ADAPTIVE COMPENSATION SIGNAL FOR A WHEELCHAIR CONTROL USING ANFIS MODEL

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Abstract: Wheelchairs users still face challenges when driving their standard design based vehicle. Given the matter, this work aims to implement an assisted control for a wheelchair, depending on the driving behaviour of the user. Therefore, a Bayesian network model will be implemented to help infer on the human behaviour. Thereafter, the inferred state of the user will serve as input to an ANFIS model. The role of the ANFIS model is to generate an assistive signal in order to compensate the input from the user.

1 INTRODUCTION

Assistive control aims to provide enhancements to the technology in order to reduce people's handicap by enabling them to perform tasks they were not able to achieve formerly. As an example, the motion in the environment has been facilitated by the use of wheelchairs. However, the use of standard wheelchairs brings up the issue of handling, as users suffer from different neuromuscular impairments. Therefore, there is a need to come up with a design that will be adapted to a specific user. This feature requires the vehicle to recognize the operation initiated by the user. In other terms, the device must learn the driving behaviour of the user. Then, the recognized human behaviour will help a navigation system to generate an assistive signal in order to compensate the handicap of the user.

Even though several approaches have been implemented to achieve the objective of modelling the human behaviour, very address the case of wheelchair driving activity. Therefore, this work reviews studies conducted in the domain of human behaviour modelling on car driving activity.

The optimal control approach (Burnham et al., 1974) considers the human as an optimal controller and tries to identify some parameters liable to influence the driver behaviour; however, the authors admit that too many assumptions were made to come up with the proposed model. The closed loop based model (Thakur, 1997) includes the mechanical time response (from the vehicle) and the human time response which is assumed to be a function of a daydream factor to determine.

Although the cognitive architecture (Dario Salvucci and Liu, 2001) seems to be more realistic, the model is difficult to implement as it requires the measurement of some internal states of the human operator such as the HRV (Heart Rate Variability).

In the other hand, many other studies have considered a model based on external observations. Among others, we can mention polynomial models (Koashi et al., 2003; Kim et al., 2004), data clustering approach (Suzuki et al., 2005), Hidden Markov Models (Kuge et al., 1998) and Bayesian Networks (Bouslimi et al., 2005). However, the comparison of Hidden Markov Model and Bayes net model (Tezuka et al., 2006) revealed that Bayesian network provided better inference even though HMM detect the change of operation earlier.

The method referred to as potential field (Koren and Boreinstein, 1991; Masoud, 2002) assumes the presence of different forces applied to the vehicle: repulsive forces are generated by obstacles while the target point applies an attractive force to the vehicle. The magnitude of the repulsive force is proportional to certainty value (how confident the algorithm is in the presence of an obstacle) and inversely proportional to the distance between the centre of the robot and the obstacle.

However, KOREN (Koren and Boreinstein, 1991) identifies four major issues associated in the application of the method:

- Trap situations due to local minima

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- No passage between two close obstacles.
- Disturbances of the obstacle cause oscillations
- Oscillations in narrow passages

EMAM's work (EMAM, 2010) on wheelchair driver behaviour also represents the influence of obstacles on the driver by similar forces (mostly repulsive), except that the attractive force depends on the driver.
Another reference (Chakravarthy and Ghose, 1998) proposes the concept of collision cone, for collision avoidance situations. Given a vehicle and an obstacle, the authors find the locus of directions of the vehicle for which there may be a collision. The collision cone is found to be a function of the velocities of the vehicle and the obstacle, their direction, the distance separating them and also their shape. Therefore, in case of possible collision (when the vehicle's velocity vector lies within the collision cone), the speed and direction can be modified to bring the velocity vector out of the collision cone. The strategy to adopt depends on the time and kinematics constraints of the vehicle. The same concept is has also been adopted in a multi-obstacle environment (Fiorini and Shiller, 1998).
Langer et al. (Langer et al., 1994) proposed a method for a behavioural response based on the DAMN architecture framework developed by J. K. Rosenblatt (Rosenblatt, 1997); the architecture is comprised of three parts:

- The perception module processes the images taken of the surrounding environment and identifies traversable regions of the terrain.
- The management module generates a map representing the surrounding terrain.
- The planning module issues the commands signals.

All the actions of the architecture are working asynchronously, sending their outputs to an arbiter which evaluates the prevailing one. Unfortunately, the authors (Langer et al., 1994) found the inability to deal with close ends as the most important and common failure when implementing such an architecture; this is because the system only deals with local representation of the terrain. Moreover, the speed of the vehicle is limited by the maximum range of the sensors and by the image acquisition rate. In addition to the latency for the full acquisition of an image, the map generation also contributes to a non real time architecture.
Another behaviour based approach (Yinka-Banjo, 2010) uses the Bayesian network model for inference. First, the robot is guided through an environment with obstacles. A database of distance to obstacles and manoeuvres of the (human) operator is updated; then, a Bayesian network is built from the data gathered. This network will serve as required knowledge of the robot for obstacle avoidance behaviour.
NEFTI et al. (Nefti et al., 2001) proposed an ANFIS model where they define three main tasks, each one representing a module that implements an ANFIS system, with sensors information as input and orientation of the robot as output. A fusion strategy implemented by a neural network selects the most appropriate output, given the information from the sensors.
A reference (Ayari and Chatti, 2007) defined two major tasks to be executed by the robot whilst another one (Shimizuhira et al., 2004) defined three. Even though ARAGHI and MENHAJ (Araghi and Menhaj, 2008) adopted a different approach using the concept of collision cones, all three studies implement a fuzzy controller serving as the decision making module.

Given the comparison of Bayesian net and Hidden Markov Model (Tezuka et al., 2006), even though the speed of state detection is an important aspect, this work favours the accuracy of the model as it will be applied to a wheelchair, which is not supposed to be as fast as a car.
Thereafter, a navigation system will be implemented using an adaptive Neuro-Fuzzy Inference System to generate the assistive control reference.

2 DRIVING STATE INFERENCE USING BAYES NETWORK

This section will briefly present the model implemented for the driving task inference, as the result is an input of the Neuro-Fuzzy model.
The model considers a scenario where the wheelchair's user moves from a point A to a point B following a straight line, and an obstacle is standing on the way, or moving across the path (figure 1).

Hence the following four states are thus defined:

- **State 1** (Straight line driving task)**:** the vehicle goes from A to B without any obstacle on the path
- **State 2** (Slow change of trajectory)**:** the user avoids an obstacle which is far ahead (or moving slowly).
- **State 3** (Rapid manoeuvre)**:** the user initiates an emergency collision avoidance manoeuvre.
- **State 4** (Recovery, from rapid manoeuvre)**:** the driver defines a new trajectory to the destination after an obstacle avoidance manoeuvre.

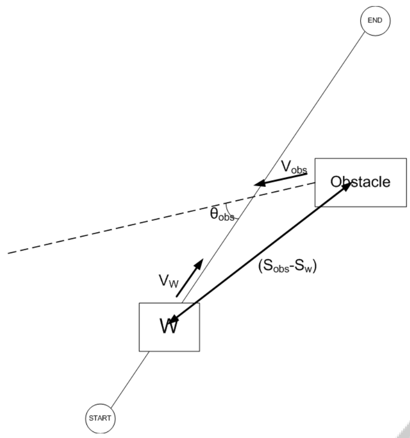


Figure 1: Scenario representation.

The structure of the model is assumed to be known and is presented on figure 2.

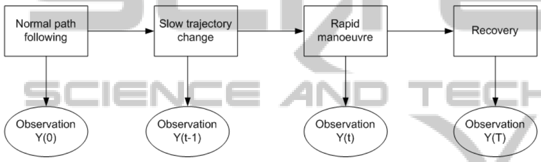


Figure 2: Bayesian network model.

Therefore, the model estimation is reduced to the estimation of the parameters. The judgment $X(t)$ is a discrete variable representing the actual state of the driving task, while the observation $Y(t)$ is the distribution of observed information, namely the command signal for the linear velocity and the command signal for the angular deviation which are both measurable at the output of the controller (in this case, a joystick).

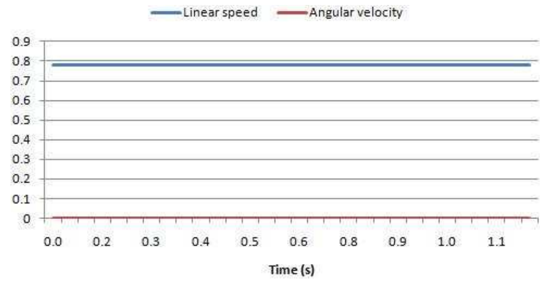
MURPHY (Murphy, 2007) developed a Bayes Net Toolbox for Matlab, which implements the EM (Expected Maximization) algorithm to find local optimal maximum likelihood estimates of the parameters. The model training is performed as the combination of time-series judgment states and observed data at that time.

The results shown in figures 3, 4, 5 and 6 compare the data from the controller and the states inferred by the model. This validates the aptitude of the model at inferring on human behaviour in wheelchair driving activity.

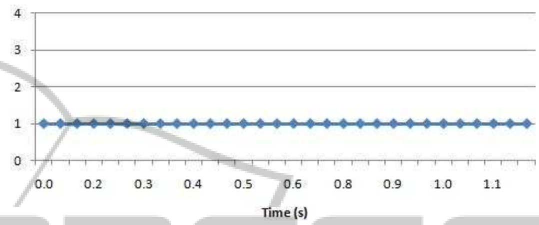
3 ANFIS MODEL

3.1 The Theory Reviewed

A simple representation of ANFIS architecture (Jang, 1993) is presented in figure 7.

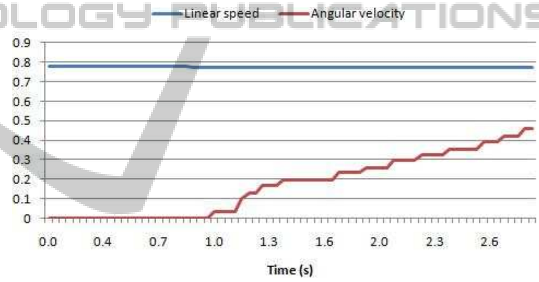


(a) Test data

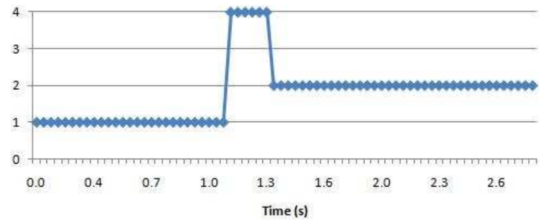


(b) Estimated state

Figure 3: State 1: Normal path following.



(a) Test data

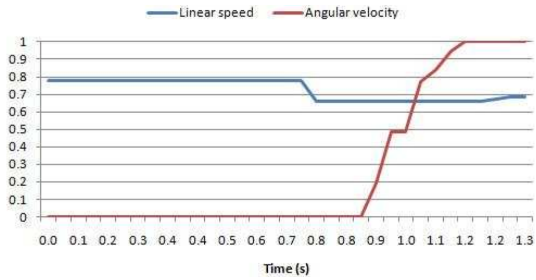


(b) Estimated state

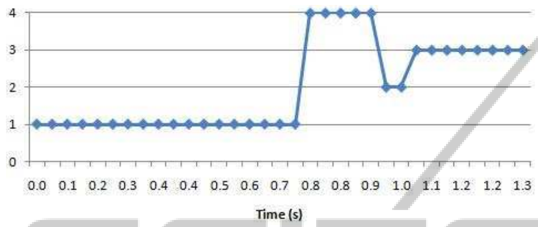
Figure 4: State 2: Slow trajectory change.

The functions of the layers as defined by DENAI et al. (Denai et al., 2004) are:

- Layer 1 generates the membership grades
- Layer 2 generates the firing strengths by multiplying the incoming signals and outputs the t-norm operator result.
- Layer 3 normalizes the firing strengths
- Layer 4 calculate rules outputs based on the consequent parameters
- Layer 5 computes the overall output as the sum-

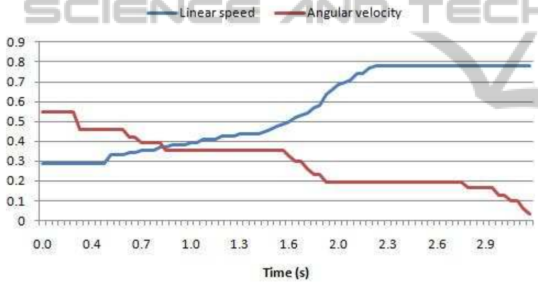


(a) Test data

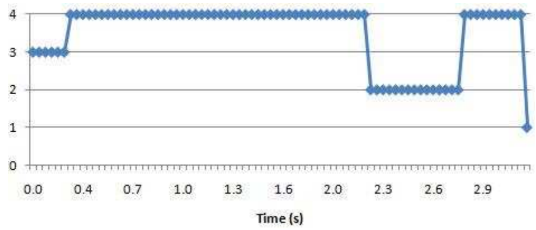


(b) Estimated state

Figure 5: State 3: Rapid manoeuvre.



(a) Test data



(b) Estimated state

Figure 6: State 4: Recovery.

mation of incoming signals.

There are basically two classes of learning algorithm for ANFIS architecture:

- In the forward pass, outputs of the nodes go forward until the fourth layer where least square methods are used to identify the conclusions.
- In the backward pass of the hybrid algorithm, errors signals are now propagated backwards and the gradient descent method updates the antecedent parameters.

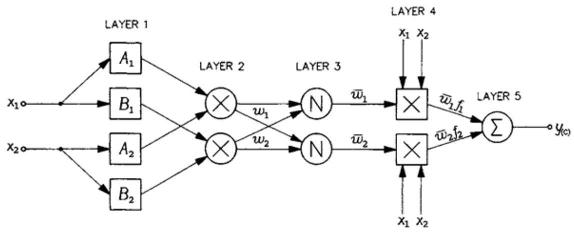


Figure 7: ANFIS architecture.

3.2 Model Definition

Our model is supposed to generate an adequate control signal, given the driving state of the driver and the environmental influences. The only external (major) factor considered in this study is the obstacle, which may be mobile or static; therefore, the influence of the surrounding environment is reduced to the distance between the vehicle and the obstacle. Note that the considered distance is measured from the vehicle to the closest impact point of the vehicle, following the displacement direction of the chair (see figure 8).

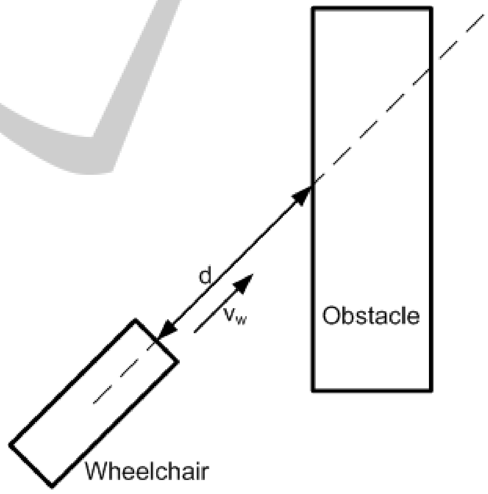


Figure 8: distance measured between the vehicle and the obstacle.

The general scheme of the model to implement for this task (figure 9) is very close to the one proposed by NEFTI et al. (Nefti et al., 2001). Four possible responses (each one corresponding to a driving state of the wheelchair driver) are computed given the distance to the obstacle, and the driving state inferred by the Bayesian network will choose the adequate output.

The distance to collision is considered to be the only input of the different systems, and each system will output two signals: the linear speed and the angular deviation. Now, lets define the rules of the different systems.

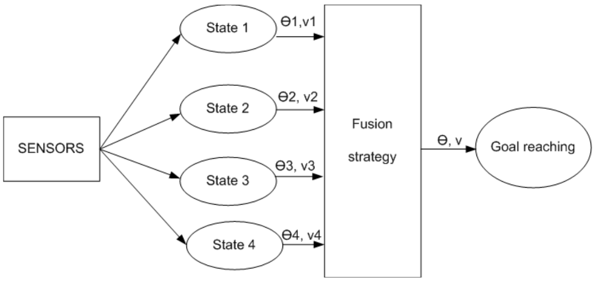


Figure 9: ANFIS model general scheme.

State 1. In the first state, the driver follows a straight line to the target. Therefore, the angle is supposed to remain zero, and the linear velocity is supposed to remain at an average value depending on the users behaviour.

$$\textit{Angle} \approx 0$$
$$\textit{Linear velocity} \approx V_{avg}$$

State 2. The second state corresponds to the slow change of trajectory. Here, we consider the two outputs: the speed and the angular deviation.

If the obstacle is far, then the speed is normal and the direction changes very slowly
If the obstacle is close, then the speed is slow and the direction changes slowly

State 3. The obstacle is relatively very close, and perhaps moving towards the vehicle, the driver initiates emergency obstacle avoidance.

If the obstacle is far, then the speed is slow and the direction changes slowly
If the obstacle is close, then the speed is very slow and the direction changes quickly

State 4. It would not be appropriate to consider the distance to collision in this case as the vehicle has overcome the obstacle and the driver tries to define the new trajectory to the target. Therefore, the goal is to get back to the normal driving path, which can be defined by normal linear velocity and no angular deviation (just like in state 1).

4 RESULTS

The experiments conducted permitted to gather the information about the X and Y position of the vehicle, as well as the deviation angle; those parameters are used to compute the distance between the vehicle and an obstacle on its way.

As mentioned in the previous section, only the second and third phases of the driving behaviour are subject to a Neuro-Fuzzy controller, as the two other states will have constant references.

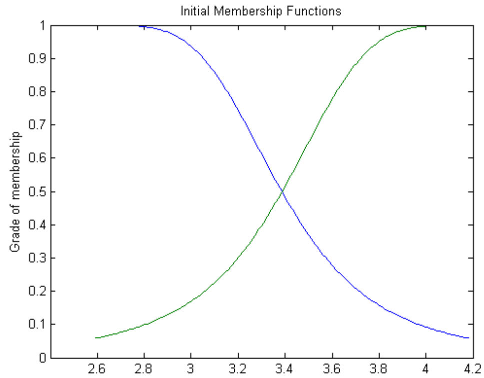


Figure 10: Initial membership functions.

The toolbox generates initial membership functions (figure 10) and uses the backpropagation algorithm for parameter tuning. The resulting membership functions of figures 11, 12 and 14 represent the membership grades as functions of the distance to collision.

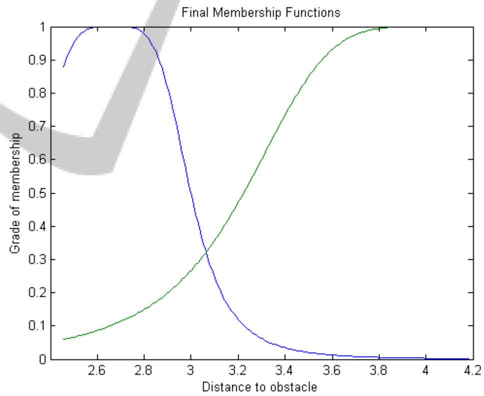


Figure 11: Final membership functions: state 2.

In figure 11, the bell-shaped function representing the set of close distances has its center at about 2.7m while the distance is more likely to be considered as far from the value of about 3.1m.

Even though the first function of figure 12 looks wider (regarding the input range) than that of the figure 11, the range is considerably smaller (from 0.7m to about 1.4m).

The two functions depicted in figure 14 have almost same widths of about 0.25m. From 1.2m to 0.85m, the user considers the distance to be critical; moreover, the narrowness of the function and the very small overlap with the function express a decision making process involving a limited output range.

Figures 13 to 15 compare the data from the user and the data generated by ANFIS models. The response of the ANFIS model in the third state shows a

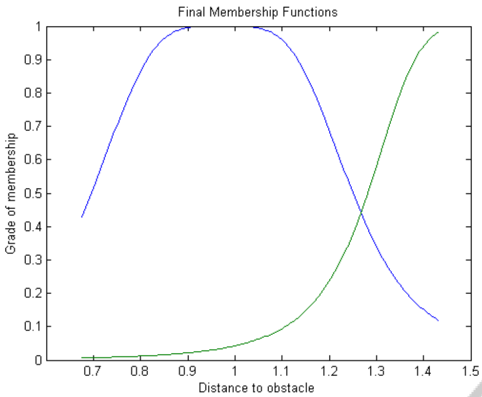
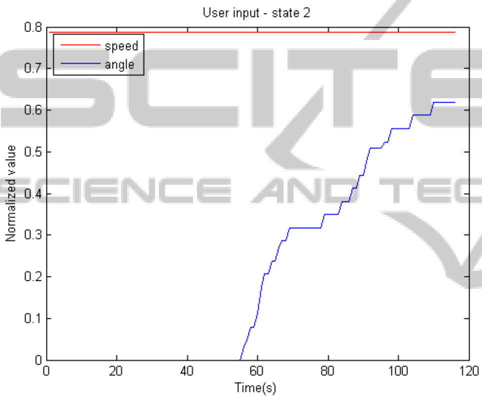
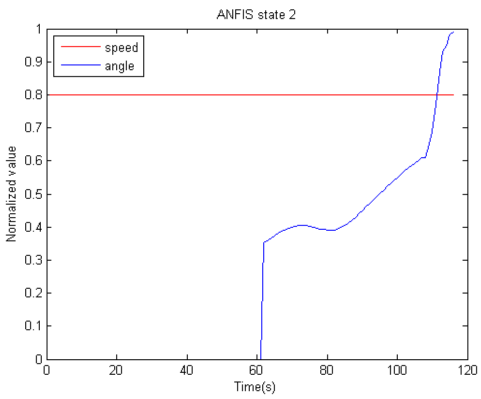


Figure 12: Membership functions for angle inference in state 3.



(a) Signal from the Joystick



(b) ANFIS generated signal

Figure 13: State 2: Slow trajectory change.

delay in reducing the linear velocity, however the angle reference tries to avoid the obstacle (changing the direction) as soon as the state is detected. Moreover, the model initiates a reduction of the speed when the driving task persists. Finally, we can note the return to the normal behaviour (maximum speed and no deviation) when the vehicle has overcame the obstacle.

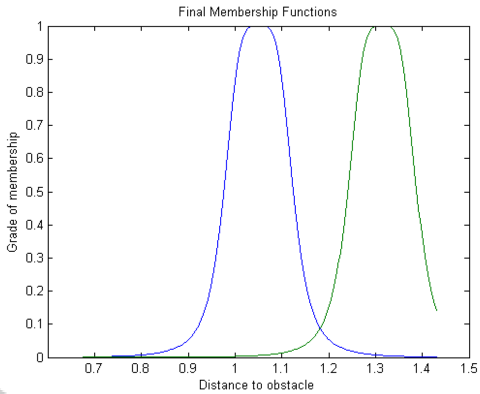
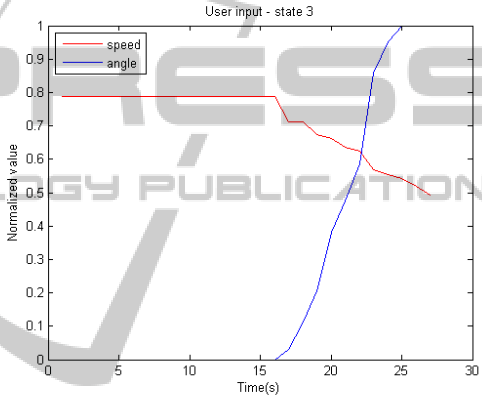
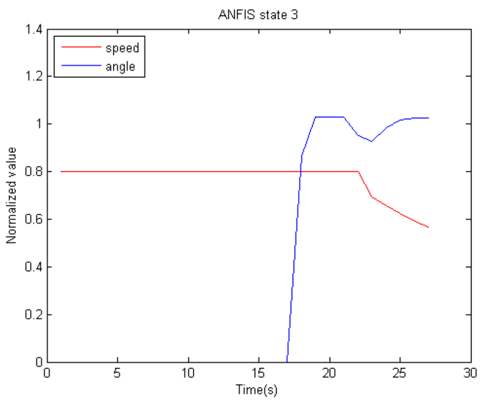


Figure 14: Membership functions for speed inference in state 3.



(a) Signal from the Joystick



(b) ANFIS generated signal

Figure 15: State 3: Collision avoidance manoeuvre.

5 CONCLUSIONS

The results show the possibility of an assisted control adapted to the behaviour of the user. The implemented ANFIS model is to serve as generator of the reference signal for the user input. The combination of the two signal is the input to the wheelchair system. A future improvement of the overall system may include a state estimator at the output of the system, in order to implement a feedback controller using optimal control theory.

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