Ethologically Inspired Robot Behavior Implementation

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Abstract—**For implementing ethologically inspired robot behavior in this paper a platform based on fuzzy automaton (fuzzy state-machine) is suggested. It can react the human intervention as a function of the robot state and the human action. This platform is suitable for implementing quite complicated action-reaction sequences, like the interaction of human and an animal, e.g. a behavior of an animal companion to the human. The suggested fuzzy model structure built upon the framework of low computational demand Fuzzy Rule Interpolation (FRI) methods and fuzzy automaton. For demonstrating the applicability of the proposed structure, some components of an action-reaction FRI model, will be briefly introduced in this paper.**

I. Introduction

The design of socially interactive robots has faced many challenges. Despite major advances there are still many obstacles to be solved in order to achieve a natural-like interaction between robots and humans.

The "uncanny valley" effect: Mori [18] assumed that the increasing similarity of robots to humans will actually increase the chances that humans refuse interaction (will be frightened from) very human-like agents. Although many take this effect for granted only little actual research was devoted to this issue. Many argue that once an agent passes certain level of similarity, as it is the case in the most recent visual characters in computer graphics, people will treat them just as people [21]. However, in the case of 3D robots, the answer is presently less clear, as up do date technology is very crude in reproducing natural-like behaviour, emotions and verbal interaction. Thus for robotics the uncanny valley effect will present a continuing challenge in the near future.

In spite of the huge advances in robotics current socially interactive systems fail both with regard to motor and cognitive capacities, and in most cases can interact only in a very limited way with the human partner. We see this as a major discrepancy that is not easy to solve because there is a big gap between presently available technologies (hardware and software) and the desire for achieving human-like cognitive and motor capacities. As a consequence recent socially interactive robots have only a restricted appeal to humans, and after losing the effect of novelty the interactions break down rapidly.

The planning and construction of biologically or psychologically inspired robots depends crucially of the current understanding of human motor and mental processes. However, these are one of the most complex phenomena of life! Thus it is certainly possible that human mental models of abilities like "intention", "human memory" etc., which serve at present as the underlying concepts for control socially interactive robots, will be proved to be faulty.

Because of the goal of mimicking a human, socially interactive robots do not utilize more general human abilities that have evolved as general skills for social interaction. Further, the lack of evolutionary approach in conceptualizing the design of such robots hinders further development, and reinforces that the only goal in robotics should be the produce "as human-like as possible" agents.

II. Ethologically Inspired Behaviour Model

In order to overcome the "uncanny valley" effect, ethologically inspired robot behavior models can be applied. The concept of ethologically inspired robot behavior models allows the study of individual interactions between animals and animals and humans. If one defines robots as mechanical or electronic agents that extend human capacities then the dog (which has been domesticated by humans) represents the first "biological robot" because some time after domestication dogs were utilized as an aid in hunting, animal husbandry, warfare, protection, transport etc [17]. The long-term (for cc 20.000 years) and successful human-dog interaction shows that humans have the ability to develop social interaction with very different agents. The human-dog relationship rests critically on our ability to produce and understand various forms of communicative cues that are emitted in an inter-specific relationship in which the two members' signaling behavior overlaps only to certain extent. Human behavior evolution has selected for increased ability to form social contact with any creatures which originates in the very social nature of nursing (parental) behavior in humans which is unique in the Primates. Humans also show a preference to use social relationship for joint action in cooperative settings.

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Finally, humans have the mental capacities (and the preference) to attribute certain human-like mental capacities to other agents (even to non-living things) which also facilitates the interaction between them.

It follows that social robots do not have to mirror exactly human social behavior (including language etc) but should be able to produce social behaviors that provide a minimal set of actions on which human-robot cooperation can be achieved. Such basic models of robots could be "improved" with time making the interaction more complex.

III. FUZZY AUTOMATON IN ETHOLOGICAL MODEL

Existing ethological models are usually descriptive verbal models based on numerous observations of animal reactions in different situations. Many of them are built around a predefined sequence of environmental situations and events, where the reaction of the animal is in details noted and evaluated. Some of the observations are partially related to actual mood of the animal e.g. tail movement or position. The knowledge representation of an ethological model is a series of observation of various facts and action-reaction rules. For mathematical modeling of such a system, the rule-based knowledge representation is straightforward. Moreover the need of following observed sequences calls a model structure of a state machine or an automaton. Adding the fact, that the observable or hidden states are continuous measures the situation is quite complicated. Summarizing the above requirements, the model have to have a rule-based knowledge representation, with the ability of describing event sequences continuous values and continuous states. The suggested modeling method is the application of the fuzzy automaton, where the state is a vector of membership values, the state-transitions are controlled by a fuzzy rule base and the observations and conclusions are continuous values. The main problem in case of practical implementation of such a fuzzy automaton based model is the size of the state-transition rule base. In classical fuzzy reasoning the rule base size is exponential to the number of observations, in this case the length of the state vector. In case of an ethological model with moderate complexity it could be 10-20 state variables i.e. thousands of rules required for the complete classical rule base (e.g. the Zadeh-Mamdani-Larsen Compositional Rule of Inference (CRI) (Zadeh [27]) (Mamdani [16]) (Larsen [15]) or the Takagi-Sugeno fuzzy inference (Sugeno [23], Takagi-Sugeno [24]).

Moreover the existing knowledge is usually a few dozen rules, which means, that most of the rules are undefined. In case of classical fuzzy reasoning this contradiction is hardly solvable.

The solution suggested in this paper for the exponential complexity problem of the required fuzzy automation state-transition rule base is the application of the Fuzzy Rule Interpolation (FRI) methods (one of the first methods was introduced in [6]). By the application of FRI methods the number of the rules required for the FRI state-transition fuzzy model can be reduced to the existing (known from the ethological model) rules. Moreover in case of automatic model generation, or fine tuning based on given input-output sample data, the application of FRI model can lead to fewer rules and hence less parameters needed to be optimized. This also means better convergence of the optimization algorithm.

The ethological model implementation introduced in this paper is built upon the framework of fuzzy automaton and low computational demand Fuzzy Rule Interpolation (FRI) methods [10], [11], [12], [13]. The knowledge representation style of FRI method fits well the conceptually "spare rule-based" structure of the existing descriptive verbal ethological models, where the "completeness" of the rule-base is essentially not required. FRI methods can provide reasonable (interpolated) conclusions even if none of the existing rules fires under the current observation. From the beginning of 1990s numerous FRI methods have been proposed [26].

IV. FUZZY RULE INTERPOLATION (FRI)

In case of classical fuzzy reasoning methods (e.g. the Zadeh-Mamdani compositional rule of inference (CRI)) it is obvious that having covering (complete) rule bases is a must. A traditional fuzzy rule based systems requires a complete rule base with all of the possible rules set, even though lots of these rules are unimportant from the viewpoint of the actual application. A fuzzy rule base is called sparse or incomplete if an observation may exists, which does not hit any of the rules in the rule base. Accordingly there can be observations, where no conclusion can be gained with traditional fuzzy reasoning techniques. On the other hand, in many embedded control application areas having no conclusion is an avoidable situation. There are some traditional overcome of such a situation in the literature e.g. applying the last real conclusion instead of the missing one, but it can also cause some unpredictable side effects. One real solution for the sparse rule base is the application of fuzzy rule interpolation (FRI) methods. This case the derivable rules are intentionally missing from the rule base, as FRI methods are capable of providing reasonable (interpolated) conclusions even if none of the existing rules fire under the current observation. The rule base of an FRI system is not necessarily complete, therefore it could contain the most significant fuzzy rules alone without risking the chance of having no conclusion for some of the observations. In this case having an efficient knowledge representation, a considerable amount of unnecessary work can be avoided during the rule base creation. On the other hand most of the FRI methods are sharing the burden of high computational demand, e.g. the task of searching for the two closest surrounding rules to the observation, and calculating the conclusion at least in some characteristic α-cuts. Moreover in some methods the interpretability of the fuzzy conclusion gained is also not straightforward [7]. There have been a lot of efforts to rectify the interpretability of the interpolated fuzzy conclusion [25]. In [1] Baranyi *et al.* give a comprehensive overview of the recent existing FRI methods.

V. FRI BASED ON VAGUE ENVIRONMENT: FIVE

In the concept of 'FIVE' an application oriented aspect, the need for low computational and resource demand has a high importance. The method was originally introduced in [10], [13] and [11] for satisfying the speed requirements of direct fuzzy control, where the conclusions of the fuzzy controller are applied directly as control actions in a real-time system.

The main idea of the FIVE is based on the fact that most of the control applications serves crisp observations and requires crisp conclusions from the controller. Adopting the idea of the Vague Environment (VE) [5], FIVE can handle the antecedent and consequent fuzzy partitions of the fuzzy rule base by scaling functions [5] and therefore turn the fuzzy interpolation to crisp interpolation. The idea of a VE is based on the indistinguishability of elements. In VE the fuzzy membership function $\mu_A(x)$ is indicating level of similarity of x to a specific element a which is a representative or prototypical element of the fuzzy set $\mu_A(x)$, or, equivalently, as the degree to which x is indistinguishable from a (see e.g. on Figure 1) [5]. Two values in a VE are ε-indistinguishable if their distance is less or equal than ε. The distances in a VE are weighted distances (1. The weighting factor or function is called scaling function (factor) [5]:

$$\delta_s(x_1,x_2)=\left|\int_{x_2}^{x_1} s(x)dx\right| \le \varepsilon , \qquad (1)$$

where $\delta_s(x_1,x_2)$ is the scaled distance of the values x_1, x_2 and $s(x)$ is the scaling function on X.

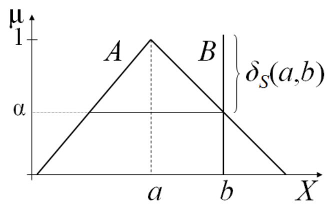

Figure 1. The α-cuts of $\mu_A(x)$ contain the elements that are (1−α)-indistinguishable from a.

If the VE of a fuzzy partition (the scaling function or at least the approximate scaling function [10], [11]) exists, the member sets of the fuzzy partition can be characterized by points in that VE (see e.g. exact scaling function s on Figure 2 and an approximate scaling function on Figure 3).

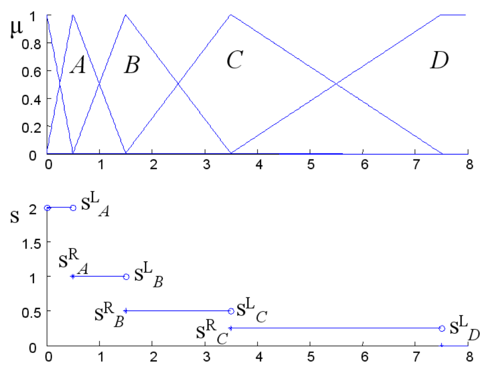

Figure 2. A Ruspini fuzzy partition and its scaling function s.

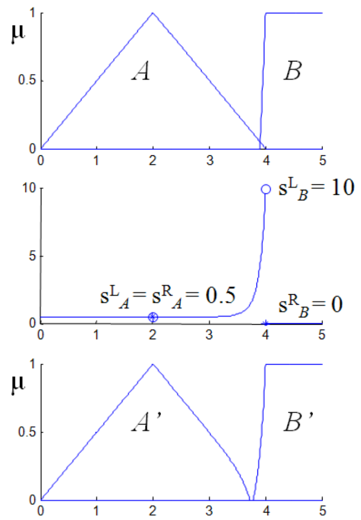

Figure 3. A fuzzy partition (A, B), its approximate scaling function s [10], [11] and the corresponding approximated partition (A', B').

Having the VE concept and the scaling function based similarity calculation, any crisp interpolation, extrapolation, or regression method can be adapted very simply for FRI [10], [11]. Because of its simple multidimensional applicability, in FIVE the Shepard operator based interpolation (first introduced in [22]) is adapted (see e.g. Figure 4).

To be more precise in case of singleton rule consequents (c_k) the fuzzy rules R_k has the following form:

$$\textbf{If}\ x_1 = A_{k,1}\ \textbf{And}\ x_2 = A_{k,2}\ \textbf{And} \dots \textbf{And}\ x_m = A_{k,m}\ \textbf{Then}\ y = c_k \qquad (2)$$

Adapting the VE concept and the scaling function based similarity calculation to the Shepard operator based interpolation, the conclusion of the interpolative fuzzy reasoning can be obtained as:

$$y(\mathbf{x})=\begin{cases} c_k & \text{if } \mathbf{x}=\mathbf{a}_k \text{ for some } k,\\ \left(\sum_{k=1}^{r} c_k/\delta_{s,k}^{\lambda}\right)\Big/\left(\sum_{k=1}^{r} 1/\delta_{s,k}^{\lambda}\right) & \text{otherwise.}\end{cases} \qquad (3)$$

where $\delta_{s,k}$ are scaled distances:

$$\delta_{s,k}=\delta_s(\mathbf{a}_k,\mathbf{x})=\left[\sum_{i=1}^{m}\left(\int_{a_{k,i}}^{x_i} s_{X_i}(x_i)dx_i\right)^2\right]^{1/2}, \qquad (4)$$

and s_{X_i} is the i^{th} scaling function of the m dimensional antecedent universe, $\mathbf{x}$ is the m dimensional crisp observation and $\mathbf{a}_k$ are the cores of the m dimensional fuzzy rule antecedents A_k.

The code of the FIVE FRI together with other FRI methods is freely available as a MATLAB FRI Toolbox [4], and it can be downloaded from [28].

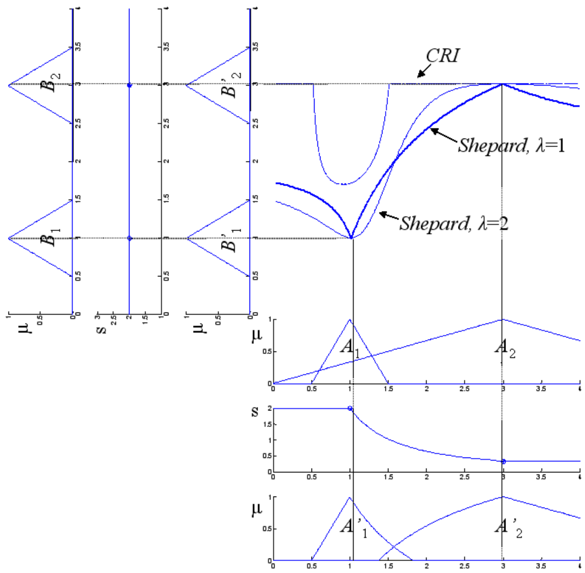

Figure 4. Interpolation of two fuzzy rules (R_i: $A_i \rightarrow B_i$), by the Shepard operator based FIVE, and for comparison the min-max CRI with COG defuzzification.

VI. FRI BASED FUZZY AUTOMATON

There are numerous versions and understanding of the fuzzy automaton can be found in the literature (a good overview van be found in [3]). In our case we start from the most common definition of Fuzzy Finite-state Automaton (FFA, summarized in [3]), where the FFA is defined by a tuple (according to [2], [3] and [19]):

$$\tilde{F} = (Q, \Sigma, \delta, R, Z, \omega), \tag{5}$$

where

Q is a finite set of states, $Q=\{q_1,q_2,...,q_n\}$.

Σ is a finite set of input symbols, $\Sigma=\{a_1,a_2,...,a_m\}$.

$R \in Q$ is the (possibly fuzzy) start state of $\tilde{F}$.

Z is a finite set of output symbols, $Z=\{b_1,b_2,...,b_n\}$.

$\delta : Q \times \Sigma \times Q \rightarrow [0,1]$ is the fuzzy transition function which is used to map a state (current state) into another state (next state) upon an input symbol, attributing a value in the fuzzy interval [0,1] to the next state.

$\omega : Q \rightarrow Z$ is the output function which is used to map a (fuzzy) state to the output.

Extending the concept of FFA from finite set of input symbols to finite dimensional input values turns to the following:

$$\tilde{F} = (S, X, \delta, P, Y, \omega), \tag{6}$$

where

S is a finite set of fuzzy states, $S = \{\mu_{s1}, \mu_{s2}, ..., \mu_{sn}\}$.

X is a finite dimensional input vector, $X = \{x_1, x_2, ..., x_m\}$.

$P \in S$ is the fuzzy start state of $\tilde{F}$.

Y is a finite dimensional output vector, $Y = \{y_1, y_2, ..., y_l\}$.

$\delta : S \times X \rightarrow S$ is the fuzzy state-transition function which is used to map the current fuzzy state into the next fuzzy state upon an input value.

$\omega : S \times X \rightarrow Y$ is the output function which is used to map the fuzzy state and input to the output value. See e.g. on Figure 5.

In case of fuzzy rule based representation of the state-transition function $\delta : S \times X \rightarrow S$, the rules have $n+m$ dimensional antecedent space, and n dimensional consequent space. Applying classical fuzzy reasoning methods, the complete state-transition rule base size can be approximated by the following formula:

$$|R| = n \cdot i^n \cdot j^m, \tag{7}$$

where n is the length of the fuzzy state vector S, m is the input dimension, i is the number of the term sets in each dimensions of the state vector, and j is the number of the term sets in each dimensions of the input vector.

According to (7) the state-transition rule-base size is exponential with the length of the fuzzy state vector and the number of the input dimensions.

Applying FRI methods for the state-transition function fuzzy model can dramatically reduce the rule base size. See e.g. [14], where the originally exponential sized state-transition rule base of a simple heuristical model turned to be polynomial thanks to the FRI.

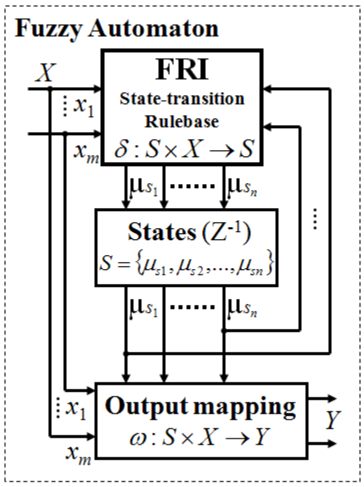

Figure 5. FRI based Fuzzy Automaton.

VII. BEHAVIOUR-BASED CONTROL

In behavior-based control systems (a good overview can be found in [20]), the actual behavior of the system is formed as one of the existing behaviors (which fits best the actual situation), or a kind of fusion of the known behaviors appeared to be the most appropriate to handle the actual situation. Beyond the construction of the component behaviors, this structure has two main tasks. The first is the behavior coordination, the decision, which behavior is needed, or in case of behavior fusion the determination of the necessity levels for each behavior in solving the actual situation. The second is the way of the behavior fusion.

In case of direct application of the suggested FRI based Fuzzy Automaton for behavior-based control structures, the output function $\omega: S \times X \rightarrow Y$ can be decomposed to parallel component behaviors and independent behavior fusion. This case we can get a very similar structure as it is expected in behavior-based control (see Figure 6).

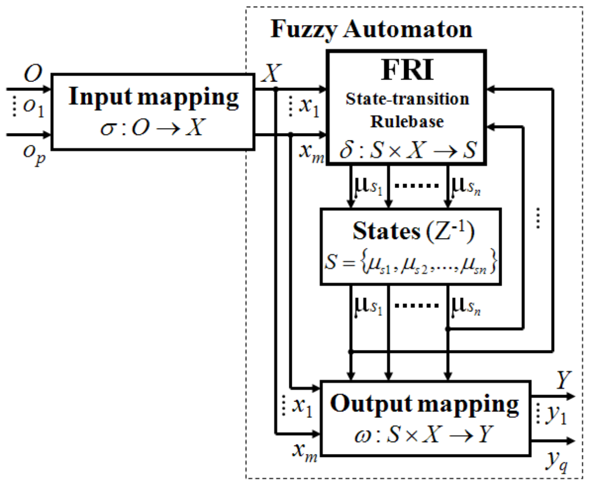

Figure 6. The suggested FRI behaviour-based structure.

VIII. Behavior Programming Example

The behavior programming example is a tiny fragment of a more complex ethological model (partially also introduced in [8] and [9]) of an dog called "Mogi Robi" (see Figure 7) behaving in an unfamiliar room in interaction with its owner and an unknown human ("Owner" and "Stranger" on Figure 8).

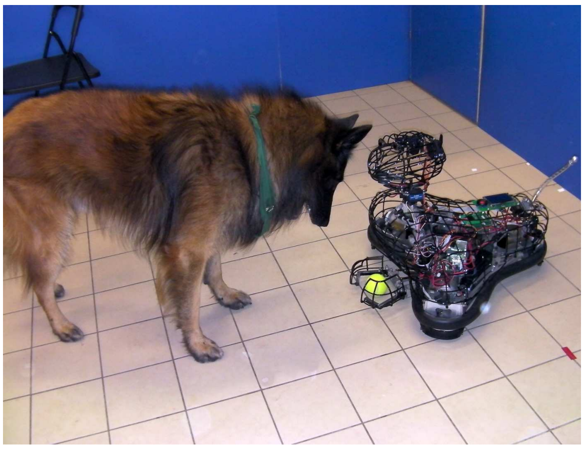

Figure 7. The "Mogi Robi" robot and its real ethological model.

The example is the definition of the state-transition FRI rules of the FRI fuzzy automaton acts as behavior coordination.

The states concerned in the example are the following:

"Missing the owner mood of MogiRobi" (`MissTheOwner`), "Anxiety level of MogiRobi" (`AnxietyLevel`) and "Room exploration mood of MogiRobi" (`ExplorationLevel`).

As a possible rule base structure for the state-transitions of the FRI fuzzy automaton, the following rules are defined (a tiny fragment of a more complex rule base):

State-transition rules related to the missing the owner mood (state) of MogiRobi:

```
If OwnerInTheRoom=False Then
MissTheOwner =Increasing

If OwnerInTheRoom=True Then
MissTheOwner =Decreasing
```

State-transition rules related to the anxiety level (state) of MogiRobi:

```
If OwnerToDogDistance=Small And
StrangerToDogDistance=High Then
AnxietyLevel=Decreasing

If OwnerToDogDistance=High And
StrangerToDogDistance=Small Then
AnxietyLevel=Increasing
```

State-transition rules related to the room exploration mood (state) of MogiRobi:

```
If AnxietyLevel=Low And
OwnerStartsGame=False And
ThePlaceIsUnknown=High Then
ExplorationLevel =High

If ThePlaceIsUnknown=Low Then
ExplorationLevel =Low

If AnxietyLevel=High Then
ExplorationLevel =Low
```

where the text in Italic are linguistic terms (fuzzy sets) of the FRI rule base.

A sample run of the example is introduced on Figure 8. At the beginning of the scene, the Owner is in the room, the Stranger is outside and the place is unknown for MogiRobi ("`ThePlaceIsUnknown=High`"). According to the state-transition rule base, MogiRobi starts to explore the room. At the step count 17, the Owner of the dog left the room, then at the step count 31 the Stranger enters and stay inside. As an effect of the changes (according to the state-transition rule base), the anxiety level of MogiRobi and the "missing the owner" is increasing, and as a result, MogiRobi gives up the room exploration (Figure 8).

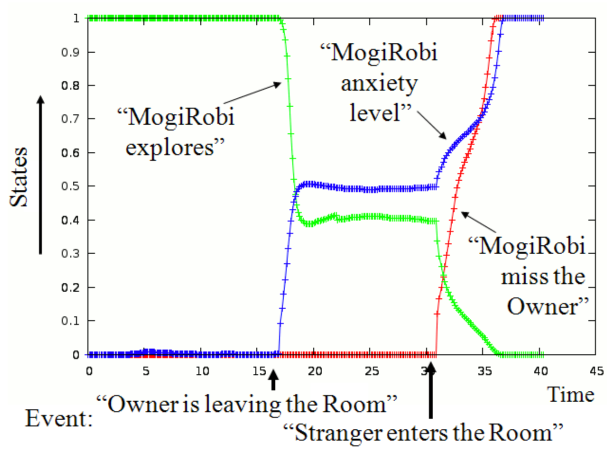

Figure 8. Some state changes during the sample run

IX. CONCLUSION

The goal of this paper was to suggest an effective platform based on low computational demand FRI fuzzy automaton for implementing ethologically inspired robot behavior models.

The suggested structure is simple and could be implemented to be quick enough to fit the requirements of real-time embedded applications. It is an easy to built and simply adaptable structure for many application areas.

Thanks to the applied FRI fuzzy automaton, during the construction of the state-transition rule base of the ethological model, it is enough to concentrate on the main actions, the rule structure need not to be complete.

ACKNOWLEDGEMENTS

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