Robot Systems with Fuzzy Signature Rule Bases

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Abstract: This paper presents some examples for fuzzy communication and intention guessing from the real life to the cooperation of intelligent mobile robots. In a special experimental environment a new communication approach is investigated for intelligent cooperation of autonomous mobile robots. Effective, fast and compact communication is one of the most important cornerstones of a high-end cooperating system. In this paper we propose a fuzzy communication system where the codebooks are built up by fuzzy signatures. 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. Thus, complex objects and situations can be described by fuzzy signatures. We use cooperating autonomous mobile robots to solve some logistic problems.

Keywords: fuzzy signature :fuzzy communication :mobile robotics.

1. Introduction

Intelligent cooperation of two or more robots has been tackled in different ways since at least the late 1980's. If one intends to build a cooperating robot system with intelligent behavior, it is impossible to foresee all scenarios potentially occurring, thus effective, fast and/or compact communication is one of the most important cornerstones of such a cooperating system. Communication is sometimes quite expensive, so very compact solutions have often priority in comparison to very precise ones. We suggest building up

a context dependent knowledge base and a common codebook in the distant on-board controller of each robot. By observation of the scenario and by "intention guessing" (i.e. analyzing the other robots' behavior), it is possible to shorten the actual communication process and to essentially reduce the amount of information that needs to be transmitted from one agent to another.

We have proposed a fuzzy communication philosophy and implementation technique, where the codebooks are built up by fuzzy signatures or fuzzy signature sets. Fuzzy signatures structure data into nested vectors of fuzzy values, each value being a further fuzzy vector. Fuzzy signatures are suitable for describing cases with different numbers of data components, with even some of the components missing, i.e. fuzzy signatures of varying structure are used. 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. Thus, complex objects and situations can be described by fuzzy signatures. This is a useful tool for building the codebook in a context dependent reconstructive communication situation. Fuzzy communication is based on the comparison and reconstruction of fuzzy signatures [1, 2].

At the end some real scenarios of autonomous mobile robot cooperation are presented. A group of autonomous intelligent mobile robots is supposed to solve simple transportation problems, where always two robots must cooperate. Exact instructions are given only to the Robot Foreman (R0) who starts behaving in a way indirectly indicating the job to be done. The other robots have no direct communication links with R0 and all the others, but they try to solve the task by intention guessing from the actual movements and positions of other robots, even though these might sometimes be ambiguous.

The research towards extending this fuzzy communication method to more complex robot cooperation is going on currently in the frame of a large EEA grant.

2. Fuzzy Communication

There are orthogonally contradicting interpretations of the idea of Fuzzy Communication. In [3] a scenario is described where the lack of precise and sufficient information in a business environment leads to employees creating their own fictive scenarios where they fill the information vacuum with conjecture and wrong assumptions, which eventually leads to catastrophic results. Another kind of scenario is taken from the Laboratory for International Fuzzy Engineering Research (Yokohama) that operated between 1989 and 1995 as the spiritual center of applied fuzzy research in Japan [4]. This latter gives a positive example for using fuzzy elements for compressed and effective communication between humans.

Scenario (based on a presentation at LIFE [4])

> *Director Tanaka receives a new secretary, Ms. Sato, on Monday. When Mr. Tanaka returns from lunch, he calls Ms.Sato and the next conversation follows:*

'Ms. Sato, I would like to have a cup of tea.'
'Yes, Mr. Tanaka. Do you prefer hot or cold tea?'
'Hot tea, please.
'Do you prefer black or green tea?'
'Give me black tea.'
'Do you need sugar?'
'No sugar, please.'
'Any milk to the tea?'
'No, thank you.'
So, Ms. Sato prepares the tea according to the request.
On Tuesday, after lunch the director calls Ms. Sato again.

'May I have a cup of tea?'
'Yes, Mr. Tanaka. Black tea, again?'
'Yes.'
'No sugar, no milk?'
'Exactly as you say.'
Now fewer questions led to the same action by the secretary.
On Wednesday, when Mr. Tanaka arrives, he does not say anything but
'May I?'
'The usual tea?'
'Yes.'
On Thursday, when the director comes in after lunch, Ms. Sato asks him:
'May I prepare your usual tea?'
'Yes, thank you.'

The Monday conversation consisted of a request and four questions and informative answers (9 sentences altogether). On Thursday there was no more need for any request, the fact that Mr. Tanaka arrived after lunch triggered the single yes/no question and after confirmation the tea was prepared (two sentences only). In the first example the story is about some employees who misinterpreted the behavior of the new chairman, having a certain "codebook" in the sense of fuzzy communication in [5], which contained rules that were not valid any more for the new situation. Thus meta-communication leads to false assumptions. In the "tea example" the codebook was built up by learning in the head of Ms. Sato, and it was adequate for the situation thus communication with Mr. Tanaka evolved into a very effective one.

In the tea scenario, the formal determination of the codebook contents could be something like "If Mr. Tanaka arrives after lunch (T), he likes to drink hot (H) black tea (B) without milk $(\neg M)$ and without sugar $(\neg S)$." With logical symbols it is $T \to B \,\&\, T \to H \,\&\, T \to M \,\&\, T \to \neg S$

If this codebook remains valid (Mr. Tanaka does not change his tea drinking habits), the simple formal model might be sufficient for the future. We might assume that this

was not Ms. Sato's first secretary position and she had learned various other contexts valid in different environments, which she essentially discarded at the point of entering Mr. Tanaka's office. In addition to the newly learned codebook elements, she has the general background knowledge base (common knowledge) that contains information like "After lunch people often drink coffee, tea, water or cold drinks", "There are hot and cold tea", "There are short, long and cappuccino style coffee", "People drinking tea or coffee sometimes add sugar and/or milk", etc. Concerning the codebook learning procedure, the next continuation of the scenario will clarify that a more structured codebook model should be applied more appropriately in order to keep the codebook flexible enough for accepting changes and additions easily. It should be remarked that expressions like often or sometimes might be formally interpreted by Precisiated Natural Language introduced by L. A. Zadeh [6] as a tool for describing verbally non-exact adverbs, modifiers, hedges, etc. that might play important roles in modeling complex imprecise phenomena, both in everyday life and in the applied sciences. Next a possible continuation of the above scenario is given.

Scenario (continued) One day Mr. Tanaka arrives from lunch and Ms. Sato asks the everyday question:

'May I prepare your usual tea?'
This time the answer is
'No, today I prefer coffee.'
'Do you drink it long or short?'
'Short please.'
'Any sugar?'
'No, thank you.'
'Any milk?'
'Yes, some milk, please.'

This way the knowledge base in the codebook might be formulated as the following:

"If Mr. Tanaka arrives after lunch (T), he usually likes to drink hot black tea (B) without milk $(\neg M)$ and without sugar $(\neg S)$, and sometimes he prefers short (E) coffee (C) with some milk (M) but no sugar $(\neg S)$." Formally it could be $(T[usually] \rightarrow B \,\&\, T[usually] \rightarrow H \,\&\, T[usually] \rightarrow \neg M \,\&\, T[usually] \rightarrow \neg S,$

$T[sometimes] \rightarrow C \,\&\, T[sometimes] \rightarrow E \,\&\, T[sometimes] \rightarrow M \,\&\, T[sometimes] \rightarrow \neg S)$

However, it is much more reasonable to order the information into a structured way:

$(T[usually] \rightarrow B \,\&\, T[sometimes] \rightarrow E; B \rightarrow H \,\&\, \neg M \,\&\, \neg S; C \rightarrow E \,\&\, M \,\&\, \neg S)$

Such codebook elements can be quite well formulated by using PNL, fuzzy logic and fuzzy sets. In the continuation of the scenario obviously the context has not changed in the sense that its already existing elements were not discarded but further elements had to be added. Generally it may not be expected that in a context like in the above scenario, where a human environment gives the base for the context, and human interactions are involved, the codebook could ever be considered as final or completed.

Both examples tell about communication between two or more humans, i.e. "man-man" communication. In both cases, from meager information the original contents should and in the latter case it also could be reconstructed. Often the problem to solve involves "man-machine" or even, "machine-machine" communication. It is possible that a similar communication channel can be opened between man and machine or between two machines where just the "skeleton" or even the "approximate skeleton" of the information that is supposed to be put through will be or can be transmitted. It is an open question, whether that kind of context dependent reconstructive type fuzzy communication that was used in the tea and coffee scenario could be utilized for engineering or other applied science purposes in the practice.

3. Context dependent Reconstructive Communication with Fuzzy Signatures

There is definitely a wide area of possible applications of compressed communication transmission, if the reconstruction at the receiving end is possible. Communication itself is very expensive. Generally speaking, it is much more advisable to build up as big as possible contextual knowledge bases and codebooks in distant computers in order to shorten their communication process 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 the other(s) It seems 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. There are also some other areas where this kind of compressed communication might help to solve difficult tasks. The next example is also taken from the partly unpublished research projects at LIFE [4]. The following example was actually implemented at LIFE in two alternative forms (hardware and simulation software), and some partly encouraging results could be observed.

It must be remarked, however, that the new considerations and approaches concerning an alternative solution of the robot communication problem will be first discussed here by the authors.

In the next sections some formal methods will be proposed for building codebooks for Context Dependent Reconstructive Communication (CDRC) where fuzzy components and PNL elements can also be considered.

3.1. Fuzzy Signatures

The original definition of fuzzy sets was $A:X\rightarrow[0,1]$, and was soon extended to *L-fuzzy sets* by Goguen [7]

$$A_s:X\rightarrow\left[a_i\right]_{i=1}^{k},a_i=\begin{cases}\dfrac{[0,1]}{\left[a_{ij}\right]_{j=1}^{k_i}},a_{ij}=\begin{cases}\dfrac{[0,1]}{\left[a_{ijl}\right]_{l=1}^{k_{ij}}}\end{cases}\end{cases} \tag{1}$$

$A_L : X \to L$, L being an arbitrary algebraic lattice. A practical special case, Vector *Valued Fuzzy Sets* was introduced by Kóczy [8], 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 (right).

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. Figure 1shows a fuzzy signature structure.

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

$$x = \begin{bmatrix} \begin{bmatrix} x_{11} \\ x_{12} \end{bmatrix} \\ \begin{bmatrix} x_{21} \\ \begin{bmatrix} x_{221} \\ x_{222} \\ x_{223} \end{bmatrix} \\ x_{23} \end{bmatrix} \\ \begin{bmatrix} x_{31} \\ x_{32} \end{bmatrix} \end{bmatrix}^T \tag{2}$$

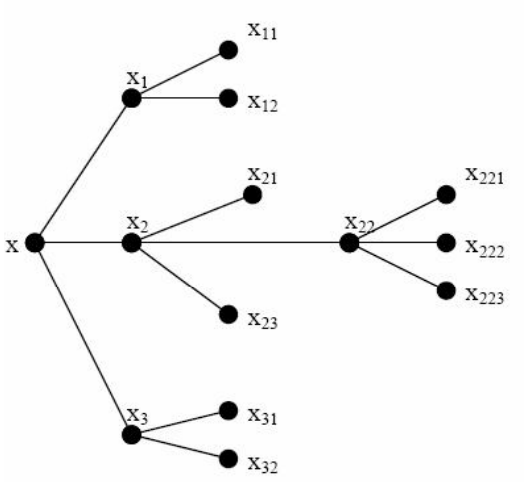


Figure 1. A Fuzzy Signature Structure

Here $[x_{11}\ x_{12}]$ from 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 $[x_{21}\ x_{22}\ x_{23}] = x_2$. Finally, the fuzzy signature structure will become $x = [x_{221}\ x_{222}\ x_{223}]$ 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. Let a_1 be the aggregating associating x_{11} and x_{12} used to derive x_1, thus $x_1 = x_{11}a_1x_{12}$. By referring to Figure 1, the aggregations for the whole signature structure would be a_1, a_2, a_{22} and a_3. The aggregations a_1, a_2, a_{22} and a_3 are not necessarily identical or different. The simplest case for a_{22} might be the min operation, the most well known t-norm. Let all aggregation be min except a_{22} be the averaging aggregation. We will show the operation based on the following fuzzy signature values for the structure in the example.

Each of these signatures contains information relevant to the particular data point x0; 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 [9].

$$x = \begin{bmatrix} \begin{bmatrix} 0.3 \\ 0.4 \end{bmatrix} \\ \begin{bmatrix} 0.2 \\ \begin{bmatrix} 0.6 \\ 0.8 \\ 0.1 \end{bmatrix} \\ 0.9 \end{bmatrix} \\ \begin{bmatrix} 0.1 \\ 0.7 \end{bmatrix} \end{bmatrix}^T \tag{3}$$

After the aggregation operation is performed to the lowest branch of the structure, it will be described on higher level as:

$$x = \begin{bmatrix} 0.3 \\ \begin{bmatrix} 0.2 \\ 0.5 \\ 0.9 \end{bmatrix} \\ 0.1 \end{bmatrix}^T \tag{4}$$

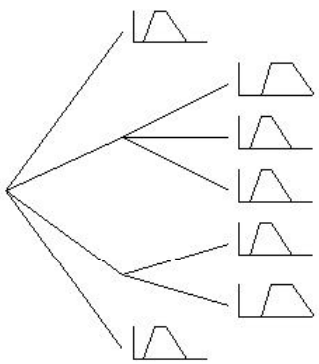
Finally, the fuzzy signature structure will be:

$$x = \begin{bmatrix} 0.3 \\ 0.2 \\ 0.1 \end{bmatrix}^T \tag{5}$$

Thus, complex objects and situations can be described by fuzzy signatures. This is a useful tool for building the codebook in a context dependent reconstructive communication situation.

3.2. 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 Figure 2). The only constraint for the membership functions is that their domain must be the [0,1] interval [10].



$$S = \begin{bmatrix} \mu_1(x) \\ \begin{bmatrix} \mu_{21}(x) \\ \mu_{22}(x) \\ \mu_{23}(x) \end{bmatrix} \\ \begin{bmatrix} \mu_{31}(x) \\ \mu_{32}(x) \end{bmatrix} \\ \mu_4(x) \end{bmatrix}$$

Figure 2. The tree structure and vector form of a fuzzy signature set

3.3. 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].

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-subtree 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 Figure 3, where $@_i$ denotes the aggregation operator of node x_i.

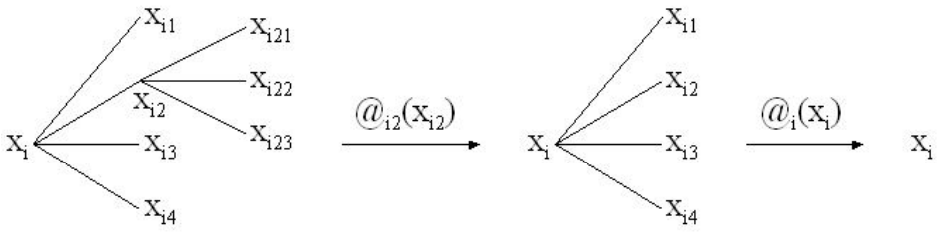


Figure 3. Recursion used to reduce a sub-tree with several layers

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 6, where h denotes the aggregation operator.

$$G = h(A_1, A_2, \ldots, A_k) \quad \forall x \in [0,1] \quad \mu_G(x) = h\left\{\mu_{A_1}(x), \mu_{A_2}(x), \ldots, \mu_{A_k}(x)\right\} \tag{6}$$

The aggregation of two fuzzy sets (A_1 and A_2) is shown in Figure 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.

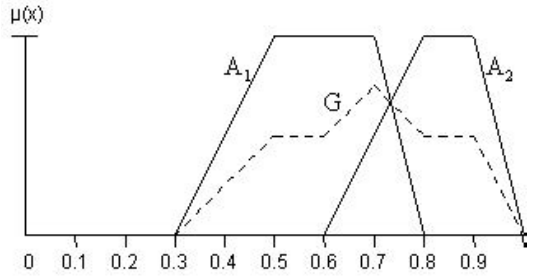


Figure 4. Aggregation of two fuzzy sets with the arithmetic mean operator

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 [14]. 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:

$$@(x_1, x_2, \ldots, x_n; w_1, w_2, \ldots, w_n) = \left\{\frac{1}{n}\sum_{i=1}^{n}(w_l \cdot x_l)^p\right\}^{\frac{1}{p}} \tag{7}$$

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 7.

$$\begin{array}{lllll} p \to -\infty & \text{WRAO} & \to & \text{minimum} \\ p = -1 & \text{WRAO} & = & \text{harmonic mean} \\ p \to 0 & \text{WRAO} & \to & \text{geometric mean} \\ p = 1 & \text{WRAO} & = & \text{arithmetic mean} \\ p \to \infty & \text{WRAO} & \to & \text{maximum} \end{array}$$

4. 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 [15].

4.1. Experimental task and environment

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

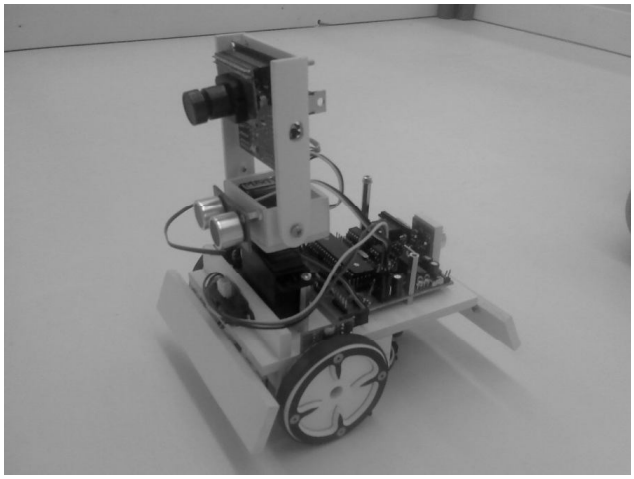


Figure 5. The real box-pushing robot

Three robots operate in a 2 × 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. 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 Figure 6 shows.

The three robots form a group which try to build the actual order of boxes according to the exact instructions given to the R0 (foreman) robot. The other robots have no direct communication links with R0, but they are able to observe the behavior of R0 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. Figure 6 presents an example of how the five boxes can be arranged.

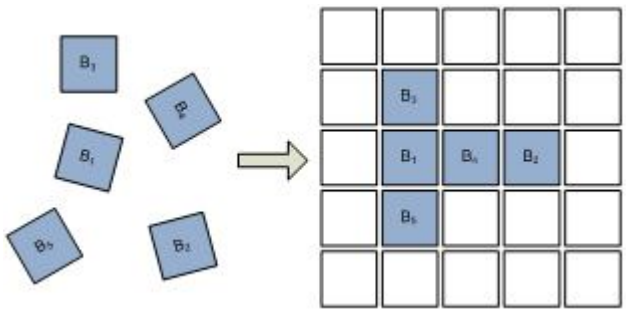


Figure 6. A box arrangement

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 R0 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 (Figure 7), $C^i_{1,2} = P$ is the "pushing or shifting combination", when two

robots (R1 and R2) are side by side at the same side of the table; $C_{1,2}^{i} = RC$ stands for "counterclockwise rotation combination"; and $C_{1,2}^{i} = RW$ denotes "clockwise rotation combination".

Now the rotation problem is suppressed, each box is right direction, because it makes the system simpler and the rotation can be considered as an initial task.

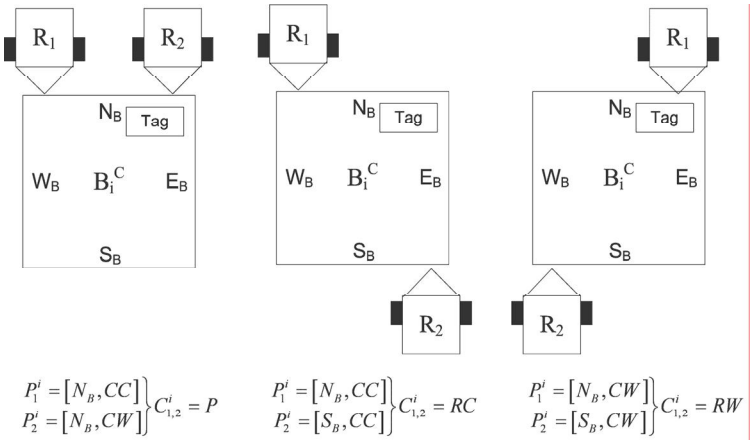


Figure 7. Allowed combinations of two robots for moving a box

4.2. The Fuzzy Signature Sets of Box State Representation

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.

The context dependent codebook is the soul of the onboard intention guessing and decision making system. It has many complex parts which build-up on fuzzy signature sets. Two main branches are the intention guessing and the state observation. The intention guessing means the other robots behaviors and actions are monitored and an intelligent manner processed for action or behavior selection. The state observation writes down the actual state of the whole working environment, the goal-area, the boxes, etc. The effective state observation of a high-scale system is a real complex task and needs strong computational intelligent algorithms.

The presentation the whole system is beyond the range of this paper, so let us see a part of the state observation subsystem. The other parts of our system are similarly formed as the presented. 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.

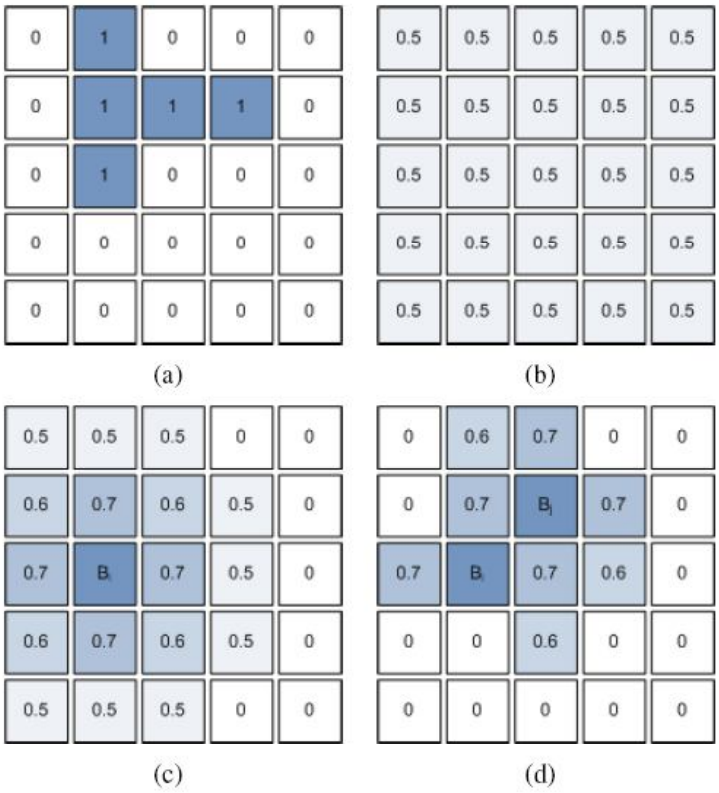


Figure 8. The arrangement-maps of robots

Here we have to say about two other elements of the observation system, the focal-point and the arrangement map. The focal-point means the area where the robot focuses its perception, as the focal-point is widen the actual inference has less impact on the action selection and robot behavior. There are three main focal-points: the box focal-point (BFP), the robot focal-point (RFP) and the goal-area focal-point (GFP). The focal-point selection is a complex task especially in case of the goal-area focal-point. For instance if one box was pushed in its position by robot foreman (R0) then the position of this box will be the next GFP, but if there are two or more boxes then GFP needs an intelligent selection. The arrangement-map (AM) depicts the fuzzy data of set-ability of a box in each position of goal-area. The actual arrangement of the boxes in goal-area is given to R0 foreman robot, so it has a precise arrangement-map as you can see in Figure 8/a. The Figure 8/b shows the arrangement-map of R1 and R2 robots in the starting phase where not any box in goal-area is. The Figure 8/c and /d show the AM if one and two boxes in the area respectively.

The above mentioned 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

Figure 9. Each node in the tree has the own meaning and has close relations to focal-points and arrangement-maps.

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 Figure 10, 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.

The fuzzy value on node x_{12} describes the rotation of the box from the North-South axis. In our case this node is always zero.

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.

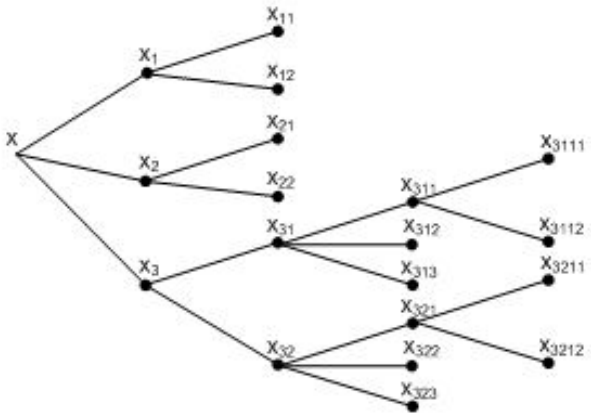


Figure 9. The box state and manipulation fuzzy signature

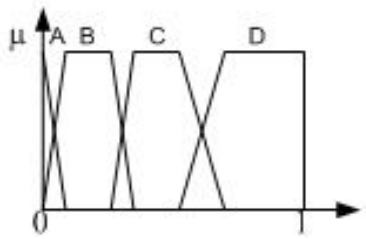


Figure 10. Fuzzy sets used in distance measurement

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.

5. 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 Figure 11 presents some steps of arranging process. Firstly the robots search the nearest disordered box and take a combination for pushing 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. Some simulation results will be downloaded from our website in the near future.

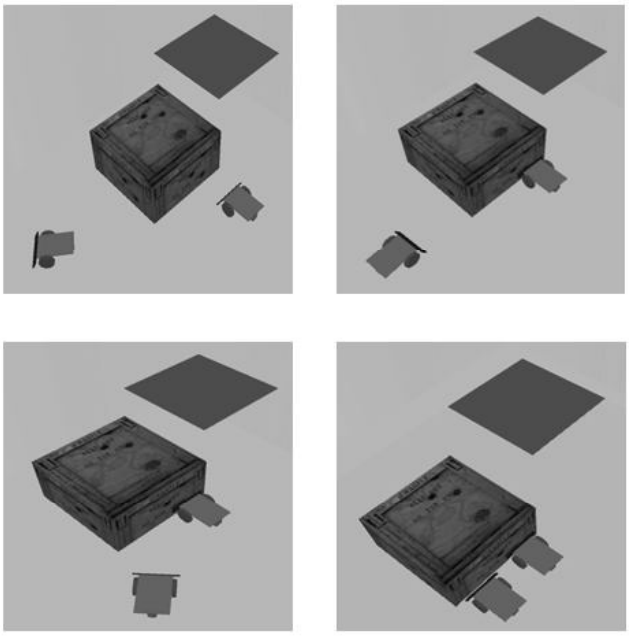


Figure 11. The robots take the starting combination

Conclusions

Fuzzy communication contains vague or imprecise components and it might lack of abundant information. If two entities (man or machine) are communicating by a fuzzy channel, it is necessary that both ends possess the same codebook. The codebook might partly consist of common knowledge but it usually requires a context dependent part that is either learned by the communicating entity or defined by expert knowledge. 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 "abundant communication". This advantage can be deployed in many areas of engineering, especially where the use of the communication channel is expensive in some sense, or where there is no proper communication channel available at all. We suggest that in distant locations and dangerous environment, further in applications where human friendly user interfaces are important, such as intelligent man-machine communication, the advantages of well designed CDRC communication systems be deeper investigated in the future.

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