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Adaptive Recurrent Wavelet Fuzzy CMAC Tracking Control for De-icing Robot Manipulator

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***Abstract*—In this paper, a controller is proposed for a *n*-link robot manipulator to achieve the high-precision position tracking based on a recurrent wavelet fuzzy cerebellar model articulation controller (RWFCMAC) which is applied to imitate an ideal controller due to it incorporates the advantages of the wavelet decomposition property, dynamic response with a fuzzy CMAC fast learning ability and an adaptive single-input fuzzy compensator (ASIFC) is designed to attenuate the effect of the approximation error caused by the RWFCMAC approximator. The online tuning laws of RWFCMAC and ASIFC parameters are derived according to gradient descent method and lyapunov function so that the stability of the system can be guaranteed. Finally, through the simulation results demonstrate the effectiveness of the proposed control scheme for novel three-link De-Icing robot manipulator with unknown dynamic functions.**

***Index Terms*—Wavelet, Cerebellar model articulation controller (CMAC), De-icing robot manipulator, single-input fuzzy compensator.**

I. INTRODUCTION

Ice coating in power networks imposes heavy load upon transmission lines and could result in trip, disconnection, power-tower collapse and power interruption, which has posed a serious challenge to many state grids. Adopting robot deicing has advantages avoiding risk of casualties, electricity supply being cut off and transfer load. The deicing robot can be used for line inspection when there is no need for deicing. The prospective will be more expansive in the future. In general, De-Icing robot manipulators have to face various uncertainties in their dynamics, such as friction and external disturbance. It is difficult to establish exactly mathematical model for the design of a model-based control system. In order to deal with this problem, the braches of current control theories are broad including classical control: neural networks (NNs) control [1–3], adaptive fuzzy logic control (FLCs) [4–6] or adaptive fuzzy-neural networks (FNNs) [7–9]. They are classified as adaptive intelligent control based on conventional adaptive control techniques where fuzzy systems or neural networks are utilized to approximate a nonlinear function of the dynamical systems. However, many adaptive approaches are rejected as being overly computationally intensive because of the real-time parameter identification and required control design.

Fuzzy logic (FLCs) and neural network (NNs) control has found extensive applications, in which FLCs are suitable for simple second order plants. However, in case of complex higher order plants, the rule antecedent requires a huge number of control rules and much effort to create. The NNs are a model-free approach, which can approximate a linear or nonlinear mapping to arbitrary accuracy [1–3]. However, the learning speed of the NNs is slow, since all the weights are updated during each learning cycle. Based on the advantages of the fuzzy and neural network, the fuzzy neural network (FNN) which incorporates advantages of fuzzy inference and neuron-learning has been developed and it’ effectiveness is demonstrated in solving control problems [10–13].

Recently, many applications have been implemented quite successfully based on wavelet neural networks (WNNs) which combine the learning ability of network and capability of wavelet decomposition property [14–17]. Different from conventional NNs, the membership functions of WNN is wavelet functions which are spatially localized, so, the WNNs are capable of learning more efficiently than conventional NNs for control and system identification as has been demonstrated in [14, 16]. As a result, WNNs has been considerable interest in the applications to deal with uncertainties and nonlinearity control system as is shown in [16–17].

To deal with disadvantages of NNs, cerebellar model articulation controller (CMAC) was proposed by Albus in 1975 [18] for the identification and control of complex dynamical systems, due to its advantage of fast learning property, good generalization capability and ease of implementation by hardware [19–21]. The conventional CMACs, regarded as non-fully connected perceptron-like associative memory network with overlapping receptive fields which used constant binary or triangular functions. The disadvantage is that their derivative information is not preserved. For acquiring the derivative information of input and output variables, Chiang and Lin [22] developed a CMAC network with a differentiable Gaussian receptive-field basis function and provided the convergence analysis for this network. The advantages of using CMAC over neural network in many applications were well documented [23–28]. However, in the above CMAC literatures, the structure of CMAC are not merited of the high-level human

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knowledge representation and thinking of fuzzy theory.

In this article, we propose the adaptive recurrent wavelet fuzzy CMAC (RWFCMAC) control system for three-link De-icing robot manipulator to achieve the high-precision position tracking. This control system combines advantages of fuzzy inference system with CMAC and wavelet decomposition capability and a delayed self-recurrent unit in the association memory space and the adaptive single input fuzzy compensator which is designed to deal with the approximation errors between the estimating RWFCMAC and the ideal controller to the stability of system is guarantied. The adaptive tuning laws of RWFCMAC parameters and single input fuzzy compensator are derived through Lyapunov method.

This paper is organized as follows: System description is described in section II. Section III presents RWFCMAC control system. Numerical simulation results of a three-link De-icing robot manipulator are provided to demonstrate the tracking control performance of the proposed RWFCMAC system in section IV. Finally, conclusions are drawn in section V.

II. SYSTEM DESCRIPTION

In general, the dynamic of an n-link robot manipulator may be expressed in the Lagrange following form:

$$M(q)\ddot{q}+C(q,\dot{q})\dot{q}+G(q)=\tau \tag{1}$$

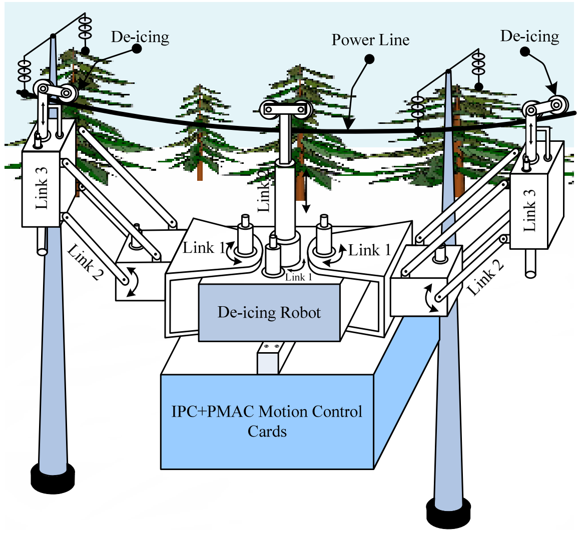
Where $q, \dot{q}, \ddot{q} \in R^n$ are the joint position, velocity and acceleration vectors, respectively, $M(q)\in R^{n\times n}$ denotes the inertia matrix, $C(q,\dot{q})\in R^{n\times n}$ expresses the matrix of centripetal and Coriolis forces, $G(q)\in R^{n\times 1}$ is the gravity vector, $\tau \in R^{n\times 1}$ is the torque vectors exerting on joints. In this paper, a new three-link De-icing robot manipulator, as shown in Fig.1 (b), is utilized to verify dynamic properties are given in section IV. By rewriting (1), the dynamic equation of robot manipulator can be obtained as follows:

$$\begin{aligned}\ddot{q} &= -M^{-1}(q)\big(C(q,\dot{q})\dot{q}+G(q)\big)+M^{-1}(q)\tau \\ &= f(x)+g(x)\tau\end{aligned} \tag{2}$$

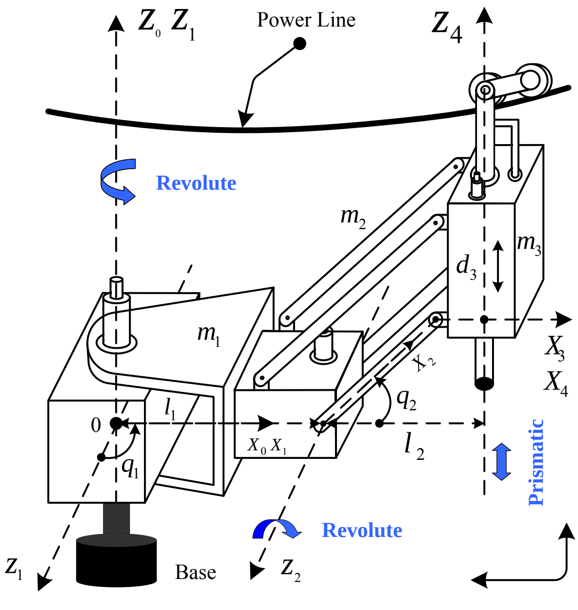
$$f(x)=\begin{pmatrix} f_1(x)\\ f_2(x)\\ \vdots \\ f_n(x)\end{pmatrix} = -M^{-1}(q)\big(C(q,\dot{q})\dot{q}+G(q)\big)\in R^{n\times 1},$$

$$g(x)=\begin{pmatrix} g_{11}(x) & \cdots & g_{1n}(x)\\ \vdots & \ddots & \vdots \\ g_{n1}(x) & \cdots & g_{nn}(x)\end{pmatrix} = M^{-1}(q)\in R^{n\times n}.$$

Where $f(x)$, $g(x)$ are nonlinear dynamic functions which are difficult to determine exactly or can not even obtain. So, we can not establish model-based control system. In order to with this problem, here we assume that actual value $f(x)$ and $g(x)$ can be separated as nominal part denoted by $F_0(x)$, $G_0(x)$, in which $G_0(x)$, is assumed to be positive, differentiable and $G_0^{-1}(x)$ exists for all q. We assume that $L(x,t)$ is represented as the unknown lumped uncertainly and $x=[q^T, \dot{q}^T]^T$ is vector which represents the joint



(a)



(b)

Fig.1. Architecture of three-link De-icing robot manipulator.

position and velocity. Finally, the system (2) can be rewritten as follows:

$$\ddot{q}(t)=F_0(x)+G_0(x)\tau+L(x,t) \tag{3}$$

The control problem is to force $q(t)\in R^n$ to track a given bounded reference input signal $q_d(t)\in R^n$. Let $e(t)\in R^n$ be the tracking error as follows:

$$e=q_d(t)-q(t) \tag{4}$$

and the system tracking error vector is defined as

$$E \underline{\underline{\Delta}} [e^T \quad \dot{e}^T \quad \cdots \quad {e^{n-1}}^T]^T \in R^{nn} \tag{5}$$

If the nominal parts $F_0(x)$, $G_0(x)$ and the uncertainly $L(x,t)$ are exactly known, then an ideal controller can be designed as follows:

$$\tau^*(t)=\frac{1}{G_0(x)}\big[\,\ddot{q}_d(t)-F_0(x)-L(x,t)+KE\,\big] \tag{6}$$

By substituting the ideal controller (6) into (3), the error dynamic equation is given as follows:

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$$e^n(t) + K^T E = 0 \qquad (7)$$

It is obvious that errors will be asymptotically tend to zero if the gain matrices of K is determined so that the roots of the characteristic polynomial (7) lie strictly in the open left haft of complex plane. However, the ideal controller in (6) can not determine, because of $L(x,t)$ is exactly unknown for practical applications. So, in order to this problem, a proposed control system is shown in Fig. 2 which consists of a RWFCMAC and an adaptive single

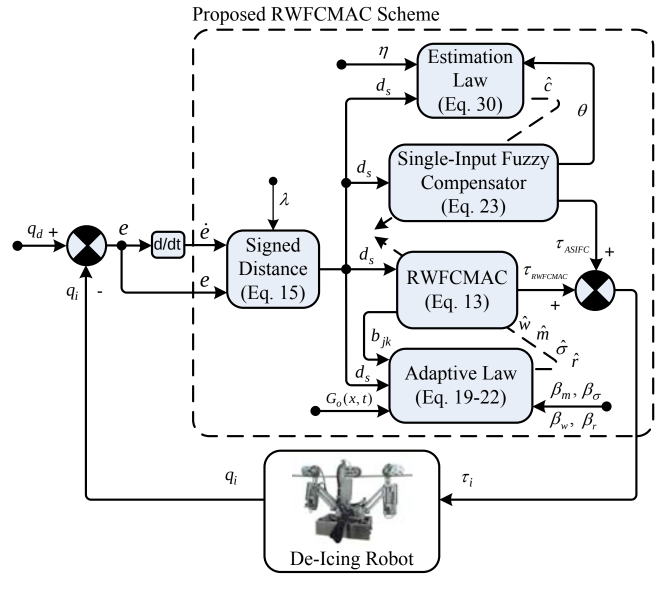

Fig. 2. Block diagram of proposed RWFCMAC control system.

input fuzzy compensator with the following form:

$$\tau = \tau_{RWFCMAC} + \tau_{ASIFC} = \hat{w}^T \hat{b} + \tau_{ASIFC}, \qquad (8)$$

Where $\tau_{RWFCMAC}$ is used to mimic the ideal controller in (6) and an adaptive single input fuzzy compensator τ_{ASIFC} is used to efficiently suppress the influence of the residual approximation error between the ideal controller and the RWFCMAC approximation.

III. ADAPTIVE RWFCMAC CONTROL SYSTEM

A. *Brief of the RWFCMAC*

The main difference between the FCMAC and the original CMAC is that association layer in the FCMAC is the rule layer which is represented as follows.

R^l : if X_1 is μ_{1jk} and X_2 is $\mu_{2jk}, \cdots, X_{n_i}$ is μ_{ijk} then

$$O_{jk} = w_{jk}$$

For $i = 1, 2, \cdots, n_i$, $j = 1, 2, \cdots, n_j$, $k = 1, 2, \cdots, n_k$ and $l = 1, 2, \cdots, n_k n_j$. (9)

Where n_i is the number of the input dimension, n_j is the number of the layers for each input dimension, n_k is the number of blocks for each layer, $l = n_k n_j$ is the number of the fuzzy rules and μ_{ijk} is the fuzzy set for ith input, jth layer and kth block, w_{jk} is the output weight in the consequent part.

Based on the [29] a novel RWFCMAC is represented and shown in Fig. 3. It is combines a wavelet function with the

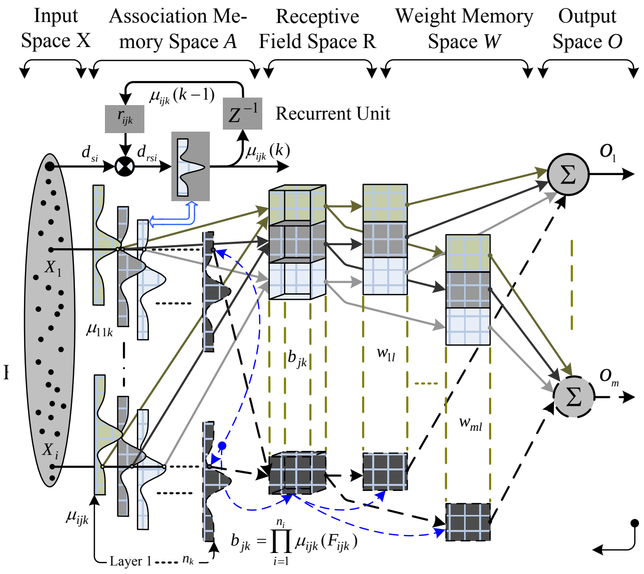

Fig. 3. Architecture of a RWFCMAC

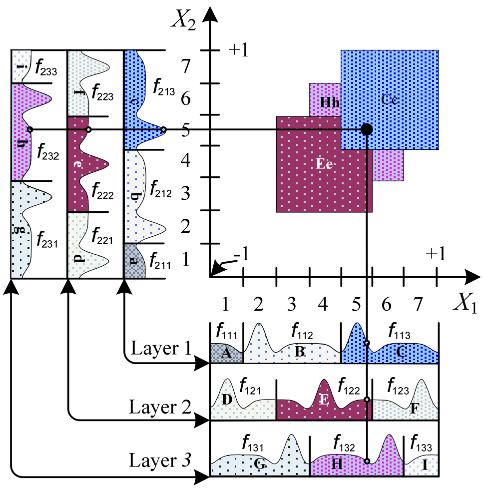

Fig. 4. Block division of RWFCMAC with wavelet function

FCMAC including input, association memory, receptive field, and output spaces, is proposed to implement the RWFCMAC estimate in RWFCMAC control system shows in Fig. 2. The signal propagation is introduced according to functional mapping as follows:

The first mapping $X : X \to A$: assume that each input state variable $X = [X_1 \quad X_2 \quad \cdots \quad X_{n_i}]$ can be quantized into n_e discrete states and that the information of a quantized state is regarded as region a wavelet receptive-field basic function for each layer. The mother wavelet is a family of wavelets. The first derivative of basic Gaussian function for each layer is given here as a mother wavelet which can be represented as follows:

$$\mu_{ijk}(F_{ijk}) = -F_{ijk} \exp\left[-\frac{F_{ijk}^2}{2}\right] \qquad (10)$$

$$i = 1, 2, \cdots, n_i, \quad k = 1, 2, \cdots, n_k$$

Where $F_{ijk} = (d_{rsi}(k) - m_{ijk})/\sigma_{ijk}$, m_{ijk} is a translation parameter and σ_{ijk} is dilation. In addition, the input of this block can be represented as

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$$d_{rsi}(k) = d_{si}(k) + r_{ijk}\mu_{ijk}(k-1) \tag{11}$$

Where r_{ijk} is the recurrent gain, k is denotes the time step, and $\mu_{ijk}(k-1)$ denotes the value of $\mu_{ijk}(k)$ through a time delay. Clearly, the input of this block contains the memory term $\mu_{ijk}(k-1)$, which stores the past information of the network and presents the dynamic mapping.

The second mapping $A: A \rightarrow R$: the information μ_{ijk} of each *k*th block and each *j*th layer relates to each location of receptive field space. The Fig. 4 illustrates a structure of two-dimension $(n_i = 2)$ RWFCMAC with wavelet basic function with $n_j = 3$ and $n_k = 3$ case. Areas of receptive field space is formed by multiple-input regions are called hypercube; i.e. in the fuzzy rules in (9), the product is used as the "and" computation in the consequent part. The firing of each state in *j*th each layer and *k*th each block can be obtained the weigh of each hypercube corresponding. Assume that in 2-D RWFCMAC case is shown in Fig. 4, where input state vector is (6, 3), then, the content of *l*th hypercube can be obtained as follows:

$$b_{jk} = \prod_{i=1}^{n_i} \mu_{ijk}(F_{ijk}) \tag{12}$$

For $j = 1, 2, \cdots, n_j$ and $k = 1, 2, \cdots, n_k$

Finally, The RWFCMAC output is the algebraic sum of the activated weighs with the hypercube elements. The output mathematic form can be expressed as follows:

$$\tau = \begin{bmatrix} w_{11} & \cdots & w_{1k} & \cdots & w_{j1} & \cdots & w_{jk} \end{bmatrix} \begin{bmatrix} b_{11} \\ \vdots \\ b_{1k} \\ \vdots \\ b_{j1} \\ \vdots \\ b_{jk} \end{bmatrix}$$

$$= \sum_{j=1}^{n_j}\sum_{k=1}^{n_k} w_{jk} b_{jk}\left(F_{ijk}\right) \tag{13}$$

$$= \sum_{j=1}^{n_j}\sum_{k=1}^{n_k} w_{jk} \prod_{i=1}^{n_i} \mu_{ijk}(F_{ijk})$$

For $j = 1, 2, \cdots, n_j$, $k = 1, 2, \cdots, n_k$ and $i = 1, 2, \cdots, n_i$.

B. On-line learning algorithm

Based on [30–31], the system tracking error vector $\underline{E} \in R^n$ is transformed into a single variable, termed the signed distance $d_{si} \in R^m$, which is the distance from an actual state $\underline{E} \in R^n$ to the switching line as shown in Fig. 5 for a 2-D input. The switching line is defined as follows:

$$\dot{e} + \lambda_1 e = 0 \tag{14}$$

Where $\lambda_{n-1} \in R^{n-1}$ is a constant. Then, the signed distance between the switching line and operating point $\underline{E} \in R^n$ can be expressed by the following equation:

$$d_s = \frac{\dot{e} + \lambda_1 e}{\sqrt{1+\lambda_1^2}} = \Gamma\left(\dot{e} + \lambda_1 e\right) \tag{15}$$

Where $\Gamma = 1\big/\left(\sqrt{1+\lambda_1^2}\right)$ is a positive constant, by taking the time derivative of (15) and using (3), (8). We have

$$\begin{aligned} \dot{d}_s &= \Gamma\left(\ddot{e} + \lambda_1 \dot{e}\right) \\ &= \Gamma\Big(-F_0(x,t) - G_0(x,t)(\hat{w}^T\hat{b} + \tau_{FC}) \\ &\quad + \ddot{q}_d(t) - L(x,t) + \lambda_1\dot{e}\Big) \end{aligned} \tag{16}$$

The energy function is defined as

$$V(d_s(t)) = \frac{1}{2} d_s^2(t) \tag{17}$$

By multiplying both sides of (16) by $d_s(t)$, yields

$$\begin{aligned} d_s(t)\dot{d}_s(t) = -\Gamma\Big(& d_s(t)F_0(x,t) - d_s(t)G_0(x,t)(\hat{w}^T\hat{b} \\ & + \tau_{FC}) + d_s(t)(\ddot{q}_d(t) - L(x,t) + \lambda_1\dot{e})\Big) \end{aligned} \tag{18}$$

With the energy function $V(d_s(t))$, the parameters updating law based on the normalized gradient descent method can be derived as follows

The updating law for the *kth* weight memory can be derived according to

$$\begin{aligned} \dot{\hat{w}}_{jk} &= -\beta_w \frac{\partial d_s(t)\dot{d}_s(t)}{\partial \tau_{RWFCMAC}} \frac{\partial \tau_{RWFCMAC}}{\partial \hat{w}_{jk}} \\ &= \beta_w \Gamma\, d_s(t) G_0(x,t) \hat{b}_{jk}(F_{ijk}) \end{aligned} \tag{19}$$

Where β_w is positive learning rate for the output weight memory w_{jk}.

The translations, dilations and recurrent gain of the *kth* mother wavelet function can be also updated according to

$$\begin{aligned} \dot{\hat{m}}_{ijk} &= -\beta_m \frac{\partial d_s(t)\dot{d}_s(t)}{\partial \tau_{RWFCMAC}} \frac{\partial \tau_{RWFCMAC}}{\partial \hat{b}_{jk}} \frac{\partial b_{jk}}{\partial f_{ijk}} \frac{\partial f_{ijk}}{\partial \hat{m}_{ijk}} \\ &= -\beta_m \Gamma d_s(t) G_0(x,t) \hat{w}_{jk} b_{jk} \frac{1 - F_{ijk}^2}{(X_i - \hat{m}_{ijk})} \end{aligned} \tag{20}$$

$$\begin{aligned} \dot{\hat{\sigma}}_{ijk} &= -\beta_\sigma \frac{\partial d_s(t)\dot{d}_s(t)}{\partial \tau_{RWFCMAC}} \frac{\partial \tau_{RWFCMAC}}{\partial \hat{b}_{jk}} \frac{\partial b_{jk}}{\partial f_{ijk}} \frac{\partial f_{ijk}}{\partial \hat{\sigma}_{ijk}} \\ &= -\beta_\sigma \Gamma d_s(t) G_0(x,t) \hat{w}_{jk} b_{jk} \frac{1 - F_{ijk}^2}{\hat{\sigma}_{ijk}} \end{aligned} \tag{21}$$

$$\begin{aligned} \dot{\hat{r}}_{ijk} &= -\beta_r \frac{\partial d_s(t)\dot{d}_s(t)}{\partial \tau_{RWFCMAC}} \frac{\partial \tau_{RWFCMAC}}{\partial \mu_{ij}} \frac{\partial \mu_{ij}}{\partial F_{ij}} \frac{\partial F_{ij}}{\partial r_{ij}} \\ &= \beta_r \Gamma d_s(t) G_0(x,t) \hat{w}_{jk} b_{jk} \frac{1 - F_{ijk}^2}{(d_s - \hat{m}_{ijk})} \mu_{ijk}(k-1) \end{aligned} \tag{22}$$

Where β_m, β_σ and β_r are positive learning rates for the

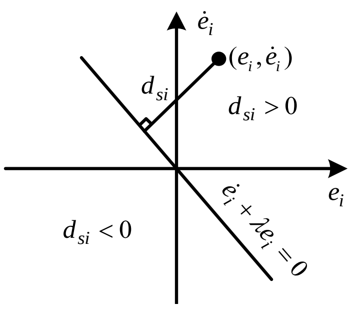

Fig.5. Derivation of a signed distance.

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translation $\hat{m}_{ijk}$, dilation $\hat{\sigma}_{ijk}$ and recurrent gain $\hat{r}_{ijk}$.

C. Single input fuzzy controller Design

The update laws of equations (19), (20), (21) and (22) require a proper choice of the learning rates β_w, β_m, β_σ and β_r in order to the convergence of the output errors are guaranteed; however, this is not easy which depends on each person's experience. In addition, the RWFCMAC is used to approximate the imprecise model or un-model of the *n*-link robot manipulator through learning. However, there exist errors between the estimating RWFCMAC and the ideal controller. So, to deal with these problems, the single input fuzzy compensator is designed to cope with the approximation errors and the stability of system is guarantied.

In this section, an adaptive single-input fuzzy compensator (ASIFC) strategy combines an adaptive fuzzy rule and a single variable, termed the signed distance $d_{si} \in R^m$ [30–31] which reduce the *n*-dimensional fuzzy rules table into one-dimensional fuzzy rules for this fuzzy compensator. Every fuzzy rule is composed of an antecedent and a consequent part, a general form of the fuzzy rules can be represented as follows:

$$R_o: \text{ If } d_{si} \text{ is } \theta_{io}, \text{ Then } \tau_i \text{ is } c_{io} \quad (23)$$
$$i = 1, 2 \cdots n_i,\ o = 1, 2, \cdots n_o$$

Where R_j, θ_{io} and w_{io} are the oth rule, the fuzzy subsets of the input and output, respectively. Here, the membership functions for the input are chosen to be a triangular type as show in Fig. 6. The can be expressed as the following form:

$$\theta_{io} = \frac{1}{a_i}\left(-\left|d_{si} - b_{io}\right| + a_i\right) \quad (24)$$

Where d_{si} is *i*th input variable, a_i is the *i*th distribution span of the membership function and b_{io} is the parameter corresponding to the value 1 of the membership function. In this paper, the de-fuzzification of the output is obtained by the height method.

$$\tau_{i\,ASIFC} = \frac{\sum_{o=1}^{n_o} \theta_{io} c_{io}}{\sum_{o=1}^{n_o} \theta_{io}} = C_i^T \theta_i \quad (25)$$

Where $\theta_i = \begin{bmatrix}\theta_{i1} & \theta_{i2} & \cdots & \theta_{io}\end{bmatrix}^T \in R^o$ is a firing strength vector of rule and $C_i = \begin{bmatrix}c_{i1} & c_{i2} & \cdots & c_{io}\end{bmatrix}^T \in R^o$ is the consequent parameter vector which is adjusted by the adaptive rule.

Assume that, the approximation error between the ideal controller and the estimating RWFCMAC is $\varepsilon(t)$. Thus; the ideal controller can be represented as the following form:

$$\tau^* = \tau_{RWFCMAC} + \varepsilon(t) \quad (26)$$

Substituting (26) and (6) into (16), then, the closed-loop filtered error dynamics becomes:

$$\dot{d}_s = \Gamma\left(\ddot{e} + \lambda_1 \dot{e}\right) = \Gamma\left(G_0(x,t)(\varepsilon(t) - \tau_{ASIFC})\right) \quad (27)$$

Theorem 1: Consider an *n*-link robot manipulator represented (2). If the control law of RWFCMAC is designed as (8) which in $\tau_{RWFCMAC}$ is represented in (13) with the online parameter update law of RWFCMAC given as (19)-(22) and the adaptive estimation law and τ_{ASIFC} are designed as (30) and (25), then the stability of the proposed RWFCMAC control system can be ensured

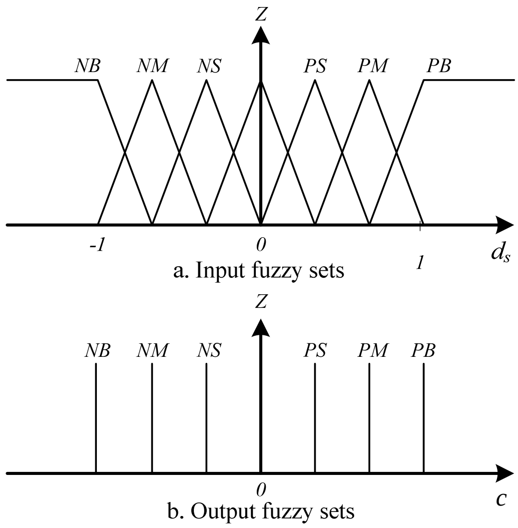

Fig. 6. Input and output membership functions of adaptive single-input fuzzy compensator.

Proof: Define a Lyapunov function candidate as

$$V(d_s(t), c) = \frac{1}{2\Gamma} d_s^2(t) + \frac{1}{2\eta} tr(\tilde{c}^T \tilde{c}) \quad (28)$$

Where η is the learning rate for the single input fuzzy compensator. By differentiating (28) with respect to time and using (25) and (27), we can obtain.

$$\begin{aligned}
\dot{V}(d_s, c) &= \frac{1}{\Gamma} d_s(t)\dot{d}_s(t) + \frac{1}{\eta} tr(\tilde{c}^T \dot{\tilde{c}}) \\
&= G_o(x,t)\left[d_s(t)\varepsilon(t) - \hat{c}^T d_s(t)\theta + \frac{1}{\eta} tr(\tilde{c}^T \dot{\tilde{c}}) \right] \\
&\le G_o(x,t)\Big[\left|d_s(t)\right|\left|\varepsilon(t)\right| - \hat{c}^T d_s(t)\theta + c^{*T} d_s(t)\theta \\
&\quad - c^{*T} d_s(t)\theta + \frac{1}{\eta} tr(\tilde{c}^T \dot{\tilde{c}}) \Big] \\
&= G_o(x,t)\Big[\left|d_s(t)\right|\left|\varepsilon(t)\right| - \tilde{c}^T d_s(t)\theta - c^{*T} d_s(t)\theta \\
&\quad \frac{1}{\eta} tr(\tilde{c}^T \dot{\tilde{c}}) \Big] \\
&= G_o(x,t)\Big[\tilde{c}^T\left[d_s(t)\theta + \frac{1}{\eta}\dot{\tilde{c}} \right] + \left|d_s(t)\right|\left|\varepsilon(t)\right| \\
&\quad - c^* \left|d_s(t)\right|\left|\theta\right| \Big]
\end{aligned} \quad (29)$$

If the estimation law and the optimal value of c are chosen as (30) and (31).

$$\dot{\hat{c}} = -\dot{\tilde{c}} = \eta d_s(t)\theta \quad (30)$$

$$c^* = \frac{\left|\varepsilon(t)\right|}{norm(\theta)} + \Omega \quad (31)$$

Where Ω is a positive constant. Then, from (29) becomes:

$$\dot{V} \le G_o(x,t)\left[|d_s(t)||\varepsilon(t)| - d_s(t)\left(|\varepsilon(t)| + \Omega norm(\theta)\right)\right]$$
$$= -G_o(q,t)\Omega|d_s(t)|norm(\theta) \le 0 \qquad (32)$$

Since $\dot{V}(d_s(t), c(t))$ is a negative semi-definite function, i.e. $V(d_s(t), c(t)) \le V(d_s(0), c(0))$, it implies that $d_s(t)$ and $\tilde{c}$ is bounded functions. Let function $h(t) \equiv G_o(x,t)\Omega|d_s(t)|norm(\theta) \le \dot{V}(d_s(t), c(t))$ and integrate function $h(t)$ with respect to time

$$\int_0^t h(t)d\tau \le V(d_s(0), c(0)) - V(d_s(t), c(t)) \qquad (33)$$

Because $V(d_s(0), c(0))$ is a bounded function, and $V(d_s(t), c(t))$ is a non-increasing and bounded function, the following result can be concluded:

$$\lim_{t\to\infty}\int_0^t h(\tau)\,d\tau < \infty \qquad (34)$$

In addition, $\dot{h}(t)$ is bounded; thus, by Barbalat's lemma can be shown that $\lim_{t\to\infty} h(t) = 0$. It can imply that d_s will be converging to zero as time tends to infinite.

IV. SIMULATION RESULTS

A three-link De-icing robot manipulator as shown in Fig.1 is utilized in this paper to verify the effectiveness of the proposed control scheme. The detailed system parameters of this robot manipulator are given as: link mass m_1, m_2, m_3 (kg), lengths l_1, l_2 (m), angular positions q_1, q_2 (rad) and displacement position d_3 (m).

The parameters for the equation of motion (1) can be represented as follow:

$$M(q) = \begin{bmatrix} M_{11} & M_{12} & M_{13} \\ M_{21} & M_{22} & M_{23} \\ M_{31} & M_{32} & M_{33} \end{bmatrix}$$

$$M_{11} = 9/4m_1l_1 + m_2(1/4c_2l_2 + l_1^2 + l_2l_1(c_1^2 - s_1^2)) +$$
$$m_3(c_2l_2^2 + l_2^2 + 2c_2l_1l_2)$$

$$M_{22} = 1/4m_2l_2^2 + m_3l_2^2 + 4/3m_1l_1^2$$

$$M_{23} = M_{32} = m_3c_2l_2$$

$$M_{33} = m_3$$

$$M_{12} = M_{13} = M_{21} = M_{31} = 0$$

$$C(\dot{q}) = \begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{32} & C_{33} \end{bmatrix}$$

$$C_{11} = -8m_2l_1l_2c_1s_1\dot{q}_1 + (-1/2m_2s_2c_2l_2^2 + m_3(-2s_2c_2l_2^2$$
$$-2s_2l_1l_2)\dot{q}_2$$

$$C_{21} = (-1/2m_2s_2c_2l_2^2 + m_3(-2s_2c_2l_2^2 - 2s_2l_1l_2)\dot{q}_1$$

$$C_{22} = -m_3s_2l_2\dot{d}_3$$

$$C_{23} = -2m_3s_2l_2\dot{q}_2$$

$$C_{32} = -m_3s_2l_2\dot{q}_2$$

$$C_{12} = C_{13} = C_{31} = C_{33} = 0$$

$$G(q) = \begin{bmatrix} (1/2c_1c_2l_2 + c_1l_1)m_2g \\ (-1/2s_1s_2l_2m_2 + c_2l_2m_3)g \\ m_3g \end{bmatrix} \qquad (33)$$

Where the shorthand notations $c_1 = \cos(q_1)$, $c_2 = \cos(q_2)$, $s_1 = \sin(q_1)$ and $s_2 = \sin(q_2)$ are used.

For the convenience of the simulation, the nominal parameters of the robotic system are given as $[m_1, m_2, m_3, l_1, l_2, g] = [3, 2, 2.5, 0.14, 0.32, 9.8]$ and the

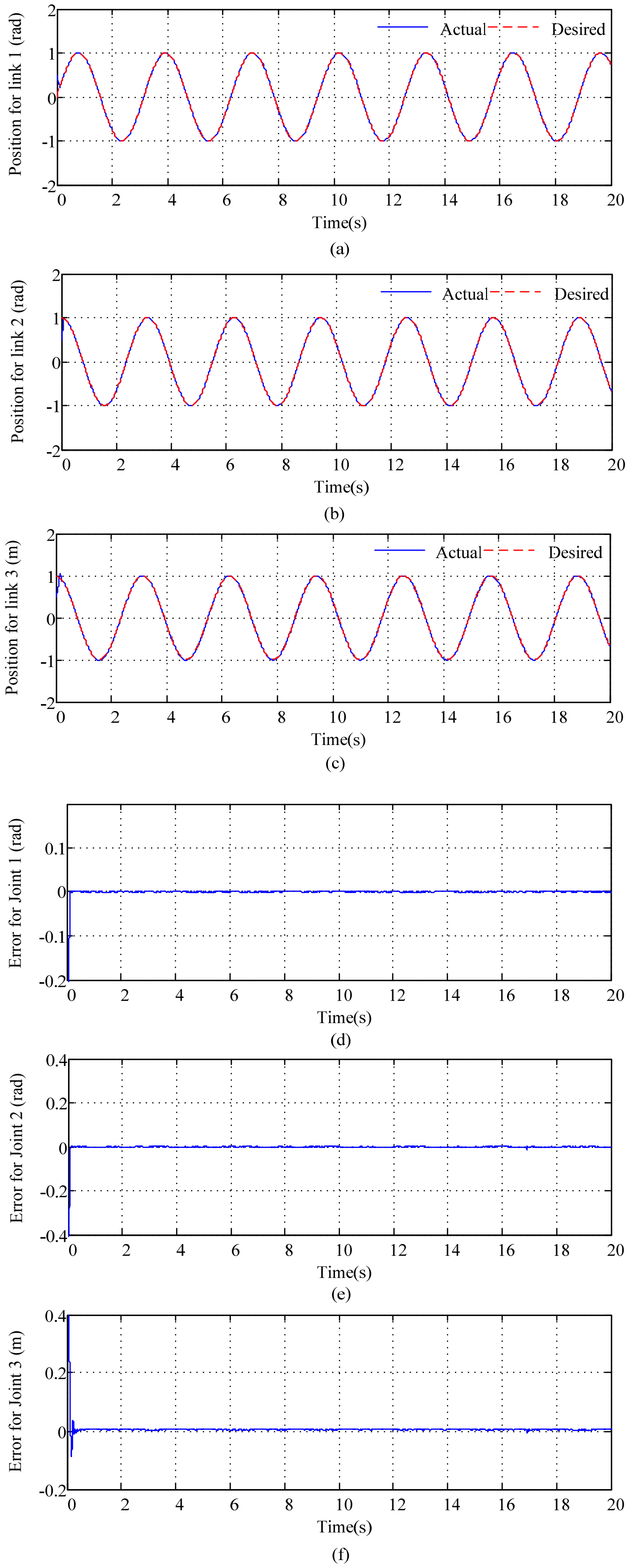

Fig. 7. Simulation position responses and tracking error of the proposed RWFCMAC control system at links 1, 2 and 3.

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initial conditions $[q_1, q_2, d_3, \dot{q}_1, \dot{q}_2, \dot{d}_3] = [0.5, 0, 0.5, 0.5, 0]$. The desired reference trajectories are $q_1(t) = \sin(2t),\ q_2(t) = \cos(2t),\ d_3(t) = \cos(2t)$.

The parameters of proposed control system are chose in the following: $\beta_w = 0.02,\ \beta_m = 0.02,\ \beta_r = 0.02$ and $\beta_\sigma = 0.02$, the inputs of RWFCMAC d_{s1}, d_{s2} and d_{s3}, the translation m_{ijk} and the dilation σ_{ijk} are selected to cover the input space $\{[-1 \quad 1][-1 \quad 1][-1 \quad 1]\}$. The number of layers for each input dimension, the number of blocks for each layer and the rules for each state variable are set respectively as follows $n_j = 3,\ n_k = 3$ and $l = n_j n_k = 9$. For the adaptive single input fuzzy compensator, the signed distance variable was divided into 7 equal-span fuzzy input subsets within $[-1, +1]$ by using the triangular membership function, the learning rate, the distribution span of the membership function and the parameter corresponding to the value of the membership function are selected as $\eta = 0.01,\ a_i = 0.2,\ b_{i1} = -1,\ b_{i2} = -0.6,\ b_{i3} = -0.3,\ b_{i4} = 0,$ $b_{i1} = -1,\quad b_{i5} = 0.3,\quad b_{i6} = 0.6,\quad b_{i7} = 1,$ for $i = 1, 2, 3$ respectively. Finally, the simulation results of the proposed WFCMAC system, the responses of joint position and tracking errors are provided in Fig. 7 (a), (b), (c) and (d), (e), (f), respectively. According to the simulation results as shown in Fig. 7, the joint-position tracking responses of the proposed RWFCMAC control system can achieve favorable tracking performance for three-link De-icing robot manipulator.

V. CONCLUSION

Due to dynamical system has a non-linear characteristic and time-varying behavior. It is difficult to establish exactly mathematical model for the design of a model-based control system. To due with these problems, the most of the control system was proposed based on the intelligent control theory to approximate non-linear function. In this paper, the novel RWFCMAC approximation with ASIFS compensator is also developed and successfully used to control the De-icing robot manipulator. In this proposed scheme, the main RWFCMAC controller incorporates the advantages of the wavelet decomposition property, dynamic response with fuzzy CMAC fast learning ability and the ASIFC compensator is designed to attenuate the effect of the approximation error. It not only ensures the stability of the system but also the input space can be reduced through the signed distance. The online tuning laws of RWFCMAC and ASIFC parameters are derived based on gradient descent method and Lyapunov function. Finally, though the simulation results of the proposed RWFCMAC system can achieve favorable tracking performance for three-link De-icing robot manipulator.

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