Enhanced Model Reference Fuzzy Logic Controller for High Performance Induction Motor Drive

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Abstract: This paper presents an enhanced technique for the adaptation mechanism of Fuzzy Model Reference Learning Control (FMRLC). the authors proposed a modification to the movement of the auto-attentive area. The modification enhances the transient response. However, it was still unsatisfactory especially if the input scaling factors were selected very large. The slow transient response is due to the chattering effect found in the control effort. In this paper, the results of applying the experience model to the enhanced FMRLC, the controller was able to reduce the chattering effect in the control effort, and hence in the transient response of the control system. Simulations are carried out using an induction motor to verify the proposed algorithm's performance.

1 INTRODUCTION

Self Organizing Fuzzy Controller (SOFC), presented in [5], reduces the fuzzy controller design dependency on expert knowledge and provides on-line adaptation of the controller parameters to compensate for process parameter variation. The algorithm adapts the nonlinear control surface identified by the rule base of the fuzzy controller, by modifying the centers of the output membership functions

Passino *et al.* proposed an adaptation mechanism [2,3,4,6] similar to SOFC, but, they embedded a reference model that describes the desired performance. Passino algorithm was referred to as Fuzzy Model Reference Learning Control (FMRLC). Longya *et al*. applied FMRLC algorithm to an induction motor in a speed control loop [7]. The controller proved high torque rejection capability and its potential to compensate for parameter variations. Moreover, in [7], the authors has presented a comparative study between FMRLC, direct fuzzy controller, and on-line fuzzy tuning scheme. The results show outstanding performance for the FMRLC.

Passino *et al.* [6] proposed one key modification to the FMRLC to increase the system accuracy without increasing the computational burden. The modification produces a FMRLC algorithm with the ability to focus the attention to the area that is currently of interest (the area that has active adaptation) and shifts this area as the attention moves to other areas. The term *Auto-Attentive* approach was added to the FMRLC to describe this new algorithm. The results showed that the proposed modification succeeded in tracking a trajectory composed of two sinusoidal waves with different frequencies.

The authors proposed a modification to the movement of the auto-attentive area. The modification enhances the transient response. However, it was still unsatisfactory especially if the input scaling factors were selected very large. The slow transient response is due to the chattering effect found in the control effort. In this paper, the results of applying the experience model to the enhanced FMRLC using auto-attentive technique are introduced. The paper introduces new modifications to enhance the auto-attentive mechanism. The modification allows the auto-attentive active region to shift faster to the area that is currently of interest. This would accelerate the learning process and enhance the transient control action. In addition, the paper introduces a new algorithm to update the rules in the unexplored area of the universe of discourse when the auto-attentive region moves. The paper is organized as follows: In section II the auto-attentive approach is discussed. Section III is devoted to the description of the proposed modification to the movement of the auto-attentive area. Section IV the simulation results of the proposed algorithm and the conventional one using induction motor speed control drive, are presented

2 AUTO-ATTENTIVE MECHANISM

The auto-attentive mechanism for FMRLC allows the centers of the input membership functions to be shifted on-line.

Consider a fuzzy controller with two inputs given by:

$$e(k) = r(k) - y(k) \qquad \text{(1-a)}$$

$$c(k) = \frac{e(k) - e(k-1)}{T} \qquad \text{(1-b)}$$

where $e(k)$ represents the error between the set point ($r(k)$) and the output of the process ($y(k)$), $c(k)$ represents The change rate of $e(k)$, T is the sampling time and k is the current sample index In addition, consider 2*N*+1 membership functions for each input. Assuming a uniform distribution of the membership functions in the interval [-1,1], the width of each membership function is given by:

$$w = \frac{1}{N} \qquad (1)$$

Then the center of each membership functions is given by:

$$C_i^e = C_{i-1}^e + w \qquad (2)$$

where C_i^e is the center of the i^{th} membership function of the 1st input (*e*), $i = -N+1, -N+2, \cdots, -1, 0, 1, \cdots, N$ and $C_{-N}^e = -1$. Similarly, the centers of the membership functions for the 2nd input (*c*) are given by:

$$C_j^c = C_{j-1}^c + w \qquad (3)$$

where $j = -N+1, -N+2, \cdots, -1, 0, 1, \cdots, N$. For FMRLC the membership functions cover the dynamic range of each input by using the input-scaling factors (input scaling factors are used to scale the inputs to the range [-1,1]). However, for the auto-attentive strategy, the input membership functions cover only a part of the dynamic range. If the active learning region (the currently fired rules) hits the borders of the auto-attentive active region, the auto-attentive active region will move one step in the direction of the movement of the active learning region. This shift is made by moving the centers of the input membership functions one step towards the segment of the input dynamic range that is currently of interest. The centers of the membership functions for each input are given by:

$$C_i^e(k) = C_i^e(k-1) + K_e(k) * w \qquad \text{(4-a)}$$

$$C_j^c(k) = C_j^c(k-1) + K_c(k) * w \qquad \text{(4-b)}$$

where K_e has the following value:

$$K_e(k) = 1 \text{ if } \min(\mu_{A_N}^e, \mu_{A_j}^c) > 0 \qquad \text{(5-a)}$$

$$K_e(k) = -1 \text{ if } \min(\mu_{A_{-N}}^e, \mu_{A_j}^c) > 0 \qquad \text{(5-b)}$$

$$K_e(k) = 0 \qquad \text{otherwise}$$

where $\mu_{A_N}^e$ and $\mu_{A_{-N}}^e$ are the membership values of the far right and left membership functions for the 1st input respectively. $\mu_{A_j}^c$ is the membership value of the j^{th} membership function for the 2nd input ($j = -N, -N+1, \cdots, -1, 0, 1, \cdots, N$). Similarly K_c is given by:

$$K_c = 1 \quad \text{if} \quad \min(\mu_{A_i}^e, \mu_{A_N}^c) > 0 \qquad \text{(5-a)}$$

$$K_c = -1 \quad \text{if} \quad \min(\mu_{A_i}^e, \mu_{A_{-N}}^c) > 0 \qquad \text{(5-b)}$$

$$K_c = 0 \qquad \text{otherwise} \qquad \text{(5-c)}$$

The centers of the output membership functions are given by:

$$C_l^u(k) = C_l^u(k-1) + p * \mu_A^l \qquad (6)$$

where p is the adaptation factor (AF) (the output of the inverse model scaled by the adaptation gain g_p, μ_A^l is the membership value of the premise of the l^{th} rule and is given by:

$$\mu_A^l = \min(\mu_{A_j}^e, \mu_{A_k}^c) \qquad (7)$$

and $l = (i + N + 1) + (j + N) * (2N + 1)$, hence, $l = 1, 2, 3, \cdots, R$ where R represents the total number of rules in the rule-base ($R = (2N+1)^2$).

In addition to the adaptation of the centers of the output membership functions given by equation (6), these centers are allowed to be reset if the auto-attentive region moves (i.e. $K_e(k) \neq 0$ or/and $K_c \neq 0$) as follows:

$$C_l^u(k) = 0 \quad (8)$$

where

$$l = (K_e(k) * N + N + 1) + (j + N) * (2N + 1)$$

if $K_e(k) \neq 0$ (9)

$$l = (i + N + 1) + (K_c * N + N) * (2N + 1)$$

if $K_c(k) \neq 0$ (10)

and the other centers of the output membership function are given by:

$$C_n^u(k) = C_{n-1}^u(k) \quad (11)$$

where

$n = (i * N + N + 1) + (j + N) * (2N + 1)$, $i = -N + 1, -N + 2, \cdots, -1, 0, 1, \cdots, N$ and $j = -N, -N + 1, \cdots, -1, 0, 1, \cdots, N$ if $K_e(k) \neq 0$ and $i = -N, -N + 1, \cdots, -1, 0, 1, \cdots, N$ and $j = -N + 1, -N + 2, \cdots, -1, 0, 1, \cdots, N$ if $K_c(k) \neq 0$.

Equation (8) indicates that the centers of the output membership function at the unexplored area are set to zero reflecting no information about the control surface in this area. Equation (11) shows how the remaining centers of the output membership functions are shifted toward the area that is currently of interest.

This algorithm has three disadvantages that affect the transient performance of the system:

(1) The movement of the auto-attentive active area is slow (single step/sample);

(2) The algorithm will not be able to build enough stable control action to match the transient performance of the reference model.

(3) The system is not able to memorize the overall control surface.

The following section proposes a possible solution to the first disadvantage.

3 ENHANCED AUTO-ATTENTIVE APPROACH

As described in section II, the auto attentive active area moves a step of width w (K_e and K_c have values of –1,0,1) in the direction of the movement of the active learning region when the active learning region hits the boundaries of the auto-attentive area. In the case where the area that is currently of interest is too far from the active learning region, the movement mechanism will be very slow. As an example, assume the auto-attentive active region covers just 1% of the dynamic range of two inputs with 11 membership functions for each input. In this case, if the auto-attentive region is at the left edge of dynamic range, and the area that is currently of interest is at the right edge, then it would take 1000 samples from the controller to move the auto-attentive region to the area of interest.

The proposed modification is to shift the centers of the input membership functions similar to equation (4) but with K_e and K_c calculated as follow:

$$K_e(k) = \lfloor e - C_N^e \rfloor \text{ if } \min(\mu^e_{A_N}, \mu^e_{A_j}) > 0 \quad (12\text{-a})$$

$$K_e(k) = \lfloor e - C_{-N}^e \rfloor \text{ if } \min(\mu^e_{A_{-N}}, \mu^e_{A_j}) > 0 \quad (12\text{-b})$$

$$K_c(k) = \lfloor c - C_N^c \rfloor \text{ if } \min(\mu^e_{A_i}, \mu^e_{A_N}) > 0 \quad (13\text{-a})$$

$$K_c(k) = \lfloor e - C_{-N}^c \rfloor \text{ if } \min(\mu^e_{A_i}, \mu^e_{A_{-N}}) > 0 \quad (13\text{-b})$$

and the centers of the output membership functions are given by:

$$C_l^u(k) = 0 \quad (14)$$

for $l = 1, 2, 3, \cdots, R$ where R is the total number of rules at the rule-base if $|K_e| > N$ or $|K_c| > N$ and l is identical to equations (10) and (11) if $|K_e| < N$ or $|K_c| < N$ and the other centers of the output membership functions will be shifted as follows:

$$C_n^u(k) = C_{n-1}^u(k) \text{ if } |K_e| < N \text{ or } |K_c| < N \quad (15)$$

where

$n = (i * N + N + 1) + (j + N) * (2N + 1)$, $i = -N + K_e, -N + K_e + 1, \cdots, -1, 0, 1, \cdots, N$ and $j = -N, -N + 1, \cdots, -1, 0, 1, \cdots, N$ if $K_e(k) \neq 0$ and $i = -N, -N + 1, \cdots, -1, 0, 1, \cdots, N$ and $j = -N + K_c, -N + K_c + 1, \cdots, -1, 0, 1, \cdots, N$ if $K_c(k) \neq 0$.

Equation (14) indicates that if the step width is larger than the entire auto-attentive area the whole centers will be rest to zeros. In the case where the step width is less than the auto-attentive region then just the part that is moved to the unexplored area will be reset and the other part will be shifted to the area that is currently of interest

4 SIMULATIONS

The induction motor model used for the simulation is given in [7]. The parameters of the model are given in Table (1).

Description	Value	Units
Rated Power	0.5	Hp
Rated current	1.3	A
Rated speed	1500	rpm
Rated line voltage	208	V
Stator inductance	0.397416	H
Rotor inductance	0.378417	H
Mutual inductance	0.372084	H
Stator resistance	9.652065	Ω
Rotor resistance	0.378417	Ω
Moment of inertia	0.00439811	kg-m^2
viscous damping constant	0.00028587	N-m-s
Number of pole pairs	2	

Table (1) Induction motor parameters

To examine the performance of the auto-attentive approach and the enhanced one, and to study the advantages and the drawbacks of such algorithms the input scaling factors were set to high values (the auto-attentive area covers 0.1% of the dynamic range of the inputs). Figures (1) and (2) show the system response when using the conventional auto-attentive approach and enhanced approach respectively. It can be noted that both of them have very poor transient performance. However, the latter is significantly better than the former. Note that neither algorithm is able to build sufficient current at the transient to match the transient performance of the reference model known that it is reachable performance by the induction machine. This is because of the adaptation mechanism as indicated before. The AF curves in both figures are high. AF curve shows that despite of the high adaptation effort the control mechanism is not able to achieve the desired performance.

Figures (3) and (4) show the response of the auto-attentive approach with an experience model using the conventional and enhanced mechanisms respectively. In both cases the experience model rule-base was built using average knowledge about the induction motor. The transient performances have been improved significantly comparatively to the controller without an experience model. This improvement is due to the ability of the mechanism (in both cases) to load near-optimal control action from the experience model to the auto-attentive area as it moves. Hence, the adaptation mechanism starts to update the rules at the auto-attentive area and update the information saved in the experience model at the same time using the learning mechanism of the experience model. Note that the AF curves in both figures have less value than in figures (1) and (2) which indicate less adaptation effort and high performance mechanism.

Figures (3) and (4) indicate that the two algorithms have superior rejection of the variation of the torque load (note the performance at the transient before and after the torque load variation). In the case of the enhanced auto-attentive algorithm the auto-attentive area goes directly to the area that is currently of interest and loads all the rules at the rule-base with values from the experience model. If the values are not optimal it needs more time to adapt them. For the conventional algorithm, the slow movement allows for better response to such situation. However, The learning process of the experience model in the enhanced algorithm is more efficient where it directly target the designated area of the control surface. On other hand, the learning mechanism of the experience model in the conventional algorithm is targeting other areas in the first few samples, which may destroy the collected information in the experience model in earlier training phases. To prove that the enhanced algorithm has better learning capability, step sequences were applied to both algorithms for longer durations with no variation in the torque load to allow for training.

Figures (5) and (6) show the response of the two algorithms after 20 seconds of training. It can be noted that the enhanced algorithm has better learning and transient performance than the conventional one (see error curves). Table (2) shows a comparison of different control algorithms to the performance of the system using some performance measurement factors. The performance factors that used in this work are the integral absolute error (IAE), the integral square error (ISE), the integral multiple time absolute error (ITAE).

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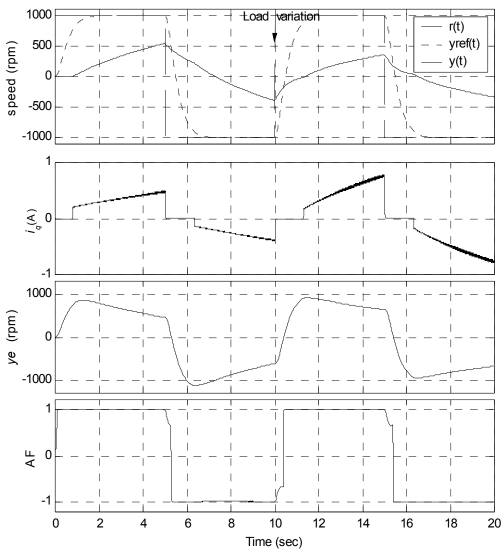

Figure (1) step response (conventional auto-attentive approach with large input scaling factors.

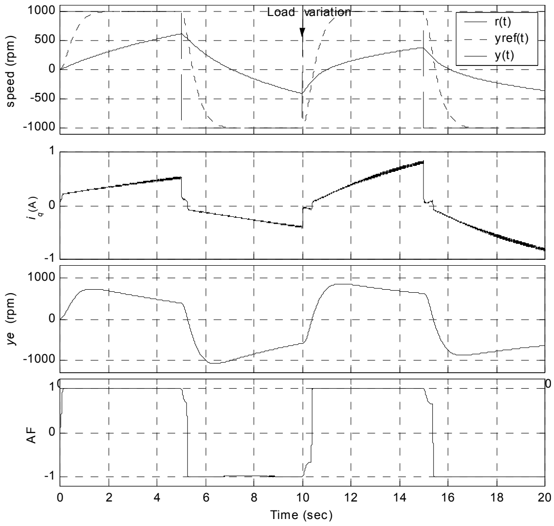

Figure (2) step response (enhanced auto-attentive approach with large input scaling factors)

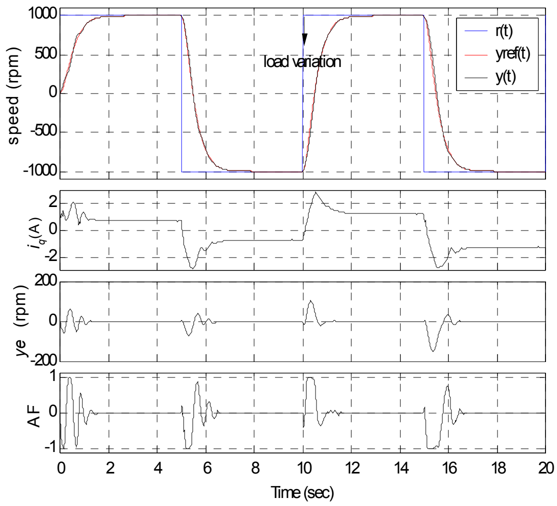

Figure (3) Control system response using auto-attentive approach with experience model

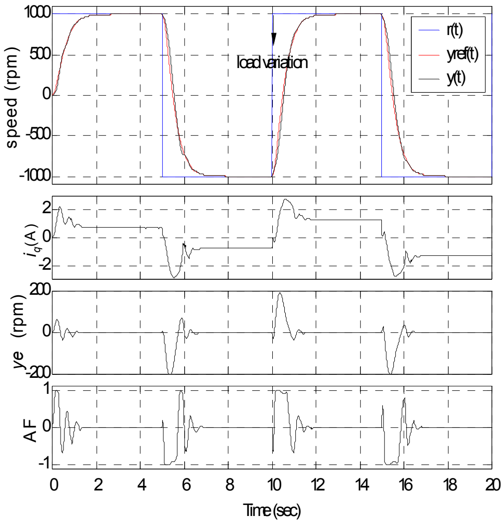

Figure (4) Control system response using enhanced auto-attentive approach with experience model

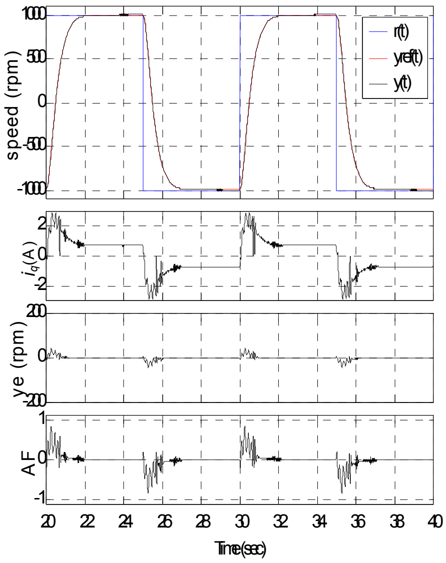

Figure (5) Control system response after 20 sec of training using conventional auto-attentive approach with experience model

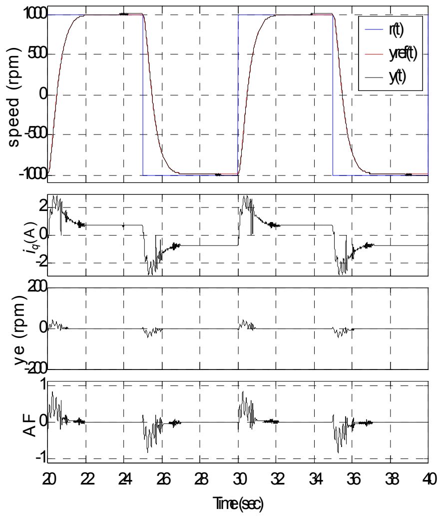

Figure (6) Control system response after 20 sec of training using enhanced auto-attentive approach with experience model

Algorithms	IAE*e+3	ISE*e+3	ITAE*e+3
Auto-Attentive approach	14	11392	148
Enhanced auto-attentive approach	14	10082	141
Auto-attentive approach with experience model after training	0.0701	2.4891	0.7252
Enhanced Auto-attentive approach with experience model after training	0.0636	1.5559	0.6202

Table (2) Performance comparison of different control algorithms (simulation results)