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Robot motion classification from the standpoint of learning control

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Abstract

In robot learning control, the learning space for executing the general motions of multi-joint robot manipulators is very complicated. Thus, when the learning controllers are employed as major roles in motion governing, the motion variety requires them to consume excessive amount of memory. Therefore, in spite of their ability to generalize, the learning controllers are usually used as subordinates to conventional controllers or the learning process needs to be repeated each time a new trajectory is encountered. To simplify learning space complexity, we propose, from the standpoint of learning control, that robot motions be classified according to their similarities. The learning controller can then be designed to govern groups of robot motions with high degrees of similarity without consuming excessive memory resources. Motion classification based on using the PUMA 560 robot manipulator demonstrates the effectiveness of the proposed scheme.

Keywords: Robot motion classification; Robot learning control; Learning space complexity; Motion similarity analysis

1. Introduction

The dynamics of robot manipulators are, in general, non-linear and complex. Therefore, conventional fixed gain, linear feedback controllers are not capable of effectively controlling the movements of multi-joint robot manipulators under different distance, velocity, and load requirements. Through the use of non-linear feedback, approaches like the computed torque method provide better compensation for the dynamic interactions present in various robot motions [15]. But, these approaches demand complete, non-linear dynamic models describing the robot manipulator, which are difficult to

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be accurately modeled and implemented in real-time. On the other hand, learning controllers, such as neural networks and fuzzy systems, are attractive alternatives in robot motion control, because they are able to tackle highly complex dynamics without explicit model dependence and identification, in addition to their capability in generalization [5,9,13,19]. However, learning controllers are usually used as subordinates to conventional controllers in governing robot motions [8,11]. The conventional controller is responsible for the major portion of the control, and brings the system close to the desired state, after which the learning controller compensates for the remaining error. Some learning control schemes do use learning controllers alone to execute motion control [6]. But, most of these schemes need to repeat the learning process each time a new trajectory is encountered. Otherwise, a neural network will consist of a huge number of neurons or a fuzzy system will require too many rules. This learning controller deficiency results mainly from the complexity of motions associated with various task requirements. Consequently, when a learning controller is given a major role in governing the general motion of a multi-joint robot manipulator, the learning space it must deal with is extremely complicated [14,17,20].

To simplify the complexity of the learning space in using learning controllers to govern robot motions, we propose, from the standpoint of learning control, that robot motions be classified according to their similarities. Thus, learning controllers can then be designed to govern groups of robot motions with high degrees of similarity with smaller memory sizes. By contrast, when robot motions are randomly arranged, learning controllers will demand larger memory sizes in motion governing. For instance, in the authors' previous paper [21], we developed a robot learning control scheme that generalizes the parameters of the fuzzy systems, which are appropriate for the governing of the sampled motions in a class of motions, to deal with the whole class of motions. Then, when the motions in the class are with high degrees of similarity, the learning control scheme can govern the class of motions with a small memory size. Thus, more robot motions can be governed by the scheme, with a fixed memory size, when they are grouped into classes of similar motions appropriately. In this study, we use a fuzzy system to perform motion similarity analysis and classification. When the fuzzy system learns to govern motion successfully, similarities between motions are evaluated by analyzing the fuzzy parameters in the fuzzy system. The rest of this paper is organized as follows. The proposed motion similarity analysis and classification and its implementation are discussed in Section 2. In Section 3, simulations based on the use of a two-joint planar robot manipulator and the PUMA 560 robot manipulator are reported. Discussions and conclusions are in Section 4.

2. Motion similarity analysis and classification

Motion similarity can be defined according to different characteristics [12,16]. For example, a number of arbitrary robot motions can be categorized into classes of motions with similar movement distances, velocities, or loads [21]. However, this classification cannot guarantee that motions in the same class will correspond to similar fuzzy parameters when governed using a fuzzy system. In the proposed approach, we aim to group similar motions to simplify the complexity in the learning space. Therefore, from the standpoint of learning control, we take similarities between motions as similarities between the fuzzy parameters of the governing fuzzy systems, and define motion similarity as follows.

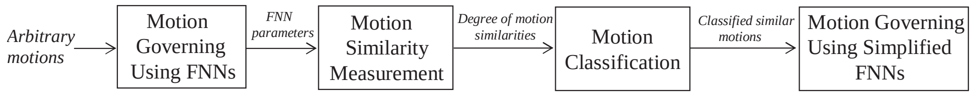

Fig. 1. Conceptual organization of the proposed robot motion similarity analysis and classification.

Definition 1 (Motion similarity). Two motions governed using the fuzzy system are said to be similar if the fuzzy parameters of the governing fuzzy systems, i.e., the fuzzy rules and input and output membership functions, are similar.

According to Definition 1, Fig. 1 shows the conceptual organization of the proposed motion similarity analysis and classification. In Fig. 1, arbitrary input motions are first governed using a fuzzy neural network (FNN). The FNN, discussed in Section 2.2, is basically a fuzzy system implemented using a neural network structure, so that the fuzzy parameters can be adjusted automatically [1,4,9]. Initially, a large number of FNN linguistic labels are used in the learning. The learning process will terminate when the FNN can successfully govern the motions up to a pre-specified accuracy. During learning, redundant fuzzy rules in the FNN are eliminated. The resultant fuzzy parameters are then evaluated via the process of motion similarity measurement. Thus, according to the degrees of similarity between these fuzzy parameters, the motions input in arbitrary fashion are classified into groups of similar motions, which can then be governed using simplified FNNs.

In evaluating the similarities between the fuzzy parameters of the governing FNNs, it is quite straightforward to compare the numbers of fuzzy rules and the shapes of the corresponding membership functions in the FNNs. In the authors' previous paper [22], we defined FNN similarity as follows.

Definition 2 (FNN similarity (I)). Two FNNs for motion governing are said to be similar if the numbers of fuzzy rules they possess are the same, and the similarity among the shapes of their corresponding membership functions is above a pre-specified threshold.

Definition 2 is very strict, because of the restriction on the number of fuzzy rules in the FNN. In addition, it takes individual checking in evaluating the similarities between the membership functions corresponding to the fuzzy rules. Thus, by comparing two fuzzy systems as a whole through evaluating the fuzzy relations representing the entire fuzzy systems, in this paper, we propose another definition of FNN similarity as follows.

Definition 3 (FNN similarity (II)). Two FNNs for motion governing are said to be similar if the fuzzy relations representing the characteristics of the FNNs are similar.

In Definition 3, the number of fuzzy rules is disregarded in the FNN similarity evaluation. Because Definition 3 is less restrictive than Definition 2, two FNNs tend to be determined as similar under Definition 3. Later, in Section 3, we evaluate the effects of these two definitions via simulations.

2.1. System implementation

In this section, we discuss how to implement the proposed motion similarity analysis and classification according to Definition 3. System implementation according to Definition 2 can be found in [22]. Assume that FN_1 and FN_2 are two FNNs with two inputs and one output, and they govern Motion 1 and Motion 2 well with N_1 and N_2 fuzzy rules, respectively. Take FN_1 as an example. Let $x \in \bar{X}_1$ and $y \in \bar{Y}_1$ be two non-fuzzy input variables representing the position and velocity of some joint of the robot manipulator, and $z \in \bar{Z}_1$ a non-fuzzy output variable representing the command sent to the robot manipulator, where $\bar{X}_1, \bar{Y}_1, \bar{Z}_1 \subset \mathfrak{R}$. Letting $F(\cdot)$ represent a fuzzy set, and $X_1 \in F(\bar{X}_1)$, $Y_1 \in F(\bar{Y}_1)$, and $Z_1 \in F(\bar{Z}_1)$ be the linguistic variables representing the two fuzzy input variables and one fuzzy output variable, respectively, the fuzzy rules in FN_1 can then be expressed as

$$\begin{aligned} &\text{If } X_1 \text{ is } A_{11} \text{ And } Y_1 \text{ is } B_{11} \text{ Then } Z_1 \text{ is } C_{11},\\ &\text{If } X_1 \text{ is } A_{12} \text{ And } Y_1 \text{ is } B_{12} \text{ Then } Z_1 \text{ is } C_{12},\\ &\dots\\ &\text{If } X_1 \text{ is } A_{1N_1} \text{ And } Y_1 \text{ is } B_{1N_1} \text{ Then } Z_1 \text{ is } C_{1N_1}, \end{aligned} \tag{1}$$

where A_{1i}, B_{1i}, and C_{1i}, $i = 1, \dots, N_1$, are linguistic values of X_1, Y_1, and Z_1, respectively. Let $R_1 \in F(\bar{X}_1 \times \bar{Y}_1 \times \bar{Z}_1)$ be the fuzzy relation representing FN_1. We can then express R_1 as

$$R_1 = \{((x, y, z), \mu_{R_1}(x, y, z)) \mid (x, y, z) \in \bar{X}_1 \times \bar{Y}_1 \times \bar{Z}_1\} \tag{2}$$

with

$$\mu_{R_1}(x, y, z) = \sup_i \min(\mu_{A_{1i}}(x), \mu_{B_{1i}}(y), \mu_{C_{1i}}(z)), \tag{3}$$

where $\mu_F(\cdot) : U \to [0, 1]$ stands for a membership function characterizing a fuzzy set F [7,10].

Similarly, the fuzzy relation R_2 representing FN_2 can be expressed as

$$R_2 = \{((x, y, z), \mu_{R_2}(x, y, z)) \mid (x, y, z) \in \bar{X}_2 \times \bar{Y}_2 \times \bar{Z}_2\} \tag{4}$$

with

$$\mu_{R_2}(x, y, z) = \sup_i \min(\mu_{A_{2i}}(x), \mu_{B_{2i}}(y), \mu_{C_{2i}}(z)), \tag{5}$$

where A_{2i}, B_{2i}, and C_{2i} are linguistic values of X_2, Y_2, and Z_2, respectively. With R_1 and R_2, we define the similarity index, $\alpha \in (0, 1)$, between FN_1 and FN_2 for governing Motions 1 and 2 as

$$\mathcal{SM}(R_1, R_2) = \alpha, \tag{6}$$

where $\mathcal{SM}(\cdot, \cdot)$ is a similarity measurement operator. Because R_1 and R_2 are in the form of fuzzy sets, the similarity evaluation between R_1 and R_2 using the operator $\mathcal{SM}$ can be realized by evaluating the similarity between the fuzzy sets corresponding to R_1 and R_2.

The similarity measurement between two fuzzy sets U_1 and U_2, $SM(U_1, U_2)$, can be defined as

$$SM(U_1, U_2) = \frac{M(U_1 \cap U_2)}{M(U_1 \cup U_2)}, \tag{7}$$

where $\cap$ and $\cup$ denote the intersection and union operators, respectively, and $M(\cdot)$ is the size of a fuzzy set. The two famous methods to measure the similarity between fuzzy sets are the geometric and set-theoretic measures [24]. For the geometric measure, similarities between fuzzy sets are computed by comparing the areas covered by the fuzzy sets according to geometric points [2,9]. In using the geometric measure, the fuzzy sets need to be normalized to place the similarity evaluation on the same scale, because various input motions may correspond to different ranges of movement distances and velocities [22]. To avoid the normalization process in similarity evaluation, we adopted the set-theoretic measure and describe the procedure as follows.

Take FN_1 as an example. We first sample the spaces, $\bar{X}$, $\bar{Y}$, and $\bar{Z}$, with n equally-spaced points, and discretize the fuzzy sets, A_{1i}, B_{1i}, and C_{1i} into $\hat{A}_{1i}$, $\hat{B}_{1i}$, and $\hat{C}_{1i}$, described as

$$\hat{A}_{1i} = \{(x_r, \mu_{A_{1i}}(x_r)) \mid r = 1,2,\ldots,n\}, \tag{8}$$

$$\hat{B}_{1i} = \{(y_s, \mu_{B_{1i}}(y_s)) \mid s = 1,2,\ldots,n\}, \tag{9}$$

$$\hat{C}_{1i} = \{(z_t, \mu_{C_{1i}}(z_t)) \mid t = 1,2,\ldots,n\}. \tag{10}$$

By using Eqs. (8)–(10), the membership function $\mu_{R_1}(x_r, y_s, z_t)$ can be derived as

$$\mu_{R_1}(x_r, y_s, z_t) = \sup_{\forall i} \min(\mu_{A_{1i}}(x_r), \mu_{B_{1i}}(y_s), \mu_{C_{1i}}(z_t)). \tag{11}$$

Let $\tilde{x}_j = (x_r, y_s, z_t)_j$, with $j = 1,2,\ldots,n^3$. The discretized fuzzy relation R_1 can then be expressed as

$$\hat{R}_1 = \{(\tilde{x}_j, \mu_{R_1}(\tilde{x}_j)) \mid j = 1,2,\ldots,n^3\}. \tag{12}$$

Similarly, the discretized fuzzy relation R_2 can be expressed as

$$\hat{R}_2 = \{(\tilde{y}_j, \mu_{R_2}(\tilde{y}_j)) \mid j = 1,2,\ldots,n^3\}. \tag{13}$$

Finally, the similarity between $\hat{R}_1$ and $\hat{R}_2$ is evaluated using $\mathcal{SM}(\hat{R}_1, \hat{R}_2)$, described in Eq. (14) [3]:

$$\begin{aligned} \mathcal{SM}(\hat{R}_1, \hat{R}_2) &= \frac{|\hat{R}_1 \cap \hat{R}_2|}{|\hat{R}_1 \cup \hat{R}_2|} \\ &= \frac{\sum_{k=1}^{n^3} \min(\mu_{R_1}(\tilde{x}_k), \mu_{R_2}(\tilde{y}_k))}{\sum_{k=1}^{n^3} \max(\mu_{R_1}(\tilde{x}_k), \mu_{R_2}(\tilde{y}_k))}, \end{aligned} \tag{14}$$

where $|\cdot|$ is the cardinality operator [23].

2.2. The FNN learning mechanism

The FNN learning mechanism used in this paper is shown in Fig. 2. The representation of a fuzzy system using a fuzzy neural network enables us to take advantage of the learning capability of the neural network for automatic tuning of the parameters in the fuzzy system. The fuzzy reasoning parameters are thus expressed in terms of the connection weights or node functions of the neural network [1,4,9,18]. We chose an FNN with a structure similar to that in [9], of course, other types of FNN can also be used. As Fig. 2 shows, the inputs to the FNN are position and velocity trajectories of input motions, q_{ri} and $\dot{q}_{ri}$, and the outputs are motion commands C_{mi}. There were five layers of nodes in the FNN: the input layer, the input membership layer, the rule layer,

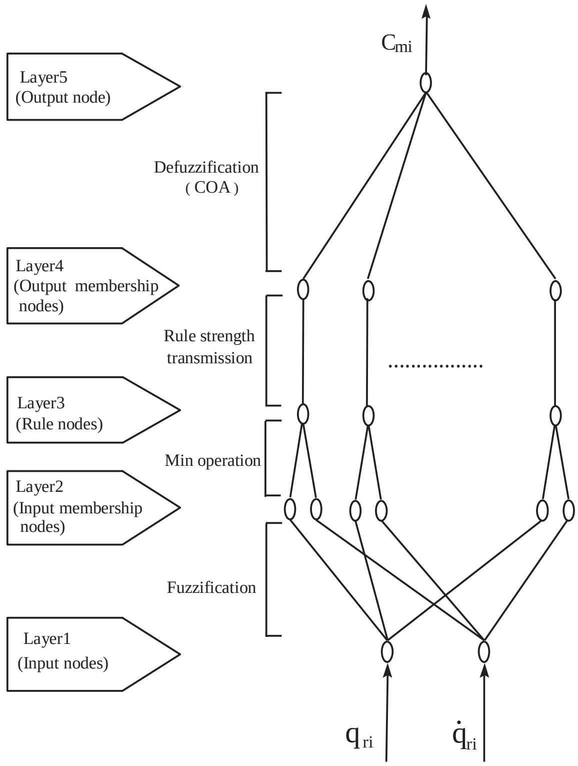

Fig. 2. The structure of the FNN.

the output membership layer, and the output layer. Gaussian functions with adjustable means and variances were used as membership functions. A gradient-descent-based back-propagation algorithm was employed for learning [6]. During the learning process, a large number of FNN linguistic labels were initially chosen in arbitrary fashion and normal fuzzy sets were used as membership functions. The learning process terminated when the FNN could govern motion successfully; i.e., the position mean square error was less than a pre-specified value. After the input motion had been learned, the similarities between membership functions corresponding to this motion were evaluated pair by pair. When membership functions were very similar, it indicates that some of the linguistic labels were unnecessary and could be eliminated. Therefore, after the learning process, the FNN would have a simplified structure and be ready for similarity measurement between motions.

3. Simulation

Simulations were performed to demonstrate the effectiveness of the proposed motion similarity analysis and classification based on the use of a two-joint planar robot manipulator and the PUMA 560 robot manipulator. The dynamics of multi-joint motions can be formulated as follows:

$$\tau = \mathbf{H}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}}) + \mathbf{G}(\mathbf{q}), \tag{15}$$

Table 1
The kinematic and dynamic parameters for the PUMA 560 robot manipulator

Link	Link mass (kg)	Inertial matrix (kg m^2)			Center of mass (m)		
		I_{xx}	I_{yy}	I_{zz}	x	y	z
Dynamic parameters							
1	17.085	0.661133	0.661133	0.098877	0	0	−0.08
2	39.423	0.365234	3.577148	3.711426	−0.216	0	−0.0675
3	18.513	0.381836	0.393555	0.06665	0	0	0.216
4	4.5645	0.012695	0.009521	0.012695	0	−0.02	0
5	1.2189	0.0007324	0.0014648	0.0007324	0	0	0
6	0.51	0.001709	0.001709	0.001	0	0	0

Joint	θ_i	α_i (deg)	a_i	d_i
Kinematic parameters				
1	θ_1	90	0	0.671 m
2	θ_2	0	0.432 m	0.15 m
3	θ_3	−90	0.02 m	0
4	θ_4	90	0	0.433 m
5	θ_5	−90	0	0
6	θ_6	0	0	0

where $\mathbf{q}$, $\dot{\mathbf{q}}$, and $\ddot{\mathbf{q}}$ stand for joint variables and their derivatives, $\mathbf{H}(\mathbf{q})$ is the inertia matrix, $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})$ is the vector of centrifugal and Coriolis terms, $\mathbf{G}(\mathbf{q})$ is the vector of gravity terms, and $\boldsymbol{\tau}$ is the vector of joint torques. The effect of gravity was ignored in the simulations. The kinematic and dynamic parameters for the two-joint planar robot manipulator are: link length, $l_1 = 0.30$ m and $l_2 = 0.32$ m, link mass, $m_1 = 2.815$ kg and $m_2 = 1.640$ kg, center of mass, $l_{c1} = 0.15$ m and $l_{c2} = 0.16$ m, and inertia, $I_1 = I_2 = 0.0234$ kg m^2; those for the PUMA 560 robot manipulator are listed in Table 1. To provide various input motions, a second-order system was used, as described below:

$$L\ddot{\theta} + B\dot{\theta} + K(\theta - \theta_\mathrm{d}) = 0, \tag{16}$$

where L is the load, K the stiffness, B the damping coefficient, and θ and θ_d the actual and desired joint positions for each joint, respectively. Different motions were generated by varying L, B, K, and θ_d. Each joint of the robot manipulator was equipped with an FNN. The inputs to the FNN were the position and velocity trajectories of the input motions, and the output was the motion command. Fifty equally-spaced points were used for the discretization of the fuzzy sets represented in the FNN. Similarities between the motions were evaluated according to the values of the similarity indices α as

$$\begin{aligned} \alpha &= \min_{1 \leqslant l \leqslant l_n} \alpha_l \\ &= \min_{1 \leqslant l \leqslant l_n} \mathscr{SM}(\hat{R}_{pl}, \hat{R}_{ql}), \end{aligned} \tag{17}$$

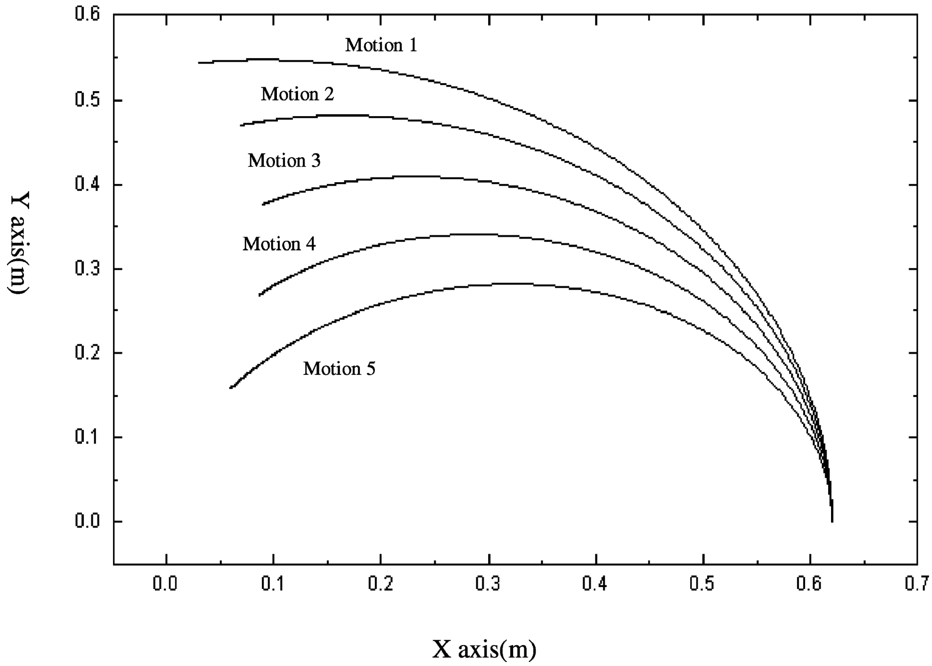

Fig. 3. A group of motions executed using a two-joint planar robot manipulator.

where $\hat{R}_{pl}$ and $\hat{R}_{ql}$ were the discretized fuzzy relations of the FNNs which governed the lth joint of the robot manipulator for Motions p and q, and l_n equal to 2 and 6 for the two-joint planar robot manipulator and the PUMA 560 robot manipulator, respectively.

In the first set of simulations, we applied the proposed approach according to Definitions 2 and 3, respectively, to analyze the similarities between the group of motions shown in Fig. 3, which were executed using the two-joint planar robot manipulator. The motions in Fig. 3 were generated to start from the same position and reach different end positions with L, B, and K in Eq. (16) being the same. Because these motions were generated under very similar kinematic and dynamic conditions, they were expected to be determined as similar by using the proposed approach. Table 2 shows the degrees of similarity between motions in Fig. 3 according to Definitions 2 and 3, respectively. In Table 2, high degrees of similarity between these five motions were observed under both definitions, and Definition 2 led to higher degrees of similarity. In Table 2, we also observed that the degrees of similarity under the analysis according to Definition 3 monotonically decreased along with the increase of the distances between these five motions. This phenomenon was not present in the similarity analysis according to Definition 2. The results implicate that FNN similarity evaluation according to Definition 3 seems to correspond to the closeness of the motions in distance, while further investigation is demanded for solid conclusions.

In the second set of simulations, we intended to evaluate how the increase of joints in the robot manipulator would affect the effects of Definitions 2 and 3. According to both definitions, we applied the proposed approach to analyze the similarities between the group of motions shown in Fig. 4, which were executed using the PUMA 560 robot manipulator. The simulation results show that all motions are determined as dissimilar when Definition 2 was used. It is because high variations

Table 2
The degrees of similarity between motions in Fig. 3 according to (a) Definition 2 and (b) Definition 3

	1	2	3	4	5
(*a*) *Definition* 2					
1	1	0.963	0.966	0.943	0.921
2		1	0.927	0.938	0.962
3			1	0.975	0.953
4				1	0.917
5					1
(*b*) *Definition* 3					
	1	0.834	0.718	0.587	0.484
		1	0.842	0.680	0.554
			1	0.784	0.622
				1	0.763
					1

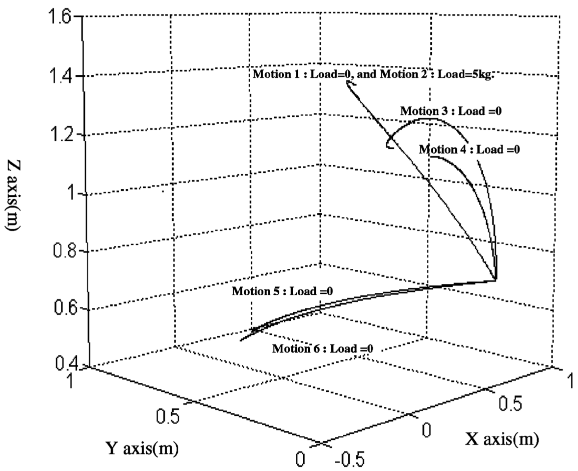

Fig. 4. A group of motions executed using the PUMA 560 robot manipulator.

were present in the rule numbers and the corresponding membership function distributions of the FNNs governing the motions executed by the six-joint PUMA 560 robot manipulator. On the other hand, some motions were still classified as similar under the less strict Definition 3. Table 3 shows the degrees of similarity between motions in Fig. 4 according to Definition 3, and Table 4 the classification of motions in Fig. 4 according to different values of similarity indices α. The results demonstrate that Definition 3 yielded better performance than Definition 2 when the six-joint robot manipulator case was involved.

In Table 4, we found that Motions 1 and 2 and Motions 5 and 6 have similarity index values higher than 0.7. In the third set of simulations, we intended to show that fuzzy parameters for governing motions with high degrees of similarity could be generalized to govern similar motions.

Table 3
The degrees of similarity between motions in Fig. 4 according to Definition 3

	1	2	3	4	5	6
1	1	0.739	0.422	0.446	0.073	0.073
2		1	0.455	0.475	0.072	0.073
3			1	0.395	0.069	0.069
4				1	0.071	0.071
5					1	0.808
6						1

Table 4
Classification of motions in Fig. 4 according to their similarities

$\bar{\alpha}$	Motion classes	Number of classes
0.9	(Motion 1), (Motion 2), (Motion 3), (Motion 4), (Motion 5), (Motion 6)	6
0.7	(Motions 1, 2), (Motions 5, 6), (Motion 3), (Motion 4)	4
0.5	(Motions 1, 2), (Motions 5, 6), (Motion 3), (Motion 4)	4
0.3	(Motions 1, 2, 3, 4), (Motions 5, 6)	2

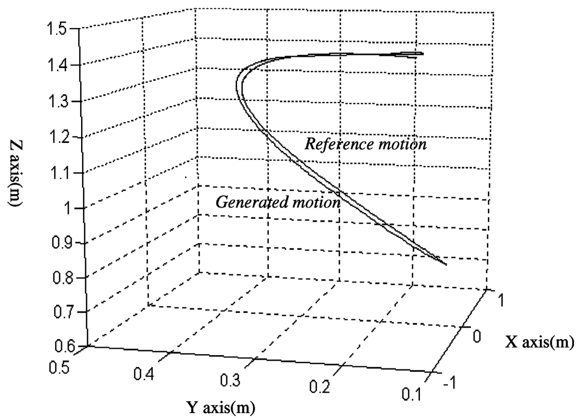

Fig. 5. Motion governing by using the FNN with generalized fuzzy parameters.

We first performed simulations for Motions 1 and 2, which were two similar motions with loads equal to 0 and 5 kg, respectively. We generalized the fuzzy parameters for the FNNs governing these two motions to govern similar motions with loads ranging between 0 and 5 kg. Fig. 5 shows the result when the load was equal to 2.5 kg, and the generated motion approximates the reference motion quite well. Similar results were observed for other loads. We also performed simulations for Motions 5 and 6, and the results were similar to those for Motions 1 and 2. Thus, we concluded that, via the proposed motion similarity analysis, motions may be classified as similar, and these similar motions can then be governed using generalized similar fuzzy parameters, implicating that the learning controller can be designed to govern more motions with smaller memory allocation.

4. Discussion and conclusion

This paper has proposed motion similarity analysis from the standpoint of learning control. Similar motions were defined as those corresponding to similar fuzzy parameters when governed using fuzzy systems. By classifying motions according to their similarities, learning controllers can be designed to govern groups of motions with high degrees of similarity with smaller memory sizes. Simulations based on the use of the PUMA 560 robot manipulator verified the effectiveness of the proposed scheme.

From the simulation results in Section 3, we can find that the motions might be categorized into different motion groups, when different similarity indices were chosen for motion similarity evaluation. With a larger (smaller) similarity index, the motions in the same group may be more similar (dissimilar); consequently, the fuzzy parameters of the FNNs for governing these motions can be generalized to govern other similar motions with higher (lower) precision. Thus, similarity index selection may depend on the demanded accuracy in motion governing using the generalized fuzzy parameters.

A point that also deserves discussion is about the effects of adopting different types of FNNs for the proposed scheme. It can be expected that when different types of FNNs were used for similarity analysis, the resulting analysis and subsequent motion classification might be somewhat different. However, we consider which types of FNNs to be used in the proposed scheme may not be that crucial, if only the motions can be classified into groups of motions with high degrees of similarity and governed by using learning controllers with smaller memory allocation.

In future works, we will apply the proposed scheme to classify general robot motions over the entire learning space, so that an organized and simplified learning space for motion governing may be achieved. Simulation results in Section 3 demonstrate that motion classification via the means of learning does not necessarily correspond to the kinematic or dynamic features, and further investigation into similarities among the general motions is then demanded. In addition, the proposed scheme will also be utilized for practical applications.

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