Decoupling of Macro-Mini Manipulator using Adaptive Neural Networks

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***Abstract*— Attaching a small manipulator (mini) with fast dynamic response at the end of a bigger manipulator (macro) with larger workspace leads to the concept of macro-mini manipulator, which is seen as a way to improve the system performance as compared to the macro manipulator acting alone, for example in terms of positioning accuracy. However, cross coupling between the two counterparts could undermine the practicality of the concept. In this paper, an adaptive neural network decoupler is presented to reduce the coupling effect of the macro-mini manipulators, without the need to have a proper dynamic model of the macro, and without alteration to the macro's controller. The stability of the proposed scheme is analyzed through the use of Lyapunov criterion. Simulation results show that by using the proposed neural network decoupler, the positioning accuracy of the macro-mini system can be improved significantly even when the macro manipulator is perturbed by external disturbances.**

I. INTRODUCTION

Robotic technologies are increasingly being employed in manufacturing and process industries to enhance automation, due to the benefits of cost effectiveness and resource effectiveness. Robotics reduces the cost of human labor, and it also helps speed up the manufacturing process which in turn increases revenue for the company. Furthermore, robots have better precision and accuracy than human workers, thus improving the quality of end products.

On the other hand, robotic technologies are not without flaws and shortcomings. Industrial robots are usually bulky and have high inertia, and this limits their responsiveness in terms of mechanical/control bandwidth. Their positional accuracy is of magnitudes lower than conventional CNC machines, due to modeling error of the manipulator, deflection caused by joint compliance or link flexibility, as well as frictions at the manipulator joints. Because of intellectual property and safety issues, the robotic systems are closed in the sense that external parties (e.g. researchers) are not allowed to open up the controllers to fine tune or improve the performance of the robots.

An add-on manipulator is one way to help improve system performance without altering the existing system. This leads to the Macro/mini manipulator concept, where the add-on mini manipulator is attached to the end point of the macro manipulator (i.e. the industrial robot). This mini manipulator can first be designed such that it is optimized both mechanically (e.g. low inertia and fast response) and via advanced control schemes. Then, the macro and the mini manipulators are combined to offer the best of both worlds: the large workspace of the macro, and the fast response as well as good precision of the mini.

Sharon and Hardt [1] were the first to introduce the concept of attaching a mini manipulator to the end of a macro manipulator. An optical sensor is installed at the end-effector to measure the position, and it is shown that the macro/mini manipulator could give better performance and improve the stability of the system as compared to a macro manipulator alone. Sharon et. al. [2] also showed that the macro/mini manipulator can increase the bandwidth of both position and force control. Following these results, several works have been done in the area of position control [3],[4], compliant motion control via impedance control [5], as well as hybrid force and motion control [6]. All the works mentioned above are based on joint-space, and several publications have also later appeared, which make use of the operation space. This include [7] which proposed an algorithm based on the redundant operational space, as well as [8] and [9] which used master slave algorithm to control the end effectors of macro/mini manipulator so that it moves along the desired path. Other notable publications in this area are for examples [10], [11], [12], and [13].

Macro-mini manipulators are seen as a method to obtain enhancements as compared to the macro acting alone. Nevertheless, certain issues have mostly been overlooked. Firstly, as mentioned earlier, the macro manipulators are usually industrial robots with controllers that are closed for alteration by the end-user. This means that any performance improvement of the overall system lies on the micro-manipulator solely. Unfortunately, the micro is placed in series with the macro manipulator at its end, and this constitutes a coupling effect between both counterparts. If the macro is vibrating, it will be difficult for the mini to maintain the desired position. This is especially serious if, for simplicity sake, the coupling is neglected in the models of the macro-mini manipulator. The controller designed based on the simplified models will not be able to compensate for the effects of the cross coupling properly. Ironically, a complete macro-mini manipulator model would not necessarily be advantageous as well, because the model could be too complicated to use for an effective control. Furthermore, it may be difficult or even impossible to obtain a full dynamic model since the physical parameters of the macro-manipulator or industrial robot are not known to third parties.

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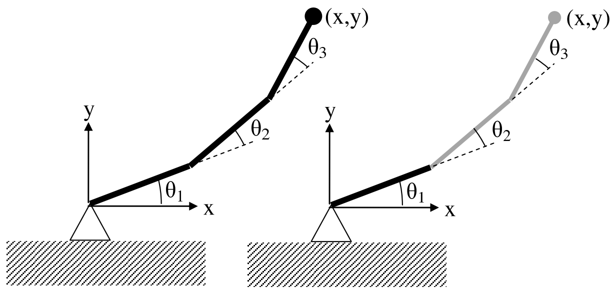

Fig. 1. Left: 3-link robot; Right: macro-mini manipulator

Neural networks as nonlinear controllers have received considerable attention from the control community, because they offer vivid advantages over conventional controllers in achieving desired performances [14],[15],[16]. In this paper, an adaptive neural network decoupler is proposed to compensate for the coupling effect between macro and mini manipulators, assuming that only the mini's controller is available for modification or enhancements. The neural network weights are tuned online based on the feedback of the tracking error, and no dynamic knowledge about the macro manipulator is needed. The closed loop stability is also proven via Lyapunov analysis, and simulation results verify that the coupling effect is significantly reduced with the aid of the adaptive neural network compensator.

This paper is organized as follows. In Section II, the model of the macro-mini manipulator will be given, followed by position control algorithm for the macro-mini manipulator which ignores the cross coupling effect in section III. In section IV, the adaptive neural network controller will be presented, along with the adaptation law as well as the stability proof. The effectiveness of the neural network decoupler will then be shown through simulation studies in section V, and the paper ends with conclusions in section VI.

II. MODEL OF THE MANIPULATORS

A. 3-DOF manipulator

Consider a 3-DOF serial-link planar manipulator, where the effect of gravity is ignored. A 3-DOF manipulator is chosen here for the clarity of presentation, but the mathematical derivation can be easily extended to higher-DOF systems. A sketch of the manipulator is shown in Fig. 1, and the dynamic model of the manipulator is as follows:

$$\begin{bmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & m_{33} \end{bmatrix} \begin{bmatrix} \ddot{\theta}_1 \\ \ddot{\theta}_2 \\ \ddot{\theta}_3 \end{bmatrix} + \begin{bmatrix} C_1 \\ C_2 \\ C_3 \end{bmatrix} = \begin{bmatrix} \tau_1 \\ \tau_2 \\ \tau_3 \end{bmatrix} \quad (1)$$

where m_{ij} and C_k are functions of the masses and lengths of the robotic links, as well as joint angles and velocities. These are common in robotics literature and thus are not elaborated here due to page limitations.

Assume also that only the x and y coordinates of the manipulator's end-point are of interest, and that the orientation with respect to the z-axis is not important. Thus the manipulator is redundant with only a 2-DOF task space.

B. 1-DOF macro and 2-DOF mini manipulator

Next, consider a macro-mini manipulator, where the macro is of 1-DOF and the mini has 2-DOF. This configuration is needed because the mini needs to be able to position its end point in a 2-DOF task space, whereas the macro only needs to bring the mini such that the desired end-point is within the mini's workspace. The macro-mini manipulator is also shown in fig. 1, and it can be seen that the 1-link macro is carrying a 2-link mini at its end. Typically, the macro is an industrial robot which is assumed to be stiff enough without being affected by the end-effector. For the 1-DOF macro, its dynamic model is:

$$\tilde{m}_{11}\ddot{\theta}_1 = \tau_1 \quad (2)$$

whereas the model of the mini manipulator is as follows:

$$\begin{bmatrix} m_{22} & m_{23} \\ m_{32} & m_{33} \end{bmatrix} \begin{bmatrix} \ddot{\theta}_2 \\ \ddot{\theta}_3 \end{bmatrix} + \begin{bmatrix} \tilde{C}_2 \\ \tilde{C}_3 \end{bmatrix} = \begin{bmatrix} \tau_2 \\ \tau_3 \end{bmatrix} \quad (3)$$

In equations (2) and (3), the terms with tilde are terms which are not exactly the same as those in the full model (1).

Combining equations (2) and (3), the following equation is obtained:

$$\begin{bmatrix} \tilde{m}_{11} & 0 & 0 \\ 0 & m_{22} & m_{23} \\ 0 & m_{32} & m_{33} \end{bmatrix} \begin{bmatrix} \ddot{\theta}_1 \\ \ddot{\theta}_2 \\ \ddot{\theta}_3 \end{bmatrix} + \begin{bmatrix} 0 \\ \tilde{C}_2 \\ \tilde{C}_3 \end{bmatrix} = \begin{bmatrix} \tau_1 \\ \tau_2 \\ \tau_3 \end{bmatrix} \quad (4)$$

By comparing equations (1) and (4), it is seen that some terms have been missing, and equation (4) should be more correctly written as:

$$\begin{aligned} &\begin{bmatrix} \tilde{m}_{11} & 0 & 0 \\ 0 & m_{22} & m_{23} \\ 0 & m_{32} & m_{33} \end{bmatrix} \begin{bmatrix} \ddot{\theta}_1 \\ \ddot{\theta}_2 \\ \ddot{\theta}_3 \end{bmatrix} + \begin{bmatrix} 0 \\ \tilde{C}_2 \\ \tilde{C}_3 \end{bmatrix} = \begin{bmatrix} \tau_1 \\ \tau_2 \\ \tau_3 \end{bmatrix} \\ &- \begin{bmatrix} \Delta m_{11} & m_{12} & m_{13} \\ m_{21} & 0 & 0 \\ m_{31} & 0 & 0 \end{bmatrix} \begin{bmatrix} \ddot{\theta}_1 \\ \ddot{\theta}_2 \\ \ddot{\theta}_3 \end{bmatrix} - \begin{bmatrix} C_1 \\ \Delta C_2 \\ \Delta C_3 \end{bmatrix} \end{aligned} \quad (5)$$

where the missing terms are written in the second row.

In this example, the macro is a simple 1-link robot and thus the missing terms in equation (5) can be easily derived. However, do note that in general, the macro is a 6-DOF industrial robot with a complicated model, which results in much more complex expression (e.g. larger matrix) for the missing terms. As such, it is advantageous to have a method to control the macro mini manipulator without the need of knowing the full model.

III. POSITION CONTROL OF THE MACRO-MINI MANIPULATOR

By ignoring the missing terms in equation (5), the controllers for the macro and the mini can be designed separately based on the models (2) and (3). The macro controller could be:

$$\tau_1 = \tilde{m}_{11}(\ddot{\theta}_{1r} + k_{d1}(\dot{\theta}_{1r} - \dot{\theta}_1) + k_{p1}(\theta_{1r} - \theta_1)) \quad (6)$$

but a knowledge of this is not required in this work. This is because most of the industrial robot manufacturers would not open their controllers for modifications due to IP as well as safety issues, and thus any performance improvement of the overall macro-mini manipulator should come from the mini manipulator itself.

The mini controller is designed as:

$$\begin{bmatrix} \tau_2 \\ \tau_3 \end{bmatrix} = \begin{bmatrix} m_{22} & m_{23} \\ m_{32} & m_{33} \end{bmatrix} J^{-1} \times \begin{bmatrix} \ddot{x}_r + k_{dx}(\dot{x}_r - \dot{x}) + k_{px}(x_r - x) - (\dot{J}\dot{\theta})_x \\ \ddot{y}_r + k_{dy}(\dot{y}_r - \dot{y}) + k_{py}(x_r - y) - (\dot{J}\dot{\theta})_y \end{bmatrix} + \begin{bmatrix} \tilde{C}_2 \\ \tilde{C}_3 \end{bmatrix} \tag{7}$$

where J is the Jacobian matrix relating the task space velocities to the joint velocities, $v = J\dot{\theta}$. It is also assumed that there exists an external measurement system such as vision which measures the task space position and/or velocity of the macro-mini manipulator.

The following assumptions are reasonable and are needed for the stability analysis of the neural network controller later:

Assumption 1: The macro manipulator along with its controller is strong enough to remain stable regardless of the motion of the mini manipulator.

Assumption 2: In the absence of cross coupling between macro and mini manipulators which equals to the missing terms of equation (5), the mini controller stabilizes the mini manipulator. This can be obtained by substituting equation (7) into (3), which gives:

$$\begin{bmatrix} m_{22} & m_{23} \\ m_{32} & m_{33} \end{bmatrix} \begin{bmatrix} \ddot{\theta}_2 \\ \ddot{\theta}_3 \end{bmatrix} + \begin{bmatrix} \tilde{C}_2 \\ \tilde{C}_3 \end{bmatrix} = \begin{bmatrix} m_{22} & m_{23} \\ m_{32} & m_{33} \end{bmatrix} J^{-1} \times \begin{bmatrix} \ddot{x}_r + k_{dx}(\dot{x}_r - \dot{x}) + k_{px}(x_r - x) - (\dot{J}\dot{\theta})_x \\ \ddot{y}_r + k_{dy}(\dot{y}_r - \dot{y}) + k_{py}(x_r - y) - (\dot{J}\dot{\theta})_y \end{bmatrix} + \begin{bmatrix} \tilde{C}_2 \\ \tilde{C}_3 \end{bmatrix} \tag{8}$$

Cancelling the common terms on each side of the equation leads to:

$$\begin{bmatrix} \ddot{\theta}_2 \\ \ddot{\theta}_3 \end{bmatrix} = J^{-1} \begin{bmatrix} \ddot{x}_r + k_{dx}(\dot{x}_r - \dot{x}) + k_{px}(x_r - x) - (\dot{J}\dot{\theta})_x \\ \ddot{y}_r + k_{dy}(\dot{y}_r - \dot{y}) + k_{py}(x_r - y) - (\dot{J}\dot{\theta})_y \end{bmatrix} \tag{9}$$

Using the Jacobians $v = J\dot{\theta}$, the acceleration can be expressed as $a = \dot{J}\dot{\theta} + J\ddot{\theta}$, which gives $\ddot{\theta} = J^{-1}(a - \dot{J}\dot{\theta})$, or:

$$J^{-1} \begin{bmatrix} \ddot{x} - (\dot{J}\dot{\theta})_x \\ \ddot{y} - (\dot{J}\dot{\theta})_y \end{bmatrix} = J^{-1} \begin{bmatrix} \ddot{x}_r + k_{dx}(\dot{x}_r - \dot{x}) + k_{px}(x_r - x) - (\dot{J}\dot{\theta})_x \\ \ddot{y}_r + k_{dy}(\dot{y}_r - \dot{y}) + k_{py}(x_r - y) - (\dot{J}\dot{\theta})_y \end{bmatrix} \tag{10}$$

Again, by cancelling the common terms, the following equations are obtained:

$$(\ddot{x}_r - \ddot{x}) + k_{dx}(\dot{x}_r - \dot{x}) + k_{px}(x_r - x) = 0 \tag{11}$$

$$(\ddot{y}_r - \ddot{y}) + k_{dy}(\dot{y}_r - \dot{y}) + k_{py}(y_r - y) = 0 \tag{12}$$

which show that the tracking errors $e_x = x_r - x$ and $e_y = y_r - y$ converge to zero.

Define $e_{vx} = \dot{e}_x + \lambda_x e_x$ and $e_{vy} = \dot{e}_y + \lambda_y e_y$. Their derivatives are thus:

$$\dot{e}_{vx} = \ddot{e}_x + \lambda_x \dot{e}_x = -k_{dx}\dot{e}_x - k_{px}e_x + \lambda_x \dot{e}_x \tag{13}$$

$$\dot{e}_{vy} = \ddot{e}_y + \lambda_y \dot{e}_y = -k_{dy}\dot{e}_y - k_{py}e_y + \lambda_y \dot{e}_y \tag{14}$$

Using these definitions, assumption 2 can also be expressed in the following way:

Assumption 3: In the absence of cross coupling between macro and mini manipulators which equals to the missing terms of equation (5), there exist Lyapunov function candidates $V_x = \frac{1}{2}e_{vx}^2$ and $V_y = \frac{1}{2}e_{vy}^2$ such that:

$$\dot{V}_x = e_{vx}\dot{e}_{vx} = e_{vx}(-k_{dx}\dot{e}_x - k_{px}e_x + \lambda_x \dot{e}_x) \leq -Q_x e_{vx}^2 \tag{15}$$

$$\dot{V}_y = e_{vy}\dot{e}_{vy} = e_{vy}(-k_{dy}\dot{e}_y - k_{py}e_y + \lambda_y \dot{e}_y) \leq -Q_y e_{vy}^2 \tag{16}$$

The controller design philosophy above is simple as it assumes a separation of the macro and mini manipulators. However, the cross coupling between the two counterparts is not being taken care of, because the missing terms in the model (5) have been neglected. A disturbance on the macro would have adverse effect on the mini and vice versa.

IV. DECOUPLING USING ADAPTIVE NEURAL NETWORK

A. Control and adaptation law

In order to handle the missing terms in equation (5) which correspond to cross coupling between macro and mini manipulators without having the full model, it is proposed to use adaptive neural networks to approximate and cancel the terms. Please be reminded that the macro controller is closed for alteration, and thus only the mini controllers can be modified. The proposed mini controller is:

$$\begin{bmatrix} \tau_2 \\ \tau_3 \end{bmatrix} = \begin{bmatrix} m_{22} & m_{23} \\ m_{32} & m_{33} \end{bmatrix} J^{-1} \times \begin{bmatrix} \ddot{x}_r + k_{dx}(\dot{x}_r - \dot{x}) + k_{px}(x_r - x) - (\dot{J}\dot{\theta})_x + NN_x \\ \ddot{y}_r + k_{dy}(\dot{y}_r - \dot{y}) + k_{py}(x_r - y) - (\dot{J}\dot{\theta})_y + NN_y \end{bmatrix} + \begin{bmatrix} \tilde{C}_2 \\ \tilde{C}_3 \end{bmatrix} \tag{17}$$

where NN_x and NN_y are the neural network controllers to be designed. In what follows, the neural network contollers have been chosen to only have one hidden layer with radial basis activiation function (RBF). The input weights are fixed, and the centers as well as the spreads are chosen to cover the expected range of the inputs, for e.g. θ_2 from $-\pi$ to π. Only the output weights are tuned adaptively. NN_x and NN_y thus have the form:

$$NN_x = w_x^T \phi_x \tag{18}$$

$$NN_y = w_y^T \phi_y \tag{19}$$

where w_x and w_y are the adaptive weights, while ϕ_x and ϕ_y are the radial basis functions of the neural network. In this work, the inputs to the network include θ_1, θ_2, θ_3, $\dot{\theta}_1$, $\dot{\theta}_2$, $\dot{\theta}_3$, x, y, x_r and y_r (refer Fig. 2). The availability of θ_1 and $\dot{\theta}_1$ is nowadays quite common as robot manufacturers increasingly offer real time interface for the user (Note: The macro controller is still closed, only the joint angles and velocities are available for real-time reading).

The following assumptions are required and are also appropriate based on the universal approximation capability of neural networks:

Assumption 4: The ideal neural networks satisfy

$$\begin{bmatrix} m_{22} & m_{23} \\ m_{32} & m_{33} \end{bmatrix} J^{-1} \begin{bmatrix} w_x^{*T}\phi_x + \delta_x \\ w_y^{*T}\phi_y + \delta_y \end{bmatrix} = \begin{bmatrix} m_{21}\ddot{\theta}_1 \\ m_{31}\ddot{\theta}_1 \end{bmatrix} + \begin{bmatrix} \Delta C_2 \\ \Delta C_3 \end{bmatrix} \tag{20}$$

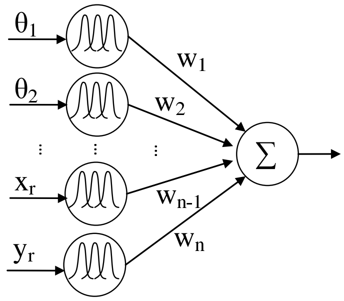

Fig. 2. Structure of the proposed neural networks

on a compact set Ω with $[\theta_1, \theta_2, \theta_3, \dot{\theta}_1, \dot{\theta}_2, \dot{\theta}_3, x, y, x_r, y_r] \in \Omega \subset R^{10}$, where w_x^{*T} and w_y^{*T} are the ideal weights, and δ_x and δ_y are the network approximation error satisfying $|\delta_x| \leq \Sigma_x$ and $|\delta_y| \leq \Sigma_y$, where $\Sigma_x > 0$ and $\Sigma_y > 0$. The assumption states that the neural networks can be used to approximate the missing terms in equation (5) on the compact set Ω.

The dynamics of e_{vx} and e_{vy}, with full consideration of the coupling terms, are derived as follows: Firstly, by substituting equation (17) into the second and third rows of equation (5), the following is obtained:

$$\begin{aligned} &\begin{bmatrix} m_{22} & m_{23} \\ m_{32} & m_{33} \end{bmatrix} \begin{bmatrix} \ddot{\theta}_2 \\ \ddot{\theta}_3 \end{bmatrix} + \begin{bmatrix} \tilde{C}_2 \\ \tilde{C}_3 \end{bmatrix} \\ &= \begin{bmatrix} m_{22} & m_{23} \\ m_{32} & m_{33} \end{bmatrix} J^{-1} \\ &\quad \times \begin{bmatrix} \ddot{x}_r + k_{dx}(\dot{x}_r - \dot{x}) + k_{px}(x_r - x) + w_x^T \phi_x - (\dot{J}\dot{\theta})_x \\ \ddot{y}_r + k_{dy}(\dot{y}_r - \dot{y}) + k_{py}(x_r - y) + w_y^T \phi_y - (\dot{J}\dot{\theta})_y \end{bmatrix} \\ &\quad + \begin{bmatrix} \tilde{C}_2 \\ \tilde{C}_3 \end{bmatrix} - \begin{bmatrix} m_{21}\ddot{\theta}_1 \\ m_{31}\ddot{\theta}_1 \end{bmatrix} - \begin{bmatrix} \Delta C_2 \\ \Delta C_3 \end{bmatrix} \end{aligned} \tag{21}$$

By assumption 4, the above equation can be written as:

$$\begin{aligned} &\begin{bmatrix} m_{22} & m_{23} \\ m_{32} & m_{33} \end{bmatrix} \begin{bmatrix} \ddot{\theta}_2 \\ \ddot{\theta}_3 \end{bmatrix} + \begin{bmatrix} \tilde{C}_2 \\ \tilde{C}_3 \end{bmatrix} \\ &= \begin{bmatrix} m_{22} & m_{23} \\ m_{32} & m_{33} \end{bmatrix} J^{-1} \\ &\quad \times \begin{bmatrix} \ddot{x}_r + k_{dx}(\dot{x}_r - \dot{x}) + k_{px}(x_r - x) + w_x^T \phi_x - (\dot{J}\dot{\theta})_x \\ \ddot{y}_r + k_{dy}(\dot{y}_r - \dot{y}) + k_{py}(x_r - y) + w_y^T \phi_y - (\dot{J}\dot{\theta})_y \end{bmatrix} \\ &\quad + \begin{bmatrix} \tilde{C}_2 \\ \tilde{C}_3 \end{bmatrix} - \begin{bmatrix} m_{22} & m_{23} \\ m_{32} & m_{33} \end{bmatrix} J^{-1} \begin{bmatrix} w_x^{*T}\phi_x + \delta_x \\ w_y^{*T}\phi_y + \delta_y \end{bmatrix} \end{aligned} \tag{22}$$

Deleting all the common terms gives:

$$\begin{aligned} &\begin{bmatrix} \ddot{\theta}_2 \\ \ddot{\theta}_3 \end{bmatrix} \\ &= J^{-1} \begin{bmatrix} \ddot{x}_r + k_{dx}(\dot{x}_r - \dot{x}) + k_{px}(x_r - x) + w_x^T \phi_x - (\dot{J}\dot{\theta})_x \\ \ddot{y}_r + k_{dy}(\dot{y}_r - \dot{y}) + k_{py}(x_r - y) + w_y^T \phi_y - (\dot{J}\dot{\theta})_y \end{bmatrix} \\ &\quad - J^{-1} \begin{bmatrix} w_x^{*T}\phi_x + \delta_x \\ w_y^{*T}\phi_y + \delta_y \end{bmatrix} \\ &= J^{-1} \\ &\times \begin{bmatrix} \ddot{x}_r + k_{dx}(\dot{x}_r - \dot{x}) + k_{px}(x_r - x) - \overline{w}_x^T \phi_x - (\dot{J}\dot{\theta})_x - \delta_x \\ \ddot{y}_r + k_{dy}(\dot{y}_r - \dot{y}) + k_{py}(x_r - y) - \overline{w}_y^T \phi_y - (\dot{J}\dot{\theta})_y - \delta_y \end{bmatrix} \end{aligned} \tag{23}$$

where $\overline{w}_x = w_x^* - w_x$ and $\overline{w}_y = w_y^* - w_y$ are the network weight errors. Again, by using Jacobians, $\ddot{\theta} = J^{-1}(a - \dot{J}\dot{\theta})$, the following equation is obtained:

$$\begin{aligned} &J^{-1} \begin{bmatrix} \ddot{x} - (\dot{J}\dot{\theta})_x \\ \ddot{y} - (\dot{J}\dot{\theta})_y \end{bmatrix} \\ &= J^{-1} \\ &\times \begin{bmatrix} \ddot{x}_r + k_{dx}(\dot{x}_r - \dot{x}) + k_{px}(x_r - x) - \overline{w}_x^T \phi_x - (\dot{J}\dot{\theta})_x - \delta_x \\ \ddot{y}_r + k_{dy}(\dot{y}_r - \dot{y}) + k_{py}(x_r - y) - \overline{w}_y^T \phi_y - (\dot{J}\dot{\theta})_y - \delta_y \end{bmatrix} \end{aligned} \tag{24}$$

Therefore, after removing all the common terms from both sides of equation, the error dynamics can be written as:

$$(\ddot{x}_r - \ddot{x}) + k_{dx}(\dot{x}_r - \dot{x}) + k_{px}(x_r - x) - \overline{w}_x^T \phi_x - \delta_x = 0 \tag{25}$$

$$(\ddot{y}_r - \ddot{y}) + k_{dy}(\dot{y}_r - \dot{y}) + k_{py}(y_r - y) - \overline{w}_y^T \phi_y - \delta_y = 0 \tag{26}$$

Finally, for $e_{vx} = \dot{e}_x + \lambda_x e_x$ and $e_{vy} = \dot{e}_y + \lambda_y e_y$, the derivatives are:

$$\dot{e}_{vx} = \ddot{e}_x + \lambda_x \dot{e}_x = -k_{dx}\dot{e}_x - k_{px}e_x + \overline{w}_x^T \phi_x + \delta_x + \lambda_x \dot{e}_x \tag{27}$$

$$\dot{e}_{vy} = \ddot{e}_y + \lambda_y \dot{e}_y = -k_{dy}\dot{e}_y - k_{py}e_y + \overline{w}_y^T \phi_y + \delta_y + \lambda_y \dot{e}_y \tag{28}$$

Assumption 5: The ideal neural network weights w_x^{*T} and w_y^{*T} are bounded by $\|w_x^*\| \leq W_x$ and $\|w_y^*\| \leq W_y$ respectively on the compact set Ω, where $W_x > 0$ and $W_y > 0$.

The adaptation laws for w_x and w_y are:

$$\dot{w}_x = \Gamma_x \phi_x e_{vx} - \sigma_x \Gamma_x |e_{vx}| w_x \tag{29}$$

$$\dot{w}_y = \Gamma_y \phi_y e_{vy} - \sigma_y \Gamma_y |e_{vy}| w_y \tag{30}$$

where $\Gamma_x > 0$ and $\Gamma_y > 0$ are gain matrices, and σ_x and σ_y are scalar parameters.

B. Stability proof

Theorem 1: Consider the dynamics of the macro-mini manipulator as given in equation (5), with the control law (17) and weight adaptation law (29)/(30), then the tracking errors e_{vx}, e_{vy}, e_x and e_y, as well as the network weight errors $\overline{w}_x$ and $\overline{w}_y$ are uniformly ultimately bounded.

Proof: The proof will be given only for the x component, as the proof for the y component is similar. Consider the following Lyapunov function candidate:

$$V_x = \tfrac{1}{2}e_{vx}^2 + \tfrac{1}{2}\overline{w}_x \Gamma_x^{-1} \overline{w}_x \tag{31}$$

The derivative of the Lyapunov function candidate is:

$$\begin{aligned} \dot{V}_x &= e_{vx}\dot{e}_{vx} + \overline{w}_x^T \Gamma_x^{-1} \dot{\overline{w}}_x \\ &= e_{vx}(-k_{dx}\dot{e}_x - k_{px}e_x + \overline{w}_x^T \phi_x + \delta_x + \lambda_x \dot{e}_x) + \overline{w}_x^T \Gamma_x^{-1} \dot{\overline{w}}_x \\ &= e_{vx}(-k_{dx}\dot{e}_x - k_{px}e_x + \lambda_x \dot{e}_x) + e_{vx}\delta_x + e_{vx}\overline{w}_x^T \phi_x \\ &+ \overline{w}_x^T \Gamma_x^{-1} \dot{\overline{w}}_x \end{aligned} \tag{32}$$

By assumption 3, the first term in the Lyapunov derivative is smaller or equal to $-Q_x e_{vx}^2$. Therefore,

$$\begin{aligned} \dot{V}_x &\leq -Q_x e_{vx}^2 + e_{vx}\delta_x + e_{vx}\overline{w}_x^T \phi_x + \overline{w}_x^T \Gamma_x^{-1} \dot{\overline{w}}_x \\ &= -Q_x e_{vx}^2 + e_{vx}\delta_x + \overline{w}_x^T (e_{vx}\phi_x + \Gamma_x^{-1} \dot{\overline{w}}_x) \end{aligned} \tag{33}$$

Substituting the adaptation law (29), and noting that $\dot{w}_x = -\dot{\overline{w}}_x$, the following is obtained:

$$\begin{aligned}\dot{V}_x &\le -Q_x e_{vx}^2 + e_{vx}\delta_x \\ &+ \overline{w}_x^T(e_{vx}\phi_x - \Gamma_x^{-1}\Gamma_x\phi_x e_{vx} + \sigma_x\Gamma_x^{-1}\Gamma_x|e_{vx}|w_x) \\ &= -Q_x e_{vx}^2 + e_{vx}\delta_x + \sigma_x\overline{w}_x^T w_x|e_{vx}|\end{aligned} \tag{34}$$

Noting that:

$$\begin{aligned}\overline{w}_x^T w_x &= \overline{w}_x^T(w_x^* - \overline{w}_x) \\ &= \overline{w}_x^T w_x^* - \overline{w}_x^T\overline{w}_x \\ &\le \|\overline{w}_x\|\|w_x^*\| - \|\overline{w}_x\|^2 \\ &\le \|\overline{w}_x\|W_x - \|\overline{w}_x\|^2 \\ &= -(\|\overline{w}_x\| - \tfrac{1}{2}W_x)^2 + \tfrac{1}{4}W_x^2\end{aligned} \tag{35}$$

where the second inequality is based on assumption 5, the following inequality for $\dot{V}_x$ is obtained:

$$\begin{aligned}\dot{V}_x &\le -Q_x e_{vx}^2 + e_{vx}\delta_x + \sigma_x\overline{w}_x^T w_x|e_{vx}| \\ &\le -Q_x e_{vx}^2 + e_{vx}\delta_x - \sigma_x(\|\overline{w}_x\| - \tfrac{1}{2}W_x)^2|e_{vx}| + \tfrac{\sigma_x}{4}W_x^2|e_{vx}| \\ &= |e_{vx}|(-Q_x|e_{vx}| + |\delta_x| - \sigma_x(\|\overline{w}_x\| - \tfrac{1}{2}W_x)^2 + \tfrac{\sigma_x}{4}W_x^2) \\ &\le |e_{vx}|(-Q_x|e_{vx}| + \Sigma_x - \sigma_x(\|\overline{w}_x\| - \tfrac{1}{2}W_x)^2 + \tfrac{\sigma_x}{4}W_x^2)\end{aligned} \tag{36}$$

To analyze the characteristics of $\dot{V}$, note that $-Q_x|e_{vx}|$ and $-\sigma_x(\|\overline{w}_x\| - \frac{1}{2}W_x)^2$ are both non-positive. At the extreme case of $-\sigma_x(\|\overline{w}_x\| - \frac{1}{2}W_x)^2 = 0$, then $\dot{V}$ is negative when:

$$-Q_x|e_{vx}| + \Sigma_x + \tfrac{\sigma_x}{4}W_x^2 < 0 \tag{37}$$

or

$$|e_{vx}| > \frac{\frac{\sigma_x}{4}W_x^2 + \Sigma_x}{Q} \tag{38}$$

On the other hand, at the extreme case of $-Q_x|e_{vx}| = 0$, then $\dot{V}$ is negative when:

$$-\sigma_x(\|\overline{w}_x\| - \tfrac{1}{2}W_x)^2 + \Sigma_x + \tfrac{\sigma_x}{4}W_x^2 < 0 \tag{39}$$

or

$$\|\overline{w}_x\| > \frac{1}{2}W_x + \sqrt{\frac{1}{4}W_x^2 + \frac{\Sigma_x}{\sigma_x}} \tag{40}$$

This means that as soon as $|e_{vx}|$ or $\|\overline{w}_x\|$ grow larger than the bounds above, $\dot{V}$ will be negative, implying that the tracking error e_{vx}, as well as the network weight error $\overline{w}_x$ are uniformly ultimately bounded. Finally, since $e_{vx} = \dot{e}_x + \lambda_x e_x$ is a stable system [17]:

$$|e_x| \le \frac{|e_{vx}|}{\lambda_x} \le \frac{\frac{\sigma_x}{4}W_x^2 + \Sigma_x}{Q\lambda_x} \tag{41}$$

implying that the tracking error e_x is uniformly ultimately bounded.

V. SIMULATION RESULTS

The effectiveness of the neural networks decoupling is verified via simulation studies. The simulation scenario is as follows: The macro is commanded to maintain at a constant angle θ_1, while the mini is controlled such that its end-point stays at a certain task-space position, given by the $x-y-$coordinates. The macro is perturbed with a strong external disturbance, which would force it to vibrate and eventually the end-point of the mini will vibrate as well due to cross coupling. The simulation example is illustrated through fig. 3.

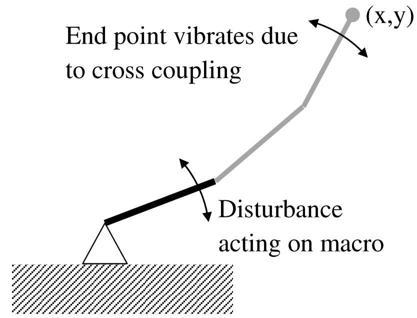

Fig. 3. Macro is perturbed while mini tries to maintain end-position

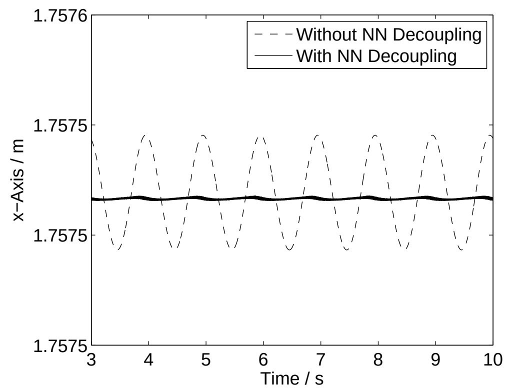

Fig. 4. End-position x-value when macro under sinusoidal disturbance

The simulation results for the cases with or without the neural network compensators, where the disturbance onto the macro is sinusoidal with 1Hz frequency, are shown in figs. 4 and 5. It is vividly seen that the end-point of the macro-mini manipulator remains almost stationary even when the macro is perturbed, if the neural network controller is activated. This is a strong improvement as compared to the case without neural network compensation.

Next, for the case where the disturbance are more random, the results are shown in figs. 6 and 7. Again, while the

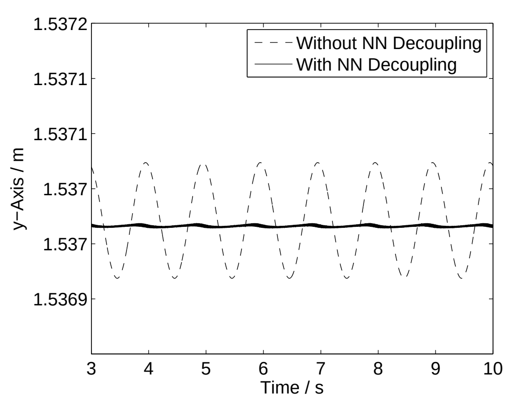

Fig. 5. End-position y-value when macro under sinusoidal disturbance

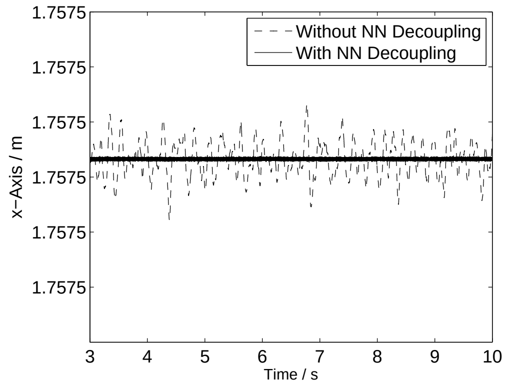

Fig. 6. End-position x-value when macro under random disturbance

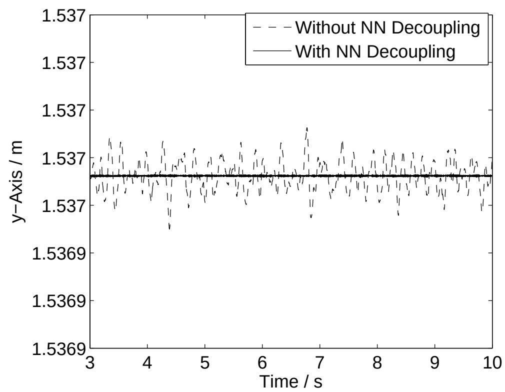

Fig. 7. End-position y-value when macro under random disturbance

positions of the macro-mini manipulator's end-point vibrate violently when neural network controllers are non existent, they are still well-maintained when the neural networks are used.

VI. CONCLUSIONS

In this paper, an adaptive neural network controller is designed to reduce the coupling effect between the macro and the mini manipulators, for the case where the macro manipulator's controller is closed for alteration by robot manufacturers, and only the mini controller can be modified. The control law together with the adaptation law for the neural network decoupler are provided in details, and the stability of the overall system is also proven using Lyapunov analysis. Finally, the effectiveness of the proposed controller is verified through simulation studies. It is seen that the end-point of the macro-mini manipulator remains almost stationary, even when the macro is perturbed by strong external disturbances. Future work includes implementing the adaptive decoupler on an actual macro-mini manipulator in order to validate the simulation results.

VII. ACKNOWLEDGMENTS

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