Simulation of the 6-DOF model of Discrete State Manipulators (DSMs) Based on Neuro-Fuzzy Architecture

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Abstract. This paper reports the simulation of neuro-fuzzy architecture of the discrete state manipulators (DSMs) with 6 degree of freedom (6-DOF) in Matlab environment. The DSMs are special kind of discrete manipulator with massive pneumatic actuators that can be switched among limited number of discrete states. We introduce three-state DSMs model, called as ternary DSMs (t-DSMs), which is driven by discrete forces and have continuous motions. The main problem of the DSMs are how to control such as the position of the manipulator by choosing the best combination of actuator's states which called as inverse static problem (ISP) of DSMs. This paper proposed an architecture which is based on the Neuro-Fuzzy Takagi Sugeno (NFTS) inference scheme with Gaussian membership functions as ISP solution of the proposed DSMs. The training algorithm needs at least one million iterations with different membership functions, employ 25.9% of the input-output correspondences dataset from the known input and output. For training database, the NFTS model generates 189 dataset from the 729 possible dataset. After one week training for searching optimized parameters within several membership function (M), the validation testing found the best error in 1.51% using M = 9.

1. Introduction

This paper proposes an effective way to control the ternary-Discrete State Manipulator (t-DSMs) through the real-time Neuro-Fuzzy controller as ISP solution of the t-DSMs. The t-DSMs generally are a special kind of mechanisms whose actuators can only be switched among three states (retract, null and extended, can be explained as 0, 0.5 and 1). Furthermore, the t-DSMs are a kind of manipulators in an effort to reduce the control procedure and complexity of computer interfacing.

Currently, t-DSMs can be hardly clustered into two categories depending on their actuators act as discrete generators for displacement or discrete generators for force. For instance, the first type of binary DSMs is the binary snake-like robots (SLRs). The SLRs are proposed by Chirikjian et al [1-4] and Dubowsky et al [5], which are kinematically constrained mechanisms employing a large number of discrete actuators in series-parallel configuration. The discrete SLRs can be configured either fully extended, just follow or fully contracted without consideration of the supplementary forces acting on them. In addition, the second type t-DSMs are the Massively Parallel Actuators (MPAs), or sometimes called as Massively Parallel Robots (MPRs). Here, the MPRs are dynamically constrained robots exhausting a large number of binary pneumatic [6] or ternary pneumatic [7] actuators, which have constant forces.

For achieving accuracy in high position/force abilities, the SLRs or MPRs model practically needs a large number of discrete actuators (by experiment around 4-7 times larger than the number of desired DOF for the manipulator). The position of the actuators can be organized in a series-parallel formation [1, 5] or in parallel configuration [7].

Moreover, the ISP solution of t-DSM type MPRs model is usually very difficult to solve and needs unique solution. The optimal results or solutions practically require complicated processes in the terms of approximation and time computing. In the past, some significant research efforts have been devoted to address the ISP solutions, such as: proposing the combinatorial heuristics algorithms [5]; applying the probabilistic methods [3]; comprehensive brute-force search methods and optimized programming by genetic approach [6]; generating the Hopfield networks and Boltzmann machines algorithms [6-7]. Generally, most of the suggested schemes or solutions are formally very effective to reduce the complexity problem, but the results shown that the computation needs large computing time. On the other hand, the result of the ISP solutions still has numerous mathematic calculations, especially if the solutions are applied to the real-time control mechanism.

2. Neuro-Fuzzy Method for Real-Time ISP Solution

This paper introduces the efficient real-time mechanism to control the state of discrete manipulators via computational intelligence methods. Here, the potentialities of using computational intelligence algorithm such as neuro-fuzzy (NF) method as the real-time solution of the ISP of t-DSMs are investigated. The proposed of t-DSMs feature six degree of freedom actuated by six force generators with double action valve control. The positions of actuators are placed in parallel with symmetrical configuration which are extended version of massive parallel arrays in several applications, such as: one DOF MPRs and six DOF game simulator with 3D MPRs. Both applications are done by Pasila et al [7-8].

For more information, NF networks are hybrid networks between humans as rational fuzzy logic with the learning ability of neural networks. This idea is coming because of the main advantages of a NF system are: it interprets IF-THEN rules from input-output connections and focuses on reducing the generalization error in the training phase (off-line phase); In addition, it has efficient calculation time on the on-line phase. This idea was first proposed in ANFIS: adaptive-network-based fuzzy inference system by JSR. Jang [9]. ANFIS later developed as multi-input-multi-output problem (MIMO case) by Palit et al [10] and applied in electrical load forecasting application by Pasila et al [11].

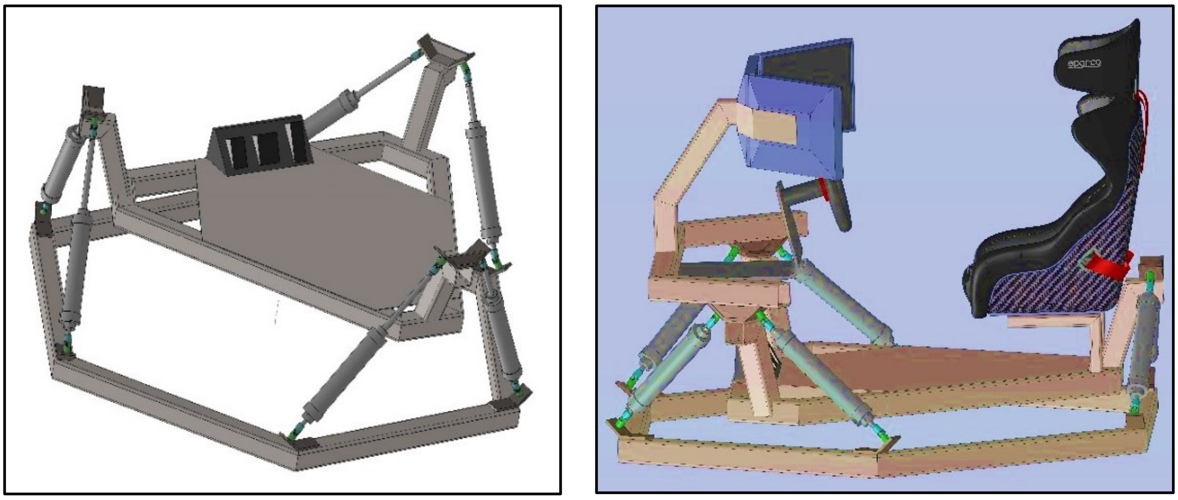
In the next section, we proposed t-DSMs mechanism with real-time controlled. The control part uses Neuro-Fuzzy Takagi-Sugeno (NFTS) inference system with Gaussian membership functions (GMFs). Concerning the ISP, the proposed model can be applied in finding the optimal number of membership functions (M) that provide a strong link between the input values α with their output variables ternary number $u = [u_1, \dots, u_6]$. In the design of the architecture of the NF, the membership function will be changed in the learning process using different M from 4 to 10.

2.1. The Ternary-Discrete State Manipulators (t-DSMs)

Moreover, figure 1 exploits the t-DSMs mechanism that is considered in this paper. It has 6 identical pneumatic actuators respectively 6-SPS-3D mechanism. The terms U, P and U are for universal, prismatic and universal joints respectively, sharing the same moveable platform (C) through their moving joint. The moveable platform is hinged to the platform at origin joints B (joints B are in the fixed platform), links to the six variable length Ci-Bi, where $i = 1, 2,..., 6$. The moving platform are hinged at the points of the common platform based Bi and displacement of points of the Ci platform respectively, correspondingly relative to the XYZ axis along to the both platform. In order to neglect the twist of the moving platform while activating the actuators, additional crank and slotted-lever in the center of both platforms are applied. Moreover, the description about the t-DSMs mechanism can be shown in table 1. The implementation mechanisms possibly will be achieved by using six double acting pneumatic cylinders with bi-directional control valves.

2.2. Neuro-Fuzzy type Takagi-Sugeno Model in Matlab

This Section presents the architecture for the new model of ternary DSMs, like shown in figure 2. The architecture is called as feedforward Neuro-Fuzzy Takagi-Sugeno, type multi-input multi-output. The inputs are six set of coordinates XYZ and Forces in the related coordinate direction while the outputs consist of the states of the actuators (u_{state}). It also uses GMFs in the fuzzyfication phase.



(a) Manipulator with pneumatic actuators (b) Overall game simulator view

Figure 1. Design of DSMs with 6 pneumatic actuators (a) and simulator view (b)

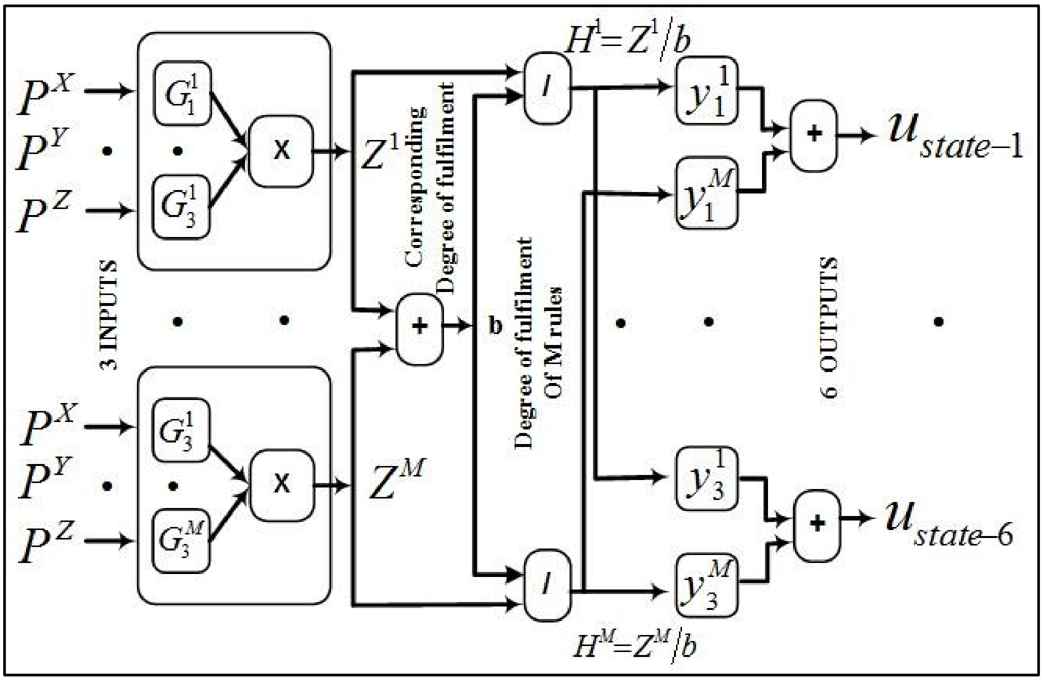


Figure 2. Feedforward Neuro-Fuzzy network type Takagi-Sugeno, 3 Inputs 6 Outputs, Learning method: LMA

Table 1. Description of t-DSMs simulator with 6 actuators

Description	Measurement	Unit/Type
Simulator Weight	391.6	Kg
Moving Pneumatics Weight	187.3	Kg
Moving Platform Weight	145,3	Kg
Diameter Top Plate	1329	Mm
Diameter Bottom Plate	1807	Mm
Material Top Plate	aluminum	6063-T6
Material Bottom Plate	aluminum	6063-T6
Maximum declivity	13	Degrees
Actuator Strokes	326	Mm
Number of actuators	6	Unit
Type of Actuator Joints	Universal-Prismatic-Universal	Unit

Moreover, we introduce the GMFs (1) as fuzzyfication functions to the NF methods G_y^n (y = 1, 2, 3; n = *1*, …, *6*), for input pairs $\alpha^{\boldsymbol{D}}$ = [P^X,P^Y,P^Z], where α^D are the input set of the positions (in X, Y and Z axis) with respect to the XYZ Euler coordinates.

$$G_y^n(\alpha_y) = exp\left(-\left[(\alpha_y - c_y^n)/\sigma_y^n\right]^2\right) \tag{1}$$

with parameters means c_y^n and variance σ_y^n together with the corresponding n-fuzzy rules (FR^n) can be written as:

$$\begin{gathered} FR^n\!: IF\ \alpha_1 is\ G_1^n\ AND\ \alpha_2 is\ G_2^n\ AND\ \alpha_3 is\ G_3^n\ AND\ \ldots \\ THEN\ Y_i^n = w_{0i}^n + w_{1i}^n \cdot \alpha_1 + w_{2i}^n \cdot \alpha_2 + w_{3i}^n \cdot \alpha_3 + \cdots \end{gathered} \tag{2}$$

here w_{0i}^n, w_{1i}^n being the Takagi-Sugeno weights (for i = 1, …, *6*, and n = 1, …, M_{OPT}, *where* M_{OPT} is the number of optimized rules for the proposed model, will be found by search mechanism), the last part of the considered Neuro-Fuzzy model calculates the output vector $\bar{u}$.

$$\overline{u_{state}} = \sum_{n=1}^{M_{OPT}} Y_i^n \left(\frac{\prod_{y=1}^{3} G_y^n(\alpha_y)}{\sum_{n=1}^{M} \prod_{y=1}^{3} G_y^n(\alpha_y)}\right) \tag{3}$$

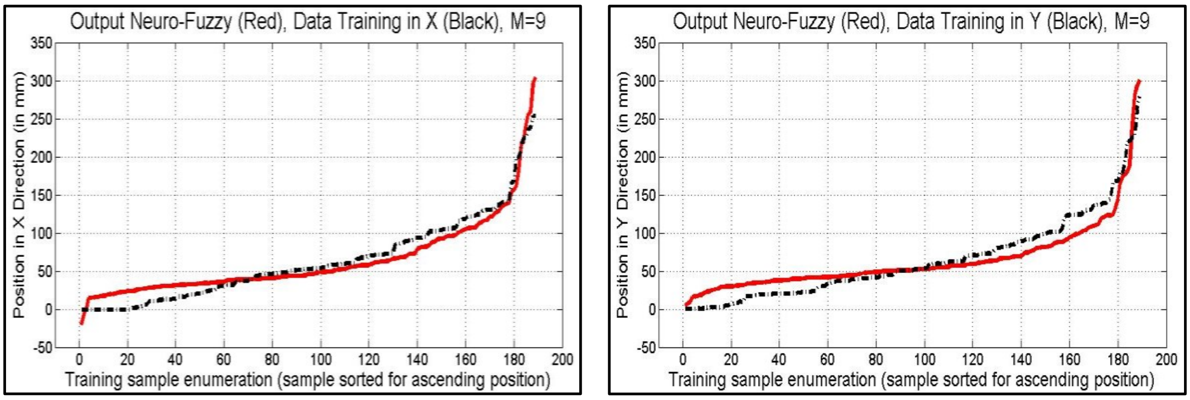
The NF output (3) consist of six outputs and still in the real form. Moreover, the outputs will be derived by alternatively approximating the activation states of actuators u_{state} through the following threshold function:

$$u_{state} = 0.5 * round(2 * abs(\overline{u_{state}})) \tag{4}$$

where *round* indicates a process to change real form of vector $\overline{u_{state}}$ into the three state numbers which are 0, 0.5 and 1. In the process to find the predicted outputs, NFTS model requires the tuning of the parameters c_y^n, σ_y^n, w_{0i}^n, w_{yi}^n (here y = 1, 2, 3; i = 1, 2,...,6; n = 1, …, M_{OPT};). The number of parameters for the considered architecture (with membership function optimal M_{OPT} is 9) is 486 parameters from four tuned NFTS parameters. The values of these parameters are found by an optimized learning procedure via Levenberg Marquardt Algorithm, LMA [10]. The learning procedure employs 25.9% of the input-output correspondences known from 729 dataset for the 6 t-DSMs respectively.

3. Results and Discussion

The simple search procedure is needed in order to find the optimized number of rules M for the six t-DSMs mechanism. This procedure is a local search method that tries to find the best local minimum from one million iterations on the learning procedures. The procedure permits the best learning parameters that minimize the total error training (e_t) in every iteration and neglects the parameters that caused bigger e_t. The optimized membership function (M) is achieved after one week of searching time. As the results, the optimized model that give best performance is M= 9 for the 6-ternary MPRs, with model performances for the ISP solution shows off-line trained t_{off} = 3218s, and $RMSE$ model e_t = 1.51 %. For the training purposes, the NTFS method uses 189 data training. The comparison between data and prediction of training performance of Neuro-Fuzzy method can be seen on figure 3 and table 2. The results in figure 3 also shown that model has ability to predict the forces accurately but with less ability in predicting the position in X and Y respectively.



(a) Training Performance of Position in X Direction (b) Training Performance of Position in Y Direction

Figure 3. Off-line training results of NFTS using 189 sample data in X (a) and Y (b) positions

Table 2. Performance Results of t-DSMs model with different Membership Function (M)

No. of Membership Function M	Average RMSE Training (%)	Off-line Trained (sec) Using LMA
4	2.05	2559
5	2.24	2668
6	1.85	2993
7	2.68	3046
8	1.92	3162
9	**1.51**	**3218**
10	1.89	3314

4. Conclusion

This paper presented six-DOF discrete state manipulators with 6 pneumatic actuators with three-state force generators, called as t-DSMs. An optimized model of Neuro-Fuzzy method type Takagi-Sugeno is found using the Levenberg-Marquardt algorithm (LMA) for the solution of inverse static problem of the considered t-DSMs. In addition, compared to the standard manipulator robot mechanism, the partitioned and parallel distributed actuator architecture proved that the considered manipulator features sufficient and accurate position generation abilities. The results show that NFTS with membership function (M) = 9 has better approximation ability compared to the other number of membership function between 4 to 10 during the off-line training phase.

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