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Adaptive Personal Space for Humanizing Mobile Robots

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1. Introduction

Human beings are fascinating creatures. Their behavior and appearance cannot be compared with any other living organism in the world. They have two distinct features with compared to any other living being; unique physical nature and emotions / feelings. Anybody who studies on humans or tries 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. Some of the problems in concern are 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, etc. In order to "humanize" robots, they (robots) should also have certain understanding of such emotions that we, humans have. The present main objective is to "teach" one such human understanding, commonly known as "personal space" to autonomous mobile robots.
As Simmons et al., 1997 described, 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 (Nakauchi & Simmons, 2002). Sometimes, even when humans interact with each other, it leads to resource conflict. At such times humans use social rules to maintain order (Sack, 1986).
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. Extensive research is being performed in the area of robotics to improve the conditions of the robots, advancing the abilities to do specific tasks, motion planning, etc. However, very little work has been performed in trying to understand how people would interact with a robot, how to make them comfortable, factors that make uncomfortable or threatening, methods or ways for robots to indicate their feelings, etc. to analyze the aesthetic qualities of the behavior patterns of robots (Nakauchi & Simmons, 2002).
As in the very beginning of the mobile robotic systems, there had been some kind of distance or space between the robots to any other object in the vicinity. This was just a mere distance for safety for easy maneuvering and for collision avoidance. As Stentz, 1996 and

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many others had mentioned, this was just a constant of space. This concept 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.

When Nakauchi and Simmons, 2002 studied about personal space and applied it to moving robots, it was shown that there were some improvements over the "blind" safe distance. They had experimented using human subjects for "correct distance" or "personal space" in order to have pleasant feeling towards two interacting parties. For the experiment, it was assumed that;

- The size of personal space of the person in front is identical to the personal space of the subject.
- When the same body direction of two people is facing, the personal space towards that direction is the half of the distance between two people.

According to the above two assumptions, the average size of the personal space was estimated. This experimentally derived average personal space had an approximate shape of an oval that is larger towards the front. Although those results were approximate, it had been aligned with the values that were reported in the cognitive science literature (Malmberg, 1980).

Another set of experiments were conducted by Walters et al., 2005 using adults and children with a robot of mechanistic appearance called PeopleBot^{R} to find the personal space zones, initial distances between robot and humans etc., in the context of the encounters and the human's perception of the robot as a social being. They had found out that the children showed a dominant response to prefer the "social zone" (as shown in Table 1), comparable to distances people adopt when talking to other humans. From the adult studies, they found that, a small number of people preferred the "personal zone" though significant minorities deviate from this pattern.

They also tried to compare human-robot interpersonal distances with human-human interpersonal distances as described by Hall, 1966. According to Hall, 1966 the generally recognized personal space zones between humans are well known and are summarized (for Northern Europeans) in Table 1.

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

Table 1. Personal space zones

In this research project we try to construct a determination system of adaptive personal space (PS) based on adaptive neural fuzzy inference system (ANFIS). In section 2 we analyze some previous work, which encouraged us to pursuit the path of personal space and to find certain parameters. In section 3 suitability of using ANFIS for constructing an adaptive PS and experimental procedure to gather data are discussed. Section 4 describes the input and output variables and the rule structure. Sections 5 and 6 give the detailed construction of an ANFIS architecture and the procedures of training, checking and testing of it. Section 7 gives some proposal to overcome certain practical limitations during the implementation of the adaptive PS. Section 8 discusses some acceptable way of assigning values for the "appearance" input variable. Finally, section 9 summarizes our efforts giving limitations and identifying future work.

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., 2005a suggested, different robot social models, perhaps with very different initial personalities, may be more acceptable to different users (e.g. a discrete servant or even a silent servant, with no obvious initiative or autonomy). They further stated that it probably cannot be assumed that people automatically treat robots socially, apart from simple elements of anthropomorphism as described by Reeves & Nass, 1998. A user-friendly robot should automatically refine and adapt its social model (personality) over a longer period of time, depending on information about and feedback from users and the robots own autonomous learning system. For example, adjustments of social distances according to a user's personality trait will be a promising direction (as proposed by Walters et al., 2005b) towards a true robot companion that needs to be individualized, personalized and adapt itself to the user (Dautenhahn, 2004).
According to Sack, 1986 and Malmberg, 1980, it is reported that the actual size of the personal space at any given instance varies depending on cultural norms and on the task being performed. For a simplified scenario for experimental analysis, appearance (mainly of the robot), previous acquaintance or familiarity of the either parties, gender, age, height of the bodies (specially interaction in the standing position), emission of any sound, emotions on the face, carrying objects, etc. were considered to be important.
Hence in this research project, construction of an automated system to generate a most suitable personal space for any environmental condition is attempted. In order to do that, from the list of above, the following three parameters namely, height (H), appearance (A), and familiarity (F) were considered (as the initial stage for simplicity) to generate an active personal space (PS) and the block diagram is shown in Fig. 1.
Input parameter height analyzes the height of the human who comes closer to a robot for interaction as meeting a very tall or very short person is little bit difficult than an ordinary person. The outer appearance of the robot, whether it looks more like a human or rather like a machine is analyzed in input variable appearance. Familiarity is the closeness that the both parties in interaction have for each other, i.e. if they are more familiar they will keep closer and vice versa.

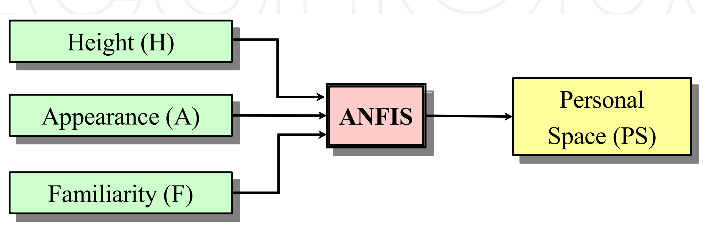

Figure 1. Block diagram of generating PS through adaptive neural fuzzy inference system

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 (Jang, 1993). 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 & Simmons, 2002 or Walters et al., 2005a 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.

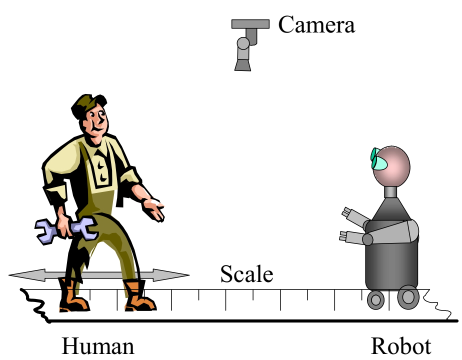

Figure 2. Experimental setup

3.2 Experimental procedure

As the experiment proceeds, one human subject is instructed to move towards the robot 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 as shown in Fig. 2. 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 robot and the human subject, one person at a time, were supposed to interact at specific duration of time and it ended once the human subject stops in front of the robot. Then 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 wards 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.

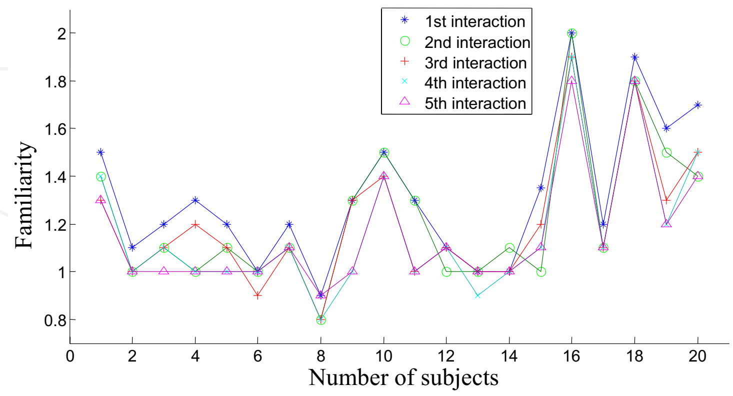

Figure 3. Personal space variation of each interaction with Robot A

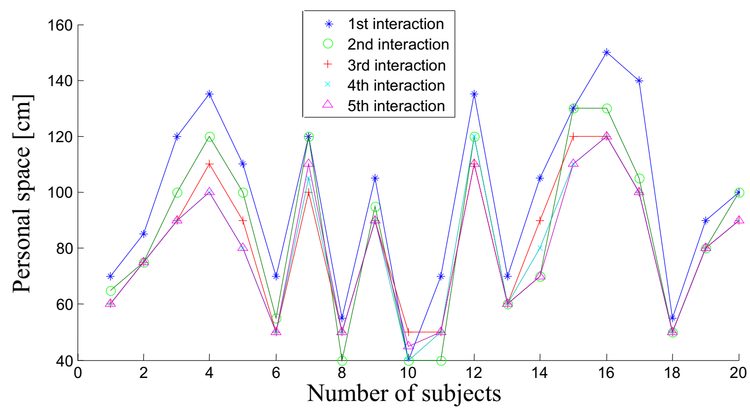

Figure 4. Personal space variation of each interaction with Robot B model

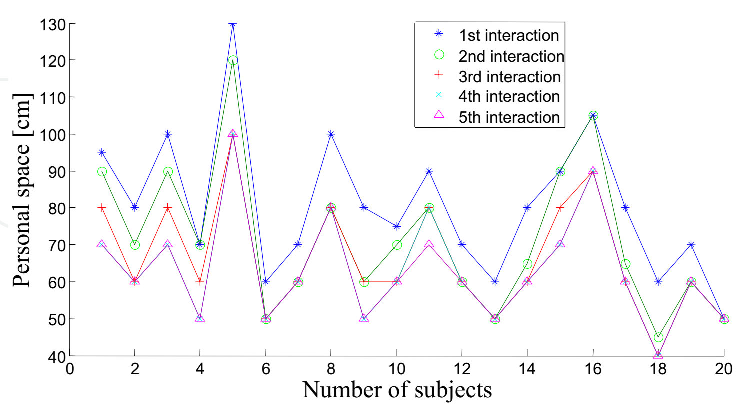

Figure 5. Personal space variation of each interaction with Robot C

Figure 5. Personal space variation of each interaction with Robot C This procedure was repeated for several rounds in order to ascertain any change of personal space due to familiarity of the robot. The data thus obtained clearly indicated the reduction of personal space with many acquaintances with the same robotic system as shown in Figs 3, 4 and 5 for robots A, B and C respectively. Starting from a large space (comparatively) got reduced with each attempt but saturated after some time. That is, after few interactions, the subject tends to keep the distance as the same. (The distance never reached zero with increased number of attempts).

Robot A Robot B Robot C

Figure 6. Robots and models used for the experiment

The robots and a robotic model used in these experiments are Robot A (PA10 robotic manipulator), Robot B (robotic model), and Root C (previously known as Carry Hospital Robot (Jin et al., 1993) re-used with several modifications) as shown in Fig. 6. The first one was a stationary robot with 200 cm in height and 20 cm average diameter, the 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 described in later.

4. Input and Output Variables

Out of the three input variables considered, height (of the human) and familiarity were two straightforward measurements while appearance was taken as a collective decision.

4.1 Input variable "height"

The height of the human subject is considered in this input variable. The universe of discourse of the input variable "height (H)" was considered to be 50 cm to 200 cm, having three membership functions "big (B)," "medium (M)," and "small (S)." Those shapes were considered to be bell type.

4.2 Input variable "appearance"

The robot outer appearance with compared to a human (or rather closeness of the robot body to the human body) is considered in this input variable. Humans are more like to reach one of their own looking rather than to that of very peculiar shaped objects. Human like robot gets the closer feeling with respect to the other crude or rather machine looking robot. The universe of discourse of the input variable "appearance (A)" was considered to be 1 to 5 (without any units), having three membership functions "big (B)," "medium (M)," and "small (S)." Those shapes were considered to be all bell type. Here the appearance value for the Robot A was given as 1, for the Robot B as 2, and Robot C as 5. Although more human like robots were required to get the records, at the time of the experiment, such robots were not available in the laboratory. Hence the universe of discourse was taken as 1 to 5.

4.3 Input variable "familiarity"

As the name implies, the way that a human subject interacts with a robot is analyzed in this variable. Namely, if a human feels more familiar with a certain robot, he will go closer to it. If there are many interactions with the same robot for many times, it is fair to assume that the two interaction parties get more familiar with each other. Due to its complexity of nature of assessing this familiarity for a certain interaction, familiarity value was taken as dividing the interaction distance by 100 for a particular situation. Therefore, more familiar interaction will have a less "familiarity" value and vice versa. Keeping in mind that more interactions mean more familiar with each other, this variable is to be set. The universe of discourse of the input variable "familiarity (F)" was considered to be 0 to 2 (without any units), having three membership functions "big (B)," "medium (M)," and "small (S)," whose forms were considered to be bell type.

R_1 : If H is S and A is S and F is S then PS is PS_1
R_2 : If H is S and A is S and F is M then PS is PS_2
R_3 : If H is S and A is S and F is B then PS is PS_3
R_4 : If H is S and A is M and F is S then PS is PS_4
R_5 : If H is S and A is M and F is M then PS is PS_5
R_6 : If H is S and A is M and F is B then PS is PS_6
R_7 : If H is S and A is B and F is S then PS is PS_7
R_8 : If H is S and A is B and F is M then PS is PS_8
R_9 : If H is S and A is B and F is B then PS is PS_9
R_{10}: If H is M and A is S and F is S then PS is PS_{10}
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R_{18}: If H is M and A is B and F is B then PS is PS_{18}
R_{19}: If H is B and A is S and F is S then PS is PS_{19}
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R_{27}: If H is B and A is B and F is B then PS is PS_{27}

Figure 7. Rule base for the ANFIS architecture

4.4 Output variable "personal space"

Considering the above three inputs that will generate 27 rules as shown in Fig. 7 in total and each having unity weight for each rule, the output variable "personal space (PS)" of the ANFIS is obtained using the weighted average defuzzification.

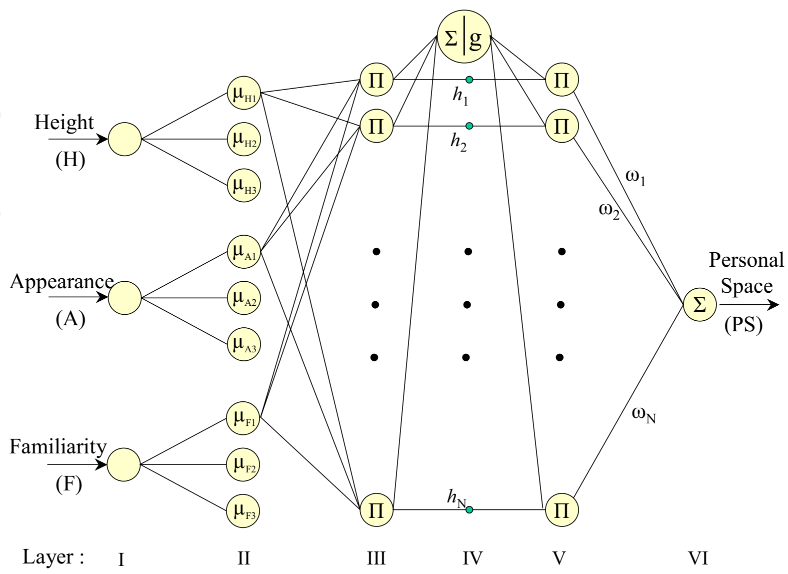

Figure 8. Active PS determination network with ANFIS

5. ANFIS Architecture

The architecture of the active PS determination network is illustrated in Fig. 8. Layer I to layer III represent the antecedent part of the fuzzy neural network, whereas layer V and layer VI represent the consequence part (Jang and Sun, 1995).
As shown in Fig. 08, 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 $i = \{1,\ldots,p\}$ (or q or r), in this layer is an adaptive node with a node function

$$O_{II,I}=\mu_{Xi},(x) \tag{1}$$

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 Xi. Hence the output from the 2nd layer will be:

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

$$O_{II,q}=\mu_{Aq}(A_j) \tag{3}$$

$$O_{II,r}=\mu_{Fr}(F_k) \tag{4}$$

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 $N=p\times q\times r$, in this layer is described by the following equation:

$$O_{III,t}= h_t= \mu_{Hp}(H_i) \times \mu_{Aq}(A_j) \times \mu_{Fr}(F_k) \tag{5}$$

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 Σ and g, generates the output through the following function:

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

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

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

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:

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

Layer VI:

Layer VI is the defuzzification layer of the fuzzy neural network. The node labeled as Σ in this layer calculates the overall output as the summation of all incoming signals. Then the personal space value for certain input variable is given by:

$$O_{VI} = PS = \frac{\sum_{m=1}^{N} W_m h_m}{\sum_{n=1}^{N} h_n} \tag{9}$$

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:

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

where γ represents a small positive learning rate having the initial value of 0.01 which was set to be an adaptive during the training process, and y_d and y_a represent the desired output and actual output respectively for the personal space value selected for the training. The ANFIS was trained setting the error tolerance to zero for forty epochs.

6. Training, Checking and Testing Data Sets

Using the collected data from the experiments, data were rearranged into three groups for training, checking and testing purposes of the active PS with ANFIS. Having considered 5 groups of height, 3 sets of appearances and 5 different interactions make the total data set of 75 (i.e., 5×3×5=75). These are shown in Fig. 9.

6.1 Train data set

Train data set was obtained by grouping the input variable "height (H)." First, the height was categorized into five groups as:

- 161 cm to 165 cm
- 166 cm to 170 cm
- 171 cm to 175 cm
- 176 cm to 180 cm
- 181 cm to 185 cm

Then for a particular height group average is taken for each attempt of interaction.
"Familiarity" was obtained as described below:
The mean familiarity $\overline{F}_i^j$ for each interaction can be defined by

$$\overline{F}_i^j = \frac{1}{N_j}\sum_{l=1}^{N_j} F_i^j(l) \tag{11}$$

where $\overline{F}_i^j(l)$ is a familiarity value to the i^{th} robot designated by the l^{th} subject who was classified into the j^{th} human group with different range of height and N_j is the total number of subjects in the j^{th} group.

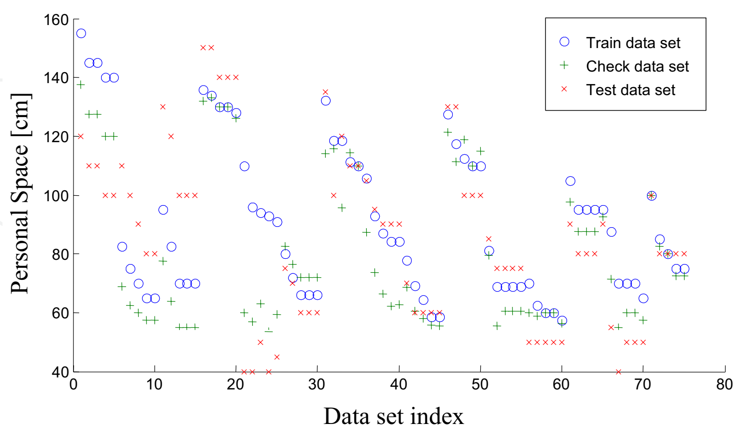

Figure 9. Training, checking and testing data for the active PS using ANFIS

According to the above criteria, obtained results for the height group one (where there were only two human subjects fallen into this category) for each robot are shown in Tables 2, 3, and 4 for robots A, B, and C respectively, where Dist. is the distance between the robot and the subject in [cm], Fam. is the familiarity and Avg. is the averaged value. The complete set of results thus obtained was used as the train data set.

Std. No#	Height [cm]	Int. 1		Int. 2	
		Dist.	Fam.	Dist.	Fam.
18	164	190	1.9	180	1.8
5	165	120	1.2	110	1.1
Avg.	164.5	155	1.6	145	1.5

Int. 3		Int. 4		Int. 5	
Dist.	Fam.	Dist.	Fam.	Dist.	Fam.
180	1.8	180	1.8	180	1.8
110	1.1	100	1	100	1
145	1.5	140	1.4	140	1.4

Table 2. Rearranged data for robot A (Appearance 1), Height group 1 (161 -- 165 [cm])

Std. No#	Height [cm]	Int. 1		Int. 2	
		Dist.	Fam.	Dist.	Fam.
18	164	55	0.6	50	0.5
5	165	110	1.1	100	1
Avg.	164.5	82.5	0.8	75	0.8

Int. 3		Int. 4		Int. 5	
Dist.	Fam.	Dist.	Fam.	Dist.	Fam.
50	0.5	50	0.5	50	0.5
90	0.9	80	0.8	80	0.8
70	0.7	65	0.7	65	0.7

Table 3. Rearranged data for robot B (Appearance 2), Height group 1 (161 -- 165 [cm])

Std. No#	Height [cm]	Int. 1		Int. 2	
		Dist.	Fam.	Dist.	Fam.
18	164	60	0.6	45	0.5
5	165	130	1.3	120	1.2
Avg.	164.5	95	1	82.5	0.8

Int. 3		Int. 4		Int. 5	
Dist.	Fam.	Dist.	Fam.	Dist.	Fam.
40	0.4	40	0.4	40	0.4
100	1	100	1	100	1
70	0.7	70	0.7	70	0.7

Table 4. Rearranged data for robot C (Appearance 5), Height group 1 (161 -- 165 [cm])

6.2 Check data set

In order to optimize the ANFIS once created using the train data set and to overcome the problem of model over fitting during the training process, another data set which does not contain the similar values but close to the original train data output values is required. For this purpose, following equation was considered to generate the check data set. When obtaining the check data set $\{x_c\}$, i.e., considering a particular column, average value x_a is subtracted from the maximum value x_{max} from the gathered data. Then half of that value is added to the minimum value x_{min} of the gathered data in the same column:

$$x_c = \left[\frac{x_{\max} - x_a}{2}\right] + x_{\min} \tag{12}$$

In this process, no change was made to the previous ANFIS structure.

6.3 Test data set

Once the ANFIS system is created using train data and fine tuned with check data, it is necessary to analyze its credibility for correct functioning and desired performance (Matlab). For that purpose another set of data called as test data is used. Construction of test data set was done as follows: Considering the output value of training and checking data sets for a same input entry, very close data value from the original data set of the experiment was selected and grouped to form the test data set. This set was used to test the ANFIS for desired functionality.
The error cost described by

$$e = \left[\frac{aps - ps}{ps}\right] \times 100\% \tag{13}$$

for the trained adaptive PS (*aps*) with that to the original values (*ps*) was calculated and is plotted in Fig. 10. The trained ANFIS output values with the data set values used to train, check, and test of it are shown in Figs. 11, 12, and 13 respectively.

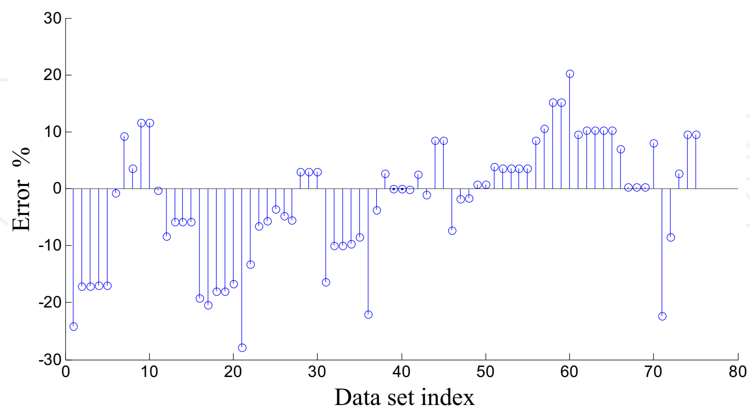

Figure 10. Error percentage of the trained ANFIS output

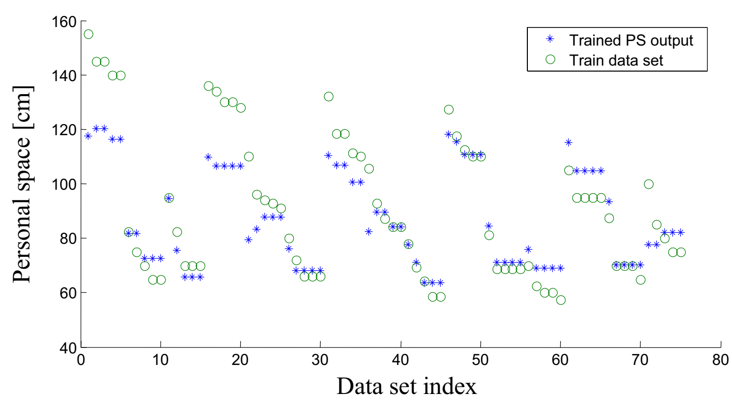

Figure 11. Trained ANFIS output with train data set values

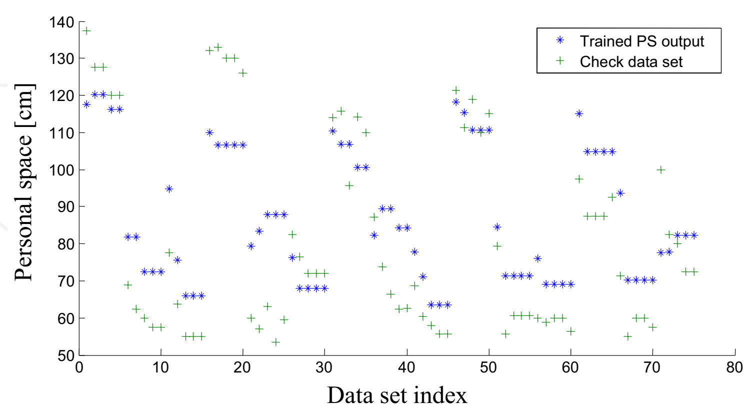

Figure 12. Trained ANFIS output with check data set values

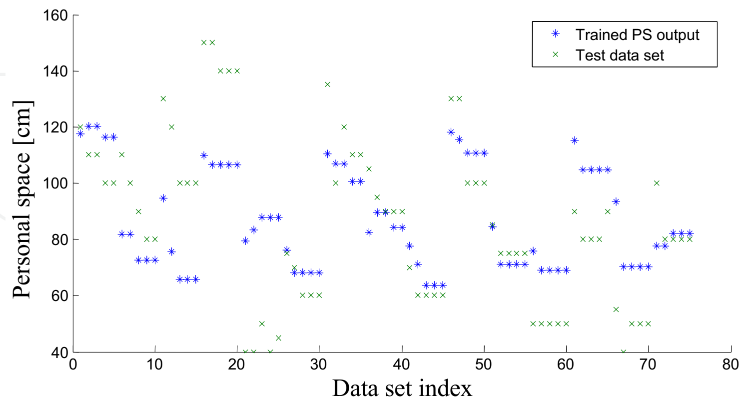

Figure 13. Trained ANFIS output with test data set values

7. Proposal to the Implementation of ANFIS

The ANFIS trained by using the data set as described in the preceding section can not be directly installed into an actual robot, because the input data, appearance (A) and familiarity (F), to the ANFIS will not be able to be collected through the robot. Therefore, in this section, we propose an ANFIS that will be implementable to a robot using only the incoming data of human height, which will be readily available from the robot by using any camera, together with the average data of appearance and familiarity for each human group with different range of height. This concept is also divided into two classes, depending on the usage of different average data of appearance and familiarity for each robot or on the usage of same average data of them for all robots.

7.1 A case with different mean appearance and familiarity for each robot

For this case, different average data of appearance and familiarity are used for the ANFIS of each robot. So, let $\overline{A}_i^j$ denote the mean appearance that was designated by any subject who was grouped into j for the specific robot i described by

$$\overline{A}_i^j = \frac{1}{N_j} \sum_{l=1}^{N_j} A_i^j(l) \tag{14}$$

where $A_i^j(l)$ is an appearance value to the i^{th} robot designated by the l^{th} subject who was classified into the j^{th} human group with different range of height and N_j is the total number of subjects in the j^{th} group.

Similarly, the mean familiarity $\overline{F}_i^j$ can be defined by

$$\overline{F}_i^j = \frac{1}{N_r} \sum_{r=1}^{N_r} \left(\frac{1}{N_j} \sum_{l=1}^{N_j} F_i^j(l) \right) \tag{15}$$

where $F_i^j(l)$ is a familiarity value to the i^{th} robot designated by the l^{th} subject who was classified into the j^{th} human group with different range of height, r is the interaction number that l^{th} subject took for the i^{th} robot, and N_r is the total number of such attempts.
By applying these data, we can implement the ANFIS to generate an active personal space, depending on the height of the human and the robot type. Fig. 14 shows the block diagram of ANFIS for a case with different mean appearance and familiarity for each robot.

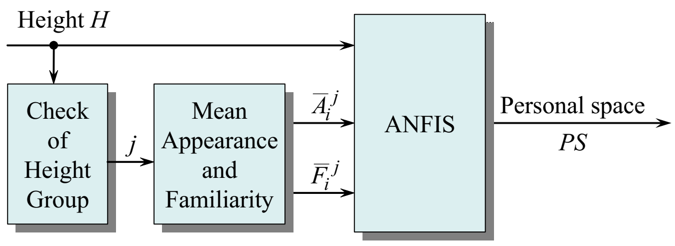

Figure 14. ANFIS for a case with different mean appearance and familiarity for each robot

7.2 A case with same mean appearance and familiarity for all robots

For this case, the identical average data of appearance and familiarity are used for the ANFIS of all robots. So, let $\overline{A}^j$ and $\overline{F}^j$ denote the mean appearance and familiarity averaged by the number of robot types that were designated by any subject who was grouped into j described by

$$\overline{A}^j = \frac{1}{M_j}\sum_{i=1}^{M_j}\overline{A}_i^j \quad \text{and} \quad \overline{F}^j = \frac{1}{M_j}\sum_{i=1}^{M_j}\overline{F}_i^j \tag{16}$$

where $\overline{A}_i^j$ and $\overline{F}_i^j$ are given by Eqs. (14) and (15), and M_j is the total number of robot types that were used for the j^{th} human group with different range of height.

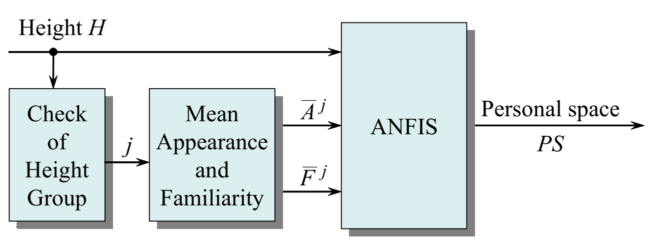

Figure 15. ANFIS for a case with the same mean appearance and familiarity for all robots

Thus, we can implement the ANFIS to generate an active personal space, depending on the height of the human. Fig. 15 shows the block diagram of ANFIS for a case with same mean appearance and familiarity for all robots.

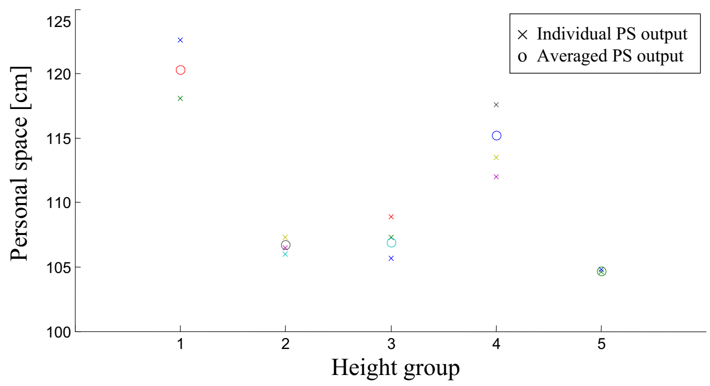

Figure 16. Personal space of each height group for Robot A

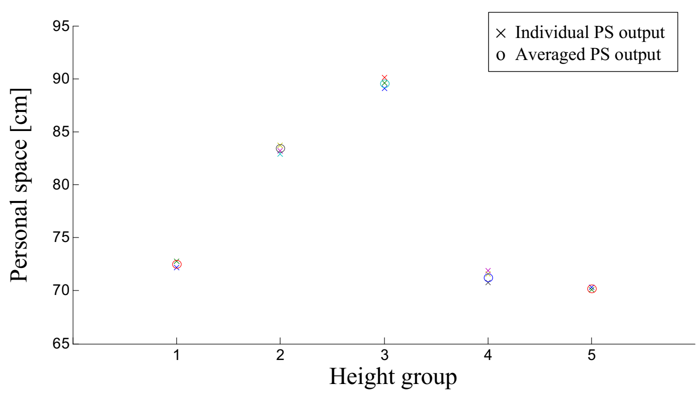

Figure 17. Personal space of each height group for Robot B

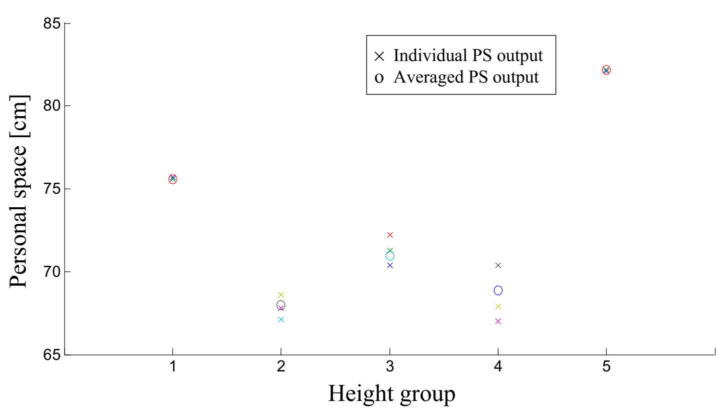

Figure 18. Personal space of each height group for Robot C

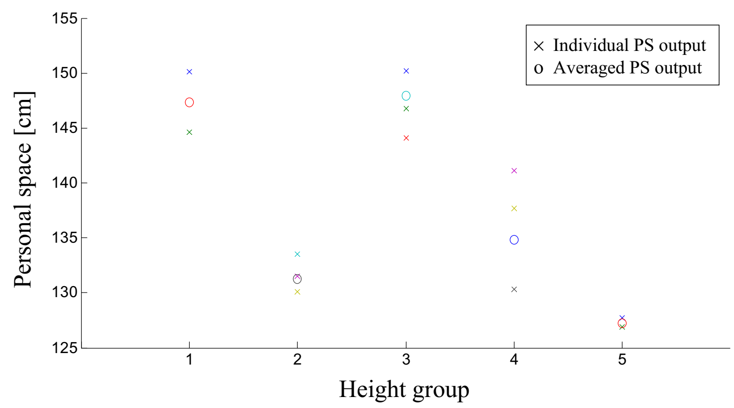

Figure 19. Personal space of each height group for any robot

The results obtained using the above simplification process for each of the height group with averaged value for the same group are plotted for each of the robots. These are shown in Figs. 16, 17, and 18 by applying the proposed method in 7.1 to Robot A, B, and C respectively. Fig. 19 shows the values obtained for all the robots after applying the proposed method in 7.2. Mean error percentage, mean squared error (MSE) and root mean squared error (RMSE) generated by each of the robots in the proposed method in 7.1 with their averaged error are tabulated in Table 5 and the comparison of errors in all the methods including the previous complete attempt is given in Table 6.

According to the error comparison as given in this table, it can be seen that although the mean error percentage of the method in 7.2 is very much higher than the other two, the comparison of MSE or RMSE with each other does not give a much of variation. Complete attempt had the lowest RMSE and the proposed method in 7.2 had the closest value to it. Even the proposed method in 7.1 had a higher value of RMSE than that of the method in 7.2. But all the methods have close RMSE values to each other. Hence it is fairly assumed that the proposed methods in 7.1 and 7.2 can be used to generate the adaptive PS as well.

	Robot A	Robot B	Robot C	Mean value
Mean %	-10.85	5.31	8.47	0.98
MSE	564.04	1251.66	537.63	784.45
RMSE	23.75	35.38	23.18	27.44

Table 5. Error in the proposed method in 7.1

	Complete attempt	Method in 7.1	Method in 7.2
Mean %	-2.09	0.98	55.12
MSE	115.09	784.45	582.97
RMSE	10.73	27.44	24.14

Table 6. Error in all methods

8. Proposal for Appearance Analysis

Input values for the “appearance” were arbitrary selected for this research project. But as it received many critics, it was necessary to apply more appropriate mechanism to obtain "appearance" values to each of the robots. Since all these about humanizing robots, the most appropriate way to analyze "appearance" of robot was consulting the human subjects once again. That is to ask each of them to rank a robot according to the outer appearance of the robot. This was much valid as it can be applied universally for any of the robot available in the world right now. Hence such an analysis will give a way to construct a "meaningful" measuring unit to rank robot's outer appearance in the future.

8.1 Method

This method analyzes the appearance of a robot at an initial stage and stored the result for the future manipulation. Once an appearance level is obtained for a particular robot, then it will be a constant for future references.

8.2 Procedure

Each of the human subjects was given a paper carrying photographs of several kinds of robots including Robots A, B, and C. They were instructed to analyze the outer appearance of each of these robots with compared to a human and rank each of the robots from a scale of one to ten. That is if a robot is more like a machine, then the rank is one, if a robot is more like a human or have many features that humans have, then the rank will be ten. Each of the human participants was instructed to think alone without discussing with each other and fill a table. Then each of these filled tables was collected and summarized the data to get the ranking of each of the robots. The summarized data is shown in Table 7, where number of votes indicates the number of people who assigned a particular rank to a particular robot.

Rank	1	2	3	4	5	6	7	8	9	10
Robot	Number of votes									
A	6	9	4			1				
B	1	3	4	5	3	2	2			
C	1		2	5	7	1	4			
D	6	1	2	2	2	4	2	1		
E	12	3	2	2		1				
F			1					2	3	14

Table 7. Summarized votes for each robot

8.3 Ranking the robots

According to the results obtained, there were two possible ways of ranking the robots i.e. according to "highest choice" and calculating "linear rank."

- Highest choice is the rank that most of the people selected for a particular robot.
- Linear rank was calculated according to the following equation.

$$R_i = \frac{1}{P_N}\sum_{j=1}^{10}(P_x \times R_j) \tag{16}$$

Linear rank of the robot i where i=A,B,C,D,E *or* F, is given by R_i having P_x number of votes in R_j rank, x is having the values of 1 to total number of participants P_N, and j is having the ranks from 1 to 10.

8.4 Results
Results obtained for the above two methods as with the previous appearance values for the robots A, b, and C are given in Table 8 for comparison.

Robot	A	B	C	D	E	F
Highest choice	2	4	5	1	1	10
Linear Rank	1.8	4	4.8	3.9	1.9	9.3
Previous value	1	2	5	--	--	--

Table 8. Comparison of results for robots

8.5 Summary
After analyzing the results it can be seen that appearance of Robots A and B are increased to higher levels as the general opinion of the participants. But appearance of Robot C was not changed aligning the previous random selection.

9. Conclusion

In this book chapter, a construction method for an automated system to generate a personal space for specific environmental condition has been attempted. Although the considered parameters were limited to only three namely, height, appearance, and familiarity, it will be possible to expand the system for any number of considerable parameters, once a very basic model has been created as performed by this research. The constructed system gave encouraging results as were seen by the comparison of test output values with the trained ANFIS output values for the same set of input environmental conditions (i.e. same input values of height, appearance, and familiarity gave very close output values of original output data values to that of active PS system output data values). Hence this system can be considered as the basic building block of constructing a fully automated, fully functional for any environmental parameters to generate an active personal space determination system.
In the implementation process, although the input “height” can be measured without any doubt, other two inputs may raise arguments. In analyzing robot for their appearances, there should be a “unit” or “measuring scale” that is acceptable to entire robotic manufacturing community. Although there is no such a “scale” at the moment, hope there may be in the future so as to ascertain the robotic outer structure to that of the human appearance making much human looking robots (or humanoids). For the “familiarity” analysis, good human recognition system (or face recognition system) is required. Until it can use such a system, participants must be asked to wear an identity tag that can be read by the robot to recognize them.
In an event of assigning values for the “appearance,” compared to the random way of putting values, above proposed method give much accepted procedure. Further, as appearance also depends on the person who looks at a robot, this method may give better results. It is also advisable to find suitable mechanisms to improve this method in the future.
Although this ANFIS cannot be treated as the ultimate solution for finding the personal space for any environment situation for any robotic system currently available in the world, this can be considered as the first step for such final advanced mechanism. But in order to achieve 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. Further, more sophisticated supportive equipment such as high speed

processing units for human recognition, memory acquisition and manipulation, image processing, etc. should be coupled. This system gave encouraging results in an offline 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.

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Human-robot interaction research is diverse and covers a wide range of topics. All aspects of human factors and robotics are within the purview of HRI research so far as they provide insight into how to improve our understanding in developing effective tools, protocols, and systems to enhance HRI. For example, a significant research effort is being devoted to designing human-robot interface that makes it easier for the people to interact with robots. HRI is an extremely active research field where new and important work is being published at a fast pace. It is neither possible nor is it our intention to cover every important work in this important research field in one volume. However, we believe that HRI as a research field has matured enough to merit a compilation of the outstanding work in the field in the form of a book. This book, which presents outstanding work from the leading HRI researchers covering a wide spectrum of topics, is an effort to capture and present some of the important contributions in HRI in one volume. We hope that this book will benefit both experts and novice and provide a thorough understanding of the exciting field of HRI.

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