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Estimating Human Intent for Physical Human-Robot Co-Manipulation

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Abstract—Human teams can be exceptionally efficient at adapting and collaborating during manipulation tasks using shared mental models. However, the same shared mental models that can be used by humans to perform robust low-level force and motion control during collaborative manipulation tasks are non-existent for robots. For robots to perform collaborative tasks with people naturally and efficiently, understanding and predicting human intent is necessary. However, humans are difficult to predict and model. We have completed an exploratory study recording motion and force for 20 human dyads moving an object in tandem in order to better understand how they move and how their movement can be predicted. In this paper, we show how past motion data can be used to predict human intent. In order to predict human intent, which we equate with the human team’s velocity for a short time horizon, we used a neural network. Using the previous 150 time steps at a rate of 200 Hz, human intent can be predicted for the next 50 time steps with a mean squared error of 0.02 \((m/s)^2\). We also show that human intent can be estimated in a human-robot dyad. This work is an important first step in enabling future work of integrating human intent estimation on a robot controller to execute a short-term collaborative trajectory.

I. INTRODUCTION

While robots have long been used in manufacturing, they are increasingly gaining the capability to work in unstructured and dynamic environments. In the future, this will include applications related to logistics, healthcare, agriculture, disaster response, and others. However, robots will also be required to successfully interact more naturally with human teammates. Interacting with people in a way that is helpful and intuitive requires that the robots both act predictably and be able to predict human intent. Specifically, in this paper we aim to create a model for predicting human intent in a collaborative object carrying task that a robot could use to be a more responsive and intuitive teammate.

In this paper, we call physical human-robot interaction for the purpose of collaboratively manipulating an object co-manipulation. In order to understand human-co-manipulation, we ran an exploratory study with 20 human dyads. Each dyad moved a long board representing a table as we measured their movement and forces on the board as in Figure 1. Many previous studies have been done on human movement in which one or two people move in tandem. Many of these are done in haptic simulations or with limited degrees of freedom in order to isolate specific behaviors. These studies have given significant insight on things like minimum jerk motion, negotiation of roles, and task-specific movements. However, we expect that due to the nature of this past work, which has mostly examined a limited number of degrees of freedom, there are limitations to how those results can be extrapolated for general purpose six dimensional co-manipulation tasks. We therefore assert it is also necessary to perform studies with natural and realistic human movement without limiting degrees of freedom. This would validate what has been learned in other studies and to allow further insight and direction for human-robot co-manipulation controller development.

There are many sources of information that a robot could use to predict human intent, including motion, force, partner posture, and verbal communication among others. In our study, we chose to focus on motion and force. We hypothesized that these variables were the most fundamental and easiest to interpret for a robot in order to predict what the person intends to do. In another paper [1], we discuss insights gained from the force information in this study and how force data can predict initiation of future motion. While in this paper we use past motion data only to predict where the co-manipulated object will move next. The interaction between force and motion in a co-manipulation task is complicated and important. In this preliminary work, we have attempted to isolate and explore each physical quantity before we later expect to integrate insights and models from both for future robot controller development.

Many models have been created to understand how people move and collaborate. In this work, we choose to train a neural network because they can be used to approximate any function and have been used to forecast time series [2]. Therefore, as long as the future human motion is in fact predictable based on the input variables, it should be possible for the neural network to predict the human motion.

After training the neural network, we show that the neural
network is also able to predict future intent of a human-robot dyad. We compare the prediction of the neural net to the actual motion of the robot. It is impossible to decouple the intent of the two people in a dyad. Therefore, in order to actually use our intention estimation for future controllers, it is important to show that the neural network can still predict the motion when one of the humans is replaced with a robot. In this paper, we do show that with a simple impedance controller on the robot, the neural network is able to accurately predict what the human-robot team will do. The contributions of this paper include the following:

- Determination that past motion of a human dyad is all that is necessary to predict human intent for at least a limited time horizon, where we define “intent” as how the team will move next.
- Development of a neural network to predict human intent based on past motion of the human dyad.
- Validation of the human intent prediction in a human-robot dyad.

The paper is organized as follows. Section II describes related work on human-robot interaction and intent modeling. The study on human-human interaction is described in Section III. The structure and training of the neural network is described in IV. In Section V we describe our robot platform and the validation of the estimate of human intent on our robot. Finally, we discuss the results in Section VI.

II. RELATED WORK

Many different control methods have been used in the last 20 years for human-robot cooperation. The first research in this area developed from what had been done with exoskeletons, because it involved both a robot and a human working together to manipulate an object. One of the first controllers for cooperative manipulation of an object by robots and humans was an impedance controller that could be used with any number of robots and humans holding the object [3]. In general, the advantage of human-robot collaboration is that humans provide intelligence and dexterity while robots may provide strength and stability [4].

To improve human-robot interaction, human-human interaction has been studied in order to understand how people communicate haptically. Ikeura et al. showed that when two people move an object, but only one knows the task, the applied force is highly correlated to the velocity and therefore can be modeled by a damping element. Of importance was the result that the spring and mass terms were much less important than the damping terms [5]. Ikeura later showed that a constant damping term does not work well for changing velocities as it slows the human-robot pair significantly compared to the human-human pair. Variable damping that depends on velocity was proposed to have both fast motion and accurate positioning when using an impedance model [6], [7]. One issue with this model is that it was determined and validated using a one-dimensional trajectory at a short distance. This makes it difficult to generalize for cooperative motion during a general six degree of freedom task. Additionally, other work has shown that a damping controller is not clearly superior to other methods. One of the proposed measures used to determine the effectiveness of a human-robot interaction controller was the interaction force between the human and the robot. As this force is usually counted as wasted energy, the hypothesis was that humans naturally try to minimize it. According to Ito et al., a controller for human-robot cooperation should minimize this interaction force as well [8]. However, damping controllers tend to have high internal forces. Motion is also not tracked as accurately because the leader essentially drags the robot into place instead of being assisted by the robot.

Many insights into human-robot interaction have been gained from the field of neuromechanics. Flash and Hogan showed that the human arm tends to follow a minimum jerk trajectory in many situations, which means humans try to move in a smooth manner. This is accurate especially when force is low and high speed is not an objective [9]. Other researchers showed how humans adapt to unknown or unstable dynamics and variable impedance controllers have been made based on this principle as well [10], [11], [12]. Ikeura used the minimum jerk model to calculate a damping constant [13] while Maeda et al. used the minimum jerk model directly to predict what the human is trying to do. Their controller estimates the final time and position that the human is attempting to reach based on the past few steps and uses position control to follow that trajectory along with impedance control to adapt to errors [14]. Kheddar et al. have found that minimum jerk does not apply to all cooperative movements. One example is when motions are longer and include walking and not just arm movement, there are phases of constant velocity along with phases of constant acceleration. They used this knowledge to create a controller based on phases of constant velocity that are only changed when a certain force threshold is surpassed [16], [17].

The minimum jerk model is one example of an invariant model, where by finding a model for a task, the dynamics can be simplified. Many models for a controller for cooperative manipulation only have a few changing parameters that include initial and final time and position. They may also include a maximum velocity or other parameter. With just a few parameters, the entire trajectory can be described. One approach to determining these models has been programming by demonstration [15].

Finally, past work has shown that the robot should be predictable. The human should not be surprised by what the robot does. Aside from being predictable, if the robot takes any leadership in the task, such as keeping an object from rotating, it should do so in a way that is understandable to the human [19]. Chipalkatty et al. showed that there is an advantage to making a controller simple enough that a human can learn it quickly. If it is complex and constantly adapting, there is a risk the human will become confused and the cooperation will be inefficient [20].

The work that has been described so far is representative of the current research in the field of physical human-robot interaction for co-manipulation. We propose that most
good human-robot interaction controllers for cooperative manipulation of an object can be judged on certain factors including low interaction forces, quick and accurate motion tracking, safety, simplicity, robot initiative, and predictability. However, very little of the past work has been based on real performance data from human-human co-manipulation trials for unconstrained tasks. The purpose of this paper was to use real human-human data and attempt to develop an estimator that allows us to predict human motion intent for a given set of tasks.

III. EXPLORATORY STUDY

As described in more detail in [1], we had 20 human dyads perform a series of table carrying tasks. Figure 1 shows one task being performed and video of the most complex task can be seen at https://youtu.be/DAbLRDN20yE. There were 12 different tasks that were each performed 3 times. Our purpose in doing this study was to understand how people collaborate moving an object with no constrained degrees of freedom. We wanted to verify that the principles other researchers have shown in past studies with simpler tasks generalize to all co-manipulation tasks. Additionally, we expected to identify new principles from human-human data that could improve future control development. The tasks chosen were based on this idea, and the tasks represented several different types of common motion. Many of the tasks were designed to isolate certain behavior (such as while translating or rotating an object) while others were open-ended. The tasks included lateral translation, forward/backward translation, rotation, “hallway” navigation, lifting over obstacles, etc. These were chosen to represent the variety of tasks that people would do in real life.

During the experiment, each partner was assigned a role as leader or follower. The leader was then given instructions on where to move the table. In half of the tasks, the follower was blindfolded and talking was prohibited. This can be thought of as a baseline for any robot controller that does not use vision-based feedback. In the other half of the trials, talking was permitted and there was no blindfold. The performance in these trials could be considered the long-term objective for performance and something against which we can benchmark our future human-robot controllers.

The table and each participant were set up with motion tracking markers. There were two force/torque sensors between the table and the handles used by the leader. A Microsoft Kinect also tracked the pose of the participants. Data was recorded from motion capture and the force/torque sensors at 200 Hz. The Kinect recorded data at 15 Hz.

A board was used as a table-like object to be transported by the dyad. The table had two handles on one side of the board. Each handle was connected to the board with a force/torque sensor in series. The table also had motion capture markers in order to get ground truth data about the pose of the table at all times. The table also carried an tablet that was oriented so that only the leader could see it. This tablet was controlled by the experimenters to show the leader the current task. It showed the leader where they were starting and where they would need to go in the task. The tablet had images with markings that corresponded to colored markings on the floor that indicated where to move.

Finally, the table also had a power strip that powered the force/torque sensors and the tablet. The power strip and ethernet cables were each connected to the wall off-board the table. One of the researchers was tasked with ensuring that these did not get in the way of the participants and that there was sufficient slack so that no or little additional force was placed on the table.

IV. NEURAL NETWORK

As a first approach to developing a nonlinear estimator of human intention, we formulated a neural network using the Google Tensorflow API.

A. Variables

Originally, we expected to train the neural net on the force and motion data from the exploratory study. As we trained the neural, we discovered that force data was difficult to use and gives inferior prediction of human intent. There are two proposed reasons for the low quality prediction: 1) the force data was noisy, 2)the relationship between the forces applied to the table by each person and the future motion of the table is complex. The second point is in part because each human dyad learns to communicate by force in their own way as shown in [21].

We discovered that more accurate predictions could be made without force. While longer term predictions may be aided with force information, and initiation of motion as well, the motion data alone is sufficient for an accurate short term prediction. This seems to indicate that the follower acts or at least could be modeled as an impedance while simply changing their equilibrium or set point during co-manipulation. This is advantageous as it means that the estimation of human intent can be used on robots without force sensors in the wrist. In initial tests, we have only included translation from all of our trials in the prediction and not rotation.

B. Topology

Our final neural network consists of 3 hidden layers each with 100 nodes. The process of choosing a neural network structure and other parameters was not exhaustive and it is possible that better structure and parameters could be obtained. However, we were limited in the process for choosing neural net parameters as it can take on the order of several minutes to train the neural net even when only training to predict a single step. In the end, a simple structure using only motion data as input worked well. Better structures, including methods other than neural networks, may exist but our purpose in this paper is to show that human intent estimation is possible. It was shown by Chipalkatty et al. that more complex predictions of future movement can actually decrease performance if they do not agree with what the human is trying to do. This is because predictions can be wrong and unpredictable. They found that it was more
important that the human understand what the robot will do next. [20]. It is important that the prediction be not only accurate, but also reliable. The inputs to the neural network are 150 past steps of velocity and acceleration in the x, y, and z direction, \( \{x_{t-149}, x_{t-148}, ..., x_{t-1}, x_t\} \). The outputs are the predicted velocity and acceleration in the x, y, and z direction for 1 time step into the future, \( \hat{x}_{t+1} \), where \( \hat{x} \) indicates a predicted value.

Our neural net formulation uses what Engel et al. describe as iterated prediction [22]. The neural network itself only predicts 1 time step into the future. Then, the prediction, \( \hat{x}_{t+1} \), is appended to the input to give \( \{x_{t-149}, x_{t-148}, ..., x_{t-1}, x_t, \hat{x}_{t+1}\} \). The first step of the input is dropped to obtain a new input of past motions for the neural net, \( \{x_{t-148}, x_{t-147}, ..., x_{t}, \hat{x}_{t+1}\} \). The new data is input into the neural net which outputs a prediction 1 step forward, but 2 total steps into the future, \( \hat{x}_{t+2} \). This is then appended to the input. The process is repeated 50 times to obtain a prediction of 50 steps, \( \{\hat{x}_{t+1}, \hat{x}_{t+2}, ..., \hat{x}_{t+49}, \hat{x}_{t+50}\} \). Because the outputs of each prediction step become the inputs for the next, the inputs and outputs must be the same variables.

C. Training

We pre-processed the data for the neural net to improve the results. The velocity and acceleration data were scaled to have 0 mean and standard deviation of 1 over the entire set of data. This was then inverted on the output to show the results in their proper units. This same scaling can be used on new data even though the mean and standard deviation will be different. All trials with bad data were thrown out. Where data was considered bad because of missing poses from motion capture where too many motion capture markers were occluded from the cameras. Each dyad was assigned randomly to training and validation sets. 75% of the data were assigned to the training set and the other 25% to the validation set.

The neural net has to be trained in a special way in order to make the iterated prediction \( \hat{x}_{t+1} \) stable beyond the first step. This process, described here, comes from [22]. Batches of data were created that randomly pulled in 32 sets of 150 steps of data from the entire training set. Another 32 sets of 150 steps were created from the validation set. The entire set of data consists of 2.5 million steps. The neural net was trained on new training batches until the cost function reached a value less than a threshold that we chose for 5 consecutive validation batches. We used the mean squared error (MSE) for the cost function.

\[
MSE = \sum_{n=1}^{32} (\hat{x}_{n,t+1} - x_{n,t+1})^2
\] (1)

The set in the batch is represented by \( n \). Once the MSE was below the threshold for 5 consecutive batches, a prediction was calculated for every possible set of 150 steps of data. A new data set was created that used 149 steps of real data and the prediction appended to the end, \( \{x_{t-148}, x_{t-147}, ..., x_{t-1}, x_t, \hat{x}_{t+1}\} \). The neural network was then trained on a combined data set that included the original data and the new data set that included the prediction. Once this training was complete, a new data set was created with 148 steps of real data and two predictions after it, \( \{x_{t-147}, x_{t-146}, ..., x_{t-1}, x_t, \hat{x}_{t+1}, \hat{x}_{t+2}\} \). The same neural net was then trained again. This is continued until the neural net will no longer converge in a reasonable time. By training the neural network on data that includes predictions, the stability of the prediction is improved.

The length of the prediction is limited by our computational resources as we train the neural network. Our neural net predicts for 50 steps, or .25 seconds into the future, because it was difficult for the neural net to predict beyond that. We do not know if this is because of a fundamental limit on the ability to predict after that amount of time. We imagine there would be such a limit as the dyad has time to make decisions on where to move, but determining how long it would be for different teams is for future work. It could also be due to limitations in the implementation of our neural network which could be improved in the future.

The neural net was trained several times with the data split up randomly by dyad each time. This ensured that the neural net would be generalizable to an entirely new dyad.

V. ROBOT PLATFORM AND CONTROLLER

The purpose of predicting human intent is to have the robot use the prediction. Our robot platform for this research is a Rethink Robotics Baxter robot mounted on an AMP-1 holonomic base from HStar Technologies as seen in Figure 2. We chose to use a holonomic base with mecanum wheels instead of something like a bipedal robot in order to validate the human intent prediction at speeds similar to two humans moving an object in every day life. This is important to ensure that it works in real world applications as limiting speed may affect the dynamics of the interaction.

We validated the neural network by predicting human intent as a human and robot carry the table together. To perform this validation, we implemented a controller that does not yet use the prediction of the neural network. The
Baxter arms are rigidly attached to the table. Each arm is running a low impedance controller with a commanded joint angle specified by the position of the arm relative to the table before the task begins. When the arms are displaced, the mobile base displaces by the same amount in order to put the arms in their original pose relative to the base.

VI. RESULTS AND DISCUSSION

Fig. 3: Comparison of velocity prediction to actual future data in the x, y, and z directions while a human dyad moves the table. Each red line is a separate 50 step prediction using the 150 steps before it.

Fig. 4: Predictions using the neural net and a polynomial estimator for velocity in one task. While both are accurate in most cases, in several cases the polynomial prediction is far from the actual data.

Fig. 5: Predictions using the neural net and a polynomial estimator for velocity in one task where white noise has been added. The noise causes the polynomial prediction to go completely unstable while the neural network prediction is fairly robust.

A. Neural Net Performance

Figure 3 shows the neural network predictions of velocity in the x, y, and z direction for a single representative task. The actual velocity is shown for the whole task in blue. The predicted velocity is shown in red starting every second and each one continues for 50 time steps or .25 seconds. As seen, the predictions are very accurate for that time scale. Here we only show velocity, but the acceleration data must also be predicted because each velocity prediction depends on the prediction of acceleration for the time step before it. Without acceleration data, the neural net performance degrades.

B. Comparison to Polynomial Fit Predictor

We developed a polynomial fit estimator to compare to our neural network. It also takes in the previous 150 steps and fits an 8th order polynomial. The 8th order was chosen...
Fig. 6: Mean squared error of the neural network prediction and the polynomial prediction for 0.5 seconds using the training data set. The neural net is specifically trained for the first 0.25 seconds which are flat, after which the performance of the neural network significantly degrades.

because it had the best performance. The polynomial is then extrapolated forward 50 steps just like the neural net prediction. These are compared for a single random task in Figure 4. The polynomial fit is accurate in many cases but is more prone to large errors. Figure 5 shows how added noise affects the polynomial fit more than the neural network. This is a major issue as filtering the function to be smooth takes away time from the prediction so that it cannot estimate as far into the future.

C. MSE of each Predictor

Figure 6 shows the MSE of the prediction from the start of the prediction to 0.5 seconds, or 100 time steps, using the data set that was used to train the neural net. Figure 7 shows the same thing using the validation set. The similarity of these shows that the neural net does not overfit the data. This is the average of the predictions from every time step. As seen, the polynomial prediction is very good but degrades quickly. The neural net is very accurate for the 0.25 seconds that it was trained for, after which it quickly degrades. Interestingly, the first 50 steps are all predicted with the same accuracy. This is due to the way the neural net is trained. Figure 8 shows the MSE with white noise added. The amplitude of the noise is consistent with the noise of the end effector position on our robot. The polynomial prediction degrades very quickly.

D. Estimation with a Robot in the Loop

We ran the estimator while a human-robot dyad moved the table. This was not guaranteed to work because the dyad could not be expected to interact like a human-human dyad. Figure 9 shows that the neural net predicted the future motion very well even though the dynamics were different. A robot could use the prediction of human intent to be a better assistant.

It is clear that the neural net estimator is able to predict human intent over a short time horizon. There may be additional methods that can improve on this prediction. However, this shows that an accurate and reliable prediction can be made.

VII. Conclusions

We have shown that human intent can be estimated accurately from previous motion of the object that is being co-manipulated. We have also shown that with a mobile robot using a very simple controller in the loop, the prediction method is still valid. This work lays the foundation for future controller development which could use the human intention as a direct input or which could mediate the human intention and modify it to improve overall performance through haptic or other means of communication. Ideally, the human and robot would share the leadership of the task. Advantages for this capability to share leadership include the following:

- The robot could be in a position to be a more efficient
leader.
- The robot could better keep away from its own joint limits.
- The robot could keep the human from violating constraints of the task (e.g., the object can not rotate more than 15 degrees of the object is person on a stretcher).
- The robot could have knowledge of the environment not known by the human operator [18].

Interestingly, although even a short prediction into the future should allow the robot to work better with the human, we have been able to predict motions over a time horizon that is comparable to human reaction time. This seems to imply that if used in a closed-loop control scheme, this estimator would be enough to help a robot perform more like a teammate and less like a tool. We expect that this research along with future controller development will allow robots to work more intuitively and effectively with humans in collaborative object manipulation tasks.

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