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Performance Analysis of Fuzzy Subtractive Clustering Based MRAC

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Abstract

In this work MRAC using Lyapunov and FSC are applied to control motion parameters of DC servo motor. Results are presented, analyzed and compared for both strategies. Observation reveals strength of FSC based MRAC compared to classical Lyapunov based MRAC method. Soft computing FSC is more effective in reducing chattering, error convergence and reference trajectory following. Data of controller adjustment parameter θ has been saved after applying classical Lyapunov based method and used to apply FSC technique to generate $\hat{\theta}$. System has been shown Lyapunov stable with mathematical proof and suitable plots. Statistical analysis also presented to prove importance of presented FSC based MRAC technique.

Keywords FSC, MRAC, ANFIS, NN, Lyapunov rule

INTRODUCTION

Design of controller with soft computing techniques is beneficial due to learning and adaptation capabilities. Ability to deal with uncertainty and vagueness is additional benefit. When reference output trajectory is available as controller target, model reference adaptive control (MRAC) is most suitable control strategy.

Estimation of cluster centers has nicely been proposed by [1]. Fuzzy model identification is proposed using benchmark system problem. Fundamentally subtractive clustering has been proposed as an extension of mountain clustering method. Subtractive clustering has been applied in [2] for a fault tracing, identification and analysis with their trend for power transformer state control. Experiment covers enabling acoustic partial discharges (PDs) positioning for the power plant transformers. Subtractive clustering improves efficiency in diagnostics, fault localizing and identification. Important issue like demand response regulation in smart grid system has nicely been addressed in [3] using the fuzzy subtractive clustering (FSC) technique. Algorithm has been discussed and scenarios analysis has been done.

Subtractive clustering techniques for framing fuzzy rules has been proposed in [4]. Proposed method as a part of urban traffic control system is beneficial than conventional control methods. Five basic clustering algorithms are nicely explained as a compilation in [5]. Detailed process flow and implementation methods are nicely introduced for each clustering technique. Conversion of clustering into initial fuzzy rules, optimization of membership functions and related software are discussed in [6]. Due to speed and robustness proposed method can be helpful in pattern recognition and related tasks.

To improve performance of expert system, tuning and designing of membership functions is proposed in [7]. Insulation oil age assessment for power transformer has been discussed. In [8] subtractive clustering based type-1 Takagi-Sugeno-Kang fuzzy logic systems (TSK FLS) are analysed and type-2 TSK FLS are discussed. Type 1 membership function has been used to get type 2 fuzzy logic systems. In [9] results of soft computing adaptive neuro fuzzy inference System (ANFIS) based MRAC are proved better than classical MRAC technique considering case study of jacketed stirred tank heater. Error statistics also has been presented to support results.

ANFIS and SC are effectively used for fiber quality modeling and optimization in [10]. Results are validated with statistical analysis. Soft computing technique like NN with SC is applied for fault detection and diagnosis for buildings and HVAC systems in [11]. Data driven technique is applied, results are discussed and validated also. Sparse neural network method with MRAC for hypersonic flight applications is discussed in [12]. Uncertainty with unknown structure is also considered. Robust adaptive controller has been designed.

Control of PMSM with soft computing based MRAC has been discussed in [13]. Non parametric dynamic linearization has been done. Performance in case of data loss also has been analysed. MRAC has been applied for DC servo motor motion control using ANFIS technique and compared with Lyapunov rule based MRAC technique in [14]. Simulation results are presented and overall system stability has been shown.

ANFIS has been efficiently used in [15] for railway transportation to predict distance between pantograph and contact line of locomotives. Results of ANFIS with fuzzy C mean clustering are also discussed. Thorough explanation about adaptive control strategies, nuances of various techniques and controller design for various types of systems are included in [16]. MRAC techniques from MIT rule, modified classical rules to latest developed techniques with stability analysis is compiled in book. Example control problems with results are discussed.

Outline of this paper is as follows. Introduction covers importance and literature survey related to FSC based MRAC. Then FSC for parameter adaptation covers algorithm and steps for FSC. Next part covers control law with stability proof. Then case study of DC servomotor motion control has been discussed with simulation results and statistical analysis. Conclusion and future scope is mentioned at end.

FSC FOR PARAMETER ADAPTATION

Fuzzy subtractive clustering (FSC) algorithm has been tested here for adaptive control case study. FSC is known as a one-pass streaming natured technique to estimate the number of clusters, the cluster centers and iterative optimization in a set of data. Ability of FSC adaptive controller parameter identification has been tested in this work. Due to optimized number of clusters FSC overcomes various soft computing issues like overfitting of data set and loss of general adaptability due to it. Subtractive clustering has advantage of dimensionality compared to use of grid partitioning for fuzzy system modeling. FSC has potential to precisely map output compared to other techniques like grid partitioning or c-means clustering.

Cluster potential or density function ω is as follows. For each data point

$$\omega_i = \sum_{j=1}^{n} \exp\left(-\frac{\|x_i - x_j\|^2}{(r_a/2)^2}\right) \qquad (1)$$

where r_a is a positive constant. Therefore, a data point will have a high density value if it has many neighboring data points. The radius r_a defines a neighborhood; data points outside this radius contribute only slightly to the density measure.

Potential of each data point needs to be revised due to reduction in density measure shown by following formula.

$$\omega_i = \omega_i - \omega_c \exp\left(-\frac{\|x_i - x_c\|^2}{(r_b/2)^2}\right) \qquad (2)$$

where r_b is a positive constant. Therefore, the data points near the first cluster center $\mathbf{x_c}$ will have significantly reduced density measure, thereby making the points unlikely to be selected as the next cluster center. The constant r_b defines a neighborhood that has measurable reductions in density measure.

Neighbourhood r_b should be chosen greater than r_a. Typically r_b=1.5 r_a. After revised potential data point with highest remaining potential is chosen as the second cluster center. For c^{th} cluster center if optimal density $\omega_c^* \leq \epsilon\, \omega_1^*$ then stop iterations.

Considering actual optimal adaptation parameter value for each iteration, derivative of density function becomes

$$\dot{\omega} = \omega_{i(new)} - \omega_i = -\hat{\theta}_k^* \exp\left(-\frac{\|x_i - x_k\|^2}{(r_b/2)^2}\right) \qquad (3)$$

CONTROL LAW WITH STABILITY PROOF

Considered general model and plant equations are

$$\dot{y}_m = -A_m y_m + B_m u_m \qquad (4) \text{ and}$$

$$\dot{y} = -A_m y + bu \text{ where } u = \hat{\theta}\xi u_m \qquad (5)$$

So

$$\dot{e} = -A_m e + (b\hat{\theta}\xi - B_m)u_m \qquad (6)$$

Error derivative can be represented by

$$\dot{e} = -A_m e + b\hat{\theta}\xi u_m - B_m u_m \qquad (7)$$

Where $A_m = \|A_m\|$, $B_m = \|B_m\|$ and $b = \|b\|$ are norms for input and system matrices.

To prove stability assume Lyapunov function

$$V = \frac{1}{2}e^2 + \frac{1}{2}\omega^T\varphi\omega + \frac{1}{2}\hat{\theta}^T\upsilon\hat{\theta} \qquad (8)$$

Where chosen φ and υ are positive definite matrices resulting in overall positive definite function.

With norms it can be observed that Lyapunov function is positive definite

$$V \leq \frac{1}{2}e^2 + \frac{1}{2}\|\varphi\|\|\omega\|^2 + \frac{1}{2}\|\upsilon\|\|\hat{\theta}\|^2 \qquad (9)$$

Taking derivative of Lyapunov function V we get

$$\dot{V} = \frac{1}{2}e\dot{e} + \omega^T\varphi\dot{\omega} + \hat{\theta}^T\upsilon\dot{\hat{\theta}} \qquad (10)$$

Data for change in adaptation parameter is used from conventional MRAC technique to train the data. So

$$\dot{\theta} = \dot{\hat{\theta}} \qquad (11)$$

We get

$$\dot{V} = \frac{1}{2}e(-A_m e + b\hat{\theta}\xi u_m - B_m u_m) + \omega^T\left(-\hat{\theta}_k^* \exp\left(-\frac{\|x_i - x_k\|^2}{(r_b/2)^2}\right)\right) + \hat{\theta}^T(\gamma u_c \xi e) \qquad (12)$$

so

$$\dot{V} = \left(-\frac{1}{2}A_m e^2\right) + \frac{1}{2}e\left(b\hat{\theta}\xi - B_m\right)u_m + \left(-\omega^T\hat{\theta}_k^* \exp\left(-\frac{\|x_i - x_k\|^2}{(r_b/2)^2}\right)\right) + \gamma u\xi e \qquad (13)$$

In above equation choice of $\xi = sign(eu_m)$ should be done. Considering error-reference relationship Sign of $\left(b\hat{\theta}\xi - B_m\right)$ and ξ are same. A_m, B_m and b are norms, so have always positive values. All four sections of right half of equation for $\dot{V}$ are negative semidefinite.

Thus FSC algorithm $\dot{\omega} = -\omega^T\hat{\theta}_k^* \exp\left(-\frac{\|x_i - x_k\|^2}{(r_b/2)^2}\right)$ and $\hat{\theta} = \gamma u_c \xi e$ leads to Lyapunov stable system with $\dot{V} \leq 0$

Case Study: Dc Servomotor Motion Control

Servo systems are useful to control position and time derivatives of position. Here Armature closed loop control has been applied. Proposed technique can be applied for large size of servo motor with high torque.

A. About System and Model

Following DC servomotor system has been considered

$$L_a \frac{di_a}{dt} + R_a i_a + k_b \omega = e_a \qquad (14)$$

$$j \frac{d\omega}{dt} + f\omega = k_\tau i_a \qquad (15)$$

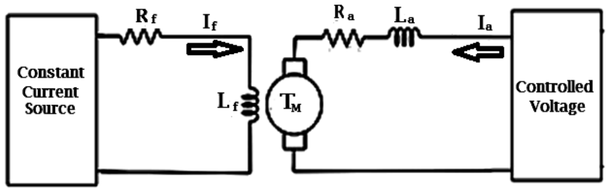

Figure 1 DC servomotor control

Figure 1 shows working and control of DC servomotor. Field and armature resistance, inductance and produced back emf are responsible for rotation and speed for a provided value of armature voltage. Proportionality constants have been used for back emf and torque.

Problem statement for control is to follow model reference trajectory desirable speed. Armature voltage input is controller effort to the system. Any variation in system parameters or in case of any load change, the system output should follow the desirable trajectory of model output.

In DC servomotor motion control, derived $\dot{\theta}$ from Lyapunov stability based method can be written as

$$\dot{\theta} = -\gamma e(\omega_p - \omega_m) \qquad (16)$$

For each iteration updates in controller adaptation parameter using FSC can be represented as

$$\dot{\hat{\theta}} = -\hat{\theta}^T \hat{\theta}_k^* \exp\left(-\frac{\left\| \omega_p - \omega_m \right\|^2}{(r_b/2)^2} \right) \qquad (17)$$

B. Simulation work results and discussion

For initial analysis Lyapunov based MRAC is applied to control the speed of DC servo motor plant as per reference model trajectory. From this part new values of adaptation parameter has been generated to test FSC based MRAC.

Parameter values for simulation are as follows. Inductance and resistance of armature are $L_a = 300$ H and $R_a = 10\ \Omega$. Values of constants are k_b=1.1 volts/(rad/msec) , k_τ=20 newton-m/amp and j=8 kg-m^2. Viscous friction f=30 (newton-m)/(rad/msec) and adaptation gain γ =0.7 is chosen for simulation.

Control law with FSC is given by

$$u = -\hat{\theta}^T \hat{\theta}_k^* \exp\left(-\frac{\left\| \omega_p - \omega_m \right\|^2}{(r_b/2)^2} \right) u_m \qquad (18)$$

Figure 2 shows output and error plots for both Lyapunov rule based and FSC based MRAC to track reference value for DC servomotor speed control. Reference trajectory for simulation has been designed to include all possible challenges.

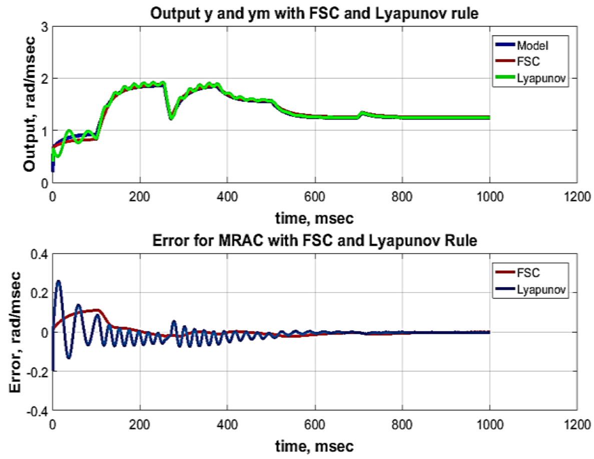

Figure 2 Output and Error plot for DC Servo System Reference Model Output

The response seems desirable in both Lyapunov based and FSC based MRAC for system. Observation of partly uncertain plant dynamics reveals that Lyapunov based MRAC is not able to approximate for uncertain part and gives average results. Use of FSC to adapt and apply control effort helps for good results in such situations. Model output varies based on variation in armature input voltage. Result plot also reveals that chattering effect can be reduced with soft computing. It can be observed that response with FSC is much smoother which practically protects device from any kind of damage. Once trained same model can be used again and again for different sets of trajectories.

Plot of adaptation parameter and controller effort reveals many points about applied control strategy. Parameter $\hat{\theta}$ is heart of adaptive controller part. For training purpose error and adaptation parameter from classical Lyapunov based MRAC are used to generate fuzzy inference system (FIS) using subtractive clustering.

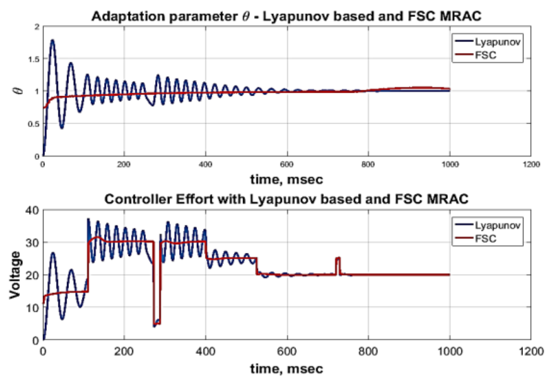

Figure 3 Adaptation Parameter and Controller Effort with Lyapunov Based MRAC and FSC

Figure 3 shows adaptation parameter generated with FSC and with Lyapunov stability Based MRAC. It also shows plot of controller effort required in both case. It shows that approximate model tries to remove oscillations and mostly approximates smooth value for new signal.

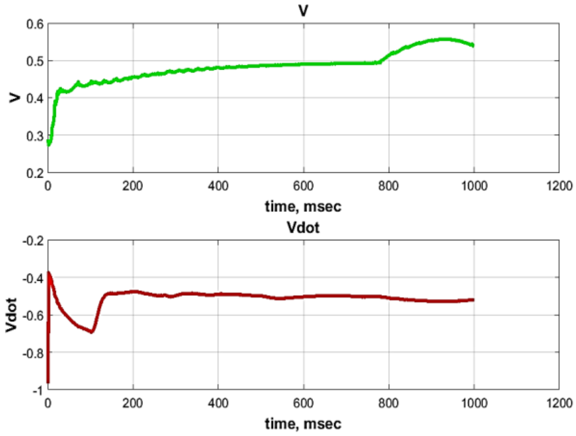

Figure 4 Lyapunov Function and its Time Derivative for FSC Based MRAC

Results shown in Figure 4 are Lyapunov Function V for MRAC based on adaptation parameter generated by FSC and its Time Derivative. As per need we can see continuous nature of function V. Observation shows that positive definite Lyapunov function and negative definite derivative term throughout simulation. It proves asymptotic stability of proposed system.

Statistical analysis of error and controller effort supports simulation results and is presented below. Four primary statistical parameters Mean-Error, Mean Square Error, Standard Deviation and Variance are derived for the system.

Table 1. Statistical analysis of Error for DC Servomotor system (rad/msec)

DC Servomotor System			
Lyapunov based MRAC		**FSC based MRAC**	
Mean-Error	0.00752	Mean-Error	0.00496
Mean Square Error	0.002	Mean Square Error	0.00112
Standard Deviation	0.04418	Standard Deviation	0.03313
Variance	0.00195	Variance	0.00109

Observation of Table 1 of results shows compared to normal controller-system dynamics, FSC based MRAC gives better response with less statistical error values. Observation of results shows that in normal controller-system dynamics, classical MRAC leads to better results, but in case of uncertainty it is not.

Table 2. Statistical analysis of Controller Effort for DC Servomotor system (voltage)

DC Servomotor System			
Lyapunov based MRAC		**FSC based MRAC**	
Mean-Controller Effort	22.48836	Mean- Controller Effort	22.60148
Mean Square Controller Effort	5.43774	Mean Square Controller Effort	5.43107
Standard Deviation	6.17136	Standard Deviation	5.68443
Variance	38.0857	Variance	32.31284

Observation of Table 2 of results shows compared to normal controller-system dynamics, FSC based MRAC leads to better results by saving controller effort.

Soft computing based MRAC saves energy and control effort due to reduction in undershoots and overshoots. Statistical analysis of error and controller effort is as per Table1. Statistical comparison give more clarity about our results. Inherent leaning and adaptation ability is natural benefit of soft computing technique for controller design.

CONCLUSION

Fuzzy subtractive technique has been used to generate adaptation parameters for motion control of DC servomotor with MRAC method. Introduction with literature survey, system fundamentals, fuzzy subtractive clustering algorithm and developments in MRAC strategies are included to understand the importance of the presented work, problem definition and simulation work for DC servomotor is presented. Data from Lyapunov based MRAC has been used to train data for fuzzy subtractive clustering technique. Result plots and discussion with comparative analysis of applied techniques has been included. Error statistics is also given. Combination of more than one advanced soft computing techniques and data from classical techniques for training purpose can be applied higher order systems for better results and can be considered as future scope of presented work.

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