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Robot Cooperation by Fuzzy Signature Sets Rule Base

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Abstract - This paper presents a novel method for control cooperating robots without any explicit communication line. We have proposed a fuzzy communication philosophy and implementation technique, where the codebooks are built up by signatures. Fuzzy signatures are used as complex state description method for intention guessing and action selection. Finally some real scenarios of autonomous mobile robot cooperation are presented.

I. Introduction

Fuzzy signatures structure data into vectors of fuzzy values, each of which can be a further vector, are introduced to handle complex structured data [1, 2, 3, 4]. This will widen the application of fuzzy theory to many areas where objects are complex and sometimes interdependent features are to be classified and similarities / dissimilarities evaluated. Often, human experts can and must make decisions based on comparisons of cases with different numbers of data components, with even some components missing. Fuzzy signatures were created with this objective in mind. This tree structure is a generalization of fuzzy sets and vector valued fuzzy sets in a way modeling the human approach to complex problems. However, when dealing with a very large data set, it is possible that they hide hierarchical structure that appears in the sub-variable structures.

This paper deals with fuzzy signatures as complex state description method in field of control of mobile robots and robot cooperation.

Intelligent cooperation is a new research field in autonomous robotics. If one would plan or build a cooperating robot system which has intelligent behaviors, one could not program the all scenarios which may appear in the life of the robots, and would realizes that effective, fast and compact communication is one of the most important cornerstones of a high-end cooperating system. We assume settings where communication itself is very expensive, so generally speaking it is advisable to build up as large as possible contextual knowledge bases and codebooks in the distant on-board robot controller computers [5, 6]. Clearly, this is in order to shorten their communication process. This is appropriate if it significantly reduces the amount of information that must be transmitted from one to another, rather than to concentrate all contextual knowledge in one of them, and then to export its respective parts whenever they are needed in the other(s). It appears to be very important in the cooperation and communication of intelligent robots or physical agents that the information exchange among them is as effective and compressed as possible [7].

In this paper we propose a fuzzy communication system where the codebooks are built up by fuzzy signatures. After an overview of this type of fuzzy communication we will deal with some real scenarios of autonomous mobile robot cooperation. The base idea of this example has come from the partly unpublished research projects at LIFE [8]. The paper presents a cooperation system where a group of autonomous intelligent mobile robots is supposed to solve transportation problems according to the exact instruction given to the Robot Foreman (R_0). The other robots have no direct communication links with R_0 and all others, but can solve the task by intention guessing from the actual movements and positions of other robots, even though they might not be unambiguous.

II. Fuzzy Signatures

The original definition of fuzzy sets was $A: X \to [0,1]$, and was soon extended to *L-fuzzy sets* by Goguen [9].

$$A_s : X \to [a_i]_{i=1}^{k}, a_i = \begin{cases} [0,1] \\ [a_{ij}]_{j=1}^{k_i} \end{cases}, a_{ij} = \begin{cases} [0,1] \\ [a_{ijl}]_{l=1}^{k_{ij}} \end{cases} \quad (1)$$

$A_L : X \to L$, L being an arbitrary algebraic lattice. A practical special case, Vector Valued Fuzzy Sets was introduced by Kóczy [1], where $A_{V,k} : X \to [0,1]^k$, and the range of membership values was the lattice of k-dimensional vectors with components in the unit interval. A further generalization of this concept is the introduction of fuzzy signature and signature sets, where each vector component is possibly another nested vector as Eq. (1) shows it.

Fuzzy signature can be considered as special multidimensional fuzzy data. Some of the dimensions are interrelated in the sense that they form sub-group of variables, which jointly determine some feature on higher level. Let us consider an example. Fig. 1 shows a fuzzy signature structure.

The fuzzy signature structure shown in Fig. 1 can be represented in vector form as follow:

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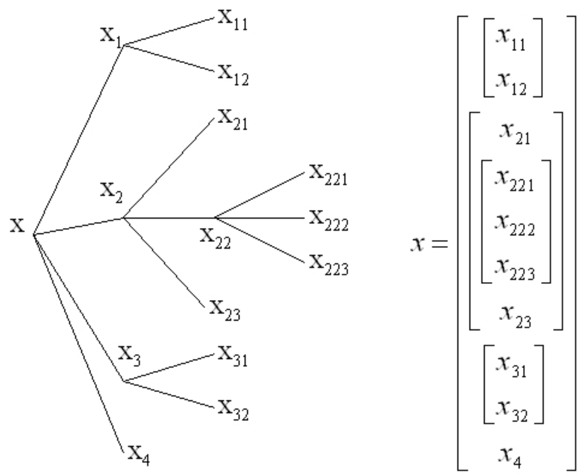

Figure 1. A Fuzzy Signature Structure

Here $[x_{11}\ x_{12}]$ form a sub-group that corresponds to a higher level compound variable of x_1. $[x_{221}\ x_{222}\ x_{223}]$ will then combine together to form x_{22} and $[x_{21}\ [x_{221}\ x_{222}\ x_{223}]\ x_{23}]$ is equivalent on higher level with $[x_{21}\ x_{22}\ x_{23}] = x_2$ and $[x_{31}\ x_{32}] = x_3$. Finally, the fuzzy signature structure will become $x = [x_1\ x_2\ x_3\ x_4]$ in the example.

The relationship between higher and lower level is governed by the set of fuzzy aggregations. The results of the parent signature at each level are computed from their branches with appropriate aggregation of their child signature.

Each of these signatures contains information relevant to the particular data point x_0; by going higher in the signature structure, less information will be kept. In some operations it is necessary to reduce and aggregate information obtained from another source (some detail variables missing or simply being locally omitted). Such a case occurs when interpolation within a fuzzy signature rule base is done, where the fuzzy signatures flanking an observation are not exactly of the same structure. In this case the maximal common sub-tree must be determined and all signatures must be reduced to that level in order to be able to interpolate between the corresponding branches or roots in some cases [4].

III. FUZZY SIGNATURE SETS

The basic structure of fuzzy signature sets is similar to that of fuzzy signatures, the only difference being that instead of having fuzzy variables on the leaves of the structure, membership functions are present (see Fig. 2). The only constraint for the membership functions is that their domain must be the [0,1] interval [10].

IV. SIGNATURE STRUCTURE MODIFICATION: THE AGGREGATION OPERATORS

The advantages of fuzzy signatures lie in organizing the available data components into a hierarchy. This hierarchy determines the arbitrary structure of our fuzzy signature observations. As some of the components of this arbitrary structure might be missing from the specific observations, some kind of structure modifying operation is essential when comparing these differently structured signatures.

Aggregation operations result in a single fuzzy value calculated from a set of other fuzzy values, while satisfying a set of axioms. The most common operators are the maximum, minimum and arithmetic mean operator [11, 12].

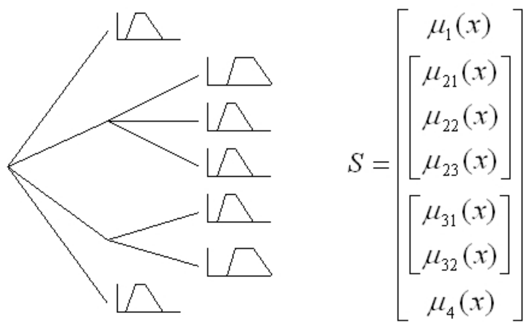

Figure 2. The tree structure and the vector form of an example fuzzy signature set

Aggregation operators can be used to transform fuzzy signature structures by reducing a sub-tree of variables to their parent node. It is necessary to mention that only whole sub-trees of the structure can be reduced. The fuzzy value (or fuzzy set) assigned to the parent node is calculated by aggregating the fuzzy values (or fuzzy sets) of its children using the aggregation operator of the parent node. This way, the depth of this branch of the structure is reduced by one.

This procedure can only be performed when all elements of the aggregated sub-tree are leaves of the structure and have an assigned value. If one of the elements of the sub-tree branches out into a sub-tree of its own, in order to reduce the whole sub-tree to the original parent node, first the sub-sub-tree has to be reduced to its parent node (which is the child node of the original sub-tree's parent node) by aggregation. After performing the aggregation, the original sub-tree can also be reduced.

For example, to reduce the sub-tree of node x_i, first the sub-tree of node x_{i2} has to be aggregated. The value obtained can then be used when calculating the aggregate value from the sub-tree of x_i. This recursive procedure is shown in Fig. 3, where $@_i$ denotes the aggregation operator of node x_i.

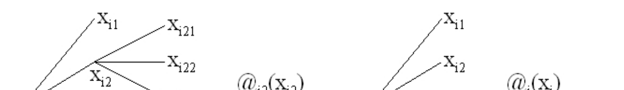

Figure 3. Recursion used to reduce a sub-tree with several layers

Because of these terms, when reducing a signature to a predefined structure it is wise to use a bottom-up method. This means to start the reduction from the leaves of the structure and work your way up one sub-tree at a time towards the intended structure.

According to the definition of fuzzy signatures, aggregation operators define the connection between a component, and its sub-components, therefore the aggregation operators are not necessarily identical for all the nodes of the structure. Finding the relevant aggregation operator for each node is a very important problem of fuzzy signatures, because when comparing two signatures, the obtained results may greatly depend on the aggregation operators used to reduce the signatures to a common structure.

It is also important to mention that when reducing a signature's sub-tree, some information is lost in all cases, because the calculated aggregated value can be the same for many different values and differently structured sub-trees.

In order to reduce fuzzy signature sets to a different structure aggregation has to be generalized to work not only on fuzzy values but on fuzzy sets as well.

When aggregating fuzzy sets, the membership values for each element *x* of [0,1] (the domain of the fuzzy sets on the leaves of the structure) are calculated for all the fuzzy sets which are subject to the aggregation. The original aggregation operator is then used on these membership values to obtain the aggregated membership value belonging to *x*. Let the fuzzy sets in the sub-tree be A_i. The membership function of the aggregated fuzzy set G is given in Eq. (2), where h denotes the aggregation operator.

$$\begin{aligned} &G = h(A_1, A_2, \ldots, A_k) \\ &\forall x \in [0,1] \quad \mu_G(x) = h\{\mu_{A_1}(x), \mu_{A_2}(x), \ldots, \mu_{A_k}(x)\} \end{aligned} \tag{2}$$

The aggregation of two fuzzy sets (A_1 and A_2) is shown in Fig. 4. In the example, the aggregation operator is the arithmetic mean operator. The resulting fuzzy set (denoted by G) is marked with a broken line.

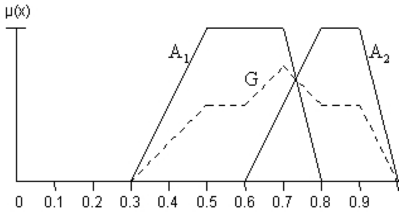

Figure 4. Aggregation of two fuzzy sets with the arithmetic mean operator

A. Weighted Relevance Aggregation Operator

With the introduction of weights [13] for each node of the fuzzy signature structure additional expert knowledge about the field can be contained within the model. The relevance weight depicts how relevant a node is in its parent's sub-tree. The weights of the nodes are taken from the [0;1] interval, and it is not necessary for the weights of the leaves in a sub-tree to add up to 1. A method for learning weights was shown in [14].

The most general form of aggregation operators is the Weighted Relevance Aggregation Operator (WRAO) introduced by Mendis *et al.* in [15]. The values and weights belonging to each child l in the sub-tree are denoted by x_l and w_l respectively. The definition of the WRAO is as follows:

$$@(x_1, x_2, \ldots, x_n; w_1, w_2, \ldots, w_n) = \left\{ \frac{1}{n} \sum_{i=1}^{n} (w_l \cdot x_l)^p \right\}^{\frac{1}{p}} \tag{3}$$

where p is the aggregation factor of the above function.

The well-known aggregation operators are all special cases of WRAO depending on the value of p in (3).

$p \to -\infty$, WRAO $\to$ minimum

$p = -1$, WRAO $=$ harmonic mean

$p \to 0$, WRAO $\to$ geometric mean

$p = 1$, WRAO $=$ arithmetic mean

$p \to \infty$, WRAO $\to$ maximum

V. Fuzzy Communication of Cooperating Robots

One of the most important parameters of effective cooperation is efficient communication. Because communication itself very expensive, it is much more advisable to build up as large as possible contextual knowledge bases and codebooks in robot controllers in order to shorten their communication process. That is, if it essentially reduces the amount of information that must be transmitted from one to another, than to concentrate all contextual knowledge in one of them and then to export its respective parts whenever they are needed in other robot(s). It appears to be very important in the cooperation and communication of intelligent robots or physical agents that the information exchange among them is as effective and compressed as possible [7].

A. Experimental task and environment

The actual stage of our research we use simulation of our real differential driven autonomous micro-robots (Fig. 5). The physical simulation is exact model of our robots in the case of scale, weight, mechanical systems and sensors.

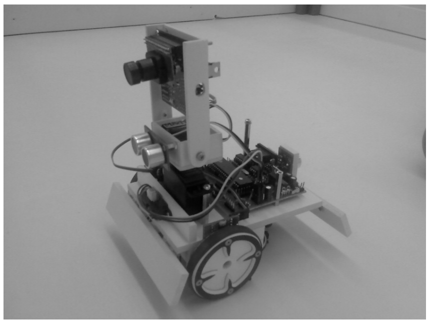

Figure 5. The real box-pushing robot

Three robots operate in a 2 x 2 m square arena. The box to be pushed is a 10 cm high and 20 cm wide and long. The goal region, located near to one corner of the arena Fig. 7. In the experiments described here the goal location is fixed but it can be moved before and during experiments.

Each robot pushes the box with two "whiskers" which have a pair of force sensors. The left and right whiskers each provides an analog force signal which is combined to give information the relative position to the box and via the control loop keep it contact on both sides and thus perpendicular to the box.

Let us examine a subset of our overall robot cooperation problem works in practice. There is an arena where five square boxes wait for ordering. Various configurations can be made from them, but here only the "T" form is enabled with any orientation as Fig. 6 shows.

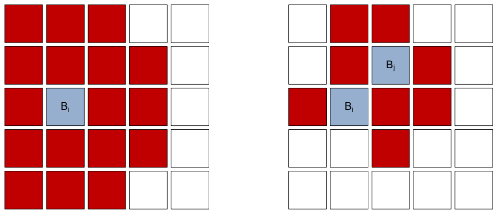

Figure 6. “T” form configurations

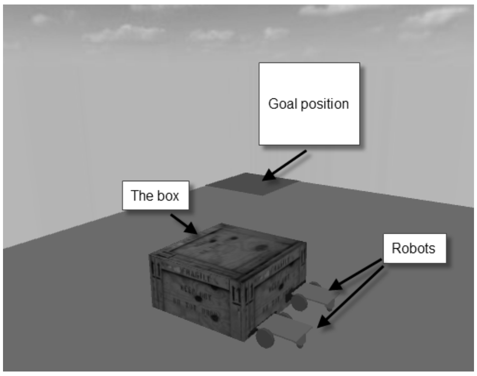

Figure 7. The simulation environment

The three robots form a group which try to build the actual order of boxes according to the exact instructions given to the R_0 (foreman) robot. The other robots have no direct communication links with R_0, but they are able to observe the behavior of R_0 and all others, and they all posses the same codebook containing the base rules of storage box ordering. The individual boxes can be shifted or rotated, but always two robots are needed for actually moving a box, as they are heavy. If two robots are pushing the box in parallel the box will be shifted according the joint forces of the robots. If the two robots are pushing in opposite directions positioned at the diagonally opposite ends, the box will turn around the center of gravity. If two robots are pushing in parallel, and one is pushing in the opposite direction, the box will not move or rotate, just like when only a single robot pushes. Under these conditions the task can be solved, if all robots are provided with suitable algorithms that enable intention guessing from the actual movements and positions, even though they might be unambiguous.

Fig. 8 presents an example of how the five boxes can be arranged.

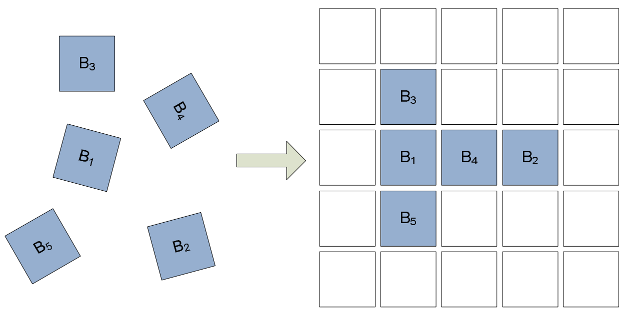

Figure 8. Examples for box arrangement

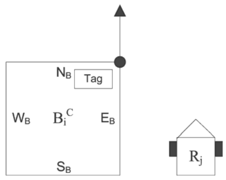

Figure 9. Symbols of boxes and robots

The box has a B_i sign which means that is the i-th Box. The R_j is the sign of the j-th robot. The R_0 is a distinct one, namely it is the robot foreman, the only robot that exactly knows the task on hand.

The cooperating combination of robots is denoted by $C^{b}_{i,j,(k)}$ where *i,j* and *k* is the number of the robots (*k* appears only in stopping combinations), and *b* is the number of the box. There are three essentially different combinations (Fig. 10), $C^{i}_{1,2} = P$ is the “pushing or shifting combination”, when two robots (R_1 and R_2) are side by side at the same side of the table; $C^{i}_{1,2} = RC$ stands for “counterclockwise rotation combination”; and $C^{i}_{1,2} = RW$ denotes “clockwise rotation combination”.

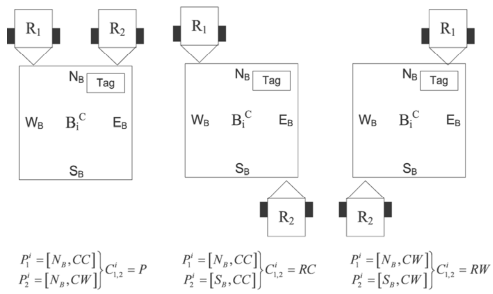

Figure 10. Allowed combinations of two robots for moving the table

B. *Fuzzy signature sets*

For the action selection or decision making each robot guesses the intentions of others and considers the actual states of the boxes. The robot uses the own codebook and sensory perceptions for this task.

Let us consider the fuzzy signature sets of the box state and manipulation necessity. Each box has the own instance of this fuzzy signature set and the actual robot makes decision about the manipulation of that box by the fuzzy signature sets.

This signature records the position, the arrangement, the dynamic and the robots working on the actual box. A possible arbitrary structure of the fuzzy signature representing the multidimensional complex features of the box is shown in Fig. 11. Each node in the tree has the own meaning.

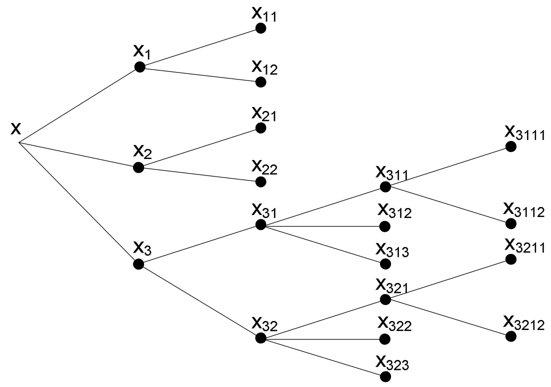

Figure 11. The box state and manipulation fuzzy signature

The node x_1 describes the actual position of the box relative for its goal position. The distance (x_{11}) can be described by one of the four fuzzy sets in Fig. 12, where in this case the fuzzy set A means that the box in position, B that it is close to the goal position, C means the near and D the far distance.

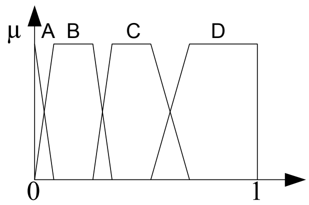

Figure 12. Fuzzy sets used in distance measurement

The fuzzy value on node x_{12} describes the rotation of the box from the North-South axis.

The x_2 node describes the accessibility of the box. The x_{21} fuzzy leaf represents the distance from robot. In this case fuzzy set A means the touching distance, fuzzy set B the close, fuzzy set C represents near and fuzzy set D the far distance respectively. The fuzzy value on node x_{22} describes any other feature of accessibility of the actual box, for instance obstacles, etc.

The node x_3 the most complex sub-tree in this structure. The fuzzy value on node x_3 describes the positions and states of other robots in viewpoint of the actual box. The sub-sub trees describe the number of touching robots, the touching points, cooperative combination and touch time, the distance and course of moving robots near the box. The detailed descriptions of this structure on fuzzy signature sets are beyond the extent of this paper.

An aggregation operator has to be defined for all nodes of the arbitrary structure. The notation $@_i$ will be used to refer to the aggregation operator assigned to node i.

The inferences on these fuzzy signatures are able to describe the actual states of the box and give a basis for the fuzzy decision process in the robot control. Every robot builds its actual knowledge-base from the fuzzy signature classes and then boxes are assigned individual signatures in each individual robot controller.

The leaves of the actual structures are fuzzy sets or membership functions therefore fuzzy signature sets are used in decision making and action selection mechanism.

VI. RESULTS

There is built up a simulated arena, where three robots cooperate to arrange some boxes. Every robot has the above described algorithms for intention guessing and action selection.

The Fig. 13 presents some steps of arranging process. Firstly the robots search the nearest disordered box and take a combination for pushing or rotating it. If they reach a pivot point then take a new combination and do it cyclic till order the actual box. This task recurs until all box get to the good place.

Numerous scenarios are simulated and result a good collaboration with 90 % of acceptability.

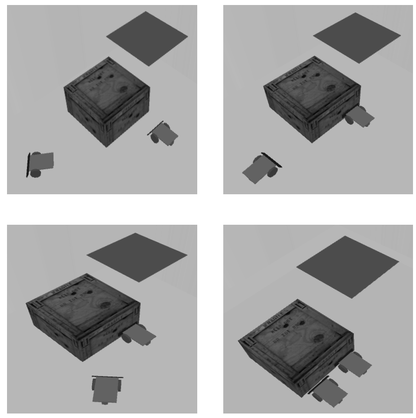

Figure 13. The robots take the starting combination

VII. CONCLUSIONS

Fuzzy communication contains vague or imprecise components and it might lack abundant information. If two robots are communicating by a fuzzy channel, it is necessary that both ends possess an identical part within the codebook. The codebook might partly consist of common knowledge but it usually requires a context dependent part that is learned by communicating. Possibly it is continuously adapting to the input information. If such a codebook is not available or it contains too imprecise information, the information to be transmitted might be too much distorted and might lead to misunderstanding, misinterpretation and serious damage. If however the quality of the available codebook is satisfactory, the communication will be efficient i.e. the original contents of the message can be reconstructed. At the same time it is cost effective, as fuzzy communication is compressed as compared to traditional communication. This advantage can be deployed in many areas of engineering, especially where the use of the communication channels is expensive in some sense, or where there is no proper communication channel available at all.

Here we illustrate clearly that the communication among intelligent robots by intention guessing and fuzzy evaluation of the situation might lead to effective cooperation and the achievement of tasks that cannot be done without collaboration and communication.

ACKNOWLEDGEMENT

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