Elective in Robotics – Locomotion and Haptic interfaces

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Multiple users on Powered Shoes

Master's Degree in Artificial Intelligence and Robotics

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1 Introduction

In virtual environment applications, users need a good sense of movement. In the past years, there have been several prototypes of interface devices (e.g., treadmills and carpets) in order to create infinite surfaces for walking. However, these systems require cumbersome drive mechanisms. Therefore, the aim of the Powered Shoes project is to provide motor-driven roller skates in order to develop a wearable locomotion interface that enables users to walk in all directions while maintaining their position.

Figure 1: Overall view of the Powered Shoes

In our work, we are going to implement a system of users wearing the Powered Shoes moving in a room of limited size. Each user needs to avoid both the other users and the walls of the room; in order to achieve this, we have used a velocity-level decentralized control based on Artificial Potential Fields.

Code and simulation results are available here: `https://github.com/verovulcano/LHI---Powered-Shoes.git`.

2 Control design

The position of each user is estimated in every instant of time using data from cameras and each user has a certain intentional velocity in order to move throughout the virtual environment. The Powered Shoes have to cancel the motion of the step by moving in the opposite direction of the walker with respect to the measured one. Even though the position of the user should be fixed in the room, the user can freely change direction while walking.

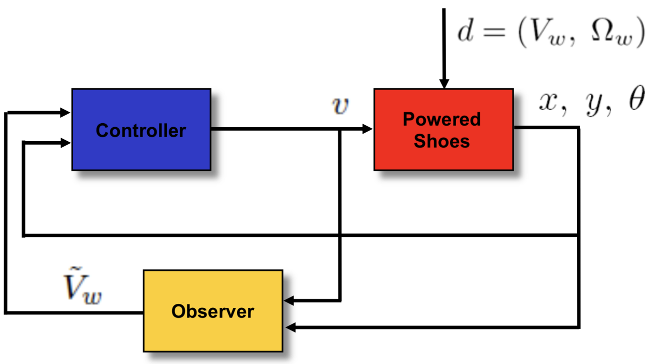


Figure 2: Block scheme of the controller

As we can see from the upper figure, the intentional velocity of the user is seen as a disturbance and is estimated by an observer starting from the user state and the control input.

2.1 Kinematic model

The state of the walker is given by:

$$q = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} \tag{1}$$

Where x and y represent the walker position in the room frame (that is the absolute frame) and θ is the angle between the walker frame and the room frame. The kinematic model is the following:

$$\begin{cases} \dot{x} = -v\cos\theta + V^r_{w,x} \\ \dot{y} = -v\sin\theta + V^r_{w,y} \\ \dot{\theta} = \Omega_w \end{cases} \tag{2}$$

Where v is the control input (velocity of the shoes), $V^r_{w,x}/V^r_{w,y}$ is the linear intentional velocity of the walker along the x/y component in the room frame and Ω_w is the angular intentional velocity of the walker. The walker motion is an unknown "disturbance" for the controller that will be estimated trough an observer. In fact, the only value that we can measure is the position of the user (i.e., x, y and θ), while its intentional velocity will be unknown. Our control design will have to take into account that this acts as a disturbance; in fact, since we cannot measure its real value, we cannot compensate for it in a direct way.

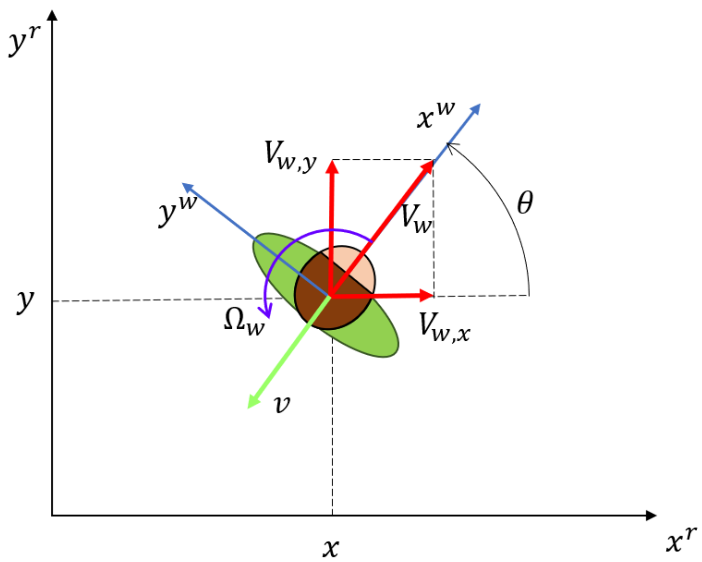


Figure 3: In this figure, the room reference frame and the user reference frame are reported.

2.2 Controller

The control input v is given by the sum of two components:

$$v = v_{ff} + u \tag{3}$$

Where v_{ff} is a feed-forward term which takes into account the intentional velocity of the user and u is the command coming from the Artificial Potential Field for avoiding collisions. In fact, the motion command given to the shoes should cancel the estimated component of the user's intentional velocity so to keep the person still in the room. This cancellation is not perfect since it just takes into account the longitudinal direction; for this reason, the user will not be perfectly fixed in the room. To account for the residual motion, we need the control action coming from the Artificial Potential Field.

Artificial Potential Fields are a method to perform reactive navigation in which a stimulus response paradigm is built: the stimulus comes from sensor readings and the paradigm is to move in a way to avoid the obstacles. In our context, each user and each wall of the room produce a repulsive potential whose resulting repulsive force is given by:

$$f_{r,i}(q) = -\nabla U_{r,i}(q) = \begin{cases} \frac{K_{r,i}}{\eta_i^2(q)}(\frac{1}{\eta_i(q)} - \frac{1}{\eta_{0,i}})^{\gamma-1}\nabla\eta_i(q) & \text{if } \eta_i(q) \leq \eta_{0,i} \\ 0 & \text{if } \eta_i(q) > \eta_{0,i} \end{cases} \tag{4}$$

In the implementation, we have considered $\eta_{0,i} = \infty$, so in this case, each user can feel a repulsive force coming from any of the other users in the room independently from distance.
Then, the total force f_t is given by the sum of all $f_{r,i}$. In particular, if we have N people in the room and we consider a generic user, we have $N-1$ forces given by each of the other users and then 4 forces given by each wall of the room.

In our case, we use the kinematic model for controlling the robot since usually, in wheeled mobile robots, there are servo loops that take as reference the velocity. For this reason, we use the total force as generalized velocity $\dot{q} = f_t(q)$.

Anyway, the robot is subject to non-holonomic constraints and violates the free flying assumption, since it cannot move in any direction of space at any given time. Therefore, we need a way to transform the repulsive force coming from the APF into something that the robot can execute. The idea is to use the pseudo-inverse to map the artificial force into generalized velocity:

$$u = G^+(q)\dot{q}_{des} \tag{5}$$

Where, in our case, $\dot{q}_{des} = f_t$ coming from the APF.

In our case:

$$G(q) = \begin{bmatrix} -\cos\theta \\ -\sin\theta \\ 0 \end{bmatrix} \tag{6}$$

So, the pseudo inverse will be:

$$G^+(q) = \begin{bmatrix} -\cos\theta & -\sin\theta & 0 \end{bmatrix} \tag{7}$$

Since the force obtained through the potential field has three components $[f_x, f_y, f_\theta]$, then the control input to apply resulting from the Artificial Potential Field is:

$$u = -f_x \cos\theta - f_y \sin\theta \tag{8}$$

Anyway, we will have to sum the feed-forward component to this value in order to get the total control input to apply to the system.

The **feed-forward term** accounts for the intentional velocity of the user. This value will be estimated through an observer, therefore, it will not be equal to the real one. Moreover, we assume that there is an imperfect cancellation of the user motion; user steps are recovered in part (of about 90%) with directional uncertainty. This uncertainty is modeled as a Gaussian noise with 0 mean and 5° of variance. Therefore, the final controller will be:

$$v = 0.9\,V_{est} - f_x \cos(\theta + n_\theta) - f_y \sin(\theta + n_\theta) \tag{9}$$

where $n_\theta \sim \mathcal{N}(0, 5°)$. The term V_{est} is given by:

$$V_{est} = G^+(q) \begin{bmatrix} \tilde{V}^r_{w,x} \\ \tilde{V}^r_{w,y} \\ 0 \end{bmatrix} \tag{10}$$

When the scalar product between the intentional velocity estimated by the observer and the control input is positive (so, the angle between them is less than $\pi/2$), the control action is set to zero. In fact, in this case, the user is moving away from the obstacle by himself with its intentional velocity, therefore an additional repulsive component is not needed.

Finally, we have added a saturation on the total velocity and on its variation equal to $\pm 1\ m/s$ and $\pm 0.8\ m/s^2$ respectively.

2.3 Observer

As we said in 2.2, we need to cancel the intentional velocity of the user. In real applications, it is impossible to know in advance the intentional velocity of the user, but we need to estimate it online, while the user is using the platform.
To achieve this task, we set up an observer that has the goal to converge to the value of the intentional velocity of the walker.

An estimate $\tilde{V}_w$ of the walker intentional linear velocity V_w can be obtained by two dynamic observers (one for each component) with states ξ_x and ξ_y.

$$\dot{\xi}_x = -v\cos\theta + k_w(x - \xi_x) \tag{11}$$

$$\tilde{V}_{w,x} = k_w(x - \xi_x) \tag{12}$$

$$\dot{\xi}_y = -v\sin\theta + k_w(y - \xi_y) \tag{13}$$

$$\tilde{V}_{w,y} = k_w(y - \xi_y) \tag{14}$$

These are intended to be copies of the dynamics along the x and y directions that are affected by the intentional velocity, but instead of having the true values, we replace them by a compensating factor made of a gain and the difference between the measured variable and the state of the observer.
In this formulation only known quantities are present (such as the measured position and the control inputs), while $\tilde{V}_{w,x}$ and $\tilde{V}_{w,y}$ are the components of the unknown walker intentional velocity. In fact, the estimate is a first-order stable filter of the intentional walker's linear velocity. The filtered signal is delayed; how much is delayed is determined by the value of k_w. In order to reduce the delay, we have to increase k_w, but a k_w which is too high can introduce more noise.

3 Implementation

All the code is written in Matlab.

Trajectory Generation

In order to prove that our method is valid, it has to work with all possible user intentional velocities and give the impression that the user can move freely in his "virtual environment".
For this reason, we generated exciting trajectories that the users have to follow.

We generated exciting random intentional velocities according to the following formula:

$$f(t) = \sum_{l=1}^{L} \frac{a_{l,j}}{lw_f}\sin(lw_f t) - \frac{b_{l,j}}{lw_f}\cos(lw_f t) \tag{15}$$

where $L = 5$, $w_f = 0.15\pi$ and all $a_{l,j}$ and $b_{l,j}$ are randomly sampled between -1 and 1 with a uniform distribution.
After that, the function $f(t)$ is scaled and translated in order to fit our extremes value. After that, the function is translated in order to obtain a velocity profile that has $f(0) = 0$, in fact the user has to start with zero velocity so to simulate a real situation. So, the final function will be:

$$F(t) = f(t)\frac{(f_{max}^{des} - f_{min}^{des})}{(\max f(t) - \min f(t))} - (\max f(t) - f_{max}^{des}) \tag{16}$$

In the case of linear velocity, we also translate the function another time in order to obtain that $F^*(0) = 0$:

$$F^*(t) = F(t + \arg\min_t f(t)) \tag{17}$$

The limits we used for linear velocity are:

$$f_{max}^{des} = 1 \qquad f_{min}^{des} = 0$$

and for the angular velocity we set

$$f_{max}^{des} = 1.5 \qquad f_{min}^{des} = -1.5$$

The resulting function is chosen as a profile for the linear and angular intentional velocity of the user. In particular, this is used as a profile for the linear velocity along the x direction and for the angular velocity; in fact, the linear component along the y direction is set to zero.

Each user follows a different velocity profile, so we have generated 8 total velocity profiles to simulate the scene (4 linear profiles and 4 angular profiles).

Room

All the people wearing the Powered Shoes are situated in the same room. To instantiate the room, we define the dimension of the walls, the initial position of the users to position in it, their intentional velocities and some other technical parameters that are going to be used in the experiments. The room is implemented as a class; in this way, we can easily handle all the information relative to the elements in it such as people and their relative velocity observers. In fact, there are several methods in order to apply and compute the inputs for all the users.

Person with Shoes

Each person in the room is represented as a Matlab class. It has a specific position in the room reference frame represented by x, y and θ and moves accordingly to a desired intentional velocity. This class has different methods that are used to recover the position or the intentional velocity of the user. For instance, the position of the user is determined by applying the input in the kinematic model seen in 2.1 and performing a simple Euler integration, but we are also able to compute the input itself. Each user, indeed, has a function that allows to determine the force due to the artificial potential considering the position of the other users and of the walls.

Observer

The observer is implemented as a Matlab class. It just updates its state at each iteration considering the discrete version of the equations in 2.3. The equations have been discretized using Euler formulation.
In the state of the observer, there is the gain k_w; after a tuning procedure, we have set it as $k_w = 2$.

4 Experiments

We have made different experiments considering various situations. For each experiment, we have run 30 seconds of simulation.

4.1 One Person

As a first simulation, we are going to put only one person in the room. In this case, the initial position of the person will be set to $q = \begin{bmatrix} 1 & 1 & \pi/3 \end{bmatrix}$, so the person is in the lower left part of the room. Since there are no other people, the only obstacles in the computation of the Artificial Potential Field will be the walls. Therefore, we expect that the person will move towards the centre of the room; in this case, he can be equidistant from all the walls. Once he is placed at the centre of the room, the control input will be such that he will keep that position.

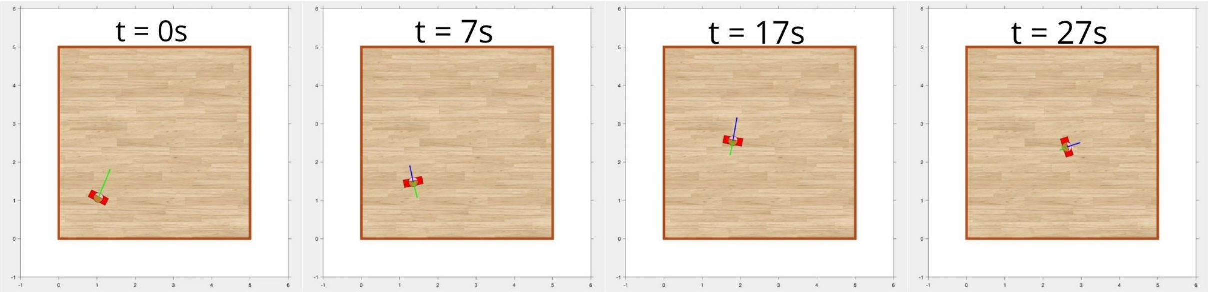


Figure 4: Evolution of one person

As we can see from these instants of time, especially in the first seconds of simulation, there is a strong control input that will try to move the person at the centre of the room despite its intentional velocity. Once he has reached the perfect position, the control action will reduce, but as soon as the person tries to move away, the control action will compensate for this motion.

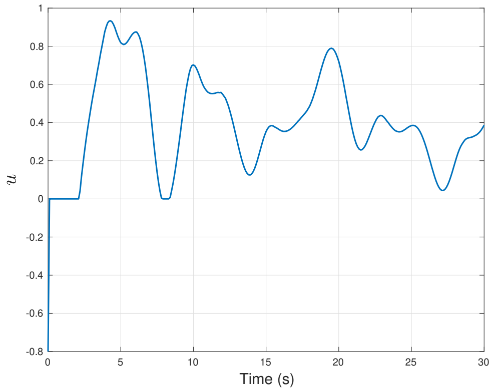


Figure 5: Control input

The input is always in the interval $[-1, 1]$, therefore it never reaches its saturation values. We also plot the component of the input only due to the Artificial Potential Field:

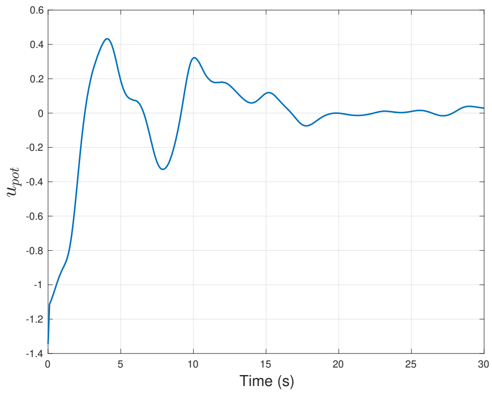


Figure 6: Projected repulsive potential

And of the clearance, that is the norm of the minimum distance between the person and the closest obstacle:

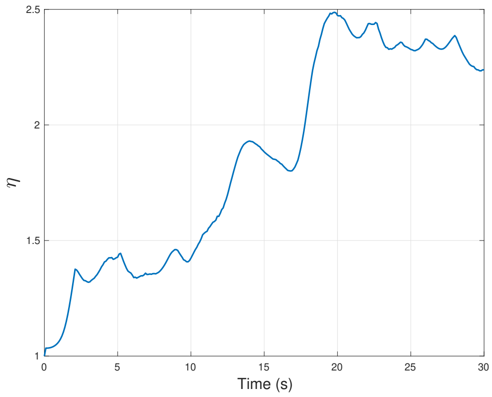


Figure 7: Clearance

As expected, the clearance increases during the simulation, in fact the person starts near the wall and ends the simulation in the center of the room. The goal is to have the clearance as big as possible.

Concerning the state of the person, we have:

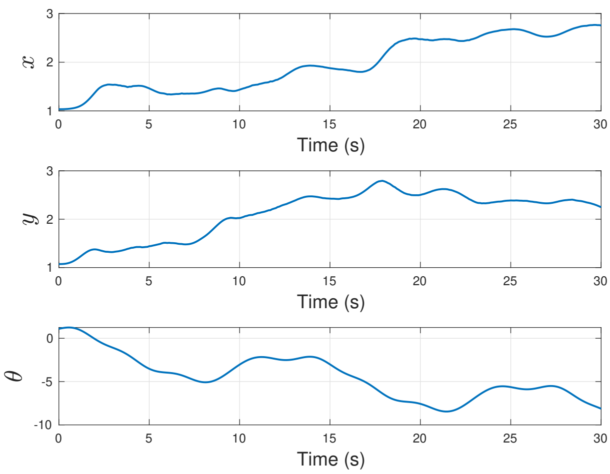


Figure 8: State variables

The coordinates of the centre of the room are $[2.5, 2.5]$, and as we can see from the plots, even if the person starts far from the centre, he will reach the desired value after half of the simulation time.

Finally, concerning the intentional velocity, we obtain:

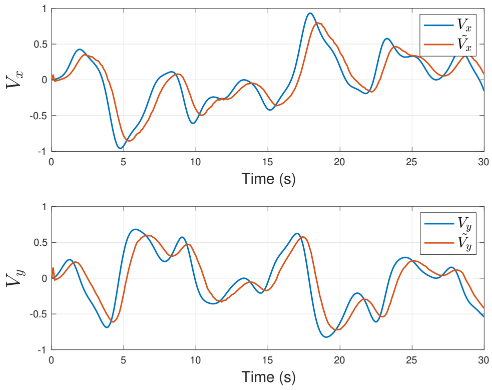


Figure 9: Intentional velocity

In this case, there is no noise in the information about the position of the user, so, at each time instant, the controller knows which is the true position of the user. The velocity observer works really well; he is able to estimate the shape of the intentional velocity despite a small delay. The value of k_w used in the simulation was set to 2; this is a small value, so there is no noise in the estimated signal.

4.2 Two People

We are going to add another person in the room, so now there are two people. Their initial positions are $q_1 = \begin{bmatrix} 2 & 2 & 0 \end{bmatrix}$ and $q_2 = \begin{bmatrix} 3 & 2 & -\pi \end{bmatrix}$, so they start face to face but then each person will move accordingly to its intentional velocity. In this case, the control actions will be such that each people will move only in half of the room; in this case, they are able to avoid each other but also to avoid the walls.

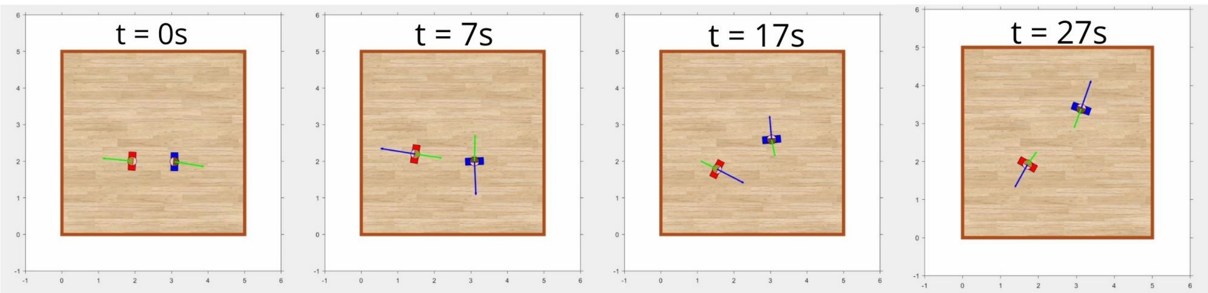
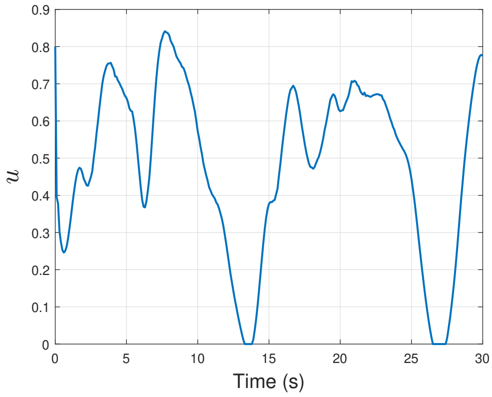
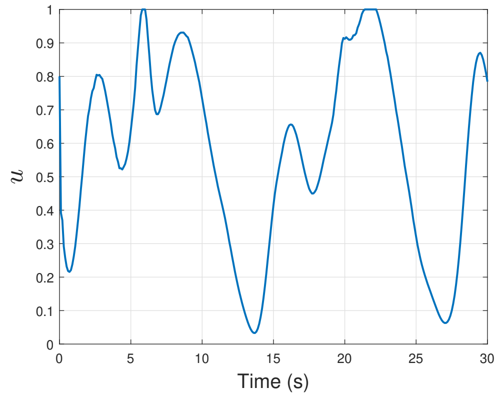


Figure 10: Evolution of two people

The control action is almost always present to correct the intentional velocity; each person, in fact, has to move away from the other, but he also has to avoid collisions with walls.



(a) Person 1

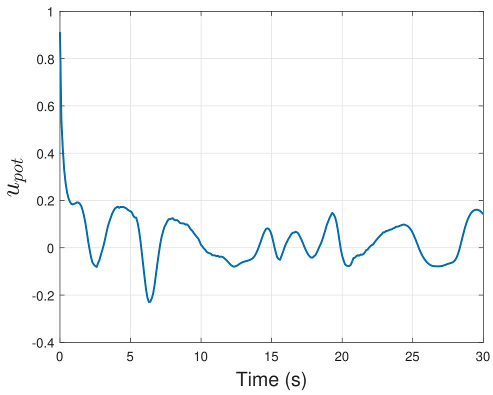


(b) Person 2

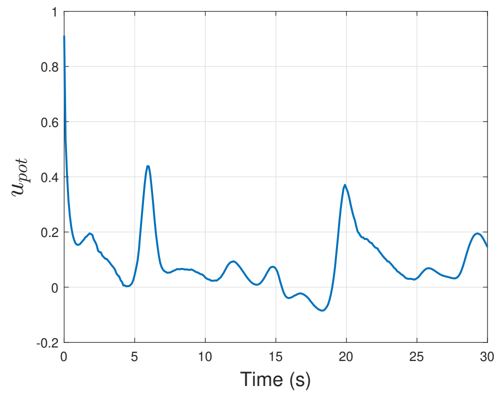
Figure 11: Control inputs

The values are quite high especially for the second person in which the input saturates around $t = 22\,s$. This implies that he was trying to leave the target position with a high intentional velocity.

Also in this case, we plot the component of the input only due to the Artificial Potential Field:



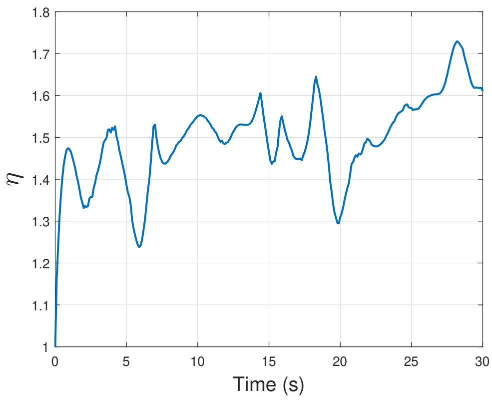
(a) Person 1



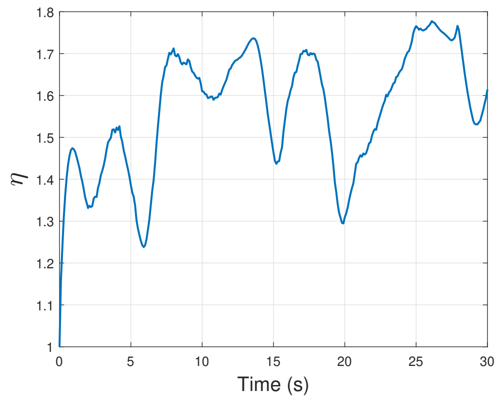
(b) Person 2

Figure 12: Projected repulsive potentials

And the trend of the clearance for each user:



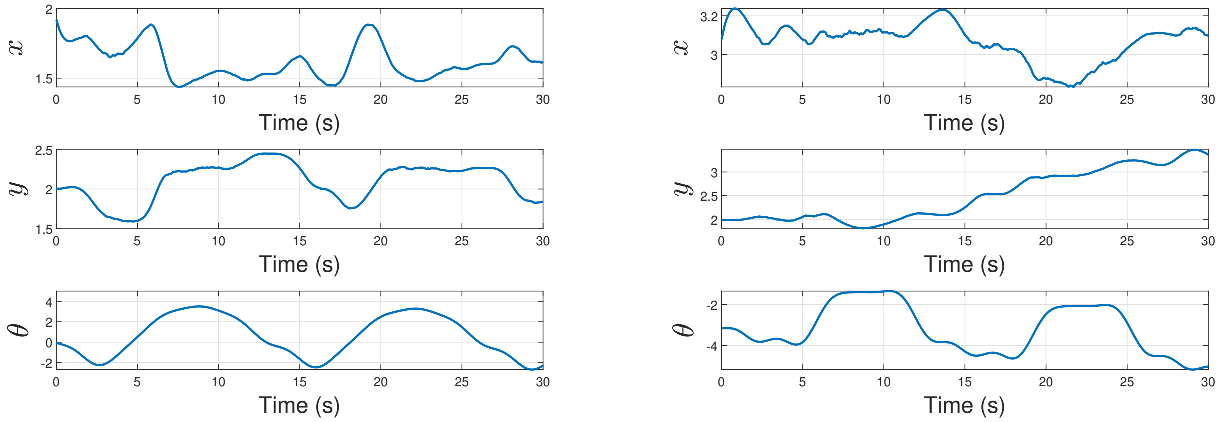
(a) Person 1



(b) Person 2

Figure 13: Clearance

Concerning the state variables:

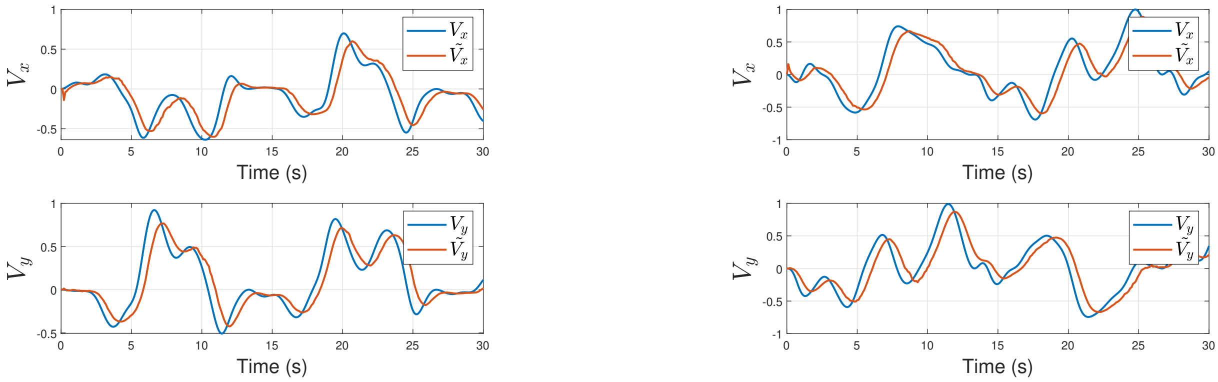


(a) Person 1 (b) Person 2

Figure 14: State variables

Both the two people move very little along the x direction. In fact, person 1 will always be between $x = 2$, that is its starting value, and $x = 1$, while person 2 will always be between $x = 3$ and about $x = 3.5$. They move very little also along the y direction; for person 1, we have that y stays in range $[2, 3]$, while for person 2, we have that $y \in [2, 2.7]$. This is due to the fact that both have an initial position that is quite near the desired one, so they do not need to move a lot.

For the intentional velocities, we have:



(a) Person 1 (b) Person 2

Figure 15: Intentional velocities

As for the case seen before, we have not added noise in the computation of the position of the users, so the controllers are perfectly able to estimate the person's position at each time instant. In fact, also the estimated velocity is quite similar to the real one despite a small delay. Also in this case, we have set $k_w = 2$.

4.3 Four People

The most challenging part of our work was to simulate four people moving in the room. Their initial position is:

$$q_1 = \begin{bmatrix} 2 & 2 & \pi/3 \end{bmatrix}$$

$$q_2 = \begin{bmatrix} 3 & 2 & \pi/4 \end{bmatrix}$$

$$q_3 = \begin{bmatrix} 3 & 3 & 0 \end{bmatrix}$$

$$q_4 = \begin{bmatrix} 2 & 3 & \pi/2 \end{bmatrix}$$

They start quite near to each other. Anyway, after few seconds of simulation, each user will converge to a position so that he can be equidistant from the walls and from the nearest neighbors.

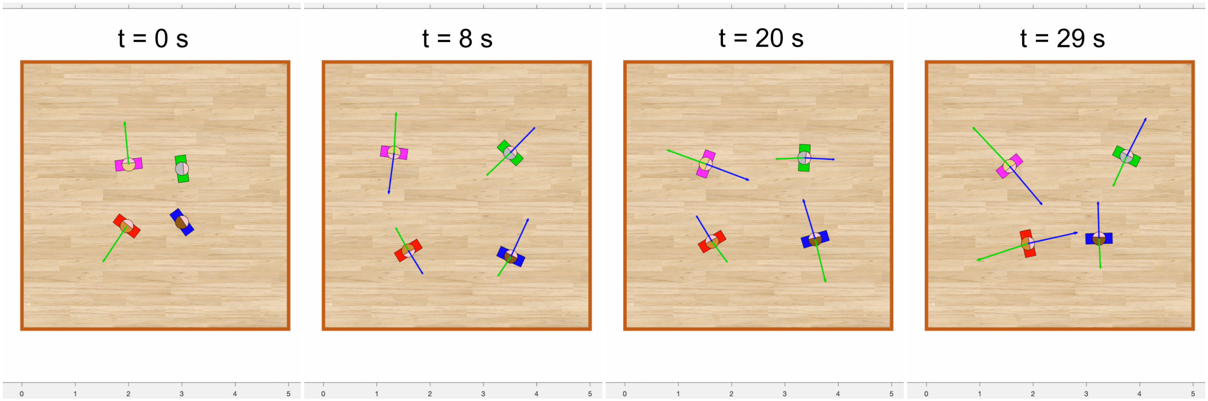
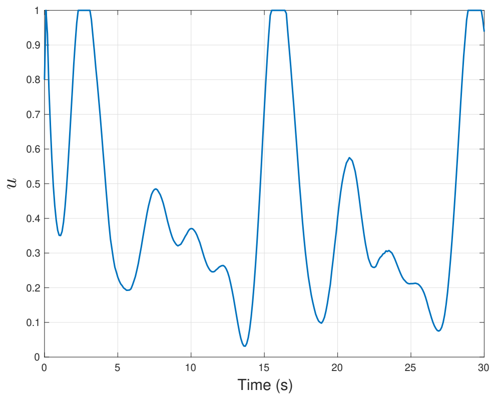


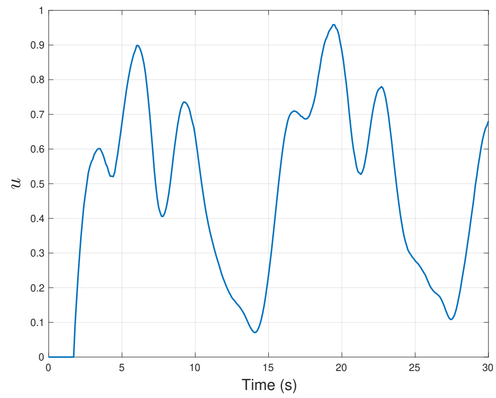
Figure 16: Evolution of four people

Once the users have reached the target positions, the control action will be such that they will try to move as small as possible. In fact, they are able to find an equilibrium configuration in such a way that they will never be too close to each other for all the duration of the simulation.

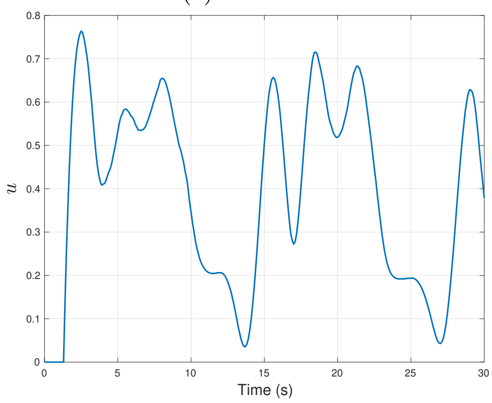
These are the results for the control actions:



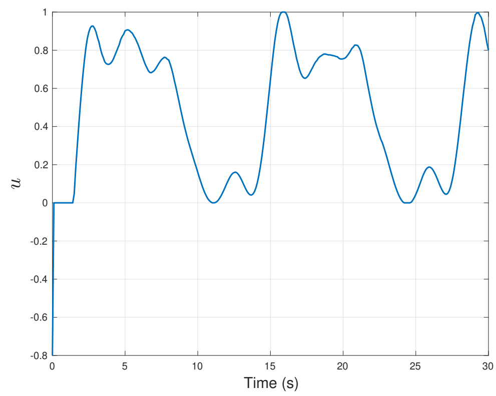
(a) Person 1



(b) Person 2



(c) Person 3

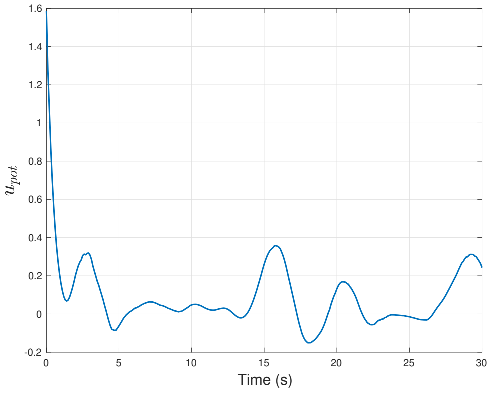


(d) Person 4

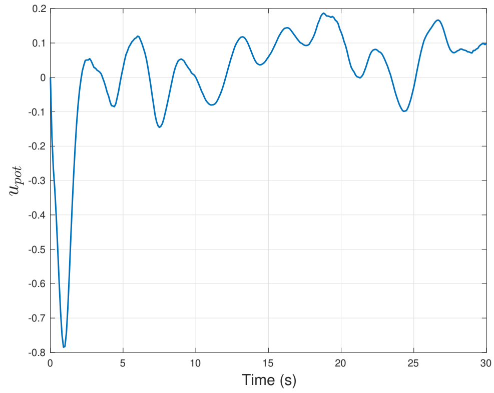
Figure 17: Control actions

For person 1, the control action saturates more than one time at its maximum value, while for person 3 we have the lowest values.

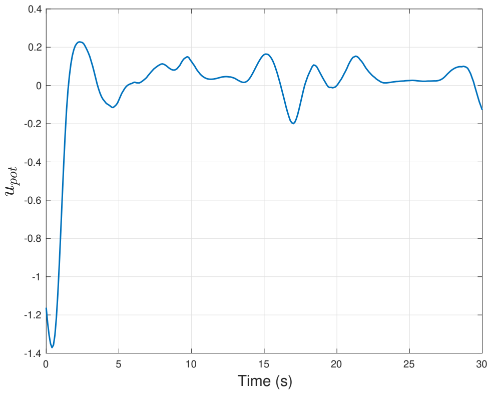
We report also the plots of the projected repulsive potentials:



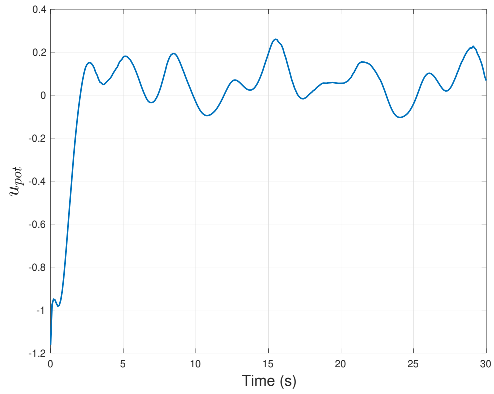
(a) Person 1



(b) Person 2



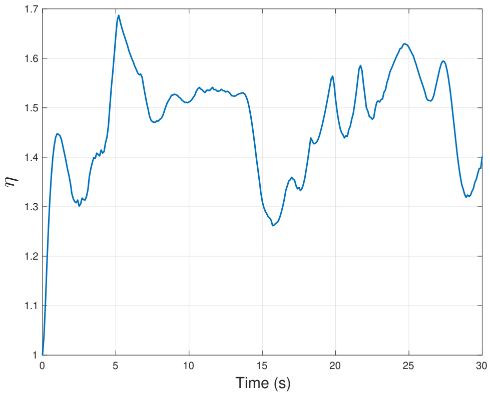
(c) Person 3



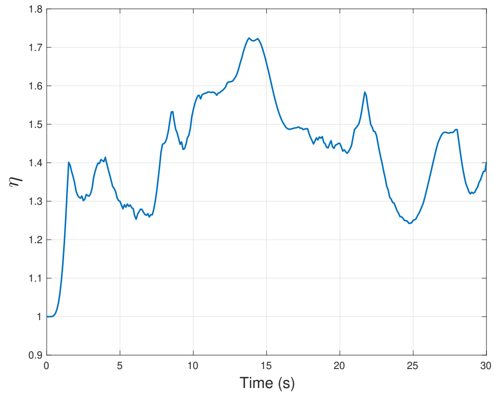
(d) Person 4

Figure 18: Projected repulsive potentials

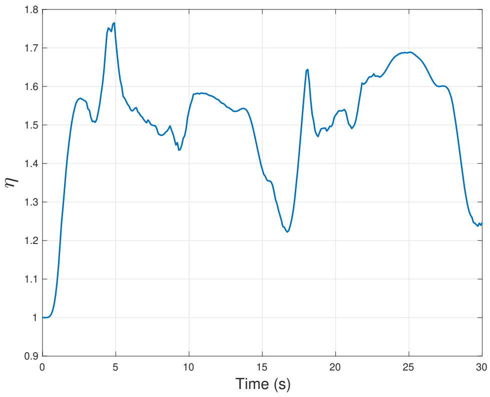
And the plots of the clearance for each user:



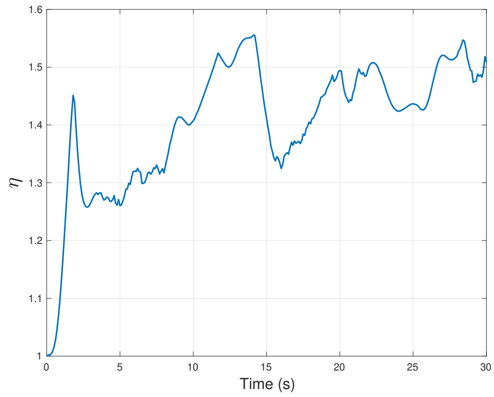
(a) Person 1



(b) Person 2



(c) Person 3

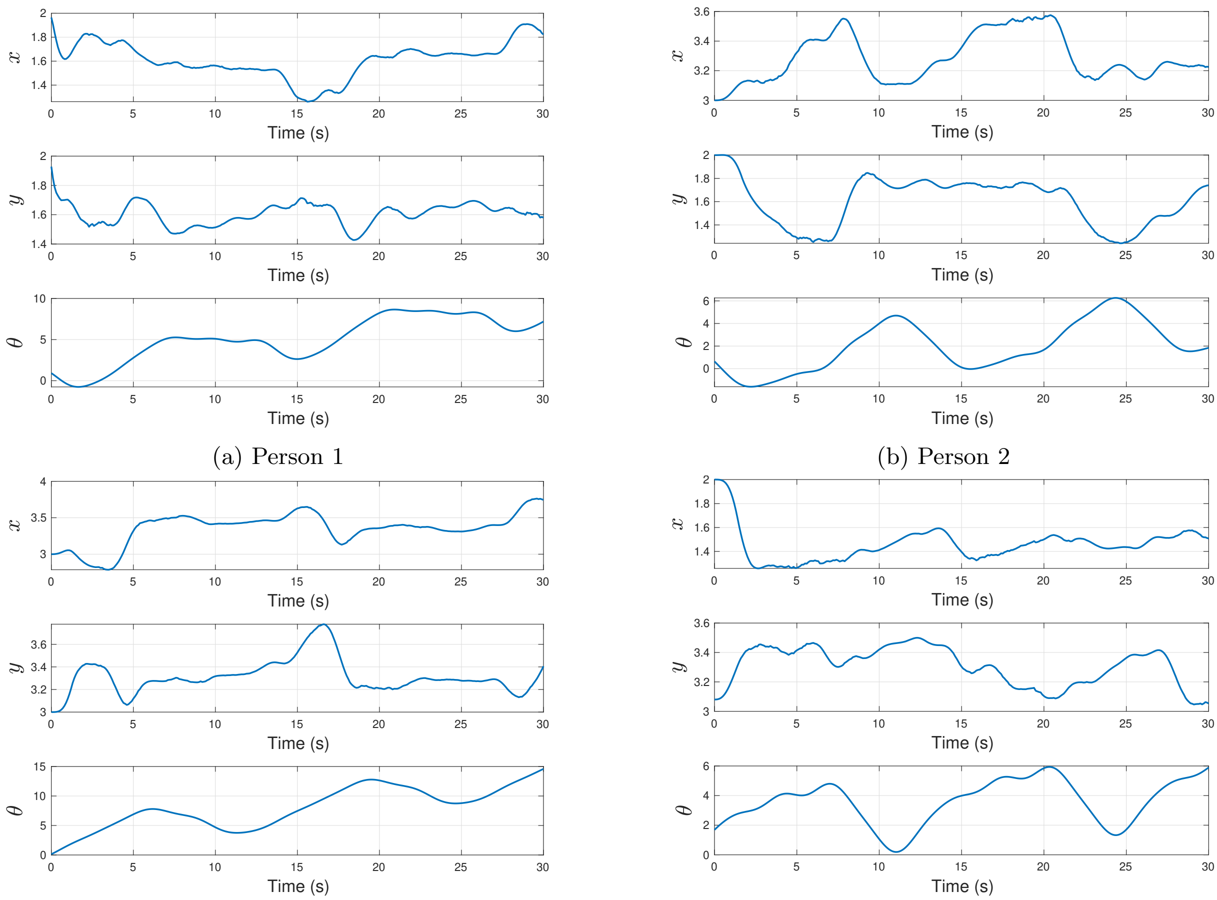


(d) Person 4

Figure 19: Clearance

By looking at the plots of the clearance for all the people, we have that at first, the clearance has a quite small value but after few seconds of simulations, it is able to reach bigger values. This is due to the fact that at the beginning the users are close to each other but they immediately distance themselves. In fact, during all the simulations, the clearance will never come back to the starting value.

Concerning the state variables:



(a) Person 1

(b) Person 2

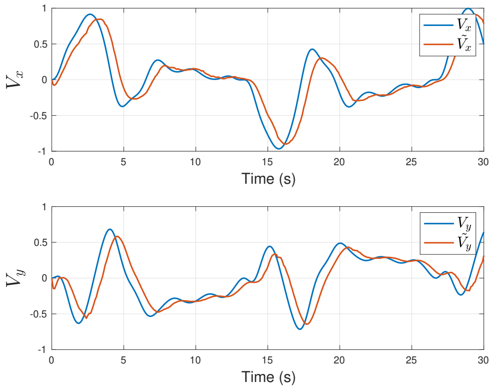
(c) Person 3

(d) Person 4

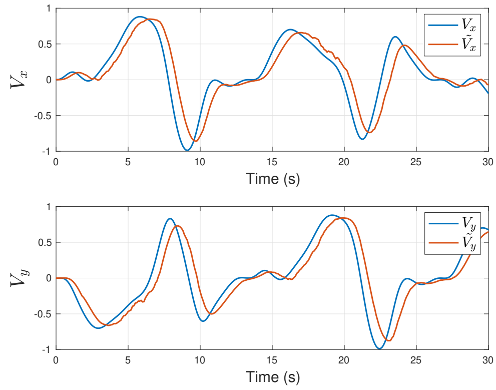
Figure 20: State variables

Each person moves just a bit from the starting configuration; in fact, at the beginning, the users are too close to each other so they just have to move away a bit so to not collide. Obviously, they should also be able to not collide with walls, so they will find an equilibrium configuration so to not hit against anything.

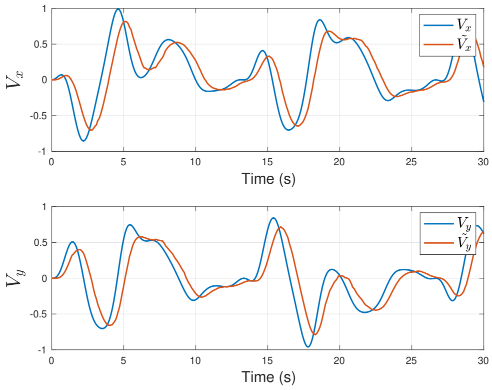
In this simulation, we have not added noise in sensor's reading, therefore, the observers for the intentional velocity are aware of which is the real position of the user in the room:



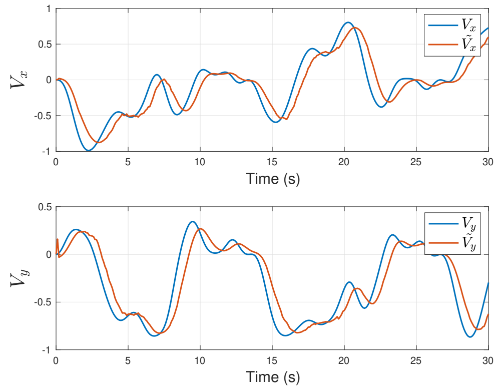
(a) Person 1



(b) Person 2



(c) Person 3



(d) Person 4

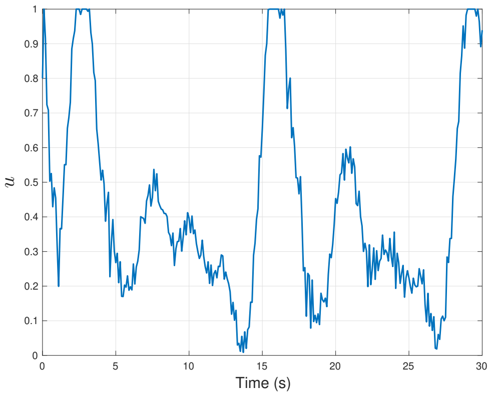
Figure 21: Intentional velocities

We have used $k_w = 2$. Since there is no noise in the estimation of the position, the shape of the estimated velocity is quite similar to the real one as expected. In fact, each observer is able to converge to the right value suddenly, except for a small delay.

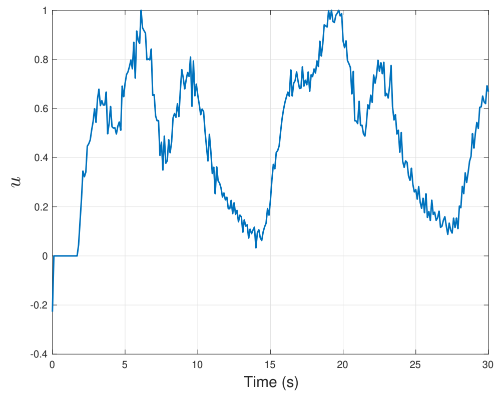
4.4 Sensor noise

To make things more challenging and realistic, we have added sensor noise in the reading of the current position of each user in the room; in this case, the controllers and the observers are not perfectly aware of which is the real position of the users. The intentional velocity trajectories and the initial positions are the same of the previous experiment; therefore the state variables of each user are exactly as before.

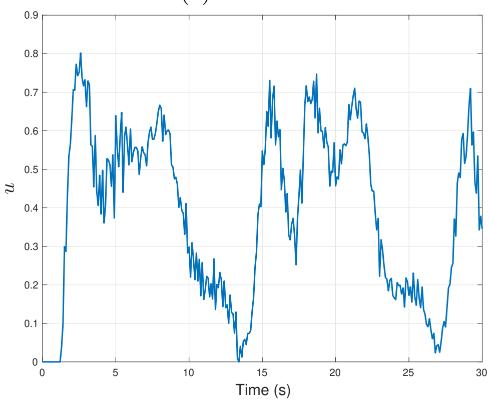
The control actions for all the people are:



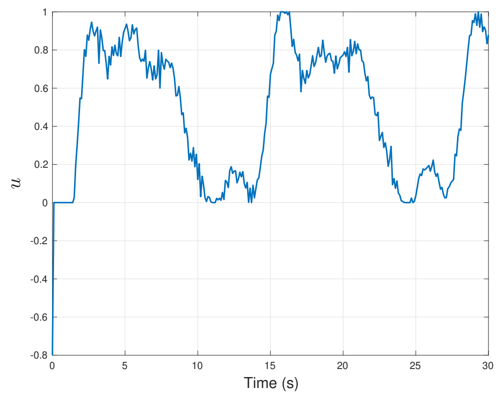
(a) Person 1



(b) Person 2



(c) Person 3

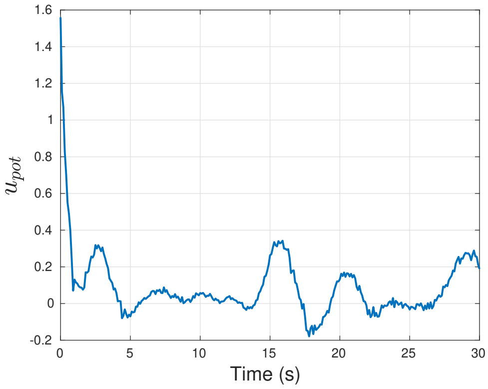


(d) Person 4

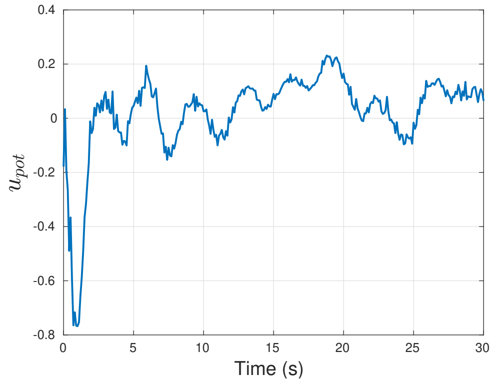
Figure 22: Control actions

Comparing these plots with the ones without noise, we can see that they have the same shape but they are not smooth; this is due to the uncertainty in the user's position.

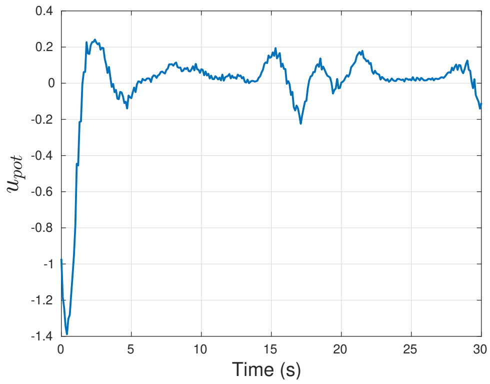
Again, we report also the plots of the projected repulsive potentials:



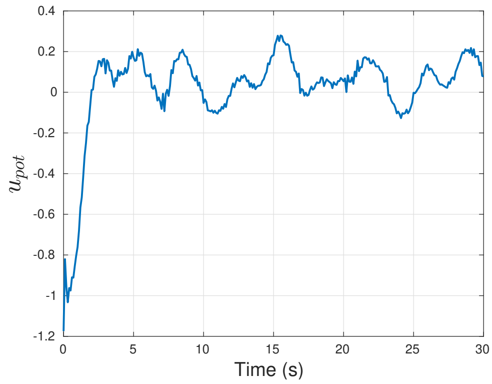
(a) Person 1



(b) Person 2



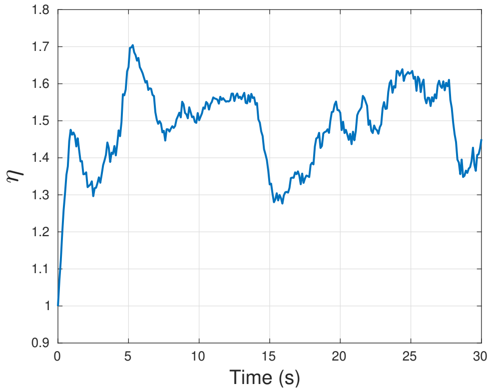
(c) Person 3



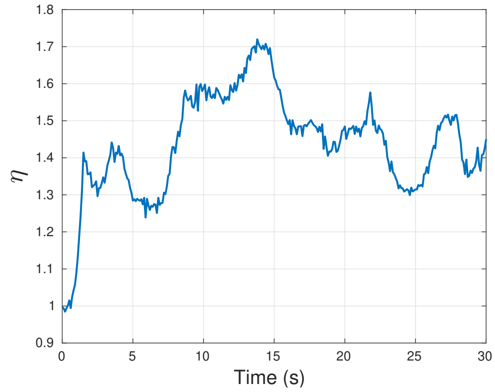
(d) Person 4

Figure 23: Projected repulsive potentials

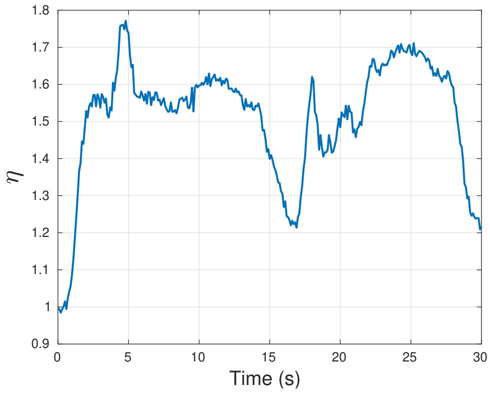
And the plots of the clearance for each user:



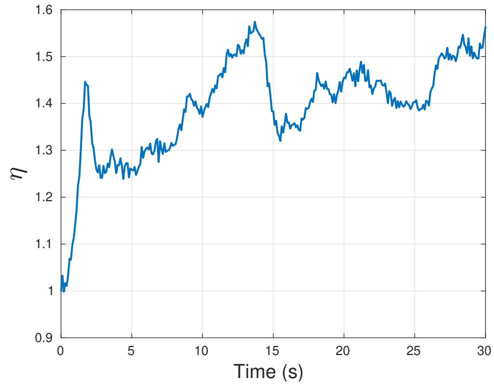
(a) Person 1



(b) Person 2



(c) Person 3

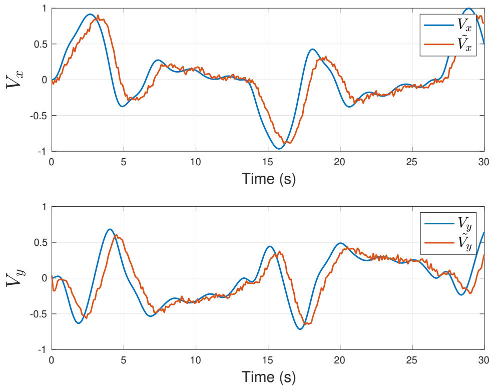


(d) Person 4

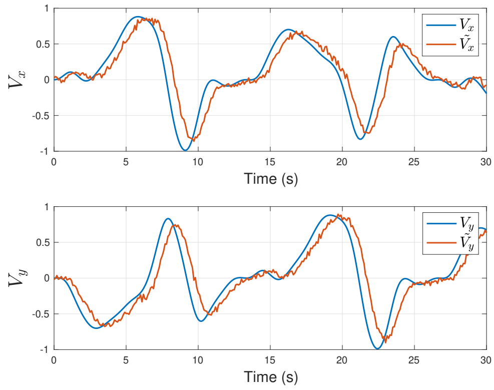
Figure 24: Clearance

As expected, the clearance has the same shape of the test without noise, but its shape is not smooth. This is due to the uncertainty in position.

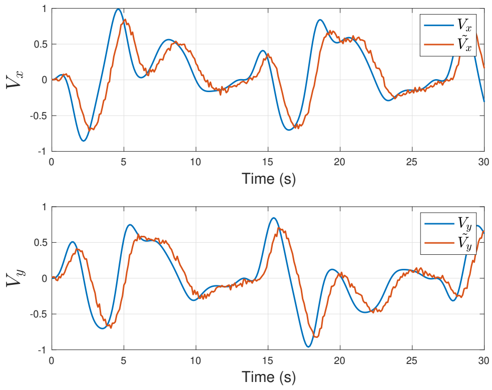
Another interesting difference is the estimation of the intentional velocities:



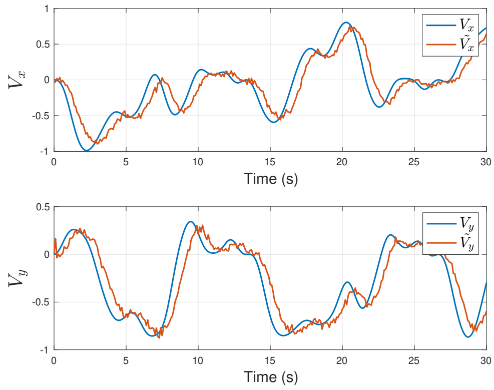
(a) Person 1



(b) Person 2



(c) Person 3



(d) Person 4

Figure 25: Intentional velocities

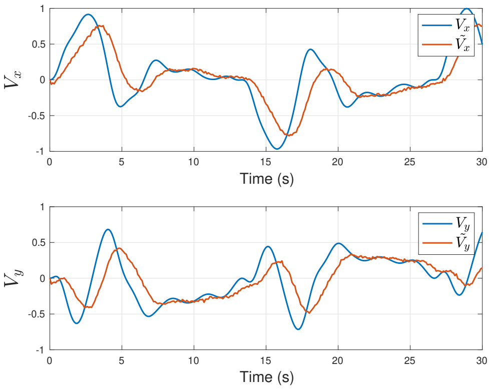
Each observer, in fact, considers the difference between the user's position and its state, so by adding a noise in the measurement of the user's position, we are also influencing the observer. The observer is still able to estimate the shape of the real intentional velocity of the user, but there is much more noise with respect to the previous case.

This noise will increase by increasing the value of k_w, so we had to perform a tuning procedure in order to find the best value of k_w; this will be illustrated in the following section.

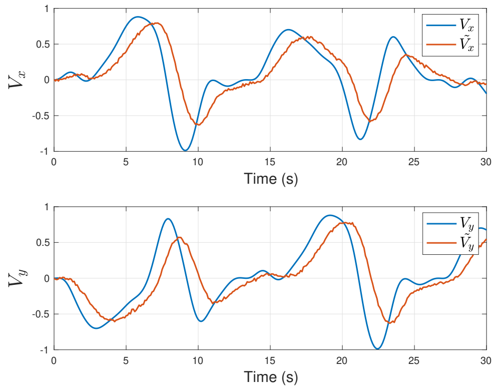
4.5 k_w tuning

We have run some experiments with different values of k_w in order to understand how it affects the performances, in particular the estimated intentional velocity; in fact, k_w is a parameter which appears in the equations of the observer. In all these experiments, we have considered 4 people in the room and sensor noise. Again, the intentional velocity trajectories and the initial positions are the same of the previous experiments.

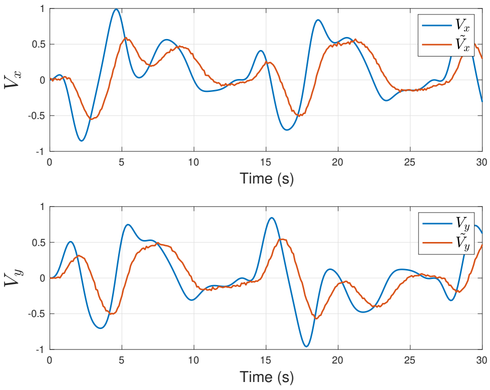
We start with $k_w = 1$:



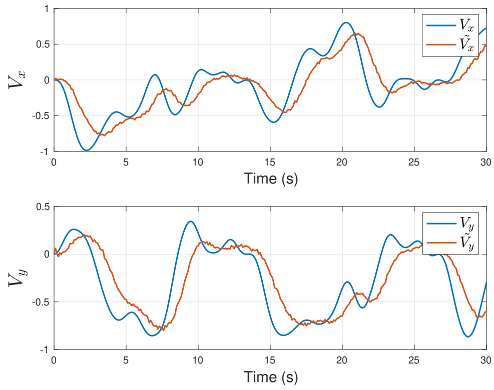
(a) Person 1



(b) Person 2



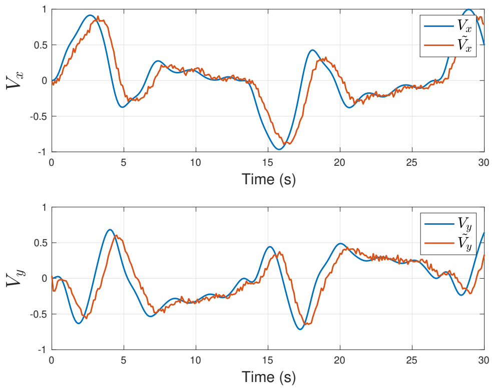
(c) Person 3



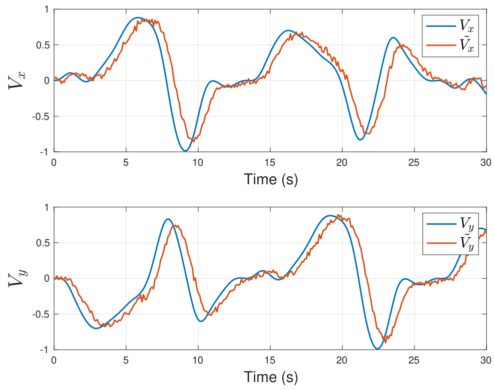
(d) Person 4

Figure 26: Intentional velocities for $k_w = 1$

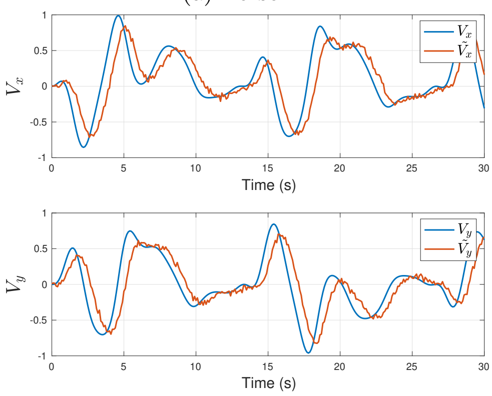
Then, we set $k_w = 2$:



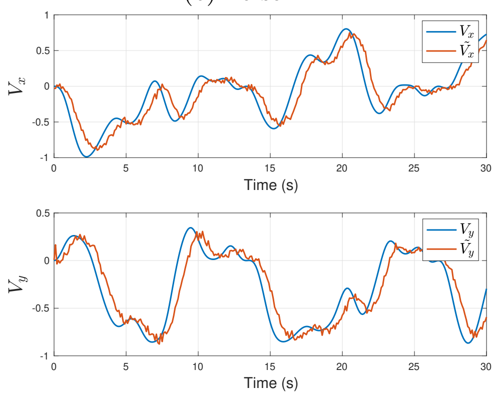
(a) Person 1



(b) Person 2



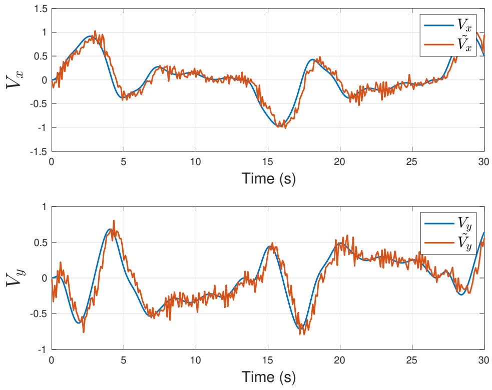
(c) Person 3



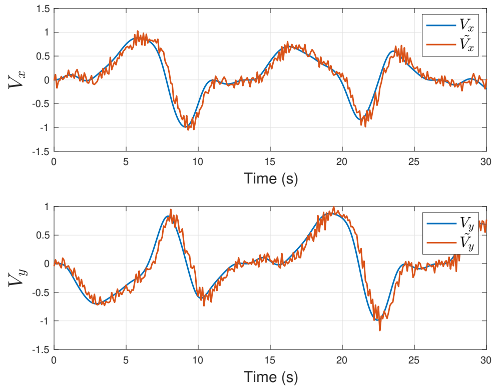
(d) Person 4

Figure 27: Intentional velocities for $k_w = 2$

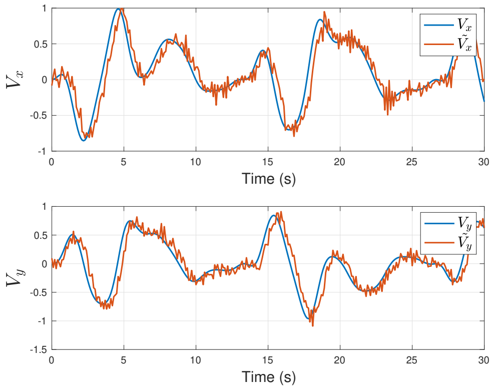
Then, we set $k_w = 5$:



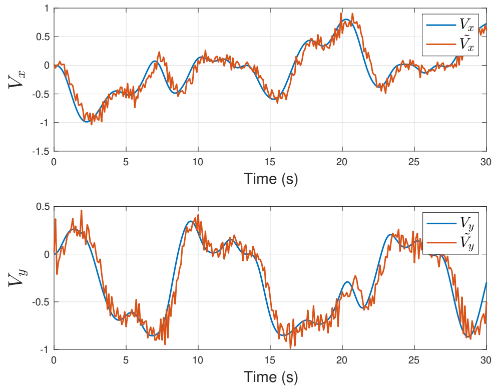
(a) Person 1



(b) Person 2



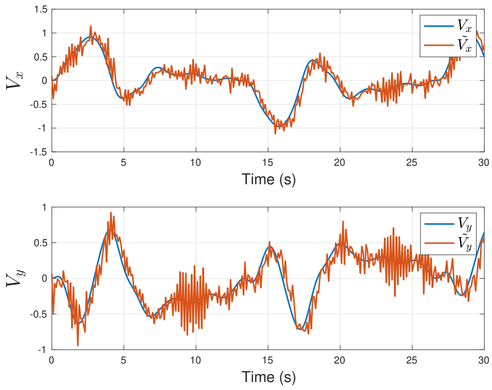
(c) Person 3



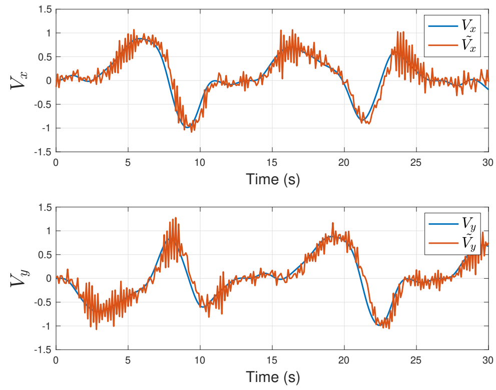
(d) Person 4

Figure 28: Intentional velocities for $k_w = 5$

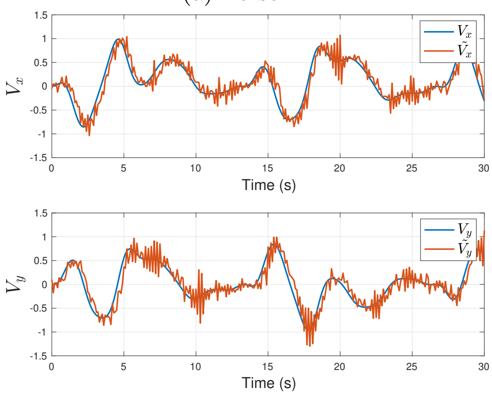
Then, we set $k_w = 7$:



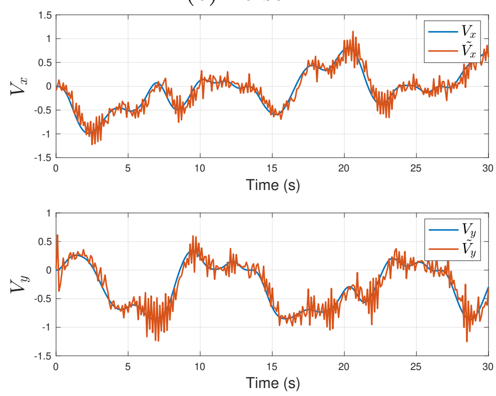
(a) Person 1



(b) Person 2



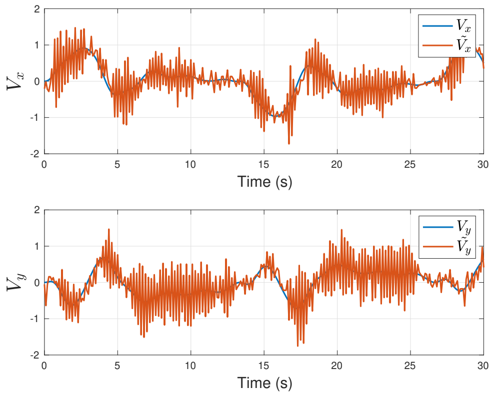
(c) Person 3



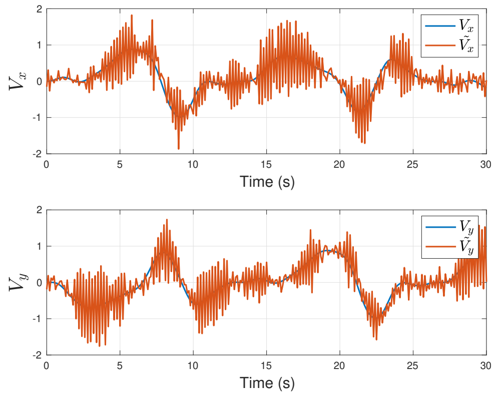
(d) Person 4

Figure 29: Intentional velocities for $k_w = 7$

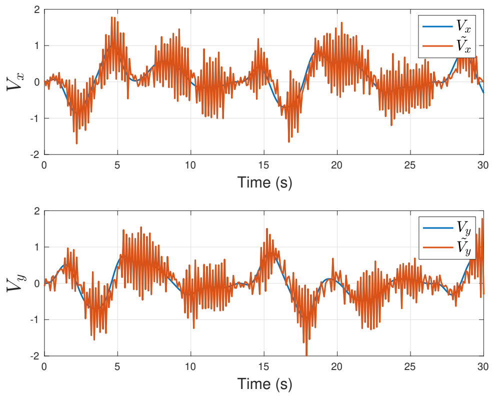
Finally, we set $k_w = 10$:



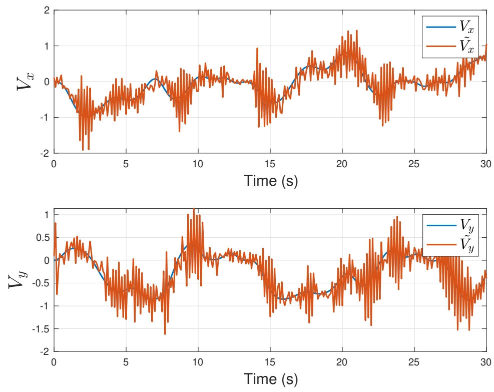
(a) Person 1



(b) Person 2



(c) Person 3



(d) Person 4

Figure 30: Intentional velocities for $k_w = 10$

By looking at these plots, we can see that increasing the value of k_w reduces the delay, but at the same time introduces noise. In fact, with $k_w = 1$, there is a small noise on the estimated signal due to sensor measurements, but there is an underestimation and also a delay in the reconstruction of the signal. With $k_w = 2$ we obtain pretty good results; in fact, the noise is not so evident as we can see from the plots and there is almost a superposition between the ground truth signal and the estimated one. By increasing the value of k_w, although the estimated signal follows the trend of the real one, the noise becomes stronger and stronger so to render the estimate no longer valid.

On the basis of the obtained results, we have used $k_w = 2$ in most of all the situations since it was a good compromise between performance and noise.

5 Conclusion

In virtual environment simulations, walking is one of the main issues to face in order to keep the sense of distance and orientation for people. Powered Shoes are a locomotion mechanism that provide such sense of walking. They are very advantageous since they allow multiple people to be in the same room without colliding against each other or hitting the walls. Moreover, in this work, we have used a decentralized controller based on Artificial Potential Field that, despite its simplicity, is able to perform well.

One of the main drawbacks of this method is that a high accuracy is needed; the control loop should know where the person is located in the room, but also its relative position with respect to other users and walls. If there is noise in sensor's reading or there is uncertainty in the estimation of the positions, we could have bad performances, especially if the number of users in the same room increases. Moreover, the controller takes into account only the longitudinal intentional velocity of the user, so it is not able to work in case a person tries to move only in the transverse direction.

In conclusion, we have simulated a scenario in which multiple users wearing Powered Shoes move in a room of limited size. Through a velocity-level decentralized control based on Artificial Potential Fields, the users are able to avoid both room's walls and other users, even if there is an imperfect cancellation of intentional motion. Moreover, intentional velocities of the users are recovered with a satisfactory accuracy through an observer.

References

[1] Hiroo Iwata, Hiroaki Yano, Hiroshi Tomioka. *Powered Shoes*

[2] Alessandro De Luca *Motion Control of the CyberWalk Platforms – Part I* (slides from the module Locomotion and Haptic Interfaces of the Elective in Robotics course)