**An autonomous human-accompanying robot using multi-model estimation and model predictive control-based motion planning**

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***Abstract*— This report proposes a method for robots to autonomously follow humans in a socially acceptable manner. Robots utilize Interactive Multiple Model approach to estimate human trajectory from noisy sensor data and predict human future motion states over a finite horizon. Robots employ the model predictive control method for motion planning. This approach enables the human-following behavior that takes into account the safety, comfortableness and naturalness of the motion. The effectiveness of the method in facilitating the socially acceptable following behavior is evaluated through a simulation.**

I. INTRODUCTION

Autonomous human-aware robot motion planning is a challenging problem and its solution has numerous appli- cations. For example, accompanying robots for elderlies will benefit from motion planning approach that enables robots to follow people in a safe and comfortable way. This requires robots to stay within a proper distance from the accompanied person while avoiding collision with him/her. Aside from the traditional requirement of robot path planning that focuses on obtaining the optimal path from one position to another in real-time, the human-aware robot motion planning needs to take the existence of humans into account. This imposes certain requirements on the robot motion, such as safety, comfortableness and naturalness. Safety serves as the funda- mental requirements for robots to interact with humans that requires robots to avoid hurting humans. Based on the def- inition in [1], comfortableness requires robots to pose little annoyance and stress for humans when interacting with them while naturalness emphasizes the similarity between robots and humans in low-level behavior patterns. In this work, we develop an approach for robots to follow humans in real-time fashion without prior knowledge of the human trajectory. The planned robot motion takes the safety, comfortableness and naturalness requirements into consideration.

We divide the human-aware motion planning into three

steps. In the first step, robots need to keep track of the human motion states in real time based on the observed human trajectory obtained from equipments such GPS sen- sors. Due to the sensor noise, measurement results need filtering. Many filtering methods exist, such as the Kalman filter [2] and the Particle filter [3]. In this work, we utilize the Interactive Multiple Model (IMM) approach. It consider different dynamics models in a uniform way and thus can capture the different motion patterns of humans. In the second step, robots need to predict human future states. This motion prediction composes an interesting but difficult topic due to the lack of a precise human dynamics model. Several methods have been utilized such as regression-based

approaches [4] and learning-based approaches [5], [6]. In this work, we extends the IMM estimator to incorporate the prediction functionality. Since the IMM approach utilizes different dynamics models, it offers possibility for provid- ing more accurate prediction results than traditional single- model approach in cases where human‘s behavior involve multiple motion models. The third step refers to the robot motion planning based on the predicted human states. Motion planning considering constraints, such as the aforementioned safety, comfortableness and naturalness requirements, tends to be difficult. Researchers have developed various methods, such as the potential field method [7] and the graph-search- based methods [8]. However, these methods usually assume simple dynamics model of robots and are thus applicable for limited conditions. Besides, these methods cannot take into account complex constraints, which renders them less suitable for human-aware motion planning. We adopt the model predictive control (MPC) approach that can explicitly model and solve for the desired robot behavior.

There are several works on the autonomous humanfollow- ing robot. [8] develops a robot for telepresence usage. It uses the laser scanner to track human positions and predicts human future path by extrapolating the estimated human position and velocity. It applies the depth-limited breadth- first search to find the future waypoints for the robot to move to. [9] uses laser range finder and data association filters for estimating human positions. Potential field method is utilized for predicting human future motion. Robot path planning is achieved by using the expansive-spaces trees method. [6] focuses on the human motion estimation and prediction. It develops a filter for human motion estimation that can deal with abrupt human direction change when he/she makes turns. Artificial neural network (ANN) is adopted for human motion prediction.

Our method differs from those works. In this work, the IMM-based estimation and prediction take different human movement patterns into account, which [9] does not deal with. Besides, this IMM-based prediction approach does not require large data training, which differs from the ANN method in [6]. MPC-based path planning enables optimal path planning in finite horizon while considering the safety, comfortableness and naturalness requirements, which meth- ods in [8] cannot achieve. Our approach provides a general and efficient way for autonomous robots to accompany humans.

The remainder of this report is organized as fol- lows. In Section II we formulate the autonomous human- accompanying problem. In Section III we introduce our

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1. METHODS

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* 1. *Human Tracking*

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0

0 20 40 60 80 100

Fig. 1. A scenario for an autonomous robot to accompany human. The red circle and the green triangle represent the human and the robot, respectively. Stars denote human destinations while blue circle and semicircles stand for obstacles.

methods for human tracking, human motion prediction and robot motion planning. Section IV describes the simulation setup and results for evaluating our approach, followed by discussions of the results. We present some concluding remarks and future work in Section V.

II. PROBLEM FORMULATION

We consider a scenario (Fig. 1) in which a human will move to several different destinations in a field and a robot autonomously accompanies him/her. In Fig. 1, stars represent destinations that the human will visit. The red circle and the

We apply the Interacting Multiple Model (IMM) approach for estimating the human motion from the noisy sensor data. The IMM approach has been generally considered as the mainstream method for maneuvering target tracking. It utilizes a bank of *r* number of Kalman filters, each designed to model a different dynamics model. IMM algorithm is a suboptimal algorithm based on the minimum mean square error criterion. In the IMM estimator, state estimate at time *k* is computed with mode probability and state estimates from each possible current model associated with one of the *r* filters, using the following formula:

*r*

*z*ˆ(*k|k*) = \ *µj* (*k*)*z*ˆ*j* (*k|k*)

*j*=1

where *r* denotes the number of models; *x*ˆ*j* (*k|k*) represents the state estimate from the *j*th filter; *µj* stands for the mode probability computed as follows:

*r*

*µj* (*k*) = 1*/c* \ *Lij* (*k*)*pij µj* (*k −* 1)

*i*=1

where *c* denotes the normalizing factor, *Lij* (*k*) stands for the likelihood function and *pij* represents the mode transition

green triangle denote the human and the robot, respectively.

probability from the *i*th

to the *j*th

filter. Each filter uses the

Several obstacles exist in the field, shown as the blue circle and semicircles. Neither the human nor the robot can step into or cross the obstacles. The positions of destinations and size of obstacles are known a priori.

In this process, the human moves to destinations sequen- tially and the robot needs to accompany the human au- tonomously. The robot has no knowledge about the human‘s destination. However, it can obtain the human positions over time from a GPS sensor. To make the robot’s behavior natural and acceptable by humans, we require the robot to satisfy the three kinds of requirements, as mentioned in Section I. To be specific, safety concern requires the robot to avoid colliding with the human or any obstacles. Comfortableness requires that the robot maintain a proper distance from the human all the time. The naturalness requirement necessitates that the robot keep pace close to that of the human. We

mixed initial state estimate and covariance from different

combination of the previous model. Readers interested in the details of the IMM approach can refer to [10].

We model the human tracking procedure with the discrete time system as follows:

*zh*(*k* + 1) = *Azh*(*k*) + *Bw w*(*k*) (1a)

*yh*(*k*) = *Czh*(*k*) + *v*(*k*) (1b)

where *zh*(*k*) and *yh*(*k*) represent the human motion state and the observation, respectively, at the time step *k*; *w*(*k*) and *v*(*k*) represent process noise and measurement noise, respectively. *z*(*k*) consists of four elements: *x, x*˙ *, y, y*˙, where *x, y* denote the longitudinal and lateral position of the human

model both the human and the robot as point masses in this

and *x*˙ *, y*˙

the corresponding velocity. We use two Kalman

work. We apply our method to the robot so that it can track human motion and plan its own behavior. The performance of the robot will be evaluated based on these three types of requirements.

filters in the IMM for human tracking, each corresponding to a different dynamics model: the uniform motion model and the turn motion model. Two models differ in the *A* matrix in Eq. (1a) while sharing the same *Bw* and *w*. In particular,

we define the matrices as follows:

starting from the new state. We use (*zr* (*k*)*, vr* (*k*)*, θr* (*k*)) to

 1 *T* 0 0

*AU* =  0 1 0 0

 0 0 1 *T*



0 0 0 1



 *,* (2a)





denote the robot state at time *k*, representing the position, velocity and heading, respectively. The control input consists of the acceleration *a* and the angular velocity *w*. We adopt a discrete-time bicycle model with limited acceleration and angular velocity for robot dynamics, which can be formulated

 1 sin(*wT* )

*w* 0

1*−*cos(*wT* ) 

*w*

as follows:

*AT* =  0 cos(*wT* ) 0 *−* sin(*wT* ) 

1 cos *θ*(*k*) 1

  ¯

 0 1*−*cos(*wT* )

*w* 1

sin(*wT* )

*w*

*,* (2b)



*zr* (*k* + 1) = *zr* (*k*) + *vr* (*k*)

sin *θ*¯(*k*)

*T* (5a)

0 sin(*wT* ) 0 cos(*wT* ) *r r*

*Bw* =

1 *T* 1 0 0 1

0 0 *T* 1

*,* (2c)

*v* (*k* + 1) = *v* (*k*) + *a*(*k*)*T* (5b)

*θr* (*k* + 1) = *θr* (*k*) + *w*(*k*)*T* (5c)

*w ∼ N* (0*, Q*) (2d)

where *AU* and *AT* stands for the *A* matrices of the uniform motion model and turn motion model, respectively; *T* rep- resents the sampling time and *w* denotes the constant turn rate.

(5d)

Considering the time step *k*, we formulate the MPC problem that incorporates the dynamics of robot and the requirement for robot motion:

*N*

We assume that only the human position can be measured. Therefore, the parameters in observation model Eq. (1b) can be defined as:

1 1 0 0 0 1

min

**A***k ,***Θ***k*

subject to

\ *w*1*||z*¯*r* (*k* + *i|k*) *− z*˜*h*(*k* + *i|k*)*||*2+

*i*=0

2

*w*2*|v*¯*r* (*k* + *i|k*) *− v*˜*h*(*k* + *i|k*)*|*2 (6a)

*z*¯*r* (*k* + *i* + 1*|k*) = *z*¯*r* (*k* + *i|k*)

*C* = 0 0 1 0

*,* (3a)

+ *v*¯*r* (*k* + *i|k*)

1 cos *θ*¯(*k* + *i|k*) 1

*T* (6b)

*v ∼ N* (0*, V* ) (3b)

These models are commonly used in the multiple model approach.

sin *θ*¯(*k* + *i|k*)

*v*¯*r* (*k* + *i* + 1*|k*) = *v*¯*r* (*k* + *i|k*) + *a*¯(*k* + *i|k*)*T*

(6c)

*θ*¯*r* (*k* + *i* + 1 *k*) = *θ*¯*r* (*k* + *i k*) + *w*¯(*k* + *i k*)*T*

We apply the above two models for human motion state estimation.

*| | |*

(6d)

* 1. *Human Motion Prediction*

*alb ≤ a*¯(*k* + *i|k*) *≤ aub* (6e)

*wlb ≤ w*¯(*k* + *i|k*) *≤ wub* (6f)

We utilize the estimated human motion state and the mode

probabilities for predicting human future states. Let *z*ˆ*h*(*k|k*)

*||z*¯*r* (*k* + *i|k*) *− z*˜*h*(*k* + *i|k*)*||*2

*≥ dc* (6g)

*i r h*

and *z*˜*h*(*j|k*) represent the estimated and predicted human

*||z*¯ (*k* + *i|k*) *− z*˜ (*k* + *i|k*)*||*2 *≥ ds* (6h)

*i*

*th r*

*obs*

position associated with the *i*

model at time *k* and *j* (*j ≥*

*||z*¯ (*k* + *i|k*) *− zp ||*2 *≥ dobs* (6i)

*k*) respectively. Using the uniform motion model and turn *r r*

motion model, we can extrapolate human positions for each model and combine them based on the mode probabilities. To be specific, the prediction procedure works as follows:

*||λz*¯ (*k* + *i|k*) + (1 *− λ*)*z*¯ (*k* + *i* + 1*|k*)*−*

*p ||*2 *≥ dobs, ∀p* = 1*, . . . , m,* 0 *≤ λ ≤* 1

*zobs*

(6j)

*r r*

*r*

*z*˜*h*(*k* + *i* + 1*|k*) = \ *µj z*˜*h*(*k* + *i|k*)*, i* = 0*, . . . , N −* 1

*j*

*j*=1

*z*¯ (*k|k*) = *z* (*k*) (6k)

*v*¯*r* (*k|k*) = *vr* (*k*) (6l)

*θ*¯ (*k|k*) = *θ* (*k*) (6m)

(4a)

*r r*

*r r* ¯

*z*˜*h*(*k|k*) = *z*ˆ*h*(*k|k*)*, j* = 1*, . . . r* (4b)

where

*z*¯ (*j|k*),

*v*¯ (*j|k*) and

*θ*(*j|k*)*, j ≥ k* represent the

*j j* planned positions and velocities of the robot at time *j* and

where *N* is the prediction horizon.

* 1. *Robot Path Planning*

As mentioned in Section I, a desirable robot motion should satisfy the comfortableness, naturalness and safety requirements. The model predictive control (MPC) method provides an effective framework for incorporating these requirements into the robot motion planning. MPC iteratively solves a constrained finite time optimal control problem with receding horizon. After obtaining the optimal series of control inputs at current state, it implements the first input and then compute for a new series of control inputs,

(**A***k ,* **Θ***k* ) stand for the set of optimal acceleration and angu- lar velocity over the time range [*k, k* + *N −* 1], obtained from

the MPC problem at time *k*. The objective function Eq. (6a) consists of two terms; the first summation denotes the square sum of differences between planned robot positions and predicted human positions over the horizon *N* and the second summation represents the sum of differences between the planned robot velocity and predicted human velocity over the horizon. This reflects the naturalness requirements that the robot stay close to the accompanied human and keep similar pace. Eqs. (6b) to (6d) represent the discrete-time robot dy- namics model. Eq. (6e) and Eq. (6f) denote the constraints on

the angular rate and acceleration, respectively, with *alb, wlb*

being the corresponding lower bounds and *aub, wub* the upper 90

bounds. Eq. (6g) imposes the comfortableness requirement

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that the robot keep a distance *dc* from the predicted human

position at every time step within the planning horizon *N* . 70

Eq. (6h) requires that the robot maintain a distance *ds* away 60

from the human, which avoids collision between the human

Y position [m]

50

and the robot. Eqs. (6i) and (6j) reflect the requirements

on the obstacle collision avoidance. In particular, Eq. (6i) 40

demands that each way point of the robot be kept outside of 30

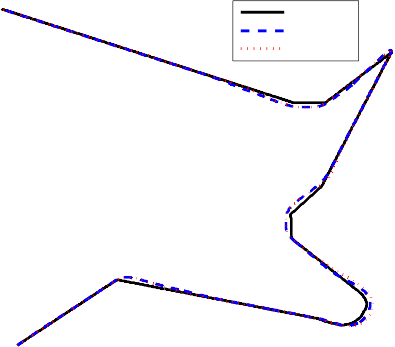
obstacles and Eq. (6j) requires that the trajectory connecting 20

the adjacent way points not intersect with obstacles. The

10

initial state takes the value of the robot‘s actual state at time

Tracking of Human Position



*k*, which are reflected in Eqs. (6k) to (6m).

At every time step, the robot solves this MPC problem with a finite horizon *N* and obtains the optimal inputs. For example, at time *k*, the optimal inputs consist of *N* pairs of acceleration and angular velocity (*a*(*k*)*, w*(*k*))*,* (*a*(*k* +

1)*, w*(*k*+1))*, . . . ,* (*a*(*k*+*N −*1)*, w*(*k*+*N −*1)). (*a*(*k*)*, w*(*k*))

is applied and a new MPC problem is formed at time *k* + 1

using the updated state (*zr* (*k* + 1)*, vr* (*k* + 1)*, θr* (*k* + 1)) as the initial conditions.

0

0 10 20 30 40 50 60 70 80 90

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|  |  |  |  |  | Reference IMM  SM | | |  |
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X position [m]

Fig. 2. Comparison of tracking performance using the IMM-based and single-model approaches

X Position Error = Ref − Est 2

1

Position [m]

1. SIMULATION RESULTS & DISCUSSION 0
2. *Simulation setup* −1

−2

IMM

SM

We have implemented a simulation to evaluate our ap-

proach.

1. *Simulation results*

We evaluate the performance of human tracking, human motion prediction and robot motion planning methods, re- spectively.

* 1. *Human tracking:* We measure the error between the estimated and real human positions and speeds at each time step to evaluate the estimation accuracy, which can be formulated as:

0 20 40 60 80 100 120 140 160

time [sec]

Y Position Error = Ref − Est 2

1

Position [m]

0

−1

−2

−3

0 20 40 60 80 100 120 140 160

time [sec]

Fig. 3. Comparison of position estimation error between the IMM-based and single-model approaches

*z* (*k*) = *zh v* (*k*) = *vh*

∆*t*

∆*t*

(*k*) *− z*ˆ*h*(*k|k*) (7a)

(*k*) *− v*ˆ*h*(*k|k*) (7b)

2

X velocity Estimation

Reference

where *zh*(*k*) and *vh*(*k*) denotes the actual human position 1

Speed [m/s]

and velocity at time *k*. Note that the ∆*t* (*k*) and ∆*t* (*k*) are

IMM

SM

vectors.

*z v* 0

−1

We compare this method with a single-model estimator

that adopts the same uniform motion model in IMM but without the turn motion model. Fig. 2 shows the tracking results using these two methods. They achieve similar esti- mation results. However, we can notice that, at the bottom right part of the plot, where the human makes a circular turn, the IMM methods estimates more accurately than the single- model approach. This occurs because the IMM estimator contains the turn motion model, which can better capture the turn motion than the uniform motion model. To obtain detailed comparison of these two methods, we compare the IMM-based and the single-model estimators using Eqs. (7a) and (7b).

−2

0 20 40 60 80 100 120 140 160

time [sec]

Y velocity Estimation 2

1

Speed [m/s]

0

−1

−2

0 20 40 60 80 100 120 140 160

time [sec]

Fig. 4. Comparison of speed estimation error between the IMM-based and single-model approaches

1

0.9

0.8

0.7

0.6

Probability

Mode probablity

4.5

4

3.5

3

distance/m

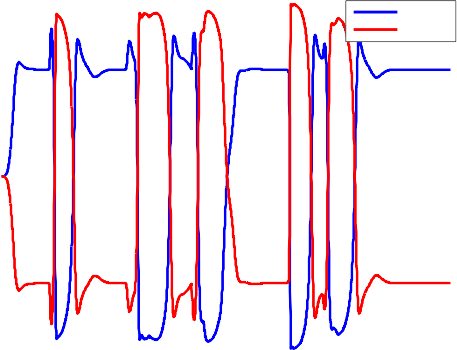
2.5

Prediction difference

imm

extpol

0.5 2



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0.4

0.3

0.2

0.1

0

0 20 40 60 80 100 120 140 160

time [sec]

1.5

1

0.5

0

0 50 100 150 200

time/s

Fig. 6. Comparison of prediction error between the IMM-based and single-

Fig. 5. Model probabilities of two models in the IMM estimator

Fig. 3 shows the estimation error on longitudinal and lateral directions using two different estimators. Two meth- ods achieves similar performance while the IMM estimator shows smaller estimation error at time 55 and 103, when the human turns around the circular obstacle and makes sharp turn after arriving at a destination, respectively. Fig. 4 com- pares the differences of speed estimation. We can notice that, IMM estimator achieves faster tracking than single-model approach when the speed changes abruptly. This makes sense as the IMM estimator incorporates turn motion model that can capture the sudden speed changes. Fig. 5 shows the mode probabilities of the uniform motion model and turn motion model over time. When the human speed changes, the mode probability of the turn motion becomes higher than that of the uniform motion. These changes illustrates the reason that the IMM estimator achieves more accurate and faster estimation than the single-model estimator at the sharp turn and circular turn. This figure demonstrates the necessity of applying IMM estimator for human tracking.

* 1. *Human motion prediction:* We evaluate the IMM-based prediction approach by measuring the prediction error over the horizon *N* . To be specific, at time *k*, the prediction error is defined as:

model approaches

works as follows:

*z*˜*h*(*k* + *i* + 1*|k*) = *z*˜*h*(*k* + *i|k*) + *v*˜*h*(*k* + *i|k*)*T,* (9a)

*i* = 0*, . . . , N −* 1

*v*˜*h*(*k* + *i* + 1*|k*) = *v*˜*h*(*k* + *i|k*)*, i* = 0*, . . . , N −* 1 (9b)

*z*˜*h*(*k*) = *z*ˆ*h*(*k*) (9c)

*v*˜*h*(*k*) = *v*ˆ*h*(*k*) (9d)

Fig. 6 compares the prediction errors using these two different methods. It shows very similar performance be- tween two approaches. However, we can notice that, when the human makes turns at time 103, the IMM-based method achieves smaller prediction error than the single-model ap- proach. This makes sense as IMM-based method considers the turn motion model that captures the turning behavior of the human. However, since we use a simple human behavior that the human keeps constant speed and moves in straight lines without changes in heading for a large portion of the trajectory, the single-model approach can achieve similar prediction performance as the IMM-based method.

* 1. *Robot motion planning:* We evaluate the performance

of the robot motion planning using the criterion of safety, comfort and naturalness. To be specific, we measure the distance and speed difference between the robot and the human at each time step. At time *k*, they can be defined as:

*i*=*N*

∆*p*(*k*) = \ *|z*˜*h*(*k* + *i|k*) *− zh*(*k* + *i*)*|* (8)

*i*=1

We compare this approach with the single-model approach and compare its prediction error with the IMM-based method using Eq. (8). Different from the IMM-based prediction approach that extrapolate the human position by a weighted sum of the predicted positions from each model, the single model method only utilizes the uniform motion model for prediction. In particular, at time *k*, the single-model method

∆*d*(*k*) = *||zr* (*k*) *− zh*(*k*)*||*2 *− dc* (10a)

∆*v* (*k*) = *|vr* (*k*) *− vh*(*k*)*|* (10b)

We compare the MPC-based motion planning with a reactive motion planning method using Eqs. (10a) and (10b). With the reactive method, the robot uses one-step prediction of human position and heads for it while keeping the safe and comfortable distance from the human and matching up with the human speed.

Fig. 7 compares the distances between the human and the

robot using these two approaches. Notice that the distances in the plot has been substracted by the comfortableness distance *dc*. Therefore, the ideal distance is 0 at each time step. **[Note:]** fill in the quantities here

3

2.5

2

1.5

distance/m

1

0.5

0

−0.5

−1

−1.5

Distance difference

mpc greedy

method while in MPC method the velocity difference only composes one term in the objective function with a smaller weight than the distance term. However, in spite of the small speed difference using the reactive method, the resultant large human-robot distance, as shown in Fig. 7, renders such closeness on speed less attractive. In fact, the proper distance between the human and the robot composes the core part of a human-accompanying robot.

1. CONCLUSION

We developed a method for human-following robots‘

0 50 100 150 200

time/s

Fig. 7. Comparison of distance between the human and the robot using two methods

Velocity difference

motion planning that considers the safety, comfortableness and naturalness of the behavior. We applied the IMM-based approach for human position estimation and prediction. MPC framework was utilized for the robot‘s motion planning. We compared the IMM-based estimation with a single model

2.5

2

1.5

1

speed/(m/s)

0.5

0

−0.5

−1

−1.5

mpc greedy

0 50 100 150 200

time/s

estimation approach. We also compared the prediction per- formances using these two approaches. Comparison results showed similar prediction accuracy between these methods but the IMM-based approach achieved better performance when the human made circular motion or sharp turns since it incorporated the turn motion model. The MPC motion planning approach was compared with a reactive motion planning method. The results showed better performance using the MPC framework in achieving smaller human- robot distance. The reactive policy achieves smaller velocity differences than the MPC method. However, this becomes less attractive as the resultant human-robot distance becomes

Fig. 8. Comparison of velocity differences between the human and the

robot using two methods

We can notice that, using MPC-based motion planning, xx% of time the distance falls within the range of [0*,* 1] with the largest and smallest distances of xxx and xxx, respectively. On the contrary, the reactive method results in distances greater than 1 for xxx% of time while the smallest

distance drops to *−xxx*. This shows the benefits of using

the MPC framework for motion planning compared to the

reactive approach. The differences mainly comes from the multiple-step prediction that the MPC method utilizes. Due to the limited angular velocity and acceleration, the robot needs to predict several steps ahead in order to stay within the proper distance from the human. The reactive method, however, only takes into account one-step prediction. This myopic strategy renders the robot less capable to adjust its control input for human’s future positions. Another benefit of using MPC method comes from its natural incorporation of various requirements by formulating them as the objective function and the constraints. In contrast, designing a reac- tive method that considers different requirements becomes time-consuming and even infeasible when the complexity of requirements increases. Fig. 8 compares the velocity differences between the human and the robot using two methods. We can notice that the reactive method results in smaller velocity difference than the MPC approach. This makes sense as we explicitly requires the robot to match up with the human speed at every time step using the reactive

very large.

In the future work, we plan to apply other prediction methods, such as the Autoregressivemoving-average method, to compare with our current method. We also plan to enable the robot to learn the human model in real time, which may provide more accurate human motion prediction and therefore better human-following behaviors.

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