Advanced robust tracking control of a powered wheelchair system

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***Abstract*—In this paper, the dynamic multivariable model of the wheelchair system is obtained including the presence of transportation lags. The triangular diagonal dominance (TDD) decoupling technique is applied to reduce this multivariable control problem into two independent scalar control problems. An advanced robust control technique for the wheelchair has been developed based on the combination of a TDD decoupling strategy and neural network controller design. The results obtained from the real-time implementation confirm that robust performance for this multivariable wheelchair control system can indeed be achieved.**

I. INTRODUCTION

WHEELCHAIRS as mobility aids to the disabled and elderly are increasing important due to the increase in ageing population and accidents. It is important to offer users smooth and safe driving conditions with a quick response. In order to achieve this, the control system should be able to respond to the user's commands in the shortest possible time and with greatest accuracy. In addition, under various conditions, a powered wheelchair system can be regarded as a nonlinear multivariable system [1].

In literature, various advanced control strategies for powered wheelchair applications have been developed: an adaptable optimal controller [2], digital controller [3], advanced digital control techniques [4] and neural control technique [5]. However, none of these techniques have treated powered wheelchairs as a multivariable system and as a consequence, it is expected that the above control strategies would not be optimal when the operating environment for the wheelchairs is rough and nonlinear.

Regarding a wheelchair as a multivariable system, decoupling control techniques can be developed in order to decompose the wheelchair system into two scalar systems which can be designed independently. Various decoupling control techniques have been proposed [6-9], but these techniques are only applicable for linear systems.

Equipped with many desirable properties such as learning by experience, ability to generalise and map nonlinear functions, robustness in the presence of noise and multivariable interactions, neural network control systems have provided effective solutions for complex and nonlinear control problems with and without uncertainties [10-12].

As neural network controllers can be developed to provide robust solutions to nonlinear multivariable control problems, we aim to develop a novel control structure applicable for powered wheelchair systems by combining neural network controllers and decoupling techniques.

The paper is organised as follows. In the next section, the dynamic multivariable model of a powered wheelchair system is obtained and developed experimentally. A conventional decoupling control method is presented in Section 3. An advanced robust control based combination of TDD and neural network is presented in Section 4. Finally, a conclusion can be found in Section 5.

II. MODELLING OF A POWERED WHEELCHAIR SYSTEM

The wheelchair system as shown in Fig. 1 has two rear driving wheels and two free caster front ones. The drive system associated with each active wheel is composed of a DC motor, and the wheelchair is fitted with an incremental optical encoder and a gear-head. The power for the drive system is supplied by a 24 V battery. A personal computer attached at the back of the wheelchair plays the role of an intelligent controller for this system.

As the powered wheelchair system is a multivariable system, its dynamic model can be presented below.

$$\begin{bmatrix} v(s) \\ \omega(s) \end{bmatrix} = \begin{bmatrix} g_{11}(s) & g_{12}(s) \\ g_{21}(s) & g_{22}(s) \end{bmatrix} \begin{bmatrix} u_1(s) \\ u_2(s) \end{bmatrix} \quad (1)$$

where $u = \begin{bmatrix} u_1(s) & u_2(s) \end{bmatrix}^T$ is the actuator voltage input vector, v(s) and $\omega(s)$ are the linear output velocity and the angular output velocity respectively.

Fig. 1: A powered wheelchair

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As servo systems, the elements of dynamic model of the wheelchair can be written in the form.

$$g_{ij}(s) = \frac{K_{ij}}{\left(1 + sT_{ij}\right)} e^{-\tau_{ij}}; i, j = 1,2 \tag{2}$$

Introducing the step inputs ranged from a minimum value of -1V to a maximum value of 1V, the corresponding output responses for this system can be obtained.

An uncertain multivariable model for this system is developed by applying inputs (ranged between -1V and 1V) to the two DC motors and 80 step responses are collected overall. As a result, three dynamic models of the wheelchair system are obtained. These dynamic models correspond to the nominal transfer matrix $G_0(s)$, the upper-bounded transfer matrix $G_1(s)$ and the lower-bounded transfer matrix $G_2(s)$ as shown in Equations (3), (4), and (5):

$$G_0(s) = \begin{bmatrix} \frac{1.4}{(1+0.8s)} e^{-0.225s} & \frac{0.125}{(1+0.4s)} e^{-0.15s} \\ \frac{0.1}{(1+0.35s)} e^{-0.2s} & \frac{1.8}{(1+0.5s)} e^{-0.2s} \end{bmatrix}. \tag{3}$$

$$G_1(s) = \begin{bmatrix} \frac{1.8}{(1+0.55s)} e^{-0.1s} & \frac{0.22}{(1+0.35s)} e^{-0.1s} \\ \frac{0.25}{(1+0.3s)} e^{-0.1s} & \frac{2.6}{(1+0.45s)} e^{-0.1s} \end{bmatrix} \tag{4}$$

$$G_2(s) = \begin{bmatrix} \frac{1}{(1+1.05s)} e^{-0.35s} & \frac{0.04}{(1+0.45s)} e^{-0.2s} \\ \frac{0.005}{(1+0.4s)} e^{-0.3s} & \frac{1}{(1+0.55s)} e^{-0.3s} \end{bmatrix} \tag{5}$$

As the transportation lag terms can be approximated as the first order as follows.

$$e^{-\tau s} = \frac{1}{1 + \tau s} \tag{6}$$

the nominal model of the wheelchair system $G_0(s)$ can be simplified to:

$$G_0(s) = \begin{bmatrix} \frac{1.4}{(1+0.8s)(1+0.225s)} & \frac{0.125}{(1+0.4s)(1+0.15s)} \\ \frac{0.1}{(1+0.35s)(1+0.2s)} & \frac{1.8}{(1+0.5s)(1+0.2s)} \end{bmatrix} \tag{7}$$

III. DECOUPLING CONTROL OF THE WHEELCHAIR SYSTEM

A. Decoupling design of the wheelchair system

As the powered wheelchair system is an uncertain multivariable system, to simplify the control design procedure, the overall system can be decomposed into two independent scalar control systems using a decoupler D(s) as shown in Fig. 2.

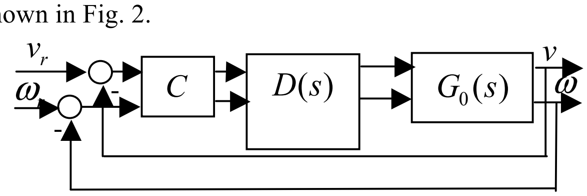

Figure 2: Decoupled control structure of the wheelchair system

Using the triangularisation technique [9], the following steps are made in order to construct the desirable decoupler D(s):

Step 1: In the first row, the element (1,1) already has the lowest degree $(\delta = 2)$.

Step 2: Subtract a multiple of the first column from the second to ensure $\delta(g_{12}) < \delta(g_{11})$

$$\frac{0.1.25}{(1+0.4s)(1+0.15s)} = a\left(\frac{1.4}{(1+0.8s)(1+0.225s)}\right) + b$$

Where:

$$a = \left(\frac{0.125}{1.4}\right)\left(\frac{(1+0.8s)(1+0.225s)}{(1+0.4s)(1+0.15s)}\right) \text{ and b=0}$$

Thus compensator is chosen as.

$$D(s) = \begin{bmatrix} 1 & -\left(\frac{0.125}{1.4}\right)\left(\frac{(1+0.8s)(1+0.225s)}{(1+0.4s)(1+0.15s)}\right) \\ 0 & 1 \end{bmatrix} \tag{8}$$

Therefore, the decoupled transfer function matrix $P_0(s) = G_0(s).D(s) =$

$$\begin{bmatrix} \frac{280}{(5+4s)(40+9s)} & 0 \\ \frac{10}{(20+7s)(5+s)} & \frac{41436(s+6.74)(s+2.89)(s+2.48)}{56(20+7s)(5+s)(5+2s)(20+3s)(2+s)} \end{bmatrix} \tag{9}$$

The obtained decoupled transfer function matrix is triangular-diagonal-dominant (TDD). The nominal transfer function matrix can be simplified further as shown below:

$$P_0(s) = \begin{bmatrix} \frac{280}{(5+4s)(40+9s)} & 0 \\ \frac{10}{(20+7s)(5+s)} & \frac{123.32(s+2.89)}{(20+7s)(5+s)(2+s)} \end{bmatrix} \tag{10}$$

B. Controller design of the wheelchair system

As the decoupled system Go(s)D(s) is triangular-diagonal-dominant, only the two diagonal elements Po(1,1) and Po(2,2) are required for controller design. Root locus techniques are then used to design two independent controllers to satisfy the second-order specification with a settling time $T_s \leq 4$s, a peak overshoot to a step input $M_p \leq 5\%$ and zero steady error to a step input.

The following controller transfer function matrix has been designed to satisfy the above performance specifications.

$$C(s) = \begin{bmatrix} 0.25\left(\frac{s+2.5}{s}\right) & 0 \\ 0 & 0.3\left(\frac{s+3}{s}\right) \end{bmatrix} \tag{11}$$

C. Results

The simulation result in Figure3 shows the responses of various models using obtained decoupler D(s) and controller C (s).

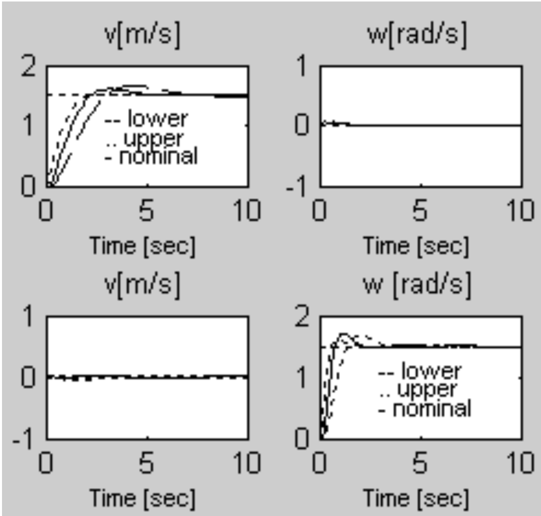

Figure 3: Conventional controller responses-simulation results

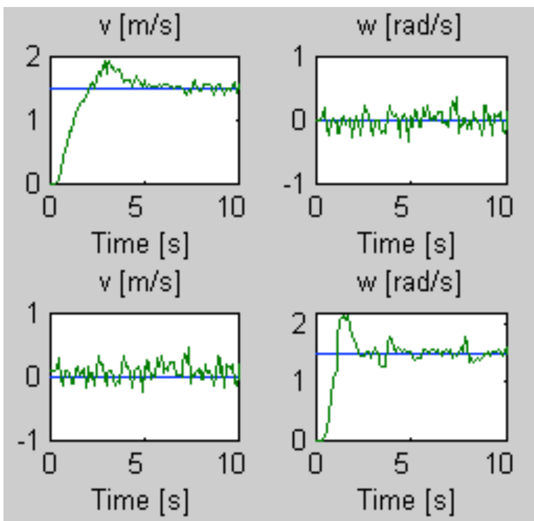

Figure 4: Conventional controller responses-practical results

To validate the performance of this design, real-time implementation is conducted. The algorithms are written in C++ using Visual C++ software. The sampling time Ts is chosen as 100 [ms]. The result is shown on Figure 4.

IV. ADVANCED ROBUST CONTROL BASED ON NEURAL NETWORK OF THE WHEELCHAIR SYSTEM

A. Advanced robust control structure

The conventional controllers are synthesised under an assumption of neglecting the effect of the element (2,1) in the equation (10). This is a valid design procedure because the decoupled system is TDD. However, as the overall model of the wheelchair may vary from the lower-bounded transfer function matrix to the upper-bounded transfer function matrix, the system performance may not be guaranteed.

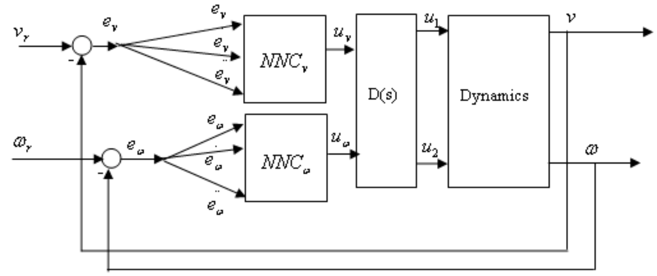

Figure 5: Neural control scheme of the wheelchair system

In order to improve the robustness of the system regardless of the changes in the wheelchair model, a neural network controller can be developed to replace the convention one.

The proposed neural controller scheme for the wheelchair system is illustrated in Figure 5.

Define $f_1(.);f_2(.)$ is the activation function of hidden layer and output layer respectively. For a given structure of the neural network controller, the output of the neural network can be calculated as follows:

$$u = \sum_{i=1}^{m} f_2(w_i \sum_{j=1}^{n} f_1(v_{ij} e_j)) \tag{12}$$

Define the objective function as following:

$$E = \frac{1}{2}(y_d - y)^2 \tag{13}$$

To minimise E, it is necessary to change the weights of neural network in the direction of negative gradient.

$$\Delta w_i = -\alpha \frac{\partial E}{\partial w_i} = -\alpha \frac{\partial E}{\partial y}\frac{\partial y}{\partial u}\frac{\partial u}{\partial w_i} \tag{14}$$

$$\Delta v_{ij} = -\alpha \frac{\partial E}{\partial v_{ij}} = -\alpha \frac{\partial E}{\partial y}\frac{\partial y}{\partial u}\frac{\partial u}{\partial v_{ij}} \tag{15}$$

$$\frac{\partial u}{\partial w_i} = f_2'\left(\sum_{i=1}^{m} w_i f_1\left(\sum_{j=1}^{n} v_{ij} e_j\right)\right) f_1\left(\sum_{j=1}^{n} v_{ij} e_j\right) \tag{16}$$

$$\frac{\partial u}{\partial v_{ij}} = f_2'\left(\sum_{i=1}^{m} w_i f_1\left(\sum_{j=1}^{n} v_{ij} e_j\right)\right) f_1'\left(\sum_{j=1}^{n} v_{ij} e_j\right) w_i e_j \tag{17}$$

In order to train the neural networks, the plant Jacobian matrix can be calculated from the nominal model of the wheelchair system. The update rules are:

$$w_i(k) = w_i(k-1) + \Delta w_i(k) \tag{18}$$

$$v_{ij}(k) = v_{ij}(k-1) + \Delta v_{ij}(k) \tag{19}$$

B. Results

Optimal neural controllers have been trained to meet the second-order specification with settling time $T_s \le 4(s)$, peak overshoot to a step input $M_p \le 5\%$, and zero steady error to a step input. The structure of the NNC_v is chosen as {3,4,1}, which is equivalent to 3 input nodes, 4 hidden nodes and a output node, whereas the structure of NNC_ω is {3,5,1}.

Convert the two element $P_0(1,1)$ and $P_0(2,2)$ into discrete form with sampling time as 100 [ms], we obtain as follows:

$$v(t) = 0.033u_v(t) + 0.027u_v(t-1) + 1.53v(t-1) - 0.56v(t-2)$$

$$\omega(t) = 0.07u_\omega(t) + 0.056u_\omega(t-1) + 1.42\omega(t-1) - 0.49\omega(t-2)$$

Therefore, the plant Jacobian matrix is calculated as:

$$J(t) = \begin{bmatrix} \frac{\partial v(t)}{\partial u_v(t)} & 0 \\ 0 & \frac{\partial \omega(t)}{\partial u_\omega(t)} \end{bmatrix} = \begin{bmatrix} 0.033 & 0 \\ 0 & 0.07 \end{bmatrix} \quad (20)$$

The sigmoid and linear activation functions are used for hidden and output layer respectively for both neural controllers with a learning rate of 0.015. Figure 6 shows the robustness of advanced controllers based on combination of TDD and neural controllers.

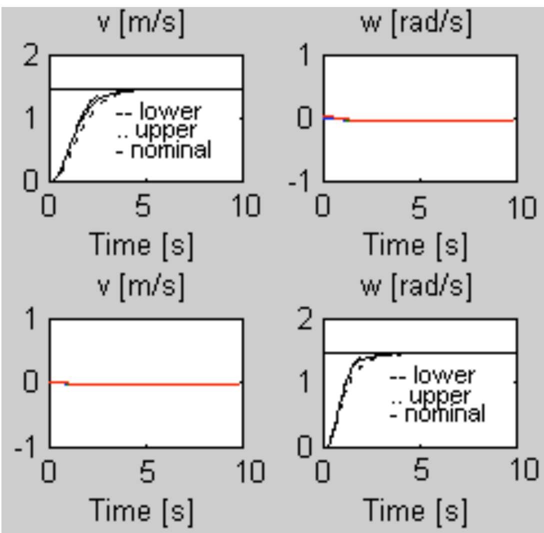

Figure 6: Robust neural controller responses - simulation results

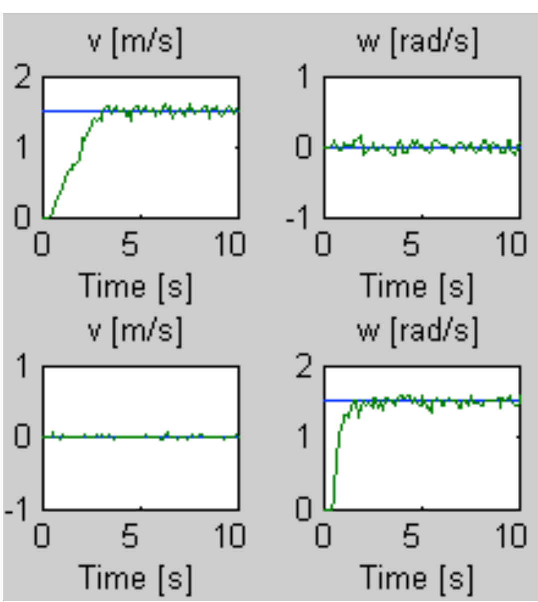

Figure 7: Robust neural controller responses - practical results

To validate the method, two real-time experiments are presented. The first one we put reference input $v_r = 1.5$(m/s) while keeping $\omega_r = 0(rad/s)$.Then we put $v_r = 0(m/s)$ and $\omega_r = 1.5(rad/s)$. The results are shown in Figure 7.

V. CONCLUSION

In this paper, we have presented a new control structure by combining the decoupling control technique with neural network controllers for the powered wheelchair system. This multivariable system is decoupled into two independent subsystems using the TDD decoupling technique, and the two neural network controllers are designed and implemented with the aim to improve the robustness and control performance of this system. The results obtained from the real-time implementation confirm that robust performance for this multivariable wheelchair control system can indeed be achieved.

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