

Kansei with Behavioral Patterns for Human-Robot Interaction in Ubiquitous Environments

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Abstract

Humans have two distinct features with compared to any other living being; unique physical nature and emotions / feelings. Anybody who studies on humans or trying to construct human like machines should consider these two vital facts. When robots are interacting with humans and other objects, they certainly have a safe distance between them and the object. But how can this distance be optimized when interacting with humans? Will there be any advantages over achieving this? Will it help to improve the condition of robots? Can it be a mere constant distance? How will the humans react? In order to ‘humanize’ robots, they (robots) should also have certain understating of such emotions that we, humans have. In this research project, authors are trying to ‘teach’ one such human understanding, commonly known as ‘personal space’ to autonomous mobile robots.

1 Introduction

As Simmons et al. [1] describe, recent research in mobile robot navigation has utilized autonomous mobile robots in service fields. To operate them in an environment with people, it requires more than just localization and navigation. The robots should recognize and act according to human social behavior to share the resources without conflict [2].

The comfort level of the humans for which the robot is working will be very important if the robot is to do its job effectively. But very little work has been performed in trying to understand how people would interact with a robot, how to make them comfortable, ways for robots to indicate their feelings, etc. to analyze the

aesthetic qualities of the robots behavior patterns [2].

1.1 Distance from the robot to the vicinity

Usually there is a ‘space gap’ between the robot to the near by. As Stentz [3] and many others had mentioned, this was just a constant of space. This mechanism was quite acceptable for the systems such as transporting, surveillance and monitoring, etc. In other words, such kind of safe distance was good for non-human interacting purposes. Can the same be applied for human interaction? Although it will give some results, it will not enhance or optimize the real requirement in need, i.e. to build up harmonious relationship with humans.

1.2 Nakauchi model

When Nakauchi and Simmons [2] studied about personal space and applied it to moving robots, it was some improvement over the ‘blind’ safe distant. In their mechanism, Nakauchi and Simmons had experimented using human subjects for ‘correct distance’ or ‘personal space’ in order to have pleasant feeling towards the two interacting parties.

1.3 Walters experiments

Another set of experiments were conducted by Walters et al. [4] to find the personal space zones, initial distances between robot and humans, etc. They also tried to compare human-robot interpersonal distances with that of the human-human interpersonal distances as described by Hall [5]. According to Hall, the generally recognized personal space zones between humans

Table 1: Personal space zones.

Zone	Range (m)	Interaction
Intimate	0 – 0.15	Loved ones
Close	0.15 – 0.45	Close friends
Personal	0.45 – 1.20	Friends
Social	1.2 – 3.60	Strangers
Public	3.60 +	Public

are well known and are summarized (for Northern Europeans) in Table 1.

2 Variation of Personal Space

Although it is possible to find a personal space for a specific instance of environment, it is highly volatile depending on the two interaction parties and not definitely a constant. As Walters et al. [4] suggested, different robot social models, perhaps with very different initial personalities, may be more acceptable to different users. For example, adjustments of social distances according to a user’s personality trait will be a promising direction.

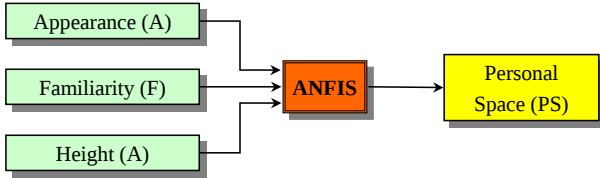


Figure 1: APS ANFIS block diagram.

The personal space at any given instance varies depending on cultural norms and on the task being performed. Appearance, familiarity, gender, age, height of the bodies, etc. were considered to be important. Height, appearance and familiarity were considered (as the initial stage for simplicity) to generate an active personal space (APS) determination system and the block diagram is shown in Figure 1.

3 ANFIS for Personal Space Determination

Adaptive Neural Fuzzy Inference System or simply ANFIS can be used as a basis for constructing a set of

fuzzy if-then rules with appropriate membership functions to generate the desired input-output combination. It is especially useful when needed to apply a fuzzy inference to already collected input-output data pairs for model building, model following, etc. where there are no predetermined model structures based on characteristics of variables in the system.

3.1 Gathering data

Considering the procedure as Nakauchi and Simmons [2] or the Walters et al. [4] to obtain a sense of personal space for robot / human interaction, a similar experimental condition was constructed. Here a robot (or a model) is kept at the end of a scaled line in a room and a human is asked to move closer to it.

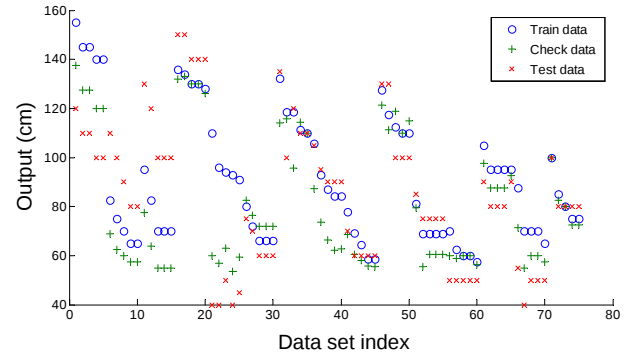


Figure 2: Input data sets (for training, checking and testing) to the APS ANFIS.

3.2 Experimental procedure

As the experiment proceeds, one human subject is instructed to move towards the robots as if he needs to talk with it. The human subject is asked to be along the scaled line and look at the robot face and move closer to it until he feels safe enough to make conversation with it. In the mean time the robotic model was positioned so as to make its face towards the human subject. During the whole time of the experiment, the robot did not do anything and the human subject did all the active tasks of walking, thinking, etc. The distance between the two parties was obtained by using a camera or by direct human observer (who reached the two parties once they got stabilized). The human subject had no previous experience with the robot and the authors wanted the human subjects to be curious as well as cautioned about the robot that they are going to meet. In other words human subjects had no

idea what kind of robotic system that they are going to face with or any capabilities that it possesses until they meet the robot.

The robots and the robotic models used in these experiments are ‘KooruKun’ (PA10 robotic manipulator), ‘BoxChyan’ (robotic model), and ‘BasinKun’ (previously known as ‘CHRCarry Hospital Robot’ re-used with several modifications). The first one was a stationary robot with 200 cm in height and 20 cm average diameter, next was a movable robot model with 100 cm height, 50 cm diameter and around 3 Kg, and the last is also a movable robot with 170 cm height, generalized circular diameter of 60 cm and weight of about 25 Kg. The data gathered are grouped for training, checking and testing for the ANFIS and are shown in Figure 2.

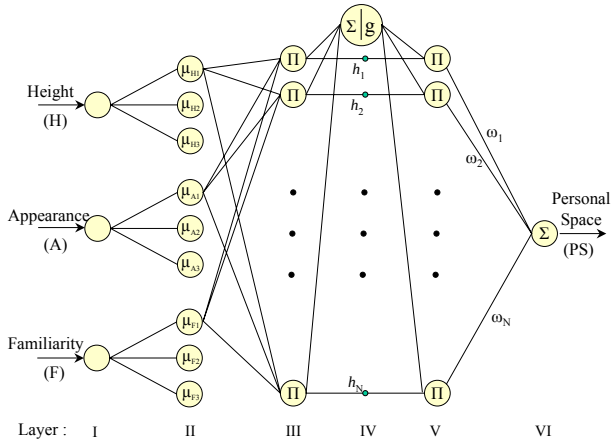


Figure 3: APS ANFIS architecture.

4 ANFIS Architecture

The architecture of the APS determination network is illustrated in Figure 3. Layer (I) to Layer (III) represent the antecedent part of the fuzzy neural network, whereas Layer (V) and Layer (VI) represent the consequence part. As shown in Figure 3, the domain of discourse of height (H) is described by fuzzy variable H with p number of linguistic values ($p = 3$), the domain of discourse of appearance (A) is described by fuzzy variable A with q number of linguistic values ($q = 3$), and the domain of discourse of familiarity (F) is described by fuzzy variable F with r number of linguistic values ($r = 3$). Hence each input variable is unique in the sense of domain of discourse. It is assumed that

each node of the same layer has a similar function, as described below. Here we denote the output of the i th node in layer (X) as $O_{(X),i}$.

Layer (I): Layer (I) consists of three types of nodes; height (H), appearance (A) and familiarity (F). The current value of height (H), i.e. the crisp input to the height node is H_i , appearance node is A_j and familiarity node is F_k . No computation is carried out at this layer.

Layer (II): This layer acts as the fuzzification layer of the fuzzy neural network. At this layer, the output of a node connected to the current value of input variable acquires the fuzzy membership value of the universe of discourse. Every node i , where $i = 1, \dots, p$ (or q or r), in this layer is an adaptive node with a node function

$$O_{II,i} = \mu_{X_i}(x) \quad (1)$$

where x is the input to node i , and X_i is the linguistic label (big, medium, small, etc.) associated with this node function. In other words, $O_{II,i}$ is the membership function of X_i and it specifies the degree to which the given x satisfied the quantifier X_i . Hence the output from the 2nd layer will be:

$$O_{II,p} = \mu_{H_i}(H_i) \quad (2)$$

$$O_{II,q} = \mu_{A_q}(A_j) \quad (3)$$

$$O_{II,r} = \mu_{F_r}(F_k) \quad (4)$$

for height, appearance and familiarity respectively.

Layer (III): In this layer, the nodes labeled as Π compute the T-norm of the antecedent part. Thus the rule evaluates the conditions of the inputs and they are continued to the layer (V) for normalization. The output of any node t , where $t = 1, \dots, N$, where $N = p * q * r$, in this layer is described by the following equation:

$$O_{III,t} = h_t = \mu_{H_i}(H_i) * \mu_{A_q}(A_j) * \mu_{F_r}(F_k) \quad (5)$$

where h_t represents the firing strength of the t th rule and there are N such rules as total.

Layer (IV): The first node of layer (IV) at fuzzy neural network, which has symbols $\sum$ and g , generates the output through the following function:

$$g(x) = \frac{1}{x} \quad (6)$$

with a linear summed input. Then the output of the first node of layer IV is given by

$$O_{IV,1} = \frac{1}{\sum_{t=1}^N h_t} \quad (7)$$

Other nodes just carry forward the outputs of previous nodes to the next layer.

Layer (V): This layer normalizes the fired rule values. Each node labeled as Π in this layer multiplies the value carried forward by previous node with the output of the first node at Layer (IV). Then the output of any m th node of this layer can be given by the following equation:

$$O_{V,m} = \frac{h_m}{\sum_{t=1}^N h_t} \quad (8)$$

Layer (VI): Layer (VI) is the defuzzification layer of the fuzzy neural network. The node labeled as $\sum$ in this layer calculates the overall output as the summation of all incoming signals. Then the personal distance value for certain input variables is given by:

$$O_{VI} = \text{Personal_Distance} = \frac{\sum_{m=1}^N w_m h_m}{\sum_{n=1}^N h_n} \quad (9)$$

where w_m denotes a constant value in the consequence part of the m th rule. The overall output is the weighted mean of w_m with respect to the weight h_m .

The connection weights are trained by applying the hybrid algorithm. The error tolerance was set to zero.

The error is calculated by comparing the output of the expert knowledge with that of fuzzy neural network for the same input data, x . The adaptation of the m th weight, w_m , at the l th time step is given by the following equation:

$$w_m(l+1) = w_m(l) + \gamma [y_d - y_a] \frac{h_m}{\sum_{n=1}^N h_n} \quad (10)$$

where γ represents a small positive learning rate, and y_d and y_a represent the desired output and actual output respectively for the personal space value selected for the training.

The trained ANFIS with check data is shown in Figure 4.

5 Summary

In this research project, a determination system of an active personal space has been analyzed. This can

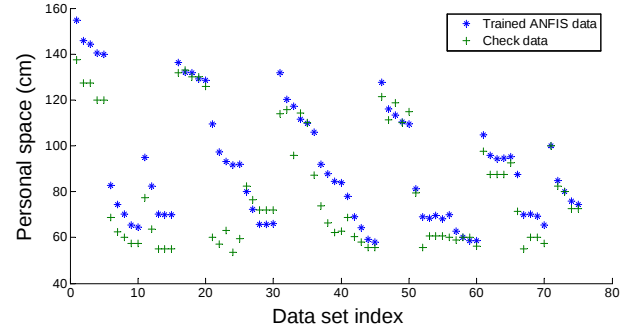


Figure 4: Trained FIS with check data.

be considered as the first step for constructing an active personal space system for any robot in any environment. But for a target as such, many experiments in vast environmental situations should have to be involved. It is a must to obtain similar data with the so-called humanoids to make this experiment complete. This system gave encouraging results in an off-line mode with limited facilities. Authors are planning to make the current system more realistic and get the functioning in a real time mode, and are continuously working on it.

References

- [1] R. Simmons, R. Goodwin, K. Z. Haigh, S. Koenig, and J. O'Sullivan, "A layered architecture for office delivery robots," in *Proc. of Autonomous Agents*, 1997, pp. 245–252.
- [2] Y. Nakauchi and R. Simmons, "A social behavioral robot that stands in line," *Autonomous Robots*, vol. 12, 2002, pp. 313–324.
- [3] A. Stentz, "Map-based strategies for robot navigation in unknown environments," in *Proc. of AAAI*, 1996, pp. 110–116.
- [4] M. L. Walters, K. Dautenhahn, K. L. Koay, et al. "Close encounters: spatial distances between people and a robot of mechanistic appearance," in *Proc. of 5th IEEE RAS Int. Conf. on Humanoid Robots*, Dec. 2005, pp. 450–455.
- [5] E.T. Hall, *The Hidden Dimension: Man's Use of Space in Public and Private*, The Bodley Head Ltd, London, UK. 1966.