Fişa suspiciunii de plagiat / Sheet of plagiarism's suspicion	Indexat la: 38/01

Opera suspicionată (OS)	Opera autentică (OA)
Suspicious work	Authentic work

OS	Pruteanu, E., Ababei, S., Culea, G., Puiu, G., Angheluţ, M., "Objective function based fuzzy clustering", *Modelling and Optimization in the Machines Building Field MOCM*, vol.1, no.14, 2008, pg. 229-232.
OA	Turčan, A., Ocelíková, E., "Fuzzy Clustering Applied on Mobile Agent Behaviour Selection", 2005, Disponibil la: http :// bmf . hu / conferences / SAMI2005 / ocelikova.pdf.

Incidenţa minimă a suspiciunii / Minimum incidence of suspicion	
p.229:28 – p.231:8	p.2:13 – p.3:24
Fişa întocmită pentru includerea suspiciunii în Indexul Operelor Plagiate în România de la www.plagiate.ro	

Precizare:

Prin notaţia p.229:28 - p.231:8 se înţelege că fragmentul de text preluat fără indicarea provenienţei în opera suspicionată este cuprins integral în opera autentică între rândul 13 al pag.2 şi rândul 24 al pag.3.

Fuzzy Clustering Applied on Mobile Agent Behaviour Selection

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Abstract: The goal od this paper is to provide a concept of possible hierarchical structructure of mechanizm for mobile agent behaviour selection. Hierarchy of the controler is composed of fuzzy classifier and several simple fuzzy systems, where each can deal with one simple situation. Fuzzy systems are able to treat and cope with uncertain and imprecise information, they have capability of expressing the knowledge in the form of linguistic rules, which sometimes are not easy to design. Fuzzy classifiers on the other hand do not need require antecendent knowledge of the space where they operate. Combination of those two techiques can leed into simple and effective system, where fuzzy classifier is employed to select the appropriate behavior, with wich one of the fuzzy controlers can deal with.

Keywords: classification, fuzzy clustering, fuzzy classifier, mobile agent

1 Introduction

Fuzzy systems have the attribute of expressing knowledge in the form of linguistic rules. They offer a possibility to implement expert human knowledge and experience in form of those linguistic rules. Even though they are relatively easy to design, no universal systematic procedure exist to design them.

2 Fuzzy Inference Systems and Fuzzy Clustering

The first and most common application of fuzzy logic techniques in the domain of mobile agents is the use of fuzzy control to implement individual behaviour units. Fuzzy logic controllers incorporate heuristic control knowledge in the form of *IF-THEN* rules, and are convenient choice when a precise linear model of the system, which is to be controlled, cannot be easily designed. They have also shown a good degree of robustnes in face of large variability and uncertaintity in parameters.

These characteristics make fuzzy control particularly suited to the needs of autonomous mobile agents.

On the other hand, fuzzy clustering, and clustering in general, have the possibility to divide a set of objects into reasonable groups (called clusters). The division of objects is based on measuring of similarity or dissimilarity between the pair of objects. Thus, result of clustering is a set of clusters, where object within one cluster are more similar to each other, than to object in another cluster. Why not treat those objects as typical or basic behavior types of the mobile agent?

2.1 Fuzzy Clustering

Fuzzy clustering algorithms allows each datum to belong into one or more clusters with certain membership degree. Larger membership values indicate higher confidence in the assignment of the datum to the cluster.

2.1.1 General Fuzzy C-means Algorithm

Fuzzy c-means algorithm has been described by [4] consists of iteration over the following steps until the termination criterion is not met:

(1) Select an initial fuzzy partition of the $\boldsymbol{N}$ objects into $\boldsymbol{K}$ clusters by selecting the $N \times K$ membership matrix U. An element $\boldsymbol{u_{ij}}$ of this matrix represents the grade of membership of object $\mathbf{x}_i$ in cluster $\mathbf{c}_j$. Typically, $\boldsymbol{u_{ij}} \in [0,1]$.

(2) Using U, find the value of a fuzzy criterion function, e.g., a weighted squared error criterion function, associated with the corresponding partition. One possible fuzzy criterion function is

$$J(\mathbf{Z}, \mathbf{U}, \mathbf{V}) = \sum_{i=1}^{C} \sum_{k=1}^{N} \mu_{ik}^{m} \left\| z_k - v_i \right\|_{\mathbf{A}_i}^{2} \quad (1)$$

Reassign patterns to clusters to reduce this criterion function value and recompute U.

(3) Repeat step (2) until entries in U do not change significantly.

Fuzzy *c*-means (FCM) algorithm is probably the most popular fuzzy clustering algorithm. Even though it is better than the hard *k*-means algorithm at avoiding local minima, FCM can still converge to local minima of the squared error criterion. The design of membership functions is the most important problem in fuzzy clustering; different choices include those based on similarity decomposition and centroids of clusters.

2.1.2 Gustafson-Kessel Algorithm

The Gustafson-Kessel (GK) algorithm is an extension of the FCM algorithm. The GK algorithm employs an adaptive distance norm in order to detect the clusters with the different shapes. Contrary to the FCM algorithm the GK algorithm gives the clusters with the different sizes in the different sizes in the different dimensions (clusters are ellipsoids). In this case every cluster has its own norm matrix $\boldsymbol{A_i}$. The matrices $\boldsymbol{A_i}$ are an optimization variable in following objective function:

$$J(\mathbf{Z},\mathbf{U},\mathbf{V},A)=\sum_{i=1}^{C}\sum_{k=1}^{N}\mu_{ik}^{m}\left(z_k-v_i\right)A_i\left(z_k-v_i\right)^T \tag{2}$$

But the objective function cannot be minimized directly because J depends on Ai linearly. It means that J can be made as small as the considered positive definite matrices Ai. Therefore Ai is constrained by:

$$\det\left|A_i\right|=\rho_i \tag{3}$$

The following result is obtained:

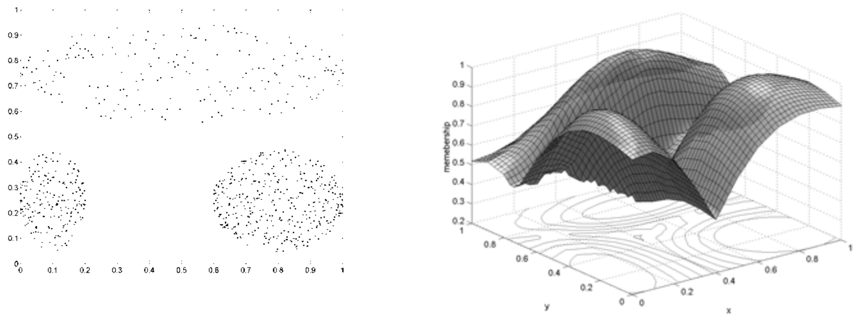
$$A_i=\left[\rho_i\det\left(F_i\right)\right]^{1/n}F_i^{-1} \tag{4}$$

where n is the dimension of the data (patterns) and Fi is the fuzzy covariance matrix of the i-th cluster and the fuzzy covariance matrix is defined as:

$$F_i=\frac{\sum_{k=1}^{N}\mu_{ik}^{m}\left(z_k-v_i\right)\left(z_k-v_i\right)^T}{\sum_{k=1}^{N}\mu_{ik}^{m}} \tag{5}$$

Such these cluster shape provides an easier and more accurate coverage of the pattern space and in the following section is shown that this method is better for a generating of the membership functions and the rules.

The GK algorithm is also data scale independent, i.e. if the data in any dimension are multiplied by a constant than the relative coordinates of the cluster centers and the matrix of membership degrees are identical. Moreover the convergence of this algorithm is ensured, but locally only.



a) b)

Figure 1
a) set of data used for clustering; b) resulting clusters after the application of the Gustafson-Kessel clustering algorithm (only the maximal values of degree of membership are visualized)

2.2 Fuzzy Clustering vs. Fuzzy Inference System

Fuzzy inference is the process of formulating the mapping from a given input to an output using the fuzzy logic. For our purposes a Takagi-Sugeno method of inference is used, where output membership functions are only linear or constant. A typical fuzzy rule in this model has the form

If x is A and y is B then z=k (6)

where *A* and *B* are fuzzy sets in the antecendent, while *k* is a crisply defined constant in the consequent part of the rule. Output surface of a such system with two input variables and one output can be seen on Fig. 2.

As said before, fuzzy clustering algorithms assign each datum degree of membership for each cluster. After having look on Fig. 3; and comparing it with Fig. 2 we can find certain similarity in both surfaces. Resulting surface of the fuzzy clustering could be used for controll as well as the fuzzy controler.

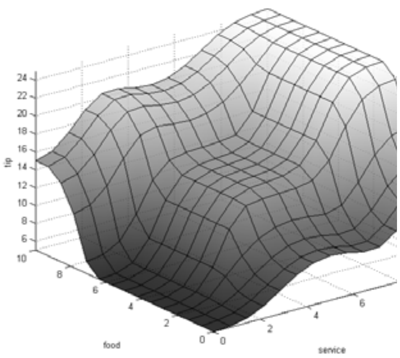


Figure 2
Surface representing fuzzy inference model

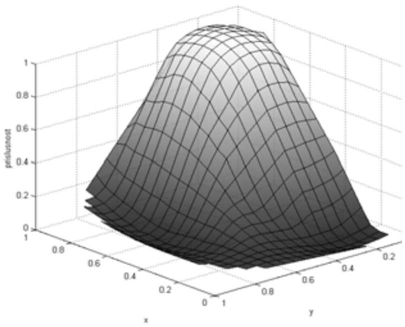


Figure 3
Surface representing membership function for one of the clusters from Fig. 1

3 Building a Hierarchy

In behavior-based control, a complex control problem is divided into a set of simpler controllers, known as behaviors, that collectively should solve the original problem. To do this, it is thus necessary to coordinate the activities of the behaviors to satisfy the initial complex system's control objectives. This is known as the behavior coordination problem (or action selection).

At first we are going to create building blocks for the individual behavior units.

3.1 Simple Behaviors

Concept of the simple behaviors is taken from the *divide and conquer* approach to solve problems. It is easier to decompose one complex behavior into a group of simple behaviours, which interaction and composition can lead to the desired complex behavior.

A good example is the mobile agent. The high-level motion control system is decomposed into a seto of special-puropose behaviors that achieve distinct tasks when subject to particular stimuli. For this example we employ hierarchy with two levels. The lowest level of behavior represents the simplest (or primitive) behaviors. These are simple, self-contained behaviors that serve a single purpose by operating in a reactive or reflexive fashion. Each of them would be insufficient for the autonomous task. They are combined to produce behavior suitable for accomplishing goal-directed operation.

3.2 Behavior Coordination Mechanisms

Behavior coordination mechanisms can be divided into two main clases: arbitration and command fusion.

3.2.1 Arbitration

Arbitration mechanisms select one behavior, from a group of competing ones and give it ultimate control of the system until the next selection cycle. This approach is suitable for arbitrating among the set of active behaviors in accord with the system's changing objectives and requirements under varying conditions. It can focus the use of scarce system resources on task that are considered to be relevant. Final behavior can be chosen either using *priority-based* arbitration mechanism, where behaviors with higher priorities are allowed to supress the output of behaviors with lower priorities, or *winner-take-all* mechanisms, where action selection results from the interaction of the behavior that compete until one wins and takes the control of the system.

3.2.2 Command Fusion

Command fusion mechanisms combine recommendations from multiple behaviors to form a control action that represents their consensus. Thus, this appproach provides for a coordination scheme, that allows all behaviors to simultaneously contribute to the control of the system in a cooperative rather than a competitive manner. The techniques mostly used are dealing with *superposition* of the simple behavior outputs.

In the proposed architecture a fuzzy classifier is employed to compute the weights for each behavior. The final action is carried out as the supperposition of all simple behaviors.

4 Mobile Agent

For the experiments with the hierarchical system composed of fuzzy clustering system for the behavior selection and Takagi-Sugeno fuzzy inference to control the simple behavior was chosen. This system was used to acomplish single (and quite simple) goal. This goal was to navigate the agent from point A to point B. This simple task has been chosen, because the focus has been put on the design of the behavior selection and the fuzzy clustering.

As can be seen in Fig. 2; the surface of the function is dependant on the placement of the clustered data. So for our purposes, we are going to do some reverse work. We will construct a set of typical situations, which we will describe by feature vector. After applying the fuzzy clustering algorithm (Gustafson-Kessel is used for its capabilities to group data into the clusters of eliptic shapes) on data set we have created, we get a function, which calculates for each point of its universe wage for the final output of the fuzzy inference systems representing simple behaviors.

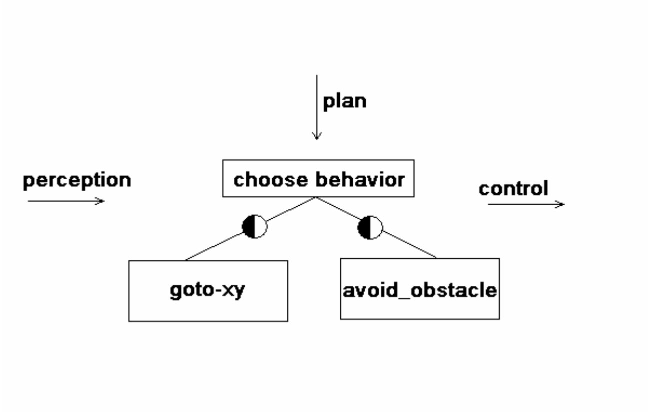
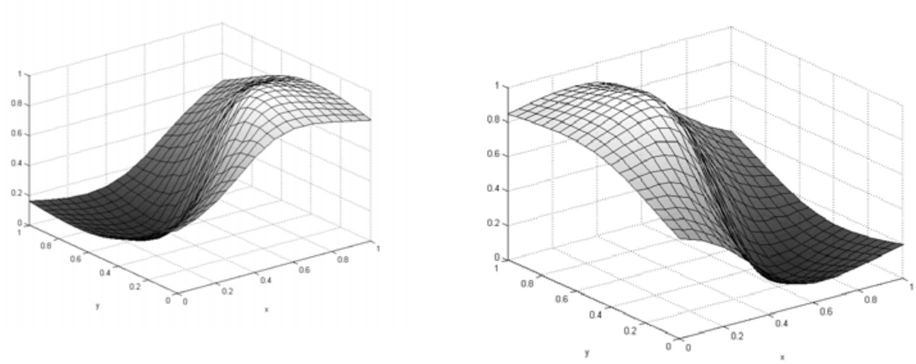


Figure 5
Structure of the system

On the Fig. 5; the structure of the system is depicted. Only two simple behaviors have been chosen *goto-xy* and *avoid_obstacle*. Over these two fuzzy inference system a fuzzy classifier is linked in order to set the wages for the computation of the final action.



a) b)

Figure 6
Wages computation for a) goto-xy b) avoid_obstacle

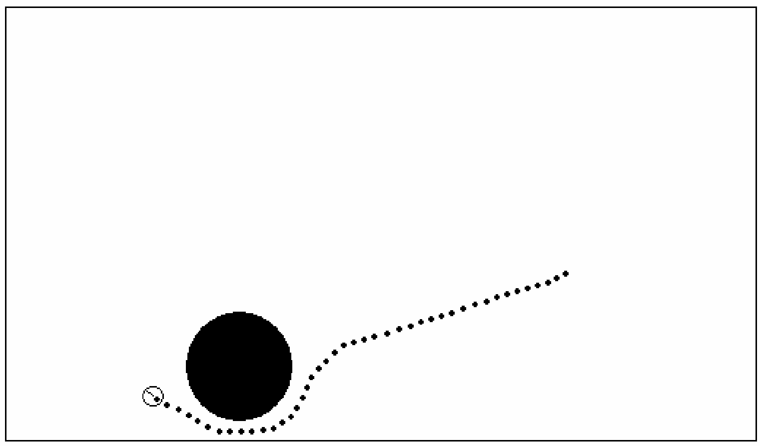


Figure 7
Path of the mobile agent; navigation to xy possition with avoidance of the obstacle

Conclusion

The hierarchy of fuzzy-behaviors provides an efficient approach to controll mobile robots. Such a hierarchy allows us to decompose overall behavior into sub-behaviors that are activated only when applicable (when conditions for activation of a single or more are stisfied), and there is no need to process all the rules that do not apply. Proposed design focused on use of the fuzzy classifier to either combine simple behaviors or to choose the most appropriate behavior. Superposition of simple behaviors allows realization of a continuum of behavioral responses governed by respective degrees of applicability.

Acknowledgement

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