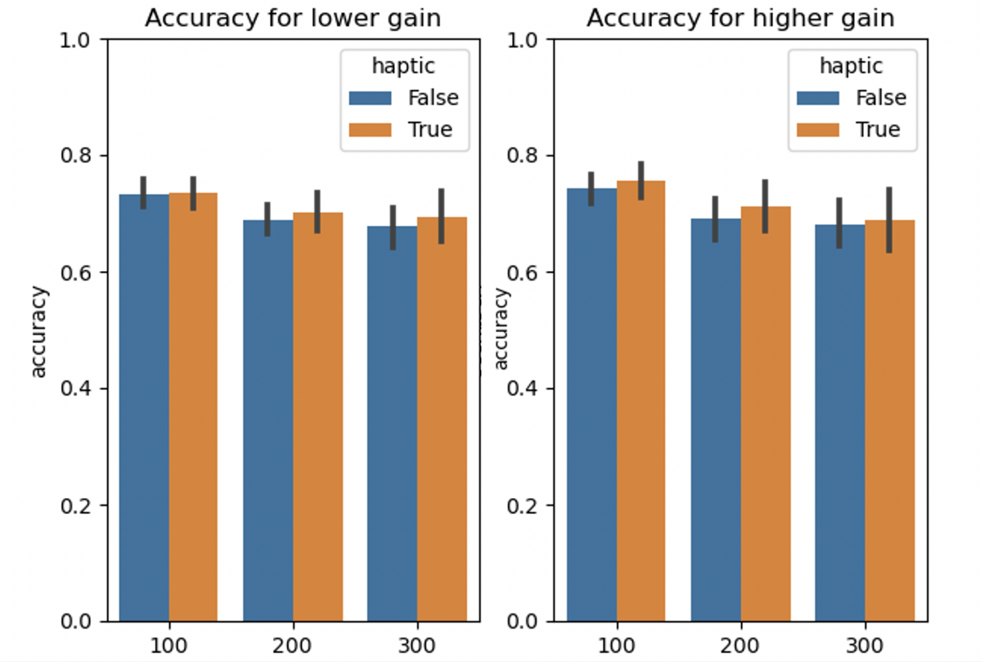

Figure 10: With haptic and without haptic comparison for DBN model

6 Discussion

In this project, we used LSTM and DBN to predict the intended movement of the participants. Both algorithms showed promising results.
For LSTM, the predicted trajectory consistently underestimates the magnitude of the intended velocity, but it demonstrates good alignment with the timing of the changes in the actual trajectory. LSTM performs better when participants worked with the high gain agent compared to the low gain agent. The reason may be that participants tend to be more passive and generate less movement when working with the high gain agent, thus less variable and easier to predict. This can be reflected in the magnitude of Fig. 5 and Fig. 6.
We employed DBN to predict human movements into the future at different time intervals, specifically 100ms, 200ms, and 300ms. As the prediction horizon increases, we observed a gradual drop in prediction accuracy. However, despite the decrease in accuracy, the advantages of using DBN over the persistence model become more pronounced as the prediction horizon extends further into the future. The DBNs with or without force feedback showed similar accuracy. This may indicate the haptic feedback did not provide extra information compared to visual feedback. However, when we reduced the DBN nodes and only try to infer the hand velocity using ball relative position, previous hand velocity and force feedback, we see an increased accuracy due to haptic feedback when participants worked with the high gain robot (Fig. 11). This coincides with the findings that haptic feedback leads to an improvement in coordination between participants and the high gain agent, but not with the low gain agent. This result indicate that haptic feedback improves the prediction of human intent when visual feedback is incomplete.

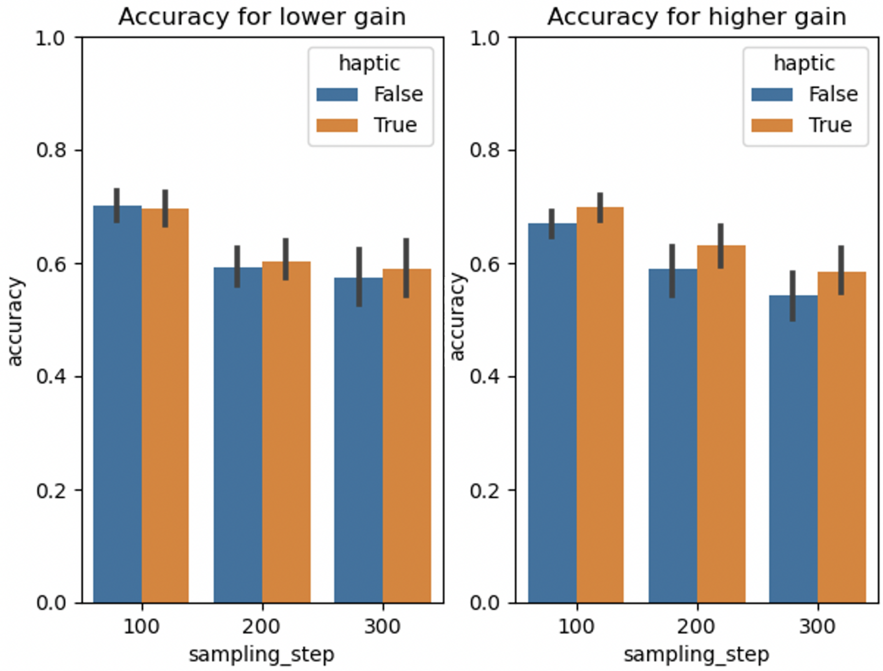

Figure 11: The accuracy of DBN with reduced nodes. Blue bars shows the DBN with two nodes: hand velocity, ball relative position. Orange bars shows the DBN with three nodes: hand velocity, ball relative position and force feedback.

Both LSTM and DBN offer unique strengths and limitations. LSTM excels at handling time series data and predicting precise values of intended velocity. On the other hand, DBN takes a single timestep as input and is limited to predicting categorical outcomes, indicating whether participants intend to move up, down, or stay still. The inability to predict exact values is a drawback of DBN compared to LSTM. However, DBN is a much more compact network than LSTM. Its simplicity and interpretability allow for a clearer understanding of the relationships between different variables. In contrast, LSTM is often regarded as a "black box" due to its complex architecture, making it more challenging to interpret the inner workings of the model.
Due to the time constraints of this project, we were unable to fully explore additional possibilities for enhancing the network structure, which could potentially lead to further improvements in prediction accuracy. Nonetheless, the intent predictor demonstrates promising potential in enhancing coordination between humans and robots. The integration of the intent predictor with the robot controller poses an important avenue for future research.

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