Experience-based Fuzzy Control of an Anthropomimetic Robot

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Keywords: Knowledge Base Control, Fuzzy Control, Machine Learning, Robot Arms, Bio-inspired Robot.

Abstract: This paper aims to present a novel experience-based solution for a black-box control problem, applied to an anthropomimetic robot. The control method is tested on a point to point control problem of a multi-jointed robot arm. The model characteristics – dynamics, kinematics, and control parameters – are considered as unspecified, and therefore we deal with a machine learning approach that follows the cybernetic concept of black-box. The only available data of the system are those obtained from measuring inputs and outputs. The control algorithm involves two levels: feedforward and feedback. The main focus is, however, on feedback level where the algorithm for experience-based estimation of kinematic coefficients is combined with fuzzy logic control in order to relate the control inputs with the robot arm motion in the global frame.

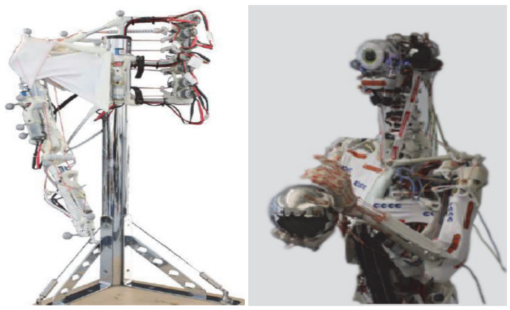
1 INTRODUCTION

Contemporary humanoid robots are constructed in order to replicate humans just by copying the outer form, while keeping the internal classical machine structure. If, however, one intended to replicate the human internal mechanics, he would face a situation: complex multi-degree-of-freedom joints, muscles crossing over several rotation axes and working in an antagonistic mode, presence of mechanical compliance, etc. Such systems can no more be modelled and controlled in a classical analytical way – a biologically-inspired approach is needed (Potkonjak et al., 2010).

Holland and Knight, 2006 have proposed a new expression - anthropomimetics. It concerns a new principle in robot construction (Fig. 1), mimicking the human body, skeleton and muscle system. The goal is to attain a high level of performances (e.g. maneuverability) analogous to human paragon. The idea of this paper is based on the work done within the project ECCEROBOT (European 7th Framework Program, project "Embodied Cognition in a Compliantly Engineered Robot").

By combining the experience-based approach with fuzzy logic, this paper aims to solve the point-to-point control problem in the absolute frame, i.e. find a way to control the anthropomimetic robot in reaching a prescribed hand tip position.

The outline of this paper is as follows. A short overview of most similar projects and related topics is presented in Section 2. Section 3 shows an empirical approach to feedforward (FF) control. The influence of each control input on the hand tip motion in the global frame is evaluated in Section 4. By implementing the fuzzy logic algorithm in Section 5 we form the final control as FF+feedback (FB) for the anthropomimetic robot arm. Efficiency of our control algorithm is shown in Section 6.



(a) (b)

Figure 1: (a): ECCEROBOT test rig. (b): The latest prototype of the ECCEROBOT.

2 RELATED WORKS

The posed problem can be considered from different points of view, as black-box modeling or identification of nonlinear systems.

Potkonjak V., Bascarevic N., Milosavljevic P., Jovanovic K. and Holland O..
Experience-based Fuzzy Control of an Anthropomimetic Robot.
DOI: 10.5220/0004117503890394
In *Proceedings of the 4th International Joint Conference on Computational Intelligence* (FCTA-2012), pages 389-394
ISBN: 978-989-8565-33-4

Rivals and Personnaz, 1995 showed that there are advantages in using nonlinear state-space models, including a larger class of nonlinear dynamical models. Several examples of nonlinear black-box model structures and approximation issues are proposed by Ljung, 2001. Relationships between fuzzy models, neural networks and classical non-parametric models are discussed. Van Mulders et al., 2009 introduced two nonlinear optimization methods for the identification of nonlinear black box systems. Each method relies on estimation of the parameters of a polynomial nonlinear state-space model by means of a nonlinear least-squares optimization. Gonzalez-Olvera et al., 2009 presented a black-box modelling of two degrees of freedom manipulator. Recurrent neural networks with output feedback are used to solve the visual servoing problem.

Another possible solution for the black-box control can be determined by applying machine learning or predictive control algorithms. Researchers in the field of robotics, Chhabra and Jacobs, 2008 introduce a new learning model for simulated two-joint arm motor control referred to as the Greedy Additive Regression (GAR) model. The model maintains a base of control sequences (i.e., motor synergies) and it is presented for learning the coefficients of a linear combination of sequences. Stulp et al., 2009 presented both, human data and experience-based learning, in order to determine if the end-effector can be brought into a position where the object can be grasped, regardless of the path. Haruno et al., 2001 proposed a new modular architecture, the modular selection and identification for control (MOSAIC) model, for motor learning and control based on multiple pairs of forward (predictor) and inverse models.

3 FEEDFORWARD LEVEL

3.1 Biologically Inspired Control

Potkonjak et al., 2012 presented the control of antagonistic drives based on a biologically inspired puller-and-follower concept for a single joint system. The pattern of the EMG activity in elbow flexors when a slow linear flexion movement is produced against small constant load is analysed by Tal'nov et al., 1999. After reaching the final value of the joint angle, the burst in the agonist (AG) EMG intensity slowly drops to a steady-state level. In order to provide fine tuning of joint position, AG activation is followed by burst in antagonist (ANT).

We apply the same logic to control the joints in the robot. Namely, the input voltage fed into the actuators must generate similar commands to muscles, followed by the appropriate activation of ANT. Fig. 2 demonstrates the input voltage of the controlled joint and its position. It allows to distinguish two input voltage components in both AG and ANT: the control signal burst mainly responsible for the joint motion; and the silent period that keeps the reached steady state position. The ratio between the maximum values of the AG and ANT inputs as well as the ratio between their burst time duration are constant for a particular joint. Therefore, in order to move the joint to the required position we should change appropriately the AG maximum value and its burst time duration, while the ANT value and its burst time duration are proportionally modified. Namely, it is assumed that antagonist activation would always make proportional contribution to joint motion, compared to agonist contribution. The joints are controlled by voltage inputs presented in Fig. 2.

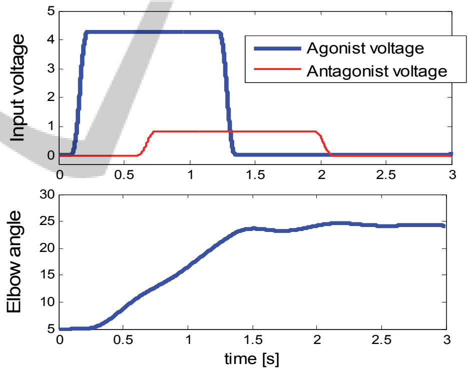


Figure 2: Top: Agonist and antagonist input voltage control. Bottom: The obtained elbow angle during appropriate control.

3.2 Experience Acquisition in Multi-jointed System

The approach used in controlling a single-joint is now generalized to the multi-jointed robot arm. In examples, a fixed-base arm with seven single-degree-of-freedom joints moved by antagonistically coupled drives is considered. The experience acquiring means the set of motion experiments performed from a set of initial hand-tip positions which define the initial region, and ending in a region of final positions. Figure 3 shows the initial and the final region. When performing a motion experiment, the joints are controlled by heuristically determined control voltages which follow the pattern presented in Fig. 2. The used pointing example does not specify the path, only the end point.

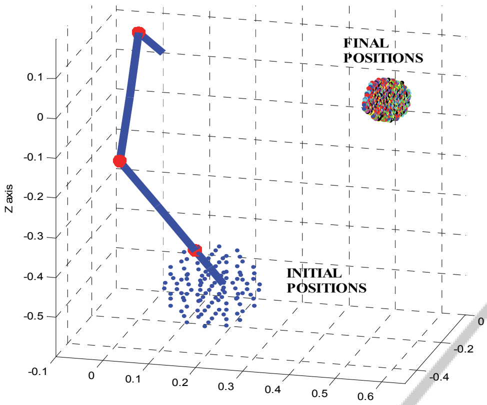


Figure 3: Recorded initial and final positions of robot hand tip.

The positions shown in Fig. 3, the initial and the final sets, together with the controls applied in these experiments are recorded and represent the system experience, the experience base. The region of initial positions is a sphere with the radius of $0.1m$, while final region is in the sphere with the radius of $0.05m$. In case of a larger sphere, we have to spend more time on experience acquisition if we intend to keep the same distances within the grid, or we may create a grid with larger distances which however would require a more complex interpolation procedure.

Created in the above described way, the experience base relates the initial positions and the input voltages, on one side, with the reached points (output) on the other. Knowledge acquiring, the training, means filling in the base. In our example, for each initial position there are $90 \div 130$ final positions in the final sphere. The distances in the initial grid are between $2.5cm$ and $3.5cm$. The relevant distance in the final set of positions concerns the final points that resulted from the same initial point: the distances are from $2cm$ to $2.5cm$.

3.3 Feedforward Exploitation in Multi-jointed System

In the exploitation stage the robot is required to reach a target point (hand-tip position F_0) that has not been previously reached in training, starting from a position (S_0) that has not been previously used. In this phase, the experience base is used to derive the appropriate input control pattern. Here, a linear interpolation scheme was applied to compute the control from a set of closest neighbors found in the base. The FF motor control represents as a linear combination of these neighboring control sequences (Chhabra and Jacobs, 2008).

The interpolation and the calculation of the FF control are done before the robot moves, i.e. off-line. Since any interpolation gives the approximate solution, the obtained control would drive the robot to a vicinity of the target point; the deviation being dependant on the competency of the knowledge base and the interpolation method; hence the closest neighbours would be used for FF interpolation. Therefore, the algorithm starts with the sequential search for the closest four initial positions around S_0, from the initial set. Also, the four final positions around F_0, from the final set, as well as the control inputs are chosen for the linear interpolation algorithm. The positions S_0 and F_0 must be inside of polyhedral defined by neighbours from the initial and the final sphere, respectively. Namely, after acquiring stage, the model shows generalization to novel tasks whose dynamics lie within the polyhedral of already learned dynamics (Haruno et al., 2001). The total control input for each motor is the summation of the sequences from experience base using the coefficients, to weight the contributions. Numerous experiments of FF interpolation, in our case of the ECCEROBOT, have shown that the distance between the position reached by FF and the target position F_0 in global frame does not exceed $6mm$. The required precision of the robot hand tip is set to $1mm$ in each axis. FF control is not sufficient to drive the hand tip into satisfactory final position. To achieve this requirement we need to extend the control by adding feedback for fine tuning. Therefore, at the moment when the tip is at $6mm$ distance from the final point, the feedback component is added.

4 FUZZY LOGIC FEEDBACK CONTROL

We shortly remind of the goal – solving the point-to-point control problem in the global frame, relying only on experience. The fuzzy logic (Zadeh, 1965) is chosen to cope with this complex problem. A fuzzy controller is implemented.

In the proposed fuzzy controller we use two input variables (position error and derivative of position error) and one output variable (voltage) for each axis. The membership functions for inputs and output are shown in Fig. 4.

As shown in Fig. 4, fuzzy membership functions comprise a range of values and can actually overlap. Triangular shapes have been adopted for the fuzzy subsets. Both input variable ranges (x_1, x_2) were founded experimentally and the inputs do not exceed defined values. The maximum feedforward position error is extended to a 10mm in a case of the lower base resolution. The “diff_error” input (and “error” as well) is calculated every 0.001s (sampling time), so derivative of the error has low values and rescaling was required to obtain reasonable range of inputs. The following five and seven fuzzy levels are chosen for the control inputs of the fuzzy controller in the fuzzification process. These numbers of sets are established as optimal values for our system. The final region of interests for “error” variable is between [-1mm, 1mm], so the first fuzzy set (NOE) has to be in that range, the second and the third set (SNE and SPE) have to overlap with the first set and have to be narrow if we want to control the error near the zero value. The fourth and the fifth set (NE and PE) cover a wider range around 5mm value and the sixth and the seventh set (VNE and VPE) cover more than 6mm values in a case of greater error. These seven sets are also required for smooth error change definition due to time. Numerous simulations showed more satisfactory results if the sets do not overlap at 0.5 degree. The number of sets depends on the (input range)/(final region range) ratio and the desired time response of the system. Analogues procedure is applied to “diff_error” sets.

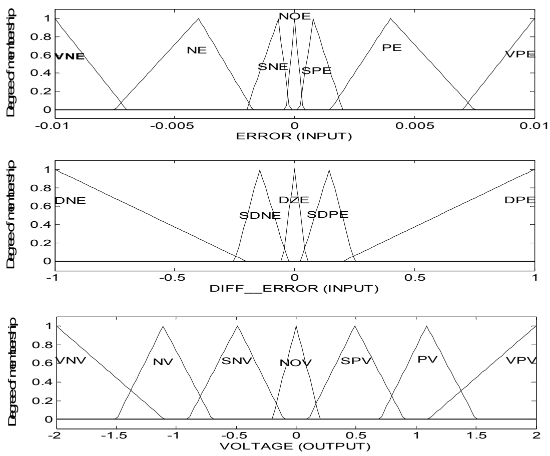


Figure 4: Membership functions for position error, derivative of position error and voltage.

Seven sets of membership functions are defined for the output variable “voltage”. We want to avoid rough fluctuations of the voltage during changeable position error and thus seven sets, including overlapping between two consecutive sets, are implemented.

If-then rule base is shown in Table 1. All possible rule combinations of fuzzy inputs and their results as outputs are presented in that table. The used fuzzy operator is *AND*. The derivation of the fuzzy control rules is heuristic in nature and based on the following theoretical criteria presented in Table 1. Finally, for our purposes the centroid defuzzification method is used.

Table 1: If-then rules.

		DERIVATIVE OF ERROR				
	AND	DNE	SDNE	DZE	SDPE	DPE
ERROR	VNE	VNV	VNV	VNV	VNV	VNV
	NE	NV	NV	SNV	SNV	NOV
	SNE	NV	SNV	SNV	NOV	SPV
	NOE	NV	SNV	NOV	SPV	PV
	SPE	SNV	NOV	SPV	PV	PV
	PE	NOV	SPV	SPV	PV	PV
	VPE	VPV	VPV	VPV	VPV	VPV

The meanings of the acronyms from Table 1 are shown in Table 2.

Table 2: The meanings of the acronym from the Table 1.

ERROR	**DIFF_ERROR**
VNE-very_negative_error	DNE – diff_negative_error
NE – negative_error	SDNE–Sdiff_negative_error
SNE – Snegative_error	DZE – diff_zero_error
NOE – no_error	SDPE– Sdiff_positive_error
SPE – Spositive_error	DPE – diff_positive_error
PE – positive_error	
VPE – very_positive_error	
VOLTAGE	
VNV – very_negative_voltage	NV – negative_voltage
SNV – Snegative_voltage	NOV – no_voltage
SPV – Spositive_voltage	PV – positive_voltage
VPV – very_positive_voltage	

5 KINEMATIC COEFFICIENTS

The fuzzy logic was implemented and now we dispose with the control signals of our process. There are $2n$ (in our case $n=7$) control inputs and only three outputs (x, y and z position), so that a question is posed: How to determine the influence of each control input on the hand tip motion in the global frame?

Although this system has fourteen inputs, the feedback phase uses only seven independent inputs, the pullers, to control the hand tip positioning. The other seven result from the puller-follower concept (Potkonjak et al., 2012).

Kinematic coefficients are defined as parameters which describe the relation between control inputs and the axes of the global frame. For each joint i (controlled by two inputs), three normalized coefficients $n_{C_{x_i}}, n_{C_{y_i}}, n_{C_{z_i}}$ are assigned, for x, y and z axis, respectively.

Suppose that pure feedforward brings the hand tip to point $\hat{F}_0 = (x_{ff}, y_{ff}, z_{ff})$. Coordinates of the points from the narrow environment (neighbours of $\hat{F}_0$) are denoted as (x_j, y_j, z_j), $j = 1,2,\dots,N$ (j-neighbour number). This chapter presents only the algorithm for the x axis – the analogues procedure is applied for y and z axes. The first calculated parameter is

$$K_{x_j} = \frac{|x_{ff} - x_j|}{|x_{ff} - x_j| + |y_{ff} - y_j| + |z_{ff} - z_j|} \tag{1}$$

which defines normalized x distance (between feedforward and the neighbouring position) in comparison to y and z distance for the current neighbour S_j. Next calculated parameter is about joint angle position in the local frame:

$$E_{q_{ij}} = |q_{ff_i} - q_{ij}|\,; \qquad P_{q_{ij}} = \frac{E_{q_{ij}}}{E_{q_{1j}} + E_{q_{2j}} + \dots + E_{q_{7j}}} \tag{2}$$

which determines normalized deviations between joint positions (q_{ff_i}; i – joint number) reached by FF, and joint positions (q_{ij}) of the neighbour. Parameter $P_{q_{ij}}$ is used to normalize the joint difference between all seven joints for the chosen neighbour in the joint space. Now, the normalized distance along x axis between $\hat{F}_0$ and each neighbour position S_j is evaluated. Equation (3) estimates coefficients (L_{x_j}) used to compare the x distances of each neighbour j from $\hat{F}_0$:

$$L_{x_j} = \frac{|x_{ff} - x_j|}{|x_{ff} - x_1| + |x_{ff} - x_2| + \dots + |x_{ff} - x_N|} \tag{3}$$

The required coefficients (K_{x_j}, $P_{q_{ij}}$, L_{x_j}) have been estimated. The influence of each coefficient should be treated equally and therefore a product of these parameters is formulated as a connection:

$$C_{x_i} = \sum_{j=1}^{N} K_{x_j} P_{q_{ij}} L_{x_j} \tag{4}$$

Equation (4) represents the influence of a particular joint i along x direction. The proper form which is used as the final kinematic coefficient is

$$n_{C_{x_i}} = \frac{C_{x_i}}{C_{x_i} + C_{y_i} + C_{z_i}} \tag{5}$$

Finally, the influence of each joint on each axis direction is calculated and can be used in final form.

The final equation for the control input during feedback phase is

$$U_i = U_{i,static} \pm n_{C_{x_i}} U_{fuzzy}(x) \pm n_{C_{y_i}} U_{fuzzy}(y) \pm n_{C_{z_i}} U_{fuzzy}(z) \tag{6}$$

The variable $U_{static}(i)$ is a static voltage of i – joint required to keep the joint in the prescribed position during steady state. For the target position the static voltage is estimated using feedforward algorithm (see Section 3.3). The signs $\pm$ in (6) are chosen experimentally using experience base. They represent the situation when the control input is increased, in which direction (positive "+" or negative "−") the hand tip moves to (for each axis).

6 SIMULATION RESULTS

Control was verified by simulation. The theory developed above is applied to the simulator of the robot arm driven by antagonistically coupled drives.

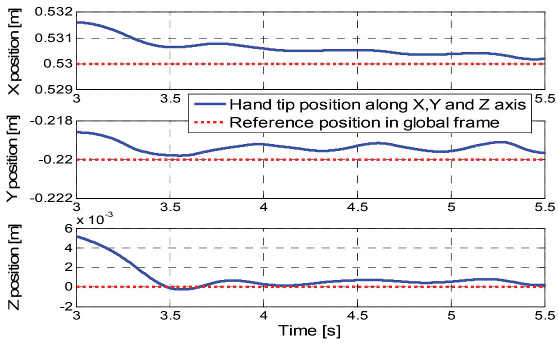


Figure 5: Hand tip position in global frame during feedforward and feedback control.

Figs. 5 and 6 depict the example where the feedforward makes the error of 5mm in z axis direction. The whole motion of the robot arm lasts 5,5s. During first 3s feedforward control is applied in order to drive the robot arm tip from initial position S_0 to position $\hat{F}_0$. In the next 2,5s the system is controlled by FF and FB. In spite of oscillations caused by fuzzy controller the final hand tip position finally comes into prescribed region, $\pm$1mm around the reference position F_0 (Fig. 5). Figure 6 shows FF and FB control signals.

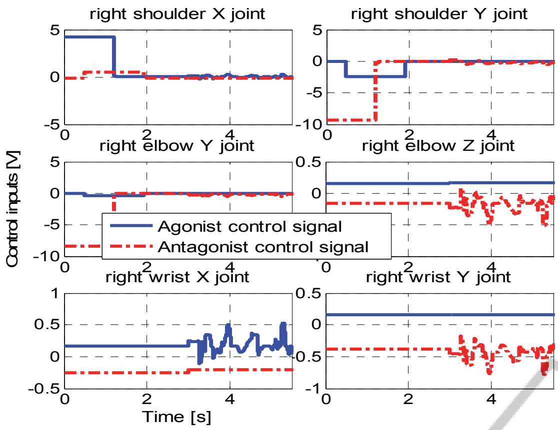


Figure 6: The feedforward and feedback control of the most representative joints in the system.

7 CONCLUSIONS

The core of this paper was the implementation of fuzzy controller along with estimation of kinematic coefficients to formulate the feedback for a robotic arm with antagonistically coupled compliant drives.

Since the suggested control algorithm relies on the experience and fuzzy logic, it is expected to be applicable to a wider class of robots. The only modification would be different training data – experience base should be customized for the specific robot skills. Since the experience acquiring stage in feedforward phase is time consuming, further research can explore solution to speed up this process. As our control depends on base resolution, the future work would consider developing of more sophisticated method to increase precision of the control algorithm (e.g. to make more complex fuzzy engine).

ACKNOWLEDGEMENTS

The research leading to these results has received funding from the European Community's Seventh Framework Programme FP7/2007-2013 - Challenge 2- Cognitive Systems, Interaction, Robotics - under grant agreement no. 231864 - ECCEROBOT; and partly by the Serbian Ministry of Science and Technological Development under contracts 35003 and 44008.

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