

## Scheme for motion estimation based on adaptive fuzzy neural network

Fredy Martínez, Cristian Penagos, Luis Pacheco

Facultad Tecnológica, Universidad Distrital Francisco José de Caldas, Colombia

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### ABSTRACT

Many applications of robots in collaboration with humans require the robot to follow the person autonomously. Depending on the tasks and their context, this type of tracking can be a complex problem. The paper proposes and evaluates a principle of control of autonomous robots for applications of services to people, with the capacity of prediction and adaptation for the problem of following people without the use of cameras (high level of privacy) and with a low computational cost. A robot can easily have a wide set of sensors for different variables, one of the classic sensors in a mobile robot is the distance sensor. Some of these sensors are capable of collecting a large amount of information sufficient to precisely define the positions of objects (and therefore people) around the robot, providing objective and quantitative data that can be very useful for a wide range of tasks, in particular, to perform autonomous tasks of following people. This paper uses the estimated distance from a person to a service robot to predict the behavior of a person, and thus improve performance in autonomous person following tasks. For this, we use an adaptive fuzzy neural network (AFNN) which includes a fuzzy neural network based on Takagi-Sugeno fuzzy inference, and an adaptive learning algorithm to update the membership functions and the rule base. The validity of the proposal is verified both by simulation and on a real prototype. The average RMSE of prediction over the 50 laboratory tests with different people acting as target object was 7.33.

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### Corresponding Author:

Fredy Martínez,

Facultad Tecnológica,

Universidad Distrital Francisco José de Caldas Bogotá, Colombia.

Email: fhmartinezs@udistrital.edu.co

## 1. INTRODUCTION

Service robotics is one of the applications of robotic systems that arouses the most interest among the general population due to its high expectations and possibilities, but at the same time is one of the areas with the most unsolved engineering problems [1]. Robots that interact with humans in human environments must solve problems of path planning, image processing, interaction with the environment, fine manipulation, communication, and in particular, direct interaction with the human being [2]. This interaction involves many engineering problems, not only considering the safety problems for both parties during the interaction, which is a net engineering problem [3, 4], but the interaction is conditioned by human behavior, which is quite unpredictable. In domestic applications, for example, applications in which the robot must be attentive to children or elderly, we expect the machine to always be close to the person under care, moving with him to provide their services, but without interfering with his normal activity. Given the unknown nature of the movement of people in the environment and the high complexity and dynamics of the environments,

adaptable tracking systems are required, with the ability to learn and work in real time. A typical characteristic of service robots is that their tasks are carried out in dynamic, unstructured and unknown environments, generally without identifiable characteristics. The robot must be able to navigate and interact in any environment in which people find themselves, which characterizes the physical structure of the robot (size, type of displacement, actuators, etc.) and its needs for sensing and acting (often equivalent to human). In addition, the processing of information and the response of the robot must be in real time. This is why these sensors are so important for autonomous robots in general [5, 6].

Currently a crucial element in the design of this type of systems are the active robotic sensors, which have become high performance tools capable of considerably reducing the processing requirements of the robot control unit. These systems have gained great commercial recognition, even at the military level, thanks to their embedded structure that, together with sensors that observe physical variables directly, process this information in real time to extract relevant information for the robot. This kind of sensors has promoted research in information-driven strategies for the development of tasks with robots, as well as the implementation of algorithms for digital signal processing and control schemes oriented to these sensor [4]. As minimum requirements, the robot must be able to define its distance and size. In other cases, it is also necessary to know its height to define interaction strategies (pick up an object from a table, for example). Depending on the application it is possible to use different kinds of sensors, in interaction with human environments are very important optical sensors [4, 6, 7], however, when the person has been identified, and the goal is to make a basic tracking of him, the most important sensors are the distance sensors [8, 9, 10].

The camera-supported optical sensors in robotics have been widely used to solve the problem of identifying and tracking people. The schemes, though far from autonomous implementation, provide high levels of performance for both problems [11, 12]. This strategy is known as Visual Servoing or Vision-Based Robot Control (VS) and is characterized by having as feedback information the image of a camera [13]. The goal is to support robot decision making with eyes that take optical information from its own perspective [14]. However, the use of cameras capable of continuously recording people's personal lives involves serious privacy issues, and despite the guarantees of encryption and non-sharing of information, fear prevails [15]. In addition, the visual information captured by the cameras is, in fact, excessive for the realization of certain tasks. Distance sensors are also widely used in these applications [11], and unlike video cameras, they have greater acceptance to work between people because they record less private information. The most important characteristic of the following task is that it is strongly focused on the person under care. This is a common case in service robots that provide some service to a person [16-18]. Practically speaking, this means that the robot must be aware of the person's behavior. Similarly, the robot will ignore other elements of the environment unless they force the robot's response [19, 20]. In this sense, we only study in our research the autonomous response of the robot to the behavior of the person.

In our research, we define the task of following people, in the context of service robots, as a high-level task that the robot performs at all times in parallel with its interaction tasks [21]. In the context of the task, the robot does not know the person's movement dynamics, whether the person is going to remain still, or where it is going when walking. In this way, the robot needs to infer the person's movement beforehand and act accordingly. In addition, the design of the movement scheme must take into account the aforementioned aspects of navigation, interaction, and sensing, as these are key elements in the robot's final action. These parameters are combined with an adaptive learning scheme and an inference machine based on fuzzy inference. These two elements form the Fuzzy Neural Network (FNN) designed for decision making, which is supplied by our active distance sensor [22, 23].

## 2. PROBLEM FORMULATION

The goal of this research is to develop a robust and high-performance software tool that allows the development of autonomous tasks of people follow-up by a small autonomous robot. The work is strongly motivated by the need for this feature as part of the routine interaction of an assistive robot that operates in unknown indoor environments.

Let  $W \subset \mathbb{R}^2$  be the closure of a contractible open set in the plane that has a connected open interior with obstacles that represent inaccessible regions. Let  $\mathcal{O}$  be a set of obstacles, in which each  $O \subset \mathcal{O}$  is closed with a connected piecewise-analytic boundary that is finite in length. The position of obstacles in the environment changes over time in an unknown way, but they are detectable by distance sensors. In addition, the obstacles in  $\mathcal{O}$  are pairwise-disjoint and countably finite in number.

Let  $E \subset W$  be the free space in the environment, which is the open subset of  $W$  with the obstacles removed. This space can be freely navigated by the robot, but it can also be occupied at any time by an obstacle. The robot knows the environment  $W$  (and  $E$ ) from observations, using sensors. These observations allow him to build an information space  $I$ . An information mapping is of the form:

$$q: E \rightarrow S \quad (1)$$

where  $S$  denote an observation space, constructed from sensor readings over time, i.e., through an observation history of the form (2).

$$\tilde{o}: [0, t] \rightarrow S \quad (2)$$

The interpretation of this information space, i.e.,  $I \times S \rightarrow I$ , is that which allows the robot to make decisions. The problem can be expressed as the search for a function  $u$  for a specific set of conditions between a certain obstacle and the robot, from a set of robot sensed data  $y \subset S$  and a target function  $g$ .

$$f: y \times g \rightarrow u \quad (3)$$

### 3. METHODOLOGY

As part of the research, the research group has previously developed an active sensor that processes distance information to define the motion of an autonomous robot in indoor environments using real-time analysis of raw data from a group of nine infrared sensors [22]. The infra-red sensor captures distance data in real time producing a large database that the robot analyzes according to previous experiences to directly define distance on the horizontal plane to the object (person). Observing the dependence of data with the topology of the environment, the active sensor uses a model based on a long short-term memory (LSTM) network to estimate distances [24]. Thanks to this model it is possible to define coordinates on the plane of the environment to an obstacle of interest, regardless of the characteristics of the obstacle or its position with respect to the robot. The historical behavior of the variables is also used to differentiate the person of interest from other elements and obstacles of the environment, however, to differentiate between different people we have used specific marks on the person of interest.

The active sensor delivers the coordinates  $x$  and  $y$  to the obstacle under study (person to follow) with respect to an axis defined on the geometrical center of the robot. This sensor has a real-time processing unit that assigns values to the raw data captured by the nine infra-red sensors using models based on an LSTM network. These data also define the heading  $\theta$  and allow to determine speed and acceleration Figure 1.

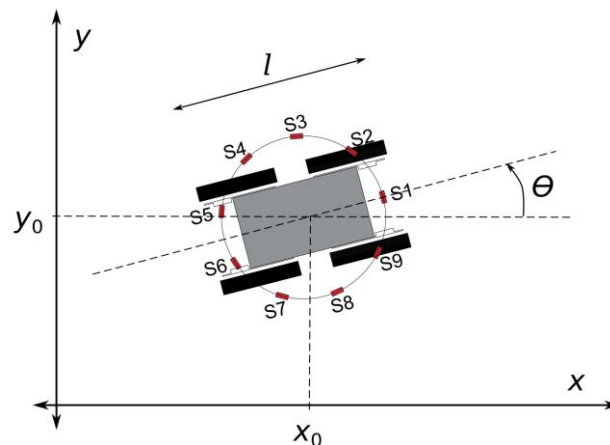


Figure 1. Variables and dimensions axes on the plane with respect to the robot

The proposed system is composed of a fuzzy neural network (FNN) and an adaptive learning algorithm Figure 2. The neural network is made up of five layers: a layer of input variables (two-dimensional distances from the robot to the obstacle, the relative velocity between robot and obstacle, the heading angle and acceleration), the second layer corresponds to the membership functions, the third layer is of reasoning rules with Takagi-Sugeno type inference, the fourth layer corresponding to the fuzzy quantification of the output variable, and the fifth layer containing the output nodes (output variable, robot heading angle). The input vector has the following format (4):

$$X = [\Delta x, \Delta y, \Delta v, \theta, ac] \quad (4)$$

We define three trapezoidal fuzzy sets for each of the input variables uniformly distributed throughout the discourse universe of each variable. This design generated a total of 243 fuzzy rules each with the following structure (5):

$$R_i: IF (\Delta x \text{ is } A_i) \text{ and } (\Delta y \text{ is } B_i) \text{ and } (\Delta v \text{ is } C_i) \text{ and } (\theta \text{ is } D_i) \text{ and } (ac \text{ is } E_i) \text{ THEN } h_i \text{ is } f_i(\Delta x, \Delta y, \Delta v, \theta, ac) \tag{5}$$

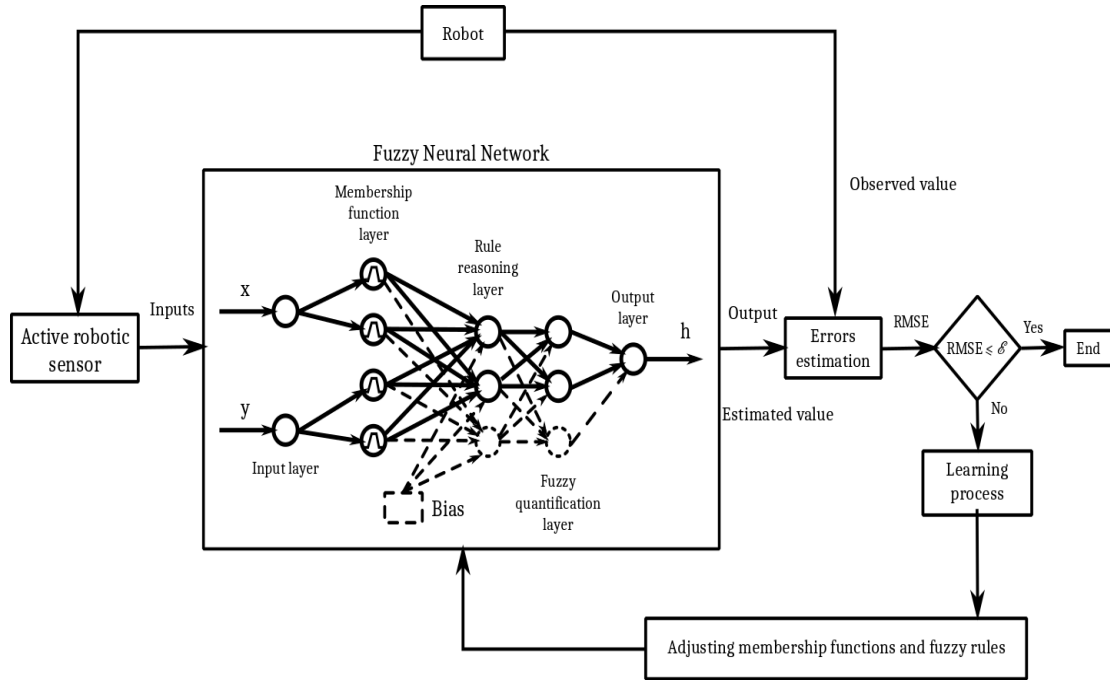


Figure 2. Proposed prediction system architecture

$A, B, C, D,$  and  $E$  correspond to a fuzzy set defined by its membership function, and  $f_i$  corresponds to the inference consequence for the output variable and according to the evaluated  $i$ th fuzzy rule. We use a Takagi-Sugeno-Kang fuzzy inference in order to obtain an output membership function defined from the input variables (a linear function defined by the input vector).

Due to the mechanical delays in the motion responses of the robot platform, we decided not to use fuzzy sets with triangular or Gaussian shapes [25], instead, we chose trapezoidal functions that allowed constant output behaviors for certain ranges of input variables Figure 3. The output inferred  $h_0$  is determined as the weighted average of the outputs of each rule for the input vector  $X_0 = [\Delta x_0, \Delta y_0, \Delta v_0, \theta_0, ac_0]$  (6), where  $\omega_i$  is the membership degree for the  $i$ th rule.

$$\hat{h}_0 = \frac{\sum_{i=1}^k \omega_i \cdot f_i(\Delta x_0, \Delta y_0, \Delta v_0, \theta_0, ac_0)}{\sum_{i=1}^k \omega_i} \tag{6}$$

We use a Least Squares Estimator (LSE) to perform parameter estimation by training the linear functions. Each of these functions has the general form (7).

$$f(X) = b_0 + b_1X(1) + b_2X(2) + b_3X(3) + b_4X(4) + b_5X(5) \tag{7}$$

To increase the performance of the prediction scheme, we use an adaptive learning algorithm to improve the inference machine, particularly by adjusting the membership functions defined initially Figure 3 from the behavior of the prediction error.

$$e = h - \hat{h} \tag{8}$$

During training each fuzzy set is replaced by a set that improves the performance of the estimator, i.e., produces less error according to the behavior of the RMSE.

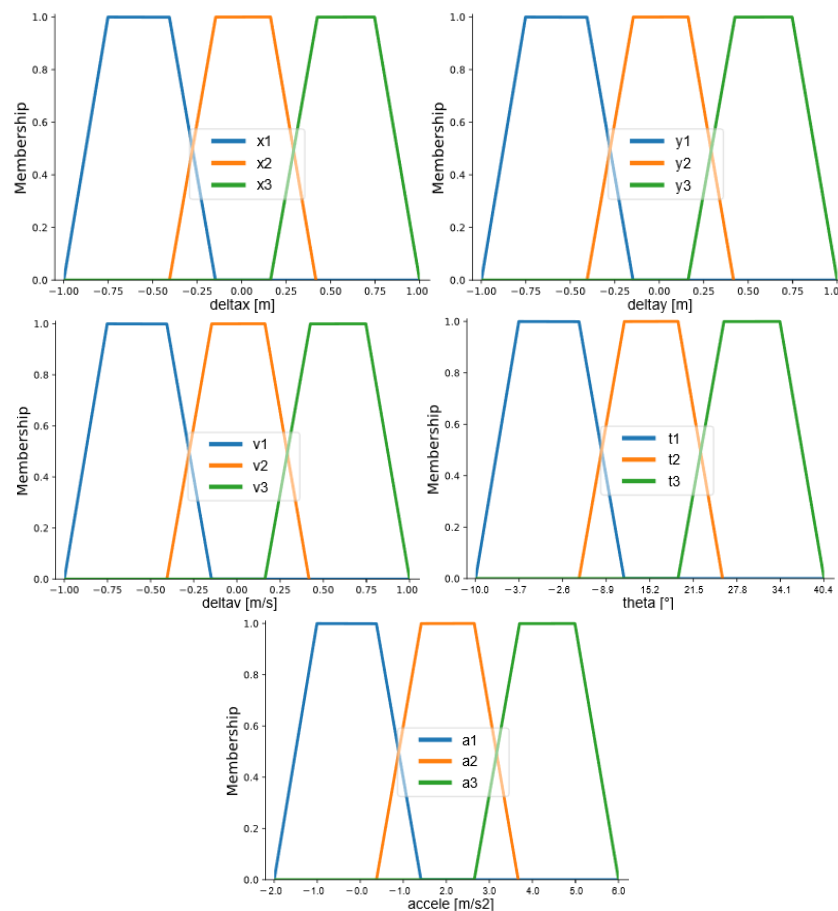


Figure 3. Initial membership functions of the five input variables

#### 4. FINDINGS

Our robot platform consists of two robots integrated in a single system: Nao robot from SoftBank Group, and our ARMOS TurtleBot 1 robot Figure 4. Our future objective is to develop our platform for service applications, we have created a first mobile functional prototype, and we are experimenting with different manipulator prototypes, but in the meantime, this integration of robots makes up our robotic solution. The Nao robot is used for direct interaction with human beings taking advantage of their morphology, sensors, actuators and responsiveness. The ARMOS TurtleBot 1 robot is used as a robust navigation platform in dynamic indoor environments. The two robots share information via a router installed in the ARMOS TurtleBot 1. The ARMOS TurtleBot 1 robot also has sufficient processing capacity for real-time execution of simple visual recognition algorithms (DragonBoard 410c of Arrow Electronics with ARM Cortex-A53 Quad-core up to 1.2 GHz per core and Qualcomm Adreno 306 @ 400MHz). The DragonBoard also collects the data read by the sensors during robot-human interaction tests, processes them and produces the training database with the input and output variables. The dataset was divided into 70% for training and 30% for testing. This division allows using most of the dataset to create the model, ensuring that statistically, the population of datasets are marginally different and that all possible patterns that will characterize the model are included. The 30% of unknown data allows validation and testing of the model.

Figure 5 shows the final membership functions for the five input variables after the learning process. With this structure the performance of the model was validated for different people identified by the robot. Figure 6 shows the prediction results for the tracking of two different people under laboratory conditions. In the tests people gently approach and move away from the robot after it has identified them as a target object. The first person was a man of 1.71 m height and medium body (76 kg weight). The second person was a man 1.74 m high with a little more volume (89 kg weight). The entire training process was conducted with five

different people. The movements in front of the robot were slow, but corresponding to the natural behavior of a person in human interaction. The model is not trained with high-speed behaviors because they do not correspond to the expected operation, and because the active sensor has a response speed limit. In the figure the black line represents the real behavior data detected by the robot sensors, while the red curve represents the behavior predicted by the model for the same instant. In blue is the tracking error in each case. As in the two cases shown, the results show that the proposed model can closely follow the movements of the target person. The average RMSE of prediction over the 50 laboratory tests with different people acting as target object was 7.33.



Figure 4. Service robot (Nao robot at the top and ARMOS TurtleBot 1 at the bottom) used in interaction and tracking tests

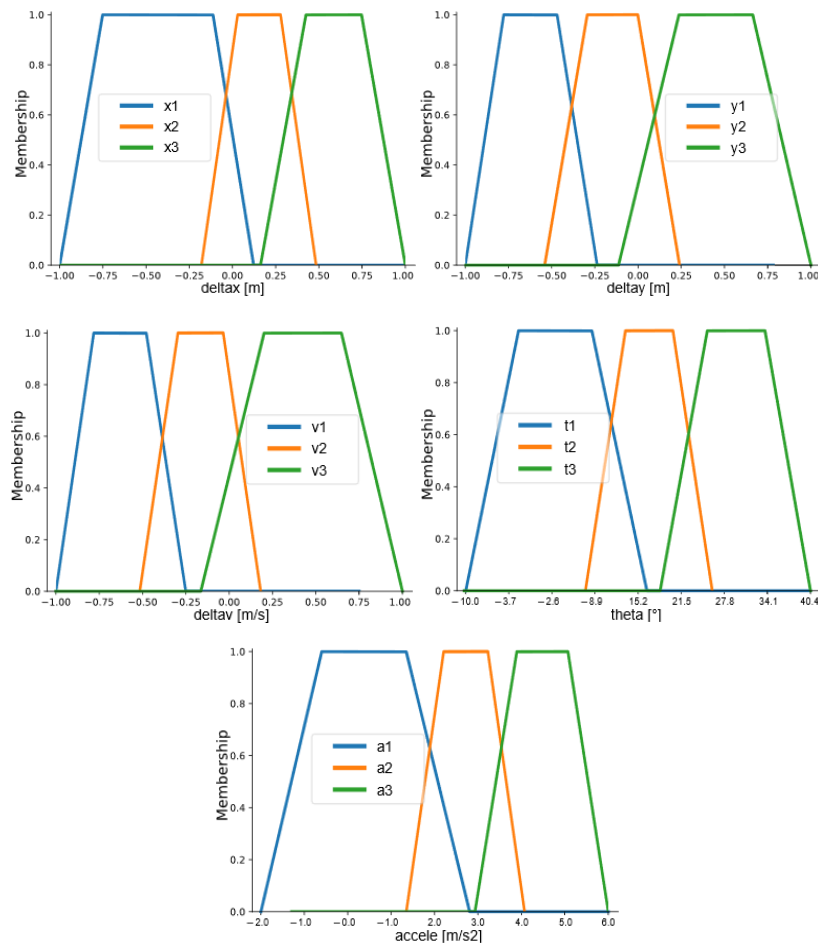


Figure 5. Final membership functions of the five input variables

## 5. CONCLUSIONS

In this paper we propose an adaptive fuzzy neural network to predict the movements of a person, in real time, by a service robot. This scheme is integrated with other subroutines in our robotic platform in order to develop complex tasks in the care of children, sick and elderly people. The proposed model uses as input variables the two-dimensional coordinates of the robot in the environment over time, as well as the estimation of its speed, orientation and acceleration. The proposed strategy presents a high performance in predicting the behavior of the target person thanks to the optimization of the parameters in the Takagi-Sugeno model. In addition, the adaptive learning scheme used optimizes the design of the belonging functions and the related fuzzy rules which improves accuracy. The size and location of the fuzzy sets was adjusted in line with the learning process. In most cases the central set was reduced, and the central value moved from the center of the discourse universe. Laboratory experiments performed with our robotic platform demonstrate the high performance of the strategy, and its high reliability to predict the behavior of the person from the readings of the active distance sensor. The average RMSE of prediction over the 50 laboratory tests with different people acting as target object was 7.33. On the model achieved it is proposed to improve the performance reducing the errors of prediction through the presentation of new patterns with a wider set of people that includes a greater class of characteristics to detect by the robot.

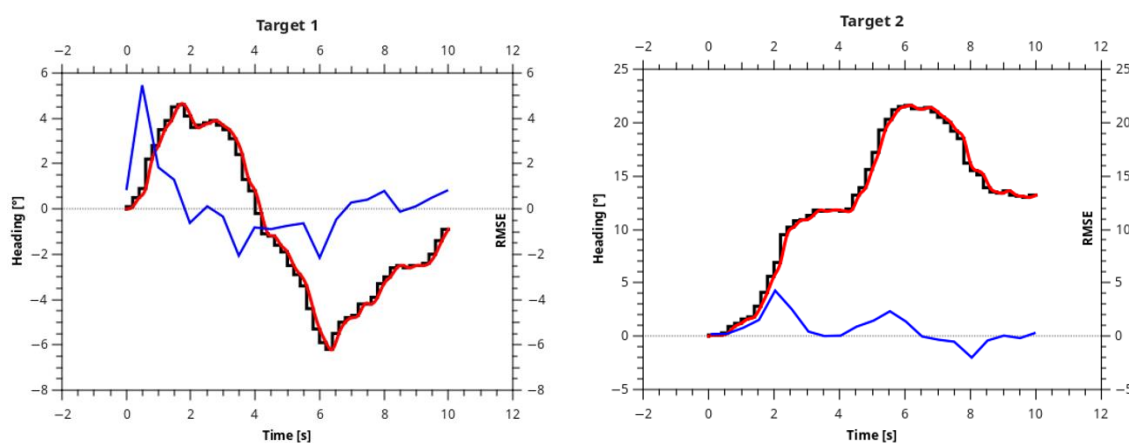


Figure 6. Predictive results for two following cases. The red curve represents the behavior predicted by the model, while the blue curve represents the tracking error

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