A novel, ethologically inspired HRI model implementation: Simulating dog-human attachment

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Abstract— **In this paper we suggest that social robots should not mirror exactly human social behavior (facial expressions, language, etc) but need to be able to produce believable social behaviors that provide a minimal set of actions by which human-companion cooperation can be achieved. For implementing such an ethologically inspired social robot behavior, a platform based on fuzzy automaton (fuzzy state-machine) is suggested.**

I. INTRODUCTION

Attachment between the dog and its owner is an indispensable characteristic of this social system that has a bi-directional nature: dogs show behavioural signs of attachment toward their owner and owners also tend to perceive this interspecies relationship as an emotional bond. Dogs' attachment to humans can be successfully evaluated by a standard laboratory procedure (SST) that was originally developed to study the factors regulating attachment behaviour in human infants towards their mother. The adapted version of the SST revealed that the dog-owner relationship is analogous to child-parent attachment behaviour. These results led us to propose that the dog possesses a unique behaviour organising 'software', because its social-affiliative behaviour organising mechanisms fit specifically in the human social world.

The essential element of the SST procedure is that separation from the attachment figure in an unfamiliar environment evokes moderate stress and anxiety which is manifested behaviourally in proximity seeking (e.g. standing by the door), while the reunion with the caregiver evokes different forms of contact-seeking behaviours (e.g. approach, physical contact). Considering dogs' major behaviour patterns showed in the SST, we could define a limited number of rules that could control the behaviour of the simulated companion (2D agent or robot) in the test situation.

II. 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 [19]) (Mamdani [13]) (Larsen [12]) or the Takagi-Sugeno fuzzy inference (Sugeno [16], Takagi-Sugeno [17]).

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 [4]). 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 [7], [8], [9], [10]. 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 ([18], [3]).

III. 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 [2]). In our case we start from the most common definition of Fuzzy Finite-state Automaton (FFA, summarized in [2]), where the FFA is defined by a tuple (according to [1], [2] and [14]):

$$\widetilde{F} = (Q, \Sigma, \delta, R, Z, \omega), \tag{1}$$

where

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

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

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

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

$\delta : Q \times \Sigma \times Q \to [0,1]$ 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.

$\omega : Q \to Z$ 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:

$$\widetilde{F} = (S, X, \delta, P, Y, \omega), \tag{2}$$

where

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

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

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

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

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

$\omega : S \times X \to Y$ is the output function which is used to map the fuzzy state and input to the output value. See e.g. on Figure 1.

In case of fuzzy rule based representation of the state-transition function $\delta : S \times X \to S$, 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:

$$|R| = n \cdot i^n \cdot j^m, \tag{3}$$

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 (3) 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. [11], where the originally exponential sized state-transition rule base of a simple heuristical model turned to be polynomial thanks to the FRI.

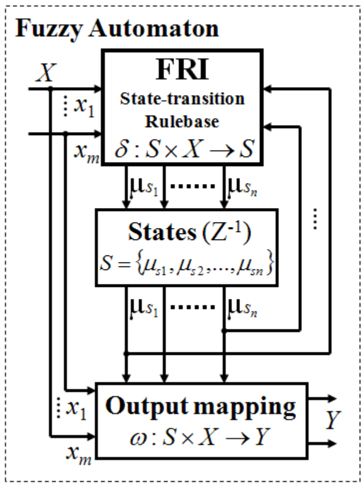

Figure 1. FRI based Fuzzy Automaton.

IV. BEHAVIOUR-BASED CONTROL

In behavior-based control systems (a good overview can be found in [15]), 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 $\omega: S \times X \to Y$ 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 2).

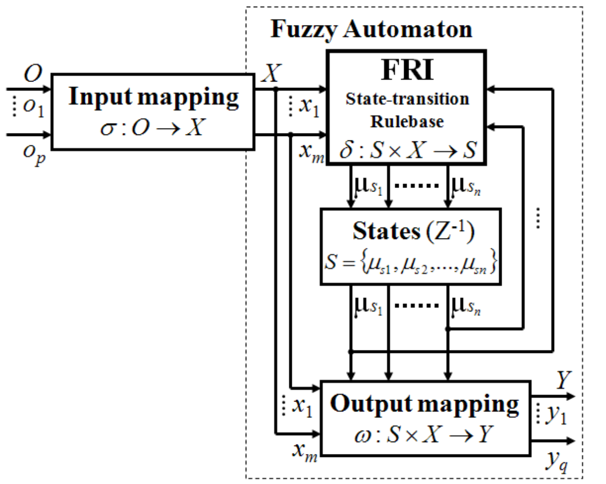

Figure 2. The suggested FRI behaviour-based structure.

V. Behavior Programming Example

The behavior programming example is a tiny fragment of a more complex ethological model (partially also introduced in [5] and [6]) of an dog called "Mogi Robi" (see Figure 3) behaving in an unfamiliar room in interaction with its owner and an unknown human ("Owner" and "Stranger" on Figure 4).

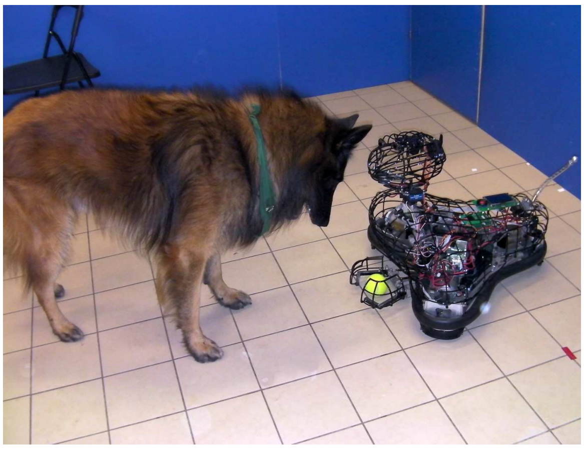

Figure 3. The "Mogi Robi" robot and its real ethological model.

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 4. 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 4).

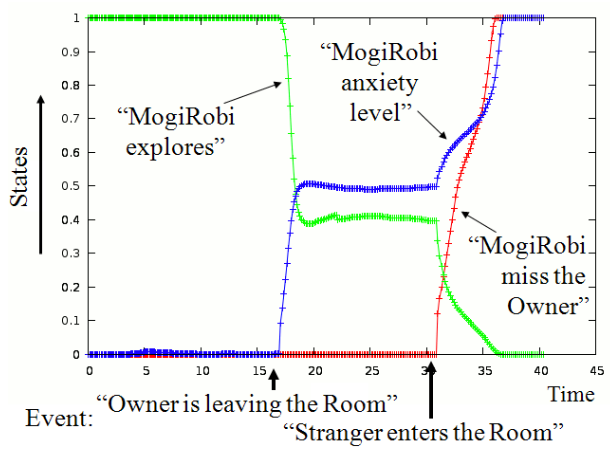

Figure 4. Some state changes during the sample run

VI. CONCLUSION

The goal of this paper was to suggest that social robots should not mirror exactly human social behavior (facial expressions, language, etc) but need to be able to produce believable social behaviors that provide a minimal set of actions by which human-companion cooperation can be achieved. For implementing such an ethologically inspired social behavior, we also suggest an effective platform based on low computational demand FRI fuzzy automaton.

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.

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