Fuzzy Modeling and Control for Intention Recognition in Human-robot Systems

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Abstract: The recognition of human intentions from trajectories in the framework of human-robot interaction is a challenging field of research. In this paper some control problems of the human-robot interaction and their intentions to compete or cooperate in shared work spaces are addressed and the time schedule of the information flow is discussed. The expected human movements relative to the robot are summarized in a so-called "compass dial" from which fuzzy control rules for the robot's reactions are derived. To avoid collisions between robot and human very early the computation of collision times at predicted human-robot intersections is discussed and a switching controller for collision avoidance is proposed. In the context of the recognition of human intentions to move to certain goals, pedestrian tracks are modeled by fuzzy clustering, lanes preferred by human agents are identified, and the identification of degrees of membership of a pedestrian track to specific lanes are discussed. Computations based on simulated and experimental data show the applicability of the methods presented.

1 INTRODUCTION

Dealing with interactions of humans and autonomous robots in common working areas is a challenging research field with regard to system stability and performance and to human safety. Research results on planning of mobile robot tasks, learning of repeated situations, navigation and obstacle avoidance have been published by (Mataric, 1990; Firl, 2014; Khatib, 1985; Palm and Bouguerra, 2013). When human agents and robots share the same workspace, both of them have to adapt their behavior, to either support their cooperation, or to enable them to do their own task separately. In this connection it is difficult to predict the behavior, motions and goals of a human agent. Even more it is important to predict the human behavior for a limited time horizon with a certain probability to enable the robot to perform adequate reactions. One class of solutions to this problem is the building of models of the human behavior by clustering methods (Mataric, 1990; F. Sadri and Xafi, 2012; R. Palm and Kadmiry, 2009). Further research activities focus on Bayesian networks (Tahboub, 2006; Han and Pereira, 2013), Hidden Markov Models (HMM) (M. Bennewitz and Thrun, 2005), Fuzzy logic or Fuzzy Cognitive Maps and reinforcement learning (Tahboub, 2006; A. Ciaramella and Straccia, 2010). Heinze addresses human intentions from the ontological point of view (Heinze, 2004). Another aspect is the (automatic) recognition of human intentions to aim at a certain goal. Some research on intention recognition describes human-robot interaction scenarios and the "philosophical and technical background for intention recognition" (Tahboub, 2006). Further research deals with "Intention Recognition in Human-Robot Collaborative Systems" (Aarno, 2007; Krauthausen, 2012), human-robot motions initiated by human intentions (T. Fraichard and Reignier, 2014), and socially inspired planning (J.V. Gomez and Garrido, 2013). In practice, the identification of a human intention needs to predict the direction of motion, the average velocity and parts of the future trajectory. In this connection, Bruce et al address a planned human-robot rendezvous at an intersection zone (J. Bruce and Vaughan, 2015). Satake et al (Satake et al., 2009) describe a social robot, that approaches a human agent in a way that is acceptable for humans. Further research on human intentions together with trajectory recognition and planning is presented by (A.F.Johansson, 2009; Chadalavada et al., 2015). The modeling of pedestrian trajectories using Gaussian processes is shown in (T. Ellis and Reid, 2009). In (Makris and Ellis, 2010) fuzzy methods, probabilistic methods and HMM approaches for mod-

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eling of human trajectories are compared. In addition to the recent research mentioned above and as an extension of our work described in (R. Palm and Lilienthal, 2016), this paper concentrates on the recognition of human intentions to move along certain trajectories. The method is based on observations of early trajectory parts, plus a subsequent extrapolation. The here discussed control principles of interaction between human and robot mainly deal with trajectory planning and external sensor feedback on a higher level of the control hierarchy. Furthermore, the time schedule of the information flow and the kinematic relationship of a human-robot system in motion is considered. The observation of the human agent by the robot supplies motion data that are Kalman-filtered to cope with uncertainties and noise. This leads to an estimation of the velocity vector of the human relative to the robot which is depicted in a ”compass dial”. From this, a set of fuzzy rules is extracted that results in a possible reaction of the robot either to prevent a collision or enable a cooperation. Our case is somehow different from the usual case of avoidance of moving obstacles due to the uncertainty to predict human intentions. A special issue is the case of *unchanged directions* of a motion both of the human and the robot that should be distinguished from a common obstacle avoidance methods (Khatib, 1985). This is tackled by a switching robot controller that computes the time for possible collisions at the intersections. According to this knowledge the controller changes the robot's speed which helps to prevent collisions at intersection of the planned paths. Due to uncertainties in the observations and to measurement noise the intersection points are extended to *intersection areas* which must not be entered at the same time neither by the human nor by the robot. Since this operation comprises only the first part of the human motion the subsequent extrapolations are updated at each time step in order to avoid larger errors. Another essential issue is the identification of lanes from trajectories usually preferred by human agents in an open area or at a factory work floor. This is motivated by the need for an early reaction of the robot to the human's intention to walk, and to plan either a collision avoidance or a cooperation action. In this paper we concentrate on the fuzzy modeling of pedestrian tracks, the identification of lanes preferred by the human agents, and the identification of a membership of a pedestrian track (or parts of it) to a specific lane.

The paper is organized as follows. In Section 2 we address the interaction between human and robot from the control structure point of view and the time schedule of the information flow. Section 3 deals with the kinematic and geometric relations between human and robot. A ”compass dial” with the relative velocities and the corresponding fuzzy rules is presented in Sect. 4. Section 5 deals with avoidance strategies at intersections. Section 6 addresses the fuzzy modeling of sets (bundles) of pedestrian tracks and the identification of the membership of a single track to a certain lane. Section 7 presents results based on simulations and experimental data, and Sect. 8 ends with a discussion and conclusions.

2 INTERACTION BETWEEN HUMAN AND ROBOT

In a shared working environment, human and robot are constituted by a common control system shown in Fig. 1. Both human and robot are driven by their individual goals (desired trajectories) x_{H_d} and x_{R_d}. Actions and reactions are represented by desired states $x_{H_d}(t_i)$ and $x_{R_d}(t_i)$. From the interaction of the two agents we obtain observable states $x_H(t_i)$ and $x_R(t_i)$.

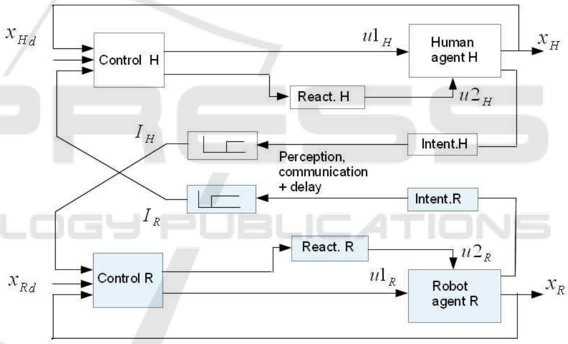

Figure 1: Human-robot interaction, control scheme.

Intentions I_H and I_R are signals (e.g. information about parts of trajectories) transmitted to/observed by the other agent. The dynamic equations can formally be written as

$$\begin{aligned}\dot{x}_H = f_H(x_H, u1_H, u2_H); \dot{x}_R = f_R(x_R, u1_R, u2_R)\\ u1_H = g1_H(x_{H_d}, x_H); u1_R = g1_R(x_{R_d}, x_R)\\ u2_H = g2_H(I_R, x_H); u2_R = g2_R(I_H, x_R)\\ I_H = h_H(x_H, x_R, x_{H_d}); I_R = h_R(x_R, x_H, x_{R_d}) \quad (1)\end{aligned}$$

The 1-st two lines of (1) denote the individual dynamics of human and robot, where the next two lines denote the 'crosswise' influence of intention and reaction between human and robot. The functions in (1) are highly nonlinear hybrid functions with continuous and switching attributes. A good example for modeling human-robot dynamics can be found in (P. Leica and Carelli, 2015). Recall here that the control problems discussed here deal with the higher control level of external sensory and trajectory generation. Furthermore the feasibility of the desired trajectory x_{R_d} and its possible variations should be guaranteed because of the nonholonomic kinematics of the robot. In our case, intentions are functions of desired and actual states. The robot controllers $g1_R$ and $g2_R$ can be designed based on the knowledge about the system dynamics (R.-E.Precup and Preitl, 2009) whereas the human controllers $g1_H$ and $g2_H$, which have been introduced due to formal reasons, cannot be designed in the same way. The same is true for the formal description f_H of the human behavior which is usually only a rough approximation of the reality. Since a modeling especially of the human's behavior is quite difficult, the modeling of both the robot and the human by TS fuzzy models from motion data is worth mentioning. In this case each of the nonlinear functions of (1) split up into n local functions like

$$f_H = \sum_{i=1}^{n} w_i(x_H) \cdot f_{H_i}(x_H, u1_H, u2_H) \tag{2}$$

$$f_R = \sum_{i=1}^{n} w_i(x_R) \cdot f_{R_i}(x_R, u1_R, u2_R)$$

where w_i are membership functions. Let furthermore the robot controllers $u1_R, u2_R$ either be designed as weighted combinations of local controllers

$$u1_R = \sum_{i=1}^{n} w_i(x_R) \cdot g1_{R_i}(x_{R_d}, x_R) \tag{3}$$

$$u2_R = \sum_{i=1}^{n} w_i(x_R) \cdot g2_{R_i}(I_H, x_R)$$

or as Mamdani expert rules formulated in Sect. 4. On the other hand, human controllers $u1_H, u2_H$ are also expressed as Mamdani expert rules which are the counterparts of the robot expert rules. A switching robot controller for collision avoidance is presented in Sec. 5. An intention may become observable in an early part of the human trajectory $x_H(t_k|k = 1...m)$ where m is the time horizon on the basis of which the robot should recognize the human's intention to move. This information is sent to the robot with a delay T_{d_H}. After that the robot starts its intention recognition and starts to plan/compute a corresponding reaction $x_{R_d}(t_i)$. The intention to react is realized as a part of the trajectory of the robot $x_R(t_k|k = j...n)$ where $(n-j)$ is the corresponding time horizon on the basis of which the human tries to recognize the robot's intention to move. Then this intention is transmitted to the human.

The sampling time of the whole process is T_{tot}. Robot and human can control the mutual cooperation only if T_{tot} meets certain requirements regarding the time constants of the system. There are two time constants involved, the time constant τ_H of the human and the time constant τ_R of the robot. Let the total process time constant be the sum of the two

$$\tau_{tot} = \tau_H + \tau_R \tag{4}$$

A rule of the thumb says that the sample time T_{tot} should be 5...30 times shorter than the largest time constant of the process ((Ed.), 1995).

3 KINEMATIC RELATIONS OF HUMAN AGENTS AND MOBILE ROBOTS IN A COMMON WORKSPACE

The analysis of the mutual observations between human and robot requires the formulation of relative positions/orientations and velocities in the local coordinate systems C_H (human) and C_R (robot) and the global coordinate system C_B (basis). First, let us assume a sufficient knowledge of the positions/orientations of robot and human both in their local systems C_H, C_R and in the basis system C_B. The relation between two coordinate systems C_A and C_B is then defined by the transformation Figure 2 shows the kinematic relations between the coordinate systems C_R, C_H, and C_B: T_{HB} between human and basis, T_{RB} between robot and basis, T_{HR} between human and robot. The orientation, of human and robot are chosen so that the y axis is pointing in the direction of motion. Next an additional coordinate system $C_{\tilde{H}}$ is defined whose y-axis points from the center of C_H to the center of C_R. This coordinate system is necessary for the formulation of the *heading angle* from human to robot. The distance between C_H (and $C_{\tilde{H}}$) and C_R is denoted by d_{HR}. In the following we assume parts of the *intended* trajectory $\mathbf{x}_{HR}(t_i)$ of the human to be measurable by the robot from which the velocity

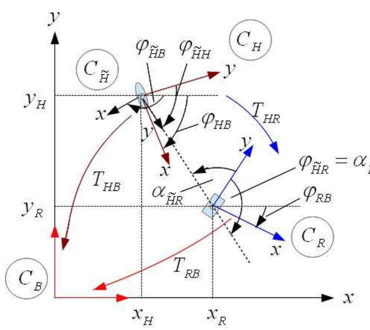

Figure 2: Transformations between frames.

$\dot{\mathbf{x}}_{HR}(t_i)$, the orientation angle $\phi_{HR}(t_i)$ and the transformation matrix $T_{HR}(t_i)$ can be estimated. Since the robot is assumed to know its own trajectory $\mathbf{x}_{RB}(t_i)$ and the transformation matrix $T_{RB}(t_i)$ we can compute the transformation matrix: $T_{HB}(t_i) = T_{RB}(t_i) \cdot T_{HR}(t_i)$. Then we measure the distance d_{HR} between C_H and C_R, and the *relative angle* $\alpha_{\tilde{H}R}$ between the line C_H – C_R and the y-axis of C_R. Finally we compute the *heading angle* $\phi_{\tilde{H}H} = \pi - (\alpha_{\tilde{H}R} + \phi_H R)$ between $C_{\tilde{H}}$ and C_H which is necessary for the qualitative relation between human and robot. Now we have all information to formulate a set of qualitative fuzzy rules for human-robot interactions.

4 FUZZY RULES FOR HUMAN-ROBOT INTERACTIONS

In the center of $C_{\tilde{H}}$ a so-called compass dial is introduced that expresses the qualitative relationship of the human intentions seen from the robot. These comprise 8 human motions relative to the robot: 'APP=approach', 'AVR=avoid right', 'MOR=move right', 'RER=recede right', 'REC=recede', 'REL=recede left', 'MOL=move left', 'AVL=avoid left'.

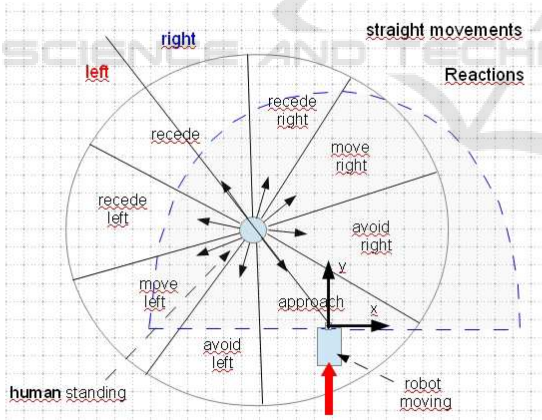

Figure 3: Compass dial for human actions.

To identify the trajectory of the human relative to the robot it is enough to know the heading angle $\phi_{\tilde{H}H}$ and the relative velocity $\Delta\mathbf{v} = |\dot{\mathbf{x}}_{HB} - \dot{\mathbf{x}}_{RB}| = |\dot{\mathbf{x}}_{HR}|$. Since $\Delta\mathbf{v}$ is an invariant it becomes clear that it can be computed in each arbitrary coordinate system. Ones the heading angle $\phi_{\tilde{H}H}$ is computed one can determine a qualitative relation between human and robot according to the compass dial in Fig. 3. A fuzzy label is attached to each motion direction of the human agent. A crisp heading angle $\phi_{\tilde{H}H}$ is fuzzified with respect to the corresponding fuzzy sets for 'approach', 'avoid right' etc (see Fig. 4).

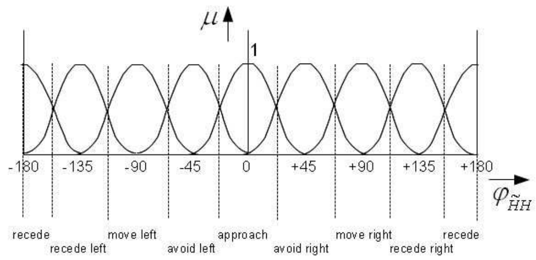

Figure 4: Fuzzy sets for human motions.

From $\alpha_{\tilde{H}R}$, $\phi_{\tilde{H}H}$, $\Delta\mathbf{v}$ and the distances $|\Delta\mathbf{x}| = |\mathbf{x}_{HR}|$ the response of the robot to the human's intention is computed in an early state of the human action. However, because of the uncertain nature of the data (system/measurement noise) one obtains estimates of positions and velocities by an appropriate Kalman filter. Noise on velocity and measurement are filtered out leading to a smooth trajectory (or part of trajectory) from which the velocity vector is estimated. The variables to be processed are $\alpha_{\tilde{H}R}$, $\phi_{\tilde{H}H}$, the distance $|\Delta\mathbf{x}| = |\mathbf{x}_{HR}|$, and the relative velocities $|\Delta\mathbf{v}|$. For $|\mathbf{x}_{HR}|$ and $|\Delta\mathbf{v}|$ fuzzy sets 'Small', 'Medium', and 'Large' of Gaussian type are defined and appropriate fuzzy rules are formulated

$$\begin{aligned} IF \quad \alpha_{\tilde{H}R} = A_i \quad \phi_{\tilde{H}H} = P_i \quad AND \\ |\Delta\mathbf{x}| = DX_i \quad AND \quad |\Delta\mathbf{v}| = DV_i \\ THEN \quad ACT_{rob} \end{aligned} \tag{5}$$

$$ACT_{rob}: \quad \phi_{HR_{rob}} = PH_i \quad AND \quad |\mathbf{v}|_{rob} = VR_i$$

i - rule number
$\alpha_{\tilde{H}R}$ - relative angle between $C_{\tilde{H}}$ and C_R
A_i - fuzzy set for the relative angle
$\phi_{\tilde{H}H}$ - heading angle between $C_{\tilde{H}}$ and C_H
P_i - fuzzy set for the heading angle
$|\Delta\mathbf{x}|$ - distance between C_H and C_R
DX_i - fuzzy set for the distance
$|\Delta\mathbf{v}|$ - relative velocity between C_H and C_R
DV_i - fuzzy set for the relative velocity
$\phi_{HR_{rob}}$ - steering angle of robot
PH_i - fuzzy set for the steering angle
$|\mathbf{v}|_{rob}$ - desired velocity of the vehicle
VR_i - fuzzy set for the desired velocity

However, not every combination makes sense. Therefore "pruning" of the set of rules and intelligent hierarchization can solve this problem. A simple set of rules for $\alpha_{\tilde{H}R} > 0$ to avoid a collision between human and robot contains only the heading angle $\phi_{\tilde{H}H}$ and the steering angle $\phi_{HR_{rob}}$ like:

$$IF \quad \phi_{\tilde{H}H} = APP \quad THEN \quad \phi_{HR_{rob}} = TR \tag{6}$$

where TR=turn right, TL=turn left, MS=move straight ahead, $MSSD$=move straight ahead/slow down.

5 SWITCHING CONTROLLER FOR COLLISION AVOIDANCE

5.1 Early Observation of Trajectories

From measured robot/human positions taken at an early point in time Kalman filtered sequences of robot and human positions $\mathbf{x}_{RB}(t_i)$ and $\mathbf{x}_{HR}(t_i)$ are gained from which the velocities $\mathbf{v}_H$ and $\mathbf{v}_R$ are estimated. Then the distance d_{HR} between C_H and C_R and the relative angle $\alpha_{\tilde{H}R}$ are measured and the angle ϕ_{HR} computed.

Despite of existent traffic rules a collision between human agent and robot may occur especially in the cases AVR, MOR, RER or AVL, MOL, REL of the compass dial. Therefore at a certain distance the robot controller switches from the 'normal mode' to a 'prediction mode' to compute an 'area of intersection' and the time to reach it. After having reached this area the controller switches back to the 'normal mode' keeping its latest velocity constant.

5.2 Uncertainty in Measurements

Uncertainties in measurements and unexpected changes in directions and velocities lead to deviations in the calculations of possible crossing points. From simulations and experiments circular areas of possible collisions can be designed. Figure 5 shows the relations for the "1 human - 1 robot" case. Let P_H be the crossing point of human and robot and α the angle of uncertainty for both human and robot at a specific time t_i. A circle with the radius $r_1 = D_1 \cdot \sin\alpha/2$ describes the uncertainty area A_H of the human to be avoided by the robot. On the other hand, the robot has its own circular uncertainty area A_R that should not overlap with A_H. Let the distance between robot and crossing point be ΔD then the radius of A_R is $r_2 = (D_1 - \Delta D) \cdot \sin\alpha/2$. From the requirement $A_H \cap A_R = \emptyset$ we obtain $\Delta D \geq r_1 + r_2$. For $\Delta D = r_1 + r_2$

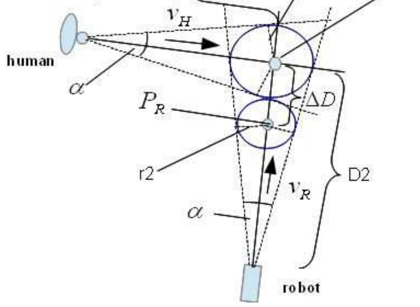

Figure 5: Crossing areas.

we obtain

$$r_2 = \frac{\sin\alpha/2}{(1+\sin\alpha/2)}(D_2 - r_1) \tag{7}$$

and finally the velocity v_r for the robot to reach the distance point P_R in the time t_{HR} that the human would need to get to P_H (see (8 a))

$$\begin{aligned} a: \quad v_{Ropt} &= \frac{(D_2 - r_1)}{t_{HR}} \cdot \frac{1}{(1+\sin\alpha/2)} \\ b: \quad v_{Ropt} &= \frac{(D_2 + r_1)}{t_{HR}} \cdot \frac{1}{(1-\sin\alpha/2)} \end{aligned} \tag{8}$$

(8 a) is valid for the case when the human passes the crossing point before the robot. To be on the safe side one should require $v_R \leq v_{Ropt}$. For the case when the human passes the crossing point after the robot we get (8 b)

with $v_r \geq v_{Ropt}$.

6 INTENTION RECOGNITION BASED ON LEARNING OF PEDESTRIAN LANES

6.1 Fuzzy Modeling of Lanes

A good option to identify/recognize human intention to aim at a specific goal is to learn from experience. The framework of "programming by demonstration" focusses on the recognition of human grasp pattern by fuzzy time clustering and modeling (R. Palm and Kadmiry, 2009). Likewise for the intention recognition it is a matter of pattern recognition, when a model is used that has been built on the basis of recorded pedestrian trajectories. For this purpose we used the "Edinburgh Informatics Forum Pedestrian Database" which consists of a large set of walking trajectories that has been measured over a period of months (edi, 2010) (see Fig. 6). The idea is to identify lanes that people normally use in a specific working area. In our case the models are built by fuzzy time clustering as follows:

1. From the whole set of data select 12 trajectories and divide them into 3 "bundels".
2. Make a clustering of each trajectory separately with $c = 10$ time clusters $C_{i,k,l} \in R^2$
k-number of set; l-number of trajectory in the set; i - number of time cluster
3. Compute the mean values of the time clusters in each set: $C_{k,i} = 1/m_k \cdot \sum_{l=1}^{m_k} C_{i,k,l}$
m_k - number of trajectories in set k. $C_{i,k} = (c_x, c_y)^T_{i,k,l}$ are the x, y coordinates of the i-th cluster centers in the

k-th set. The connections of $C_{i,k}$ $i = 1 \ldots c$ represent finally the lanes $k = 1 \ldots 3$. Fig.7 shows the results for all 3 sets.

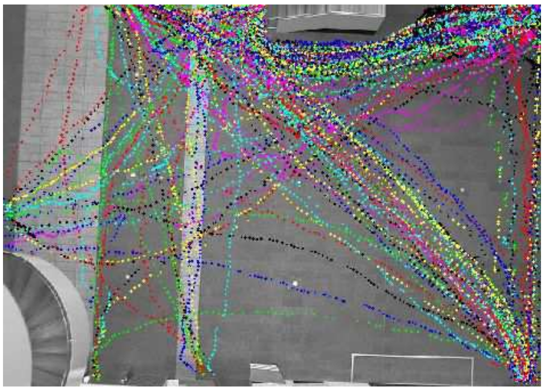

Figure 6: Edinburgh pedestrian data.

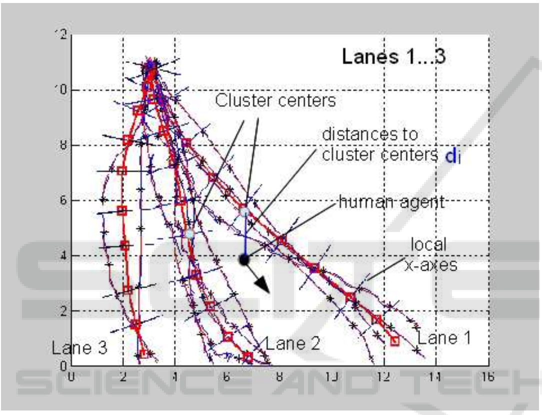

Figure 7: Lanes 1...3, average trajectories.

6.2 Recognition of Intentions to Follow Certain Lanes

In order to recognize the intention of a human agent to aim at a certain goal, the membership of his trajectory (or part of it) to one of the lanes is to be computed. The membership of a point $\mathbf{x} = (x,y)^T$ to a cluster center $C_{i,k}$ is here defined by

$$w_{i,k} = \frac{1}{\sum_{j=1}^{c} \left(\frac{d_{i,k}}{d_{j,k}}\right)^{\frac{2}{m_{proj}-1}}} \qquad (9)$$

where $d_{i,k} = (\mathbf{x} - \mathbf{x}_{i,k})^T(\mathbf{x} - \mathbf{x}_{i,k})$, $\mathbf{x}_{i,k}$ - i-th cluster center in the k-th lane, $m_{proj} > 1$ - fuzziness parameter (Runkler and Palm, 1996). The algorithm works as follows:

1. Compute the closest distances $d_{i_{min},k} = min_j(|\mathbf{x} - \mathbf{x}_{j,k}|)$ to the cluster centers $C_{j,k}$ $(j = 1 \ldots c, k = 1 \ldots m_k)$
2. Compare the membership functions $w_{i_{min},k}$ and select the lane with the highest membership:
$(w_{i_{min},k})_{max} = max(w_{i_{min},k})$, $k = 1 \ldots m_k$ or
$k_{max} = argmax(w_{i_{min},k})$.

However, only one data point is obviously not sufficient for intention recognition. Therefore moving averages $(\bar{w}_{i_{min},k})_{max}$ over a predefined number of time steps n are computed

$$(\bar{w}_{i_{min},k})_{max}(t_j) = \frac{1}{n}\sum_{i=0}^{n-1}(w_{i_{min},k})_{max}(t_j - i) \qquad (10)$$

With this the influence of noise is further reduced and the degree of membership of a human trajectory to a particular lane is reliably identified.

7 SIMULATION RESULTS

7.1 Collision Avoidance at Intersections

In the 1st simulation the "1 human - 1 robot" case is considered where the estimations of the crossing points are made during motion. This experiment is a combination of real human walking data from the Edinburgh Data and a simulated robot. At each time point the crossing points of the two tangents along the velocity vectors are computed and the robot velocity will be adjusted according to eq.(8 a). Figure 8 shows the plot before the crossing point and Fig. 9 shows the time schedule before and after the crossing point. In the case of stationarity the velocity is limited at a

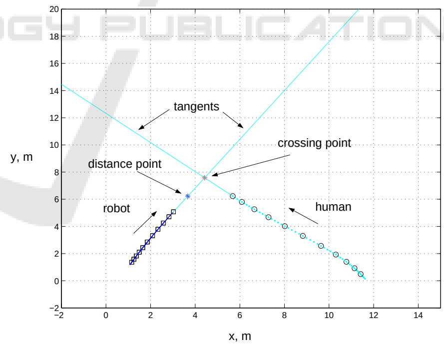

Figure 8: Motion before crossing, case 1.

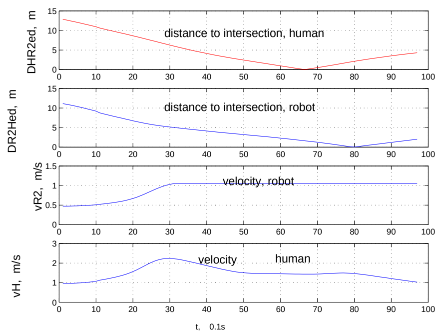

Figure 9: Time schedule before and after crossing, case 1.

predefined distance between robot and actual crossing point in order to prevent from too high robot velocities. Fig. 9 shows that after 3s the robot has reached a velocity that guarantees the human to pass the crossing point 1.5 second before the robot. Case 2 (eq.(8 b)) is shown in Figs. 10 and 11. Here the robot passes the intersection before the human with a time difference of 2.5 seconds.

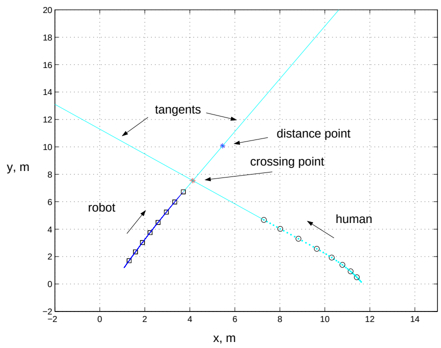

Figure 10: Motion before crossing, case 2.

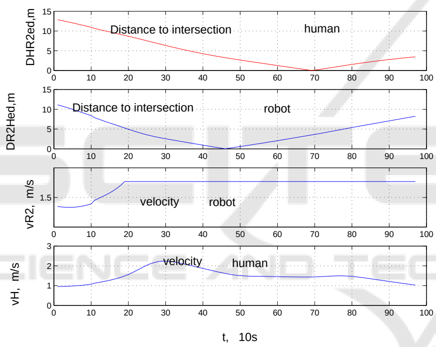

Figure 11: Time schedule before and after crossing, case 2.

7.2 Recognition of Lanes While Tracking

From 11 trajectories of the Edinburgh-data 3 different lanes were identified beeing used in both directions with different velocities. Lanes 1, 2, and 3 are modeled off line on the basis of 4, 5, and 2 trajectories, respectively. The modeling results are representative trajectories/paths of bundles of similar trajectories. In our example, 3 from 20 test trajectories (tracks) were selected from the Edinburgh-data which have not been used for modeling but whose entry/exit areas coincide with those of the modeled lanes (see Fig. 12). During motion the degrees of membership (see Fig. 13) for each track are computed according to (9) and (10) with a moving average about 10 time steps. Here, from the membership degrees in Figs.14-16 one can see, that from only a few samples the membership of a track to a lane can be recognized.

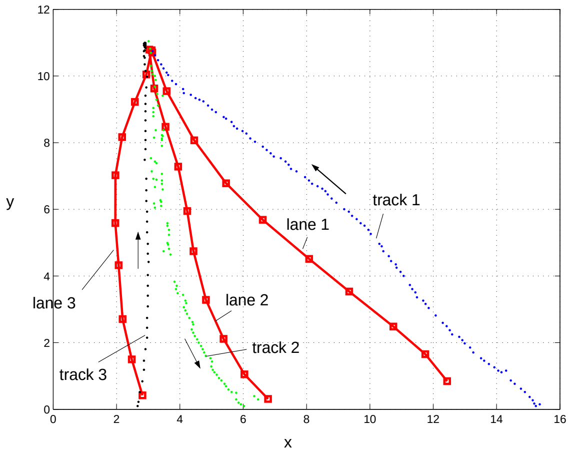

Figure 12: Lanes 1-3, test tracks.

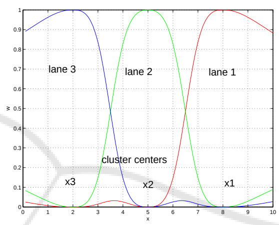

Figure 13: Membership functions.

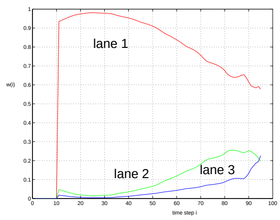

Figure 14: Memberships track 1.

8 CONCLUSIONS

The problem of the recognition of human intentions is part of a control task for human-robot interaction and cooperation. A prominent role plays the prediction of human motions to plan corresponding on line reactions and maneuvers. The time schedule for the information exchange and the kinematic relations have been discussed, a general scheme of regarding fuzzy control rules for the human-robot interaction is presented and collision avoidance and optimization strategies are discussed. Another method to recognize intentions is the fuzzy modeling of pedestrian tracks, the identification of lanes preferred by human agents, and the identification of a membership of a pedestrian track to a specific lane. Examples with both simulated and real data show the applicability of the methods presented, whereas - because of the lack of space - we confined ourself to the *switching controller* and the *recognition of lanes*.

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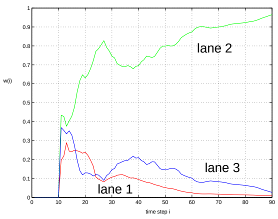

Figure 15: Memberships track 2.

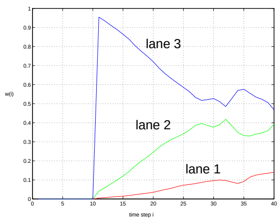

Figure 16: Memberships track 3.

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