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Adaptive Neural Network Second-order Sliding Mode Control of Dual Arm Robots

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Abstract: An adaptive robust control system is considered for dual-arm manipulators (DAM) using the combination of second-order sliding mode control (SOSMC) and neural networks. The SOSMC deals with the system robustness when faced with external disturbances and parametric uncertainties. Meanwhile, the radial basis function network (RBFN) is to constitute an adaptation mechanism for approximating the unknown dynamic model of DAM. The stability of model estimator-integrated controller is analyzed using Lyapuov theory. To show the effectiveness of proposed controller, a four DOFs-DAM is applied as an illustrating example. The results reveal that the controller works well, excellently adapt to no information of robot modeling.

Keywords: Dual-arm manipulator, modelling estimation, neural network, robust adaptive control.

1. INTRODUCTION

Dual-arm manipulators (Fig. 1) are trending to widely application in not only industry but also habitual human life. As robotic co-workers, dual-arm robots can work the same tasks as humans while still guaranteeing the working environment safety. Instead of human role, dual-arm robots are completely able to work in hazardous environments such as pick the radioactive materials up in nuclear factory. As humanoid robots, dual-arm robots with human size are increasingly used in health care and domestic applications such as household chores. The mimic human behaviors, good communication and good interaction with humans are highly required for such the robots.

The researchers have made the significant attention to DAM in which many control strategies have been proposed [1–22]. The traditional methods, such as nonlinear feedback control [1], input-output linearization [2, 3], were applied for controlling DAM. We frequently meet hybrid force/position mode in dual-arm control studies [4–6]. Considering the elasticity of robot arms, paper [6] designed control laws for not only the hybrid force/motion but also vibrating suppression of DAM. Several other papers have a tendency to impedance control on improving the dynamic interaction between robot and environment while assuring the desired motion [7, 8]. Such the control methods [1–8] are not effective in case of modelling imprecision and unknown robot parameters. Furthermore, the stability of robots subjected to parameter uncertainties and external disturbances is not assured.

Fig. 1. An ABB YuMi® dual-arm robot. (Photo courtesy of ABB corporation).

The robust control techniques such as sliding mode control (SMC) [9], combining with modern control methods such as fuzzy logic [10], neural networks [11–17] applied for manipulators treat well the problems of parametric uncertainties and unmodeled systems. The papers related to these topics are classified into two groups: one [11–13] for single-arm manipulators (SAM) and the other [15–17] for DAM.

In the first group, Ge *et al.* [11] developed an RBFN

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controller for singe-arm robotic systems in which neural network modeling approach was used to estimate a part of dynamic model composed of mass matrix $\mathbf{M}(\mathbf{q})$ and gravity vector $\mathbf{G}(\mathbf{q})$. Using RBFN as well, Lee and Choi [12] enhanced paper [11]] by adding the experiment results. In addition, their controller approximates the nonlinear dynamics of SAM by adjusting centers and variances of Gaussian function instead of directly estimating the nonlinear components of robot dynamics. Both studies [11] and [12] developed the controllers using the foundation of passivity based control, a control method was proposed by Slotine and Li [14]. Wang and Chai [13] introduced a terminal SMC for SAM in which a RBFN was integrated to approximate the nonlinear dynamics.

The second group concentrates on adaptive control problems of DAM. Hacioglu *et al*. [15]] combined fuzzy logic with SMC for controlling the cooperative motion of a four DOFs-DAM. The fuzzy logic component was applied for regulating the gains of SMC law in which triangular membership functions were used for fuzzificating the inputs composed of tracking error and its derivative. Based on the core of Slotine and Li adaptive control [14] together with RBFN, Liu *et al*. [16] constructed an adaptive control system for DAM with hysteresis outputs. The RBFN was utilized for designing the adaptation laws to estimate the unknown robot dynamics. Jiang *et al*. [17] proposed a fuzzy adaptive control system for the DAM taking dead-zone nonlinearity of the actuators into account. The fuzzy logic technique was used for approximating the dynamic model of robot.

Machine learning field is applied in several recent articles [18,19,25,26] to constitute online learning algorithms for SAM. However, the learning speed of robot systems mentioned in [18, 19] is rather slow since the structures of controllers are very complicate with many perceptron layers.

Concentrating on high level control in practice, a small number of authors successfully developed and applied the complicated control schemes for industrial DAM since most of control systems of commercial robots are closed to researchers [13]. The modern robots nowadays still widely remain the standard PID controllers because of their indispensable advantages [20]. Several recent studies [20–22] have focused on developing the industrial application of high-level robot control rather than improving the theoretically complex control schemes. Caccavale *et al*. [20] experimentally investigated the impedance control of 6DOFs DAM in which the mechanical impedance behavior was defined in terms of geometrically consistent stiffness. The control structure composed of two loops: the inner loop with PID mechanism was responsible for inner motion of each arm while the outer loop with force and moment sensors imposed the desired impedance behaviors. With the foundation of industrial PID controller, Kruse [21] introduced hybrid motion/force control for a dual-arm industrial robot. The primary components of this system composed of vision-guided motion control, squeeze force control, redundancy resolution, load compensation, and collision avoidance. The desired position was generated from joystick by operator for the object via Microsoft Kinect and the autonomous force controller kept a stable grasp. Gestures detected by the Kinect were applied for dictating the various operation modes. Together with trajectory generation, Nicolis *et al*. [22] experimentally applied the force and velocity control task for an ABB dual-arm prototype manipulator without any force sensor.

From the review mentioned above, we propose a study on low-level control of DAM which has the improvement points and contributions as follows

1) Articles [11–13] developed RBFN based adaptive controls for SAM using either passive control [11, 12] or SMC [13]. Dissimilar to these papers, we design the RBFN based SOSMC for DAM. Control of DAM is much more difficult than that of SAM. Dynamic model of DAM is more complicate than that of SAM. While SAM shows open kinematic modeling, DAM remains complex dynamic coupling and kinematic redundancy. Together with constituting the nonlinear differential equations describing the physical behavior of DAM, the kinematic and dynamic constraints of closed geometrical chain inherently exist. Furthermore, the complex reaction forces between 1st arm- object -2nd arm easily leads to the conflicting motions.

2) Also focusing on DAM, but article [16] dealt with RBFN control with foundation of Slotine and Li method. Meanwhile, our paper treats RBFN control based on core of SOSMC technique. More importantly, Liu *et al*. [16] only concentrate on adaptive control while our study solves both adaptive and robust control problems.

3) As will be seen later, while adaptive law of paper [11] only estimates two components including $\mathbf{M}(\mathbf{q})$ and $\mathbf{G}(\mathbf{q})$ of robot dynamics, we design an adaptive RBFN controller that approximates more dynamic components than the controller of article [11], consisting of $\mathbf{M}(\mathbf{q})$, $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})$, $\mathbf{J}(\mathbf{q})$, $\mathbf{F}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}})$, and $\mathbf{G}(\mathbf{q})$.

In this paper, an adaptive robust control system constructed comprises of two main components: a robust SOSMC controller and an adaptive RBFN mechanism. The control system is designed with the support of neural networks and SOSMC techniques. SOSMC is utilized to create the frame of controller while RBFN is applied for designing an adaptation mechanism. This mechanism is integrated into the control loop for estimating the unknown dynamics of DAM. The adaptation law approximates entirely dynamic model. Classified as a robust control technique, SOSMC is able to work well in spite of modeling inaccuracy. SOSMC trends to robust stability of robot where the system responses are keep consistently in the case of large variation of system parameters. In fact, many robot parameters are uncertainties. For example, a robot picks objects up with various weights and volumes. The load mass is changeable in a large range depending on each operating case, then mass matrix varying in terms of object mass is a parametric uncertainty. Additionally, SOSMC considerably reduces the chattering of state trajectories without support of any supplemental technique. Describing the fully physical behavior of robot by a dynamic model is not possible. In practice, many parts of a dynamic system cannot be modeled. To estimate these components, we use the feedforward multilayer neural networks to construct an adaptation mechanism lying in the feedback loop. This mechanism identifies the un-modeled part of robot dynamics then sends this information to controller. In estimator design, the radius basis function (Gaussian functions) is selected as the activation function of networks. Thus, SOSMC integrating RBFN creates a robust adaptive control system of DAM in which the system achieves two important properties: (i) Together with asymptotically stabilizing the robot system, the controller guarantees the system robustness in case of large variation of parameters and disturbances (ii) The controller still works well in the case of no information of many components of dynamic model. The control system itself adjusts the system responses in terms of the adaptive trends.

Notaion: $\mathbf{A} \in R^{n\times m}$ indicates a matrix with n rows and m columns whose elements are real values, $n, m \in Z$. $\mathbf{B} \in R^n$ indicates a column vector with n real elements, $n \in Z$. A symmetric matrix $\mathbf{C} \in R^{n\times n}$ is positive definite if $\exists \mathbf{q} \in R^n$ so that $\mathbf{q}^T\mathbf{C}\mathbf{q} > 0$.

2. DYNAMIC MODEL

2.1. Motion equation

Dynamic model of DAM is more complex than that of SAM due to the existence of closed kinematic loop and constraints. A physical model of a DAM is illustrated in Fig. 2. The robot has two arms in which each arm has r links and n degrees of freedom. Correspondingly, a set of rotating angles of $2r$ robot links $\mathbf{q} = \begin{bmatrix} q_1 & \cdots & q_{2n} \end{bmatrix}^T \in R^{2n}$ is defined as an output vector. The physical characteristics of each link is described by mass m_i, rotational inertia I_i, and length l_i ($i = 1, ..., 2r$).

Using the method of Lagrange multipliers, the mathematical model of DAM described in paper [17] composes of $2n$ fully nonlinear differential equations which is rewritten in matrix form as

$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{G}(\mathbf{q}) = \mathbf{J}^T(\mathbf{q})\mathbf{F}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}}) + \mathbf{U} + \mathbf{W}, \quad (1)$$

where $\mathbf{M}(q) \in R^{2n\times 2n}$ indicates an inertial matrix, $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}}) \in R^{2n\times 2n}$ denotes a Coriolis-centripetal matrix, $\mathbf{G}(\mathbf{q}) \in R^{2n}$ is a gravitational vector, $\mathbf{U} \in R^{2n}$ is

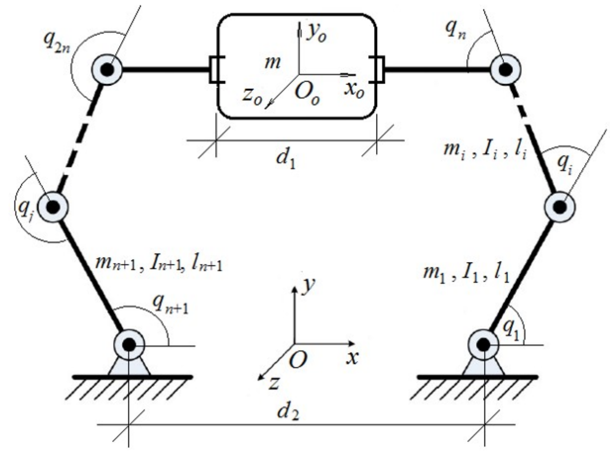

Fig. 2. Physical model of a dual-arm robot [16].

torques at robot joints, $\mathbf{W} \in R^{2n}$ denotes external disturbances, $\mathbf{J}(\mathbf{q}) \in R^{2n\times 2n}$ denotes a Jacobian matrix, and $\mathbf{F}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}}) \in R^{2n}$ indicates reaction forces between object and robot arms.

2.2. Inverse kinematics

The desired trajectory of load is calculated from position equation

$$\mathbf{r}_m = \begin{bmatrix} x_m & y_m & z_m \end{bmatrix}^T = \mathbf{h}(l_i, d_1, d_2, \mathbf{q}), \quad (2)$$

where $\mathbf{h} \in R^3$ is a vector of real-valued functions and $i = 1$, ..., $2r$. Using inverse kinematics, we can obtain the desired rotating angles as

$$\mathbf{q}_d = \mathbf{g}(\mathbf{r}_m, d_1, d_2, l_i, \mathbf{q}), \quad (3)$$

where $\mathbf{g} \in R^{2n}$ indicates a vector of trigonometric functions. Differentiating equation (3) with respect to time, we obtain the velocity and acceleration components, $\dot{\mathbf{q}}_d$ and $\ddot{\mathbf{q}}_d$, correspondingly.

3. CONTROL SYSTEM DESIGN

A robust adaptive control system designed for $2n$ DOFs dual-arm robots comprises of three main blocks: a plant with dynamic model (1), a robust SOSMC controller situated on feedfoward loop, and a neural network based estimator lying on feedback loop. First, a conventional SOSMC law is constituted in case of obviously known dynamic model. Then, this control law is transferred to adaptive form where many modules of dynamic model (or components of controller, equivalently) are considered as unknowns and should be estimated. Based on RBFN, an adaptation mechanism is constituted for approximating many modelling components consisting of $\mathbf{M}(\mathbf{q})$, $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})$, $\mathbf{J}(\mathbf{q})$, $\mathbf{F}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}})$, and $\mathbf{G}(\mathbf{q})$. For convenience in approoximating the dynamic model, the robot model (1) is rewritten as

$$\ddot{\mathbf{q}} = \mathbf{f}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) + \mathbf{M}^{-1}(\mathbf{q})(\mathbf{U} + \mathbf{W}), \tag{4}$$

where

$$\mathbf{f}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) = \mathbf{M}^{-1}(\mathbf{q})[\mathbf{J}^T(\mathbf{q})\mathbf{F}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) - \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} - \mathbf{G}(\mathbf{q})]$$

is complex nonlinear dynamics of system.

As will be seen later, $\mathbf{f}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) = \mathbf{f}\{\mathbf{M}(\mathbf{q}), \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}}), \mathbf{J}(\mathbf{q}), \mathbf{F}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}), \mathbf{G}(\mathbf{q})\}$ willbe indetified by RBFN tenchnique in the case that the robot dynamics (1) can not be fully modeled. The detailed contents of control design process are presented below.

3.1. SOSMC

A robust controller is designed for DAM using SOSMC to track the motion of end-effectors according to generated path $\mathbf{r}_d(t) = \begin{bmatrix} x_m(t) & y_m(t) & z_m(t) \end{bmatrix}^T$. Using inverse kinematics presented in Section 2.2, one obtains desired rotating angles $\mathbf{q}_d(t)$ of robot links from desired trajectory $\mathbf{r}_d(t)$ of load. In other words, the controller will drive the angles $\mathbf{q}(t)$ of robot links rotate towards references $\mathbf{q}_d(t)$ asymptotically. Consider the exponential dynamics of sliding manifold

$$\dot{\mathbf{s}} + \boldsymbol{\lambda}\mathbf{s} = \mathbf{0} \tag{5}$$

with sliding surface defined by

$$\mathbf{s} = (\dot{\mathbf{e}} + \boldsymbol{\lambda}\mathbf{e}) \in R^{2n}, \tag{6}$$

where

$$\mathbf{e} = (\mathbf{q} - \mathbf{q}_d) \in R^{2n} \tag{7}$$

is tracking error, $\boldsymbol{\lambda} = \mathrm{diag}(\lambda_1, \cdots, \lambda_{2n}) \in R^{2n \times 2n}$ denotes a diagonal matrix of positive gains characterized for convergence rate of $\mathbf{s}$ and $\mathbf{e}$. Submitting (4) into (5), one takes the control input

$$\mathbf{U} = \mathbf{M}(\mathbf{q}) \begin{bmatrix} \ddot{\mathbf{q}}_d - 2\boldsymbol{\lambda}(\dot{\mathbf{q}} - \dot{\mathbf{q}}_d) \\ -\boldsymbol{\lambda}^T\boldsymbol{\lambda}(\mathbf{q} - \mathbf{q}_d) - \mathbf{f}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) \end{bmatrix} - \mathbf{W} \tag{8}$$

that makes the outputs $\mathbf{q}$ approach to references $\mathbf{q}_d$ exponentially. As seen at equations (5)-(7), the stability of system states $\mathbf{q}$ spends two times of exponential convergence: the first time corresponds to sliding surface and the second time corresponds to tracking error. To remain the infinity consistency of the states $(\mathbf{q}, \dot{\mathbf{q}})$ on sliding surface, the switching action should be supplemented into control input (8). The SOSMC law now becomes

$$\mathbf{U} = \mathbf{M}(\mathbf{q}) \left[\ddot{\mathbf{q}}_d - 2\boldsymbol{\lambda}(\dot{\mathbf{q}} - \dot{\mathbf{q}}_d) - \boldsymbol{\lambda}^T\boldsymbol{\lambda}(\mathbf{q} - \mathbf{q}_d) - \mathbf{f}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})\right] - \mathbf{W} - \mathbf{K}sgn(\mathbf{s}) \tag{9}$$

with $\mathbf{K} = \mathrm{diag}(K_1, \cdots, K_{2n}) \in R^{2n \times 2n}$ being a diagonal matrix of positive gains.

3.2. Neural network based SOSMC

In practice, the controller does not know the behavior of many un-modeled parts of dynamical system. In this case, these parts should be identified. We use RBFN technique to estimate the components $\mathbf{M}(\mathbf{q})$, $\mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})$, $\mathbf{J}(\mathbf{q})$, $\mathbf{F}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$, and $\mathbf{G}(\mathbf{q})$ of un-modeled dynamics $\mathbf{f}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$ by creating an adaptation law. The sliding mode control structure in the case of lack of a part of system modelling, as follows:

$$\mathbf{U} = \mathbf{M}(\mathbf{q}) \left[\ddot{\mathbf{q}}_d - 2\boldsymbol{\lambda}(\dot{\mathbf{q}} - \dot{\mathbf{q}}_d) - \boldsymbol{\lambda}^T\boldsymbol{\lambda}(\mathbf{q} - \mathbf{q}_d) - \hat{\mathbf{f}}(\mathbf{z})\right] - \mathbf{W} - \mathbf{K}\mathrm{sgn}(\mathbf{s}), \tag{10}$$

where $\hat{\mathbf{f}}(\mathbf{z})$ is an estimation of $\mathbf{f}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$.

The algorithm of neural network to estimate $\mathbf{f}(\mathbf{z})$ is chosen as follows:

$$\mathbf{f}(\mathbf{z}) = \mathbf{W}^T\mathbf{h}(\mathbf{z}) + \boldsymbol{\varepsilon}, \tag{11}$$

where $\mathbf{z}$ is a matrix of neuron inputs, $\mathbf{W}$ is a matrix of weights, $\boldsymbol{\varepsilon}$ is approximation error of network, and $\mathbf{h}(\mathbf{z})$ is a matrix of activation functions. The existence of error $\boldsymbol{\varepsilon}$ is due to the numerous of hidden nodes in RBF network. $\mathbf{W}$ is chosen so that $|\boldsymbol{\varepsilon}|$ is minimum. We are able to find a RBF network so that $\|\boldsymbol{\varepsilon}\| \leq \varepsilon_N$ with ε_N being a positive constant. For RBF network, the nonlinear filtering is defined as Gaussian function

$$\mathbf{h}(\mathbf{z}) = \exp\left(-\frac{\|\mathbf{z} - \mathbf{c}\|^2}{2\mathbf{b}^2}\right), \tag{12}$$

where $\mathbf{c} = [c_{ij}]$ is a matrix of means, $\mathbf{b} = [b_j]$ is a vector of variances.

We need to construct an adjustment mechanism for identifying un-modeled factor $\mathbf{f}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) \in R^{2n}$. Define the state inputs of RBF network as

$$\mathbf{z} = \begin{bmatrix} \mathbf{e} & \dot{\mathbf{e}} & \mathbf{q}_d & \dot{\mathbf{q}}_d & \ddot{\mathbf{q}}_d \end{bmatrix}^T. \tag{13}$$

The output of RBF network is approximation $\hat{\mathbf{f}}(\mathbf{z})$ determined by

$$\hat{\mathbf{f}}(\mathbf{z}) = \hat{\mathbf{W}}^T\mathbf{h}(\mathbf{z}). \tag{14}$$

Since the modeling error $\boldsymbol{\varepsilon}$ is tiny, it can be eliminated as seen in formula (14).

3.3. RBFN adaptation mechanism and system stability

We constitute an adjustment mechanism to estimate the un-modeled component $\hat{\mathbf{f}}(\mathbf{z})$ of system based on Lyapunov stability. We define a Lyapunov candidate

$$V = \frac{1}{2}\mathbf{s}^T\mathbf{s} + \frac{1}{2}\mathrm{trace}\left(\tilde{\mathbf{W}}^T\boldsymbol{\Gamma}^{-1}\tilde{\mathbf{W}}\right), \tag{15}$$

where $\boldsymbol{\Gamma} = \mathrm{diag}(\Gamma_1, \Gamma_2 \ldots, \Gamma_m)$ is a positive definite diagonal matrix of adaptation gains, $\tilde{\mathbf{W}} = \hat{\mathbf{W}} - \mathbf{W}$ is error matrix of weights, $\hat{\mathbf{W}}$ is estimation of weight matrix $\mathbf{W}$.

Differentiating Lyapunov function (15) with respect to time yields

$$\dot{V} = \mathbf{s}^T\dot{\mathbf{s}} + \text{trace}\left(\tilde{\mathbf{W}}^T\mathbf{\Gamma}^{-1}\dot{\hat{\mathbf{W}}}\right). \tag{16}$$

Furthermore, inserting (4) into derivative of sliding surface (6), one obtains

$$\dot{\mathbf{s}} = f(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}}) + \mathbf{M}^{-1}(\mathbf{q})\mathbf{U} - \ddot{\mathbf{q}}_d + \boldsymbol{\lambda}(\dot{\mathbf{q}} - \dot{\mathbf{q}}_d). \tag{17}$$

Substituting control law (10) into (17) leads to

$$\dot{\mathbf{s}} = -\tilde{\mathbf{f}} - \boldsymbol{\lambda}\mathbf{s} - \mathbf{M}^{-1}\mathbf{K}\text{sgn}(\mathbf{s}) \tag{18}$$

with

$$\tilde{\mathbf{f}} = \hat{\mathbf{f}}(\mathbf{z}) - \mathbf{f}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}}) = \tilde{\mathbf{W}}^T\mathbf{h}(\mathbf{z}) \tag{19}$$

being estimation error of un-modeled component $\mathbf{f}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}})$. Submitting (18) into (16) with the notation, $\mathbf{s}^T\left[\dot{\mathbf{M}}(\mathbf{q},\dot{\mathbf{q}}) - 2\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\right]\mathbf{s} = 0$, we receive

$$\dot{V} = -\mathbf{s}^T\boldsymbol{\lambda}\mathbf{s} - \mathbf{s}^T\mathbf{M}(\mathbf{q})^{-1}\mathbf{K}\text{sgn}(\mathbf{s}) + \text{trace}\left\{\tilde{\mathbf{W}}^T\left[\mathbf{\Gamma}^{-1}\dot{\hat{\mathbf{W}}} - \mathbf{s}^T\mathbf{h}(\mathbf{z})\right]\right\}. \tag{20}$$

The following adaptation mechanism

$$\dot{\hat{\mathbf{W}}} = \mathbf{b}\Gamma h(\mathbf{z})\mathbf{s}^T \tag{21}$$

leads the derivative of Lyapunov function to

$$\dot{V} = -\mathbf{s}^T\boldsymbol{\lambda}\mathbf{s} - \mathbf{s}^T\mathbf{M}^{-1}\mathbf{K}\text{sgn}(\mathbf{s}). \tag{22}$$

Since both $\mathbf{M}(\mathbf{q})$ and $\mathbf{K}$ are positive definite matrices, then $\mathbf{M}(\mathbf{q})^{-1}\mathbf{K}$ is positive definite. Therefore, $\dot{V} \le 0$ or $\mathbf{s}$ is bounded, equivalently. The asymptotical stability of sliding surface, $\lim_{t\to\infty}\mathbf{s} = \mathbf{0}$, which yields exponential stability of tracking error $\mathbf{e}$. Hence, $\mathbf{q} \to \mathbf{q}_d$ asymptotically as $t \to \infty$.

4. REMARKS AND COMPARISONS

Many adaptive control techniques [24] are discussed in control literature such as model reference adaptive control (MRAC), online parameter identifiers, and adaptive observers. However, the dynamic model of system must be linearly parameterized when using these methods while neural network based approach does not need this modification. In principle, RBFN-SOSMC shows more advantages than other adaptive control techniques [24] in following statements:

(i) RBFN-SOSMC based modelling estimator (16)&(23) can identify almost all unknown dynamics of robot without the requirement of linear parameterization. In other words, since adaptation mechanisms, parameter estimators of other adaptive control methods [24] indirectly identify the unknown dynamics by approximating robot uncertain parameters, the robot dynamics (or control structure, equivalently) must be linearly parameterized.

(ii) RBFN-SOSMC can approximates both structure and parameters of robot dynamics because the learning behaviors of neural networks. Meanwhile, the other methods [24] require knowing the structure of dynamic model even though the many robot parameters are unknowns. In other words, the conventional adaptive methods [24] only work effectively in case of robot parameter variations with fixed frame of dynamic system, it cannot estimate the system structure as RBFN based methods go on.

(iii) Since RBFN based controls can approximate whole model of robot, the RBFN based controller adapts well in the existence of both structured and unstructured (parametric) uncertainties while traditional adaptive techniques [24] only treats with parametric uncertainties.

5. A SIMULATION EXAMPLE

The controllers (9) and (10) together with RBFN identifier (14)&(21) are designed for the generalized case of $2n$ DOFs dual-arm robots. For simulation, proposed controllers (9)&(10) are applied to 4DOFs-DAM [15] where its physical model is represented in Fig. 3. Dynamic model (1) specialized for this case reduces to four nonlinear differential equations. The components

$$\mathbf{q} = [q_i]^T \in R^4,\ \mathbf{M}(\mathbf{q}) = [m_{ij}] \in R^{4\times4},$$
$$\mathbf{C}(\mathbf{q},\dot{\mathbf{q}}) = [c_{ij}] \in R^{4\times4},\ G(\mathbf{q}) = [g_i]^T \in R^4,$$
$$\mathbf{J}^T(\mathbf{q}) = [J_{ij}] \in R^{4\times4},\ \mathbf{F}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}}) = \begin{bmatrix} F_1 & F_2 & F_{s1y} & F_{s2y}\end{bmatrix}^T,$$
$$\mathbf{U} = [u_i]^T \in R^4,\ \text{and}\ \mathbf{W} = [w_i]^T \in R^4$$

of dynamic model are determined according to paper [15]. The elements of above-metioned matrices and vectors are described in appendix section.

The desired motions of end-effectors are depicted in Fig. 10(a). In 2 seconds of the first phase, the proposed controllers track the end-effectors to rectangular load from

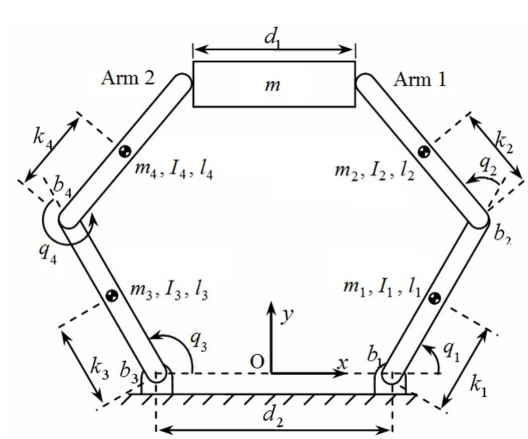

Fig. 3. Model of a 4 DOFs dual-arm robot [15].

Table 1. Characteristics of DAM and its controllers.

Dynamic model [15]
$m_1 = m_2 = m_3 = m_4 = 1.5$ (kg); $I_1 = I_2 = I_3 = I_4 = 0.18$ (kgm^2); $l_1 = l_2 = l_3 = l_4 = 1.2$ (m); $k_1 = k_2 = k_3 = k_4 = 0.48$ (m); $\mu = 0.35$; $m = 2$ (kg); $d_1 = 0.25$ (m); $d_2 = 1.2$ (m); $b_1 = b_2 = b_3 = b_4 = 110$ (Nm/s).
Generated path - Initial condition [15]
$(x_{i1}, y_{i1}, x_{i2}, y_{i2}) = (0.76, 0.6, -0.76, 0.6)$; $(x_{f1}, y_{f1}, x_{f2}, y_{f2}) = (-0.275, 1.4, -0.525, 1.4)$; $(x_o, y_o) = (0, 1.4)$; $r_m = 0.4$; $(\psi_i, \psi_f) = (-\pi, 0)$; $q_1(0) = 0$; $q_2(0) = \frac{5\pi}{6}$; $q_3(0) = \pi$; $q_4(0) = -\frac{5\pi}{6}$; $\dot{q}_1(0) = \dot{q}_2(0) = \dot{q}_3(0) = \dot{q}_4(0) = 0$;
SOSMC
$\lambda = diag(5,5,5,5)$; $\mathbf{K} = \mathrm{diag}(50,50,50,50)$;
RBFN-SOSMC
$\lambda = diag(7,7,9,6)$; $\mathbf{K} = \mathrm{diag}(55,55,55,55)$; $\hat{\mathbf{W}}(0) = \mathbf{0}$; $\mathbf{c} = 0.1\begin{bmatrix} -1.5 & -1 & -0.5 & 0.1 & 0.5 & 1 & 1.5 \\ -1.5 & -1 & -0.5 & 0.1 & 0.5 & 1 & 1.5 \\ -1.5 & -1 & -0.5 & 0.1 & 0.5 & 1 & 1.5 \end{bmatrix}$; $\mathbf{b} = \begin{bmatrix} 2.5 & 2.5 & 2.5 & 2.5 & 2.5 & 2.5 & 2.5 \end{bmatrix}$;

initial positions $(x_{i1}, y_{i1}, x_{i2}, y_{i2})$ in terms of path

$$x_m(t) = x_f + (x_i - x_f)e^{-10t^2}, \tag{23}$$

$$y_m(t) = y_f + (y_i - y_f)e^{-10t^2}, \tag{24}$$

where $(x_{f1}, y_{f1}, x_{f2}, y_{f2})$ are the final positions of end-effectors. In next 2 seconds, the dual-arms pick up and move the object around a haft of a circle with trajectory

$$x_m(t) = x_o + r_m \cos\psi(t), \tag{25}$$

$$y_m(t) = y_o + r_m \sin\psi(t) \tag{26}$$

for avoiding an obstacle. Here, (x_o, y_o) is obstacle position, r_m is radius of circle having center (x_o, y_o), ψ is polar angle.

DAM motions are simulated using parameters in Table 1. The initial conditions of weight matrix of RBFN are chosen to be zeros indicating no the prior knowledge of robot dynamics. The external random disturbance shown in Fig. 3 is put into the robot system to check the robust property with disturbance of control systems.

As shown in Figs. 5-8, four links of robot rotate asymptotically to wanted angles. SOSMC receives full information of robot model while RBFN-SOSMC must estimate this information. Certainly, the approximated knowledge is always inferior to true knowledge. Therefore, SOSMC responses show better quality in comparison with RBFN-SOSMC responses. However, RBFN-SOSMC shows the good ability in industrial application rather than SOSMC because requirement of full information of system modelling is too difficult in practice.

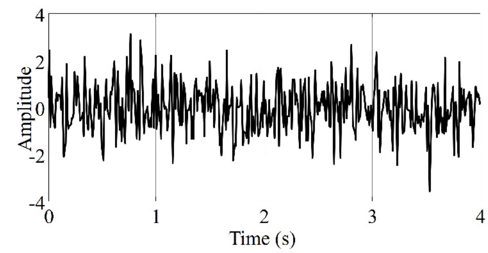

Fig. 4. External disturbance.

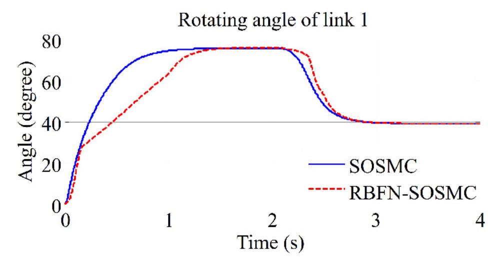

Fig. 5. Motion of link 1.

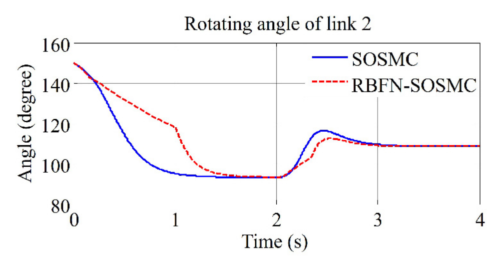

Fig. 6. Motion of link 2.

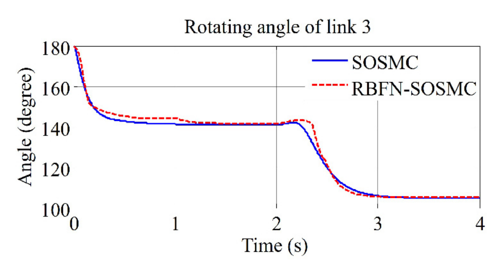

Fig. 7. Motion of link 3.

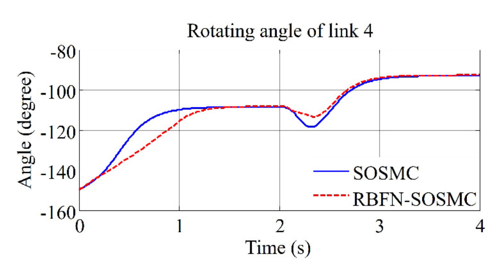

Fig. 8. Motion of link 4.

Fig. 9 represents the approximations $\hat{\mathbf{f}}(\mathbf{z}) \in R^4$ of robot dynamics. RBFN-SOSMC directly estimates the un-

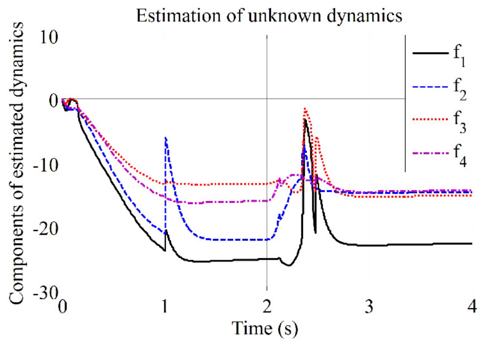

Fig. 9. Approximation of robot dynamics, $\hat{f}(z)$.

known dynamics $f(q, \dot{q}, \ddot{q})$ of robot model while the other adaptive control techniques [24] indirectly approximate the system model thru parameter estimation. Note that $\hat{\mathbf{f}}(\mathbf{z})$ is a vector that contains four estimated components. As seen in Section 3.3, the main objective of RBFN estimator is not to find the true value of system model. The main task of RBFN estimator is combining with SOSMC controller to stabilize the robot system. There are many estimated models making the system stable. Therefore, the RBFN based control system does not care to find out the precise model as long as the system is stable. In this regard, the estimation quality does not indicate much important signification.

Fig. 10 shows the motion trajectories of end-effectors. The controllers guarantee good transportation of load while preventing obstacle. The SOSMC quality is better than RBFN-SOSMC one because the duty of RBFN-SOSMC is heavier, structure of RBFN-SOSMC is more complex than those of SOSMC.

6. CONCLUSION

A robust adaptive control system has been constituted for $2n$ DOFs dual-arm robots. The control system achieves both robustness and adaptation in which the system rejects well external disturbances and no information of robot model is required. An application example for 4DOFs-DAM shows the superiority of proposed control system. Combining fuzzy logic with RBFN and SOSMC will be conducted in future research in which fuzzy logic will be applied for optimizing SOSMC gains while RBFN will be used for modelling approximation.

APPENDIX A

For dynamic model of 4 DOFs-DAM [15], the elements of mass matrix is given by

$$m_{11} = m_1k_1^2 + m_2l_1^2 + m_2k_2^2 + I_1 + I_2 + 2m_2l_1k_2\cos q_2;$$
$$m_{22} = m_2k_2^2 + I_2;\ m_{13} = m_{23} = m_{14} = m_{24} = 0;$$

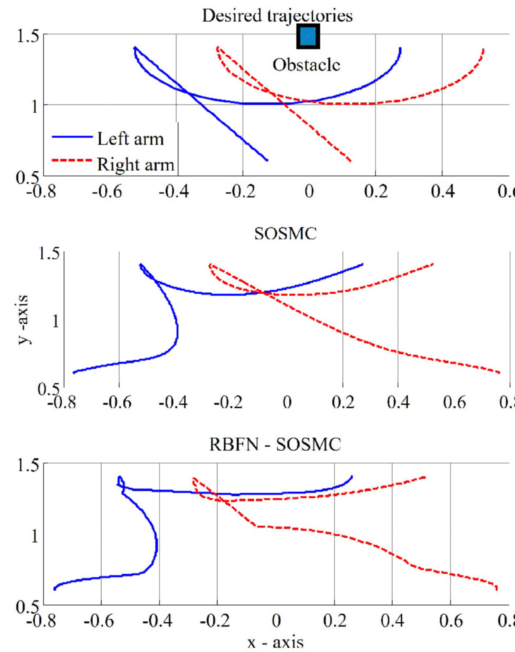

Fig. 10. Trajectories of end-effectors.

$$m_{33} = m_3k_3^2 + m_3l_3^2 + I_3 + A_5 + 2A_6\cos q_4;$$
$$m_{44} = m_4k_4^2 + I_4;\ m_{31} = m_{32} = m_{41} = m_{42} = 0;$$
$$m_{12} = m_{21} = m_2k_2^2 + I_2 + m_2l_1k_2\cos q_2;$$
$$m_{34} = m_{43} = m_4k_4^2 + I_4 + m_4l_3k_4\cos q_4.$$

The elements of damping matrix are

$$c_{12} = -m_2l_1k_2\sin q_2(\dot{q}_2 + 2\dot{q}_1);$$
$$c_{21} = m_2l_1k_2\dot{q}_1\sin q_2;$$
$$c_{34} = -m_4l_3k_4\sin q_4(\dot{q}_4 + 2\dot{q}_3);$$
$$c_{43} = m_4l_3k_4\dot{q}_3\sin q_4;$$
$$c_{11} = b_1,\ c_{22} = b_2,\ c_{33} = b_3,\ c_{44} = b_4,$$
$$c_{13} = c_{14} = c_{23} = c_{24} = c_{31} = c_{32} = c_{41} = c_{42} = 0.$$

The elements of Jacobian matrix given by

$$J_{11} = -l_1\sin q_1 - l_2\sin(q_1 + q_2);$$
$$J_{12} = J_{14} = J_{22} = J_{24} = 0;$$
$$J_{13} = -l_1\cos q_1 - l_2\cos(q_1 + q_2);$$
$$J_{31} = J_{33} = J_{41} = J_{43} = 0;$$
$$J_{21} = -l_2\sin(q_1 + q_2);\ J_{23} = -l_2\cos(q_1 + q_2);$$
$$J_{32} = l_3\sin q_3 + l_4\sin(q_3 + q_4);$$
$$J_{34} = -l_3\cos q_3 - l_4\cos(q_3 + q_4);$$
$$J_{42} = l_4\sin(q_3 + q_4);\ J_{44} = -l_4\cos(q_3 + q_4).$$

The components of gravity vector are

$$g_1 = g_2 = g_3 = g_4 = 0$$

due to considering the motion of DAM in Oxy plane.

The components of reaction forces $\mathbf{F}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$ are given by

$$F_{s1y} = F_{s1y} = 0.5m\ddot{y}_m, \tag{A.1}$$

$$F_1 = \begin{cases} m\dfrac{1}{\mu}\sqrt{(g/2)^2 + (\ddot{y}_m/2)^2} & \text{if } \ddot{x}_m \geq 0, \\ m\left(\dfrac{1}{\mu}\sqrt{(g/2)^2 + (\ddot{y}_m/2)^2} - \ddot{x}_m\right) & \text{if } \ddot{x}_m < 0, \end{cases} \tag{A.2}$$

$$F_2 = \begin{cases} m\left(\dfrac{1}{\mu}\sqrt{(g/2)^2 + (\ddot{y}_m/2)^2} + \ddot{x}_m\right) & \text{if } \ddot{x}_m \geq 0, \\ m\dfrac{1}{\mu}\sqrt{(g/2)^2 + (\ddot{y}_m/2)^2} & \text{if } \ddot{x}_m < 0, \end{cases} \tag{A.3}$$

where

$$x_m = d_2/2 + l_1\cos q_1 + L_2\cos(q_1+q_2) - d_1/2, \tag{A.4}$$

$$y_m = l_3\sin q_3 + l_4\sin(q_3+q_4) \tag{A.5}$$

are characterized for motion trajectory of load.

The inverse kinematics of 4 DOFs-DAM is described by

$$q_1 = \tan^{-1}\{y_m/(x_m + 0.5d_1 - 0.5d_2)\} - 0.5q_2 + n\pi, \tag{A.6}$$

$$q_2 = \pm\cos^{-1}\left\{\frac{1}{2l_1l_2}\left[\begin{array}{c}(x_m + 0.5d_1 - 0.5d_2)^2 \\ +y_m^2 - l_1^2 - l_2^2\end{array}\right]\right\} + n2\pi, \tag{A.7}$$

$$q_3 = \tan^{-1}\{y_m/(x_m + 0.5d_2 - 0.5d_1)\} - 0.5q_4 + n\pi, \tag{A.8}$$

$$q_4 = \pm\cos^{-1}\left\{\frac{1}{2l_3l_4}\left[\begin{array}{c}(x_m + 0.5d_2 - 0.5d_1)^2 \\ +y_m^2 - l_3^2 - l_4^2\end{array}\right]\right\} + n2\pi. \tag{A.9}$$

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