Autonomous Robot Behaviours for Co-operative Agents using Fuzzy Logic and Subtractive Clustering

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Abstract

Intelligent autonomous robots and multi-agent systems, having different skills and capabilities for specific subtasks, have the potential to solve problems more efficiently and effectively. In this paper both fuzzy logic (FL) and subtractive clustering (SC) are used for the design of autonomous robot behaviours. The design procedure is conducted in two stages: first subtractive clustering is applied to extract fuzzy model from experimental data; then adaptive neuro-fuzzy inference system (ANFIS) is applied to improve the fuzzy model performance. This technique produces good result (0.01% root mean square error) and has the advantage of being closer to natural human language, by describing the robot behaviours using a set of linguistic rules.

Keywords: Robot Behaviours, Subtractive Clustering, Neuro-fuzzy Modelling.

1 Introduction

An autonomous robot is defined as a physical device, which performs a predefined task in a dynamic and unknown environment without any kind of external help. Having the ability to sense the state of the environment the robot is able to perform its control actions with the help of what is called control architecture. In most multi-agent type architectures the control is divided into vertical functional modules or behaviours where each of the behaviour is responsible for a well-defined task.

Classical control theory is based on mathematical models that describe the behaviour of the plant or system under consideration. The main idea of fuzzy control [4] is to build a model of a human control expert who is capable of controlling the plant without thinking in mathematical model terms.

Fuzzy logic modelling techniques can be classified into three categories, namely the linguistic (Mamdani-type), the relational equation, and Takagi, Sugeno and Kang (TSK). In linguistic models, both the antecedent and the consequence are fuzzy sets while in the TSK model the antecedent consists of fuzzy sets but the consequence is made up of linear equations. Fuzzy relational equation models aim at building the fuzzy relation matrices according to the input-output process data. To model a nonlinear system Jang [2] has introduced an adaptive neuro-fuzzy inference system (ANFIS) based on TSK model.

In this paper subtractive clustering is used to derive a fuzzy model from experimental data for the design of autonomous robot behaviours. Then ANFIS is used as a post-processor to improve model capability and efficiency.

2 Subtractive Clustering Method

In order to obtain a set of R rules avoiding the problems inherent to grid partitioning, e.g., rule explosion, subtractive clustering is applied [1]. This technique, is employed since it allows a scatter input-output space partitioning.

Subtractive clustering is an extension of the mountain clustering method [3]. Mountain clustering is relatively simple and effective. However, its computation grows exponentially with the dimension of the problem because the method must evaluate the mountain function over all grid points. Using subtractive clustering data points (not grid points) are considered as the candidates for cluster centers. The computation is simply proportional to the number of data points and independent of the dimension of the problem under consideration.

Consider a collection of n data points $\{x_1, \ldots, x_n\}$ in an M-dimensional space. Without the loss of generality, the data points are assumed to have been normalised within a hypercube. Since each data point is a candidate for cluster centers, a density measure at data x_i is defined as:

$$D_i = \sum_{j=1}^{n} e^{-a\|x_i - x_j\|^2} \tag{1}$$

where $a = \frac{4}{r_a^2}$ and $r_a > 0$.

Hence, a data point will have a high density value if it has many neighboring data points. The radius r_a defines a neighbourhood; data points outside this radius contribute only slightly to the density measure.

After computing the density measure for each point, the one with the higher density is selected as the first cluster center. Let x_{c_1} be the centre of the first group and D_{c_1} its density. Then, the density measure for each data point x_i is revised by the formula:

$$D_i = D_i - D_{c_1} e^{-\beta\|x_i - x_{c_1}\|^2} \tag{2}$$

where $\beta = \frac{4}{r_b^2}$ and $r_b > 0$.

The radius r_b represents the radius of the neighbourhood for which significant density measure reduction will occur. The radius for reduction of density should be to some extent higher than the neighbourhood radius to avoid closely spaced clusters. The value is typically, $r_b = 1.5 r_a$. Since the points closer to the cluster center will have their density measure strongly reduced, the probability for those points to be chosen as the next cluster is lower. This procedure is carried out iteratively, until the stopping criteria are reached. The algorithm is:

if $D_k > \varepsilon^{up} D_{c_1}$
  Accept x_k as the next cluster center and continue
else if $D_k < \varepsilon^{down} D_{c_1}$
  Reject x_k and end the clustering process
else
  Let $d_{\min}$ be the shortest distance between x_k and all previously found cluster centers
  if $\frac{d_{\min}}{r_a} + \frac{D_k}{D_{c_1}} \geq 1$
    Accept x_k as the next cluster center and continue
  else
    Reject x_k and set the density at x_k to 0
    Select the data point with the next highest density as the new x_k and re-test
  end if
end if

Here, ε^{up} specifies a threshold above which the point is selected as a center, and ε^{down} specifies the threshold below which the point is definitely rejected. Typically, $\varepsilon^{up} = 0.5$ and $\varepsilon^{down} = 0.15$. If the density measure fails in the gray region, then checking of data points is required to identify where they provide a good trade-off between having a significant density measure and being sufficiently far from existing clusters.

At the end of clustering procedure, a set of fuzzy rules will have been obtained. Each cluster will represent a rule. However, since the clustering procedure is conducted in a multidimensional space, fuzzy sets must be obtained. As each axis of the multidimensional space refers to a variable, the centers of the membership functions for that variable are obtained by projecting the center of each cluster in the corresponding axis. As for the widths, they are obtained on the basis of the neighbourhood radius r_a, defined while performing subtractive clustering. Since Gaussian membership functions are used, their standard deviations are computed as:

$$\sigma_{ij} = r_a \frac{\max(x_{kj}) - \min(x_{kj})}{\sqrt{8}}, k = 1, \quad . \quad , \mathrm{N} \qquad (3)$$

3 Adaptive Neuro-Fuzzy Inference System

Jang [2] introduced the ANFIS (Adaptive neuro-fuzzy inference system). Figure 1 provides an example of a simple fuzzy inference system (FIS) represented in an ANFIS network. In the ANFIS architecture, FIS is described in a layered, feed-forward network structure where some of the parameters are represented by adjustable nodes (represented as rectangular entities in the figure) and the others as fixed nodes (represented as spherical entities in the figure). The raw inputs are fed into the layer 1 nodes that represent the membership functions. The parameters in this layer are called premise parameters and they are adjustable. The second layer represents the T-norm operators that combine the possible input membership grades in order to compute the firing strength of the rule. In the basic ANFIS method these parameters are not adjustable. The third layer implements a normalisation function to the firing strengths producing normalised firing strengths. The fourth layer represents the consequent parameters that are adjustable. The fifth layer represents the aggregation of the outputs performed by weighted summation. This is not adjustable.

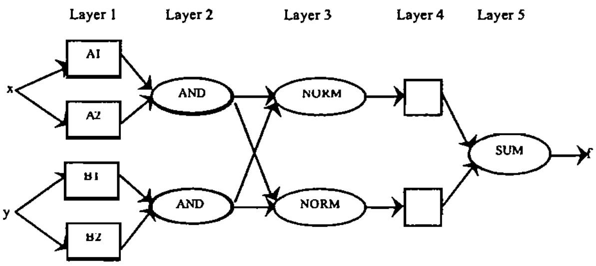

Figure 1: An ANFIS structure for a simple FIS

4 Problem Statement

In section 2 and 3 an algorithmic methodology was described to identify fuzzy control strategies using any n-dimensional input-output space. In this paper the proposed algorithmic methodology is applied to identify an autonomous robot's (MIABOT V2, Figure 2) control strategy to avoid objects (neighbour robots). The robot's control architecture is multi-agent type and consists of multiple controllers (fuzzy behaviours). Each of the behaviours is designed to perform a particular task such as to orientate the mobile robot towards the goal, to avoid neighbour robots (agents) and either to find or reach the goal.

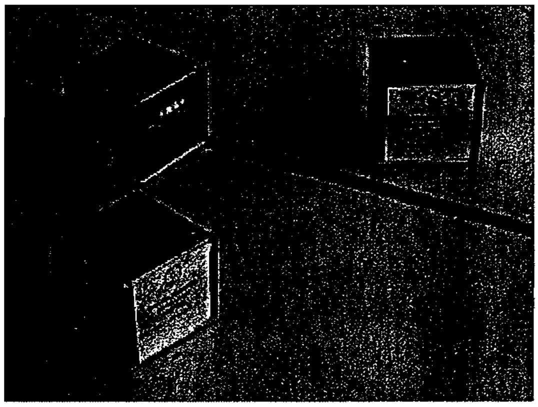

Figure 2: MIABOT V2 mobile robots

5 Simulation Results

In this section experimental results are presented to show the validity of the proposed algorithmic methodology. The strategy of the control action is based on three inputs: speed of the robot u, distance d and angle ϑ between the robot and the neighbour robots (obstacles). Hence the model has three input variables and two output (left velocity UL, right velocity UR) variables subtractive clustering is used to take input-output training data and generate a Sugeno-type fuzzy inference system that models the data behaviour. Of the original 209 experimental data points, 176 data points are used as training data and 33 data points as checking data. Figure 3 shows the input output data.

Using subtractive clustering the result for the first and second output is shown in figure 4 (top) and figure 5 (top). Checking data are compared with observation data and the root mean square error

(RMSE) is 0.0066 and 0.0610 respectively. To improve the model's accuracy ANFIS is employed. Figure 4 (Bottom) and figure 5 (Bottom) illustrate the new model in which in both cases the RMSE has been reduced to 0.0019 and 0.0133 respectively. Finally figure 6 illustrates at which point the training and checking error settles.

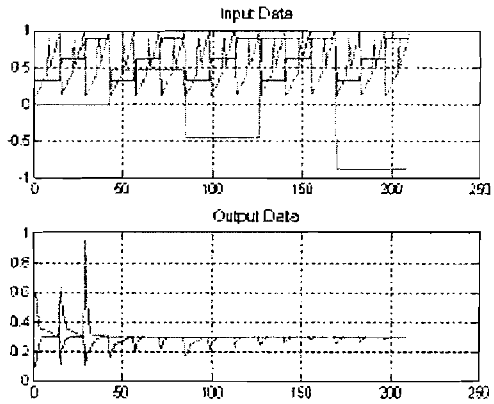

Figure 3: Input-output experimental data points

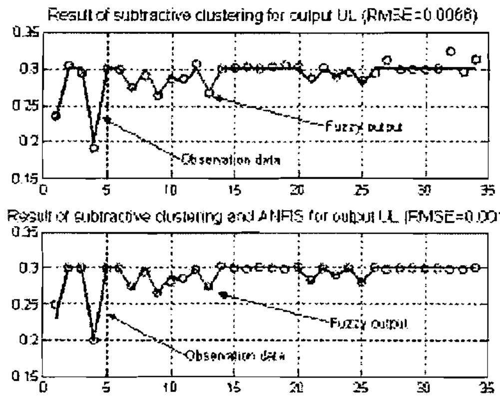

Figure 4: Fuzzy model for output (UL)

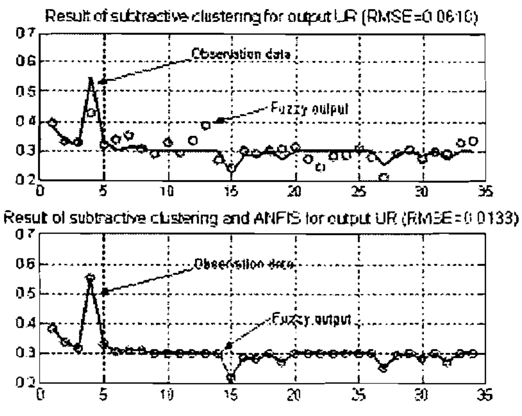

Figure 5: Fuzzy model for output (UR)

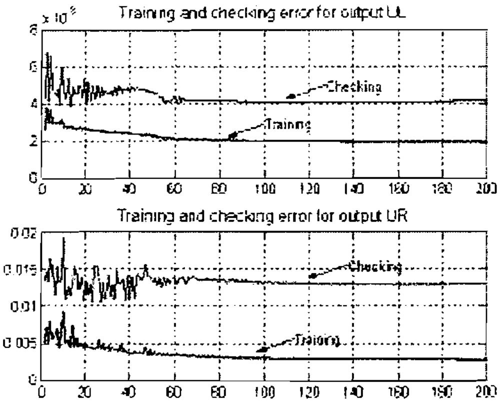

Figure 6: Settle of training and checking error

6 Conclusions

In this paper, a hybrid method of subtractive clustering and neuro-fuzzy modelling using ANFIS was presented. The proposed method can be applied to construct an identification method of fuzzy control strategies based on availability of input/output mapping data. In the first stage subtractive clustering was applied in order to obtain a fuzzy model of the robot behaviour. Then, a adaptive neuro-fuzzy inference system was used to improve the model's accuracy. Simulation results shows that the proposed method can produce very accurate results (RMSE 0.0019 and 0.013 respectively).

References

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