An advanced control strategy of an electrical - powered hospital bed

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***Abstract*—This paper develops a multivariable control technique for low-level control of an intelligent hospital bed. First, multivariable hospital bed models, nominal, upper bounded and lower bounded models, are obtained via an experimental identification procedure. Based on the obtained nominal model, the triangular diagonal dominance (TDD) decoupling technique is applied to reduce a complex multivariable system into a series of scalar systems. For each scalar system, an online adaptive control strategy is then developed to cope with system uncertainties. Compared to the conventional control method, real-time experimental results showed that our proposed multivariable control technique achieved better performance. Experimental results also confirmed that desirable system performance was guaranteed under system uncertainty conditions.**

I. INTRODUCTION

In recent years, powered hospital beds have been specifically developed for service tasks to support patients during medical treatments and to reduce occupational risks for nurses. In order to achieve this, many successful studies have been proposed. Generally speaking, all of these studies have been focused on two aspects: mechanism design and integration of advanced technologies into the hospital bed.

The first aspect is the mechanism design of the multi-functional hospital bed. In [1-3], different multi-functional beds were proposed to assist bedridden patients to change their position without nursing help. With the second aspect, advanced technologies are applied to monitor the patient's health status or to prevent a negative consequence for bedridden patients. A study of the field-programmable gate array (FPGA) system [4] provided a solution to protect patients from pressure ulcers while a noninvasive bed sensing system [5] was developed to detect the heartbeat, respiration, body movement, and scratching motion of a person lying or sleeping on the bed.

In literature, none of the approaches has been concerned with how the smart bed operates while it moves in the real environment. Moreover, no papers estimate how uncertain factors impact on the hospital bed, such as environment conditions (hard platform, glass, high friction way) or even the obvious case of a patient lying on the bed. Therefore, this paper contributes a new solution to deal with the control problem of the hospital bed in real-time environments.

In this study, the hospital bed is regarded as a linear multivariable system with uncertainties. A nominal transfer function model obtained from experiments is used as a main model for the hospital bed. A TDD decoupling technique [6] is then applied to eliminate interactions between control signals. As a result, a multivariable problem is converted into single variable problems. For each single variable control problem, a closed-loop proportional-integral (PI) controller is then designed to guarantee the stability of the overall system.

Artificial Neural Network (ANN) is known as a powerful tool to solve the nonlinear problem. It has many advantages such as learning by experiment, ability to generalize and map nonlinear functions, robustness in the presence of noise and multivariable interactions [7]. To improve the performance of the overall system, we develop an advanced control method by combining the TDD decoupling technique and an online adaptive neural network controller.

The structure of our study is organized as follows. In the first part of section II, the power hospital bed and its nominal model are revealed. Then the decoupling control design of the hospital bed is shown in the remaining part of this section. Based on ANN, the advanced control method is proposed in section III. Real-time experimental results of the proposed method and a comparison between the proportional-integral (PI) controller and the online adaptive NN controller are presented in section IV. Finally, a conclusion can be found in Section V.

II. DECOUPLING CONTROL DESIGN OF THE HOSPITAL BED

A. The powered hospital bed and its dynamic model

In order to achieve our goal, our work focuses on the low level control of the hospital bed system. Based on our related work [8], the low level system of the hospital bed consists of HDC2450 controller, two incremental optimal encoders and two direct current (DC) motors. The hospital bed system is shown in Fig.1.

HDC2450 controller plays the role of receiving commands from central processing unit (Mac mini computer), feedback from incremental optical encoders. Power control method is used to increase or decrease the motor speed. The controlling command is sent to HDC2450 controller through RS232 to issue the appropriate power to DC motors.

The hospital bed is regarded as a multivariable system with two inputs and two outputs. Let the dynamic model be

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

Where $u = [u_1(s) \quad u_2(s)]^T$ is the power input vector, $v(s)$ and $\omega(s)$ are the linear velocity output and the angular velocity output, respectively. $G_{ij}(s)$ is the single-input-single-output transfer function models as written in the form.

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$$G_{ij}(s) = \frac{K_{ij}}{(1+sT_{ij})} e^{-s\tau_{ij}} \quad i,j = 1,2 \tag{2}$$

The linear and angular velocity can be calculated as in:

$$v = \frac{1}{2} r(w_r + w_l) \tag{3}$$

$$\omega = \frac{r}{2b}(w_r - w_l) \tag{4}$$

Where r is wheel diameter. Symbol b is defined as the wheelbase as shown in Fig.2. w_r and w_l are angular velocites of the right-hand and left-hand wheel.

Fig.1 The hospital bed

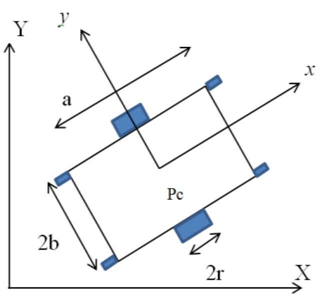


Fig.2.The hospital bed system

As various uncertain factors affect to the hospital bed, it's difficult to obtain the precise transfer model. According to [7], we operate the hospital bed with various input values on the different conditions of the floor surfaces (slippery, high friction or carpet). After obtaining 100 output responses, the lower bounded, nominal, upper bounded models are calculated and written in Eq. (5):

$$G_{lower}(s) = \begin{bmatrix} \frac{0.93}{(1+0.24s)} e^{-0.07s} & \frac{0.015}{(1+0.07s)} e^{-0.07s} \\ \frac{0.048}{(1+0.06s)} e^{-0.04s} & \frac{0.28}{(1+0.3s)} e^{-0.07s} \end{bmatrix}$$

$$G_{nom}(s) = \begin{bmatrix} \frac{1}{(1+0.8s)} e^{-0.1s} & \frac{0.025}{(1+0.1s)} e^{-0.2s} \\ \frac{0.06}{(1+0.1s)} e^{-0.1s} & \frac{0.51}{(1+0.65s)} e^{-0.1s} \end{bmatrix} \tag{5}$$

$$G_{upper}(s) = \begin{bmatrix} \frac{1.17}{(1+1.43s)} e^{-0.35s} & \frac{0.03}{(1+0.36s)} e^{-0.25s} \\ \frac{0.08}{(1+0.2s)} e^{-0.35s} & \frac{1.09}{(1+1.29s)} e^{-0.3s} \end{bmatrix}$$

The time delay part can be approximated as follows

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

The nominal model of the hospital bed system can be simplified to:

$$G_{nom}(s) = \begin{bmatrix} \frac{1}{(1+0.8s)(1+0.1s)} & \frac{0.025}{(1+0.1s)(1+0.2s)} \\ \frac{0.06}{(1+0.1s)^2} & \frac{0.51}{(1+0.1s)(1+0.65s)} \end{bmatrix} \tag{7}$$

B. Decoupling design of the hospital bed

Fig.3 presents the block diagram of the decoupler incorporated with the decoupling matrix for a multivariable system is shown in Eq. (8).

$$H(s) = \begin{bmatrix} H_{11}(s) & H_{12}(s) \\ H_{21}(s) & H_{22}(s) \end{bmatrix} \tag{8}$$

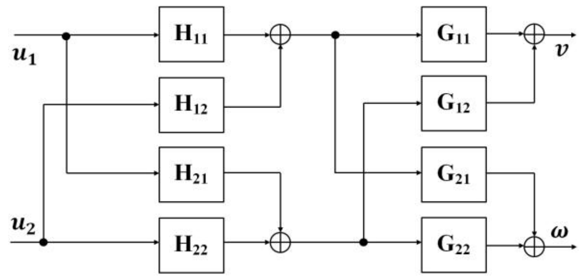


Fig.3.The configuration of decoupler with the system

Using the Triangular Diagonal Dominance technique [6], The desired decoupler $H(s)$ is given by Eq.9.

$$H(s) = \begin{bmatrix} 1 & \frac{-0.025(1+0.8s)}{1+0.2s} \\ 0 & 1 \end{bmatrix} \tag{9}$$

Through the desired decoupler $H(s)$, the nominal transfer function matrix can be simplified as shown below.

$$P(s) = G_{nom}(s)H(s)$$

$$P(s) = \begin{bmatrix} \frac{1}{(1+0.8s)(1+0.1s)} & 0 \\ \frac{0.06}{(1+0.1s)^2} & \frac{7.25(s+11.17)}{(s+1.54)(s+10)^2} \end{bmatrix} \tag{10}$$

C. Decoupled PI controller design of the hospital bed

The structure of decoupled PI controller is presented in Fig.4. Block P plays the role of transforming inputs U^*_{c11}, U^*_{c22} to outputs P_l,P_r. P_l,P_r are power values to issue two DC motors.

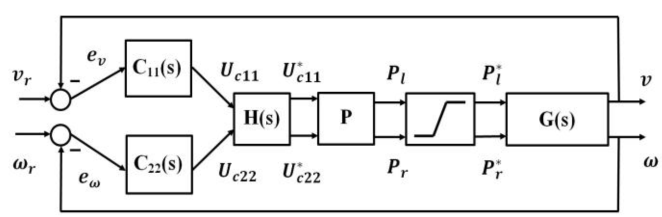


Fig.4.The control system of the hospital bed

Two elements P(1,1) and P(2,2) are used to design PI controllers C(1,1) and C(2,2), respectively. In order to obtain the PI's controller parameters, Root Locus technique is used to achieve this. Requirements of each PI controller are a settling time Ts < 4s and a peak overshoot < 10%. The diagonal matrix C(s) is described for two PI controllers after tuning PI parameters, as shown in Eq. (11).

$$C(s) = \begin{bmatrix} 1.6 + 2\frac{1}{s} & 0 \\ 0 & 1.8 + 3\frac{1}{s} \end{bmatrix} \quad (11)$$

III. Advanced Neural Control Method

The decoupled PI controllers are obtained from the nominal transfer model. As the impact of uncertain factors, the overall model of the hospital bed may vary. Therefore, the system operation may not be guaranteed. To deal with this problem, an advanced control algorithm is proposed.

A. Online adaptive neural network control design

Based on [9], the block diagram of advanced decoupled controller is illustrated in Fig.5.

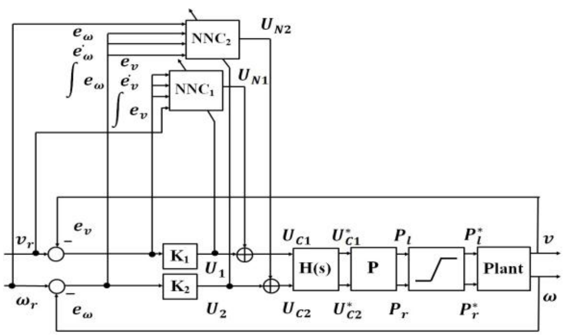


Fig.5 The advance robust neural network control scheme

Two online adaptive neural network controllers (NNCs) are developed to let the linear velocity output (v) and the angular velocity (ω) track the desired reference linear velocity v_r and the desired reference angular velocity ω_r, respectively. The online adaptive neural network controller NNC$_1$ has 4 inputs ($v_r, e_v, \dot{e_v}, \int e_v$) and 1 output U$_{N1}$ while the online adaptive neural network controller NNC$_2$ also has 4 inputs ($\omega_r, e_\omega, \dot{e_\omega}, \int e_\omega$) and 1 output U$_{N2}$.

During the training process, U$_1$ and U$_2$ are used as teaching signals to adjust the neural network parameters. K$_1$ and K$_2$, two feedback controllers, are fixed for the close-loop system. The output of NNC$_1$ and NNC$_2$ are given by the following equations:

$$U_{N1} = \left(\sum_{j=1}^{m} W_j^1 f\left(\sum_{i=1}^{n} \overline{W_{ij}^1} Z_i^1 + \overline{b_j^1}\right) + b^1\right) \quad (12)$$

$$U_{N2} = \left(\sum_{j=1}^{m} W_j^2 f\left(\sum_{i=1}^{n} \overline{W_{ij}^2} Z_i^2 + \overline{b_j^2}\right) + b^2\right) \quad (13)$$

Where f_1 is the activation function of hidden layer, as shown in Eq. (14)

$$f(n) = \frac{1 - e^{-2n}}{1 - e^{-2n}} \quad (14)$$

Define the cost function as follows:

$$J_1 = \frac{1}{2}(v_r - v)^2 \quad (15)$$

$$J_2 = \frac{1}{2}(\omega_r - \omega)^2 \quad (16)$$

In the proposed control scheme

$$e_v = e_1 = \frac{U_{C1} - U_{N1}}{K_1} \quad (17)$$

$$e_\omega = e_2 = \frac{U_{C2} - U_{N2}}{K_2} \quad (18)$$

To minimize the cost function J, it is necessary to change the weights of the neural network controller to the direction of a negative gradient. Applying the chain rule, the results are obtained as following

$$\Delta W_j^k = \frac{\partial J_k}{\partial W_j^k} = \frac{\partial J_k}{\partial e_k}\frac{\partial e_k}{\partial U_{Nk}}\frac{\partial U_{Nk}}{\partial W_j^k} \quad (19)$$

$$\Delta b^k = \frac{\partial J_k}{b^k} = \frac{\partial J_k}{\partial e_k}\frac{\partial e_k}{\partial U_{Nk}}\frac{\partial U_{Nk}}{b^k} \quad (20)$$

$$\Delta\overline{W_{ij}^k} = \frac{\partial J_k}{\overline{W_{ij}^k}} = \frac{\partial J_k}{\partial e_k}\frac{\partial e_k}{\partial U_{Nk}}\frac{\partial U_{Nk}}{\overline{W_{ij}^k}} \quad (21)$$

$$\Delta\overline{b_j^k} = \frac{\partial J_k}{\overline{b_j^k}} = \frac{\partial J_k}{\partial e_k}\frac{\partial e_k}{\partial U_{Nk}}\frac{\partial U_{Nk}}{\overline{b_j^k}} \quad (22)$$

Thus,

$$\Delta W_j^k = -\frac{e_k}{K_k} f\left(\sum_{i=1}^{n} \overline{W_{ij}^k} Z_i^k + \overline{b_j^k}\right) \text{ and } \Delta b^k = -\frac{e_k}{K_k} \quad (23)$$

$$\Delta\overline{W_{ij}^k} = -\frac{e_k}{K_k} f'\left(\sum_{i=1}^{n} \overline{W_{ij}^k} Z_i^k + \overline{b_j^k}\right) W_j^k Z_i^k \quad (24)$$

$$\Delta\overline{b_j^k} = -\frac{e_v}{K_1} f'\left(\sum_{i=1}^{n} \overline{W_{ij}^k} Z_i^k + \overline{b_j^k}\right) W_j^k \quad (25)$$

The proposed updating laws are as following

$$b^k = \begin{cases} b^k - \mu\Delta b^k \text{ if } |\Delta b^k| \le 30\%.b^k \\ b^1 \end{cases}$$

$$\overline{b_j^k} = \begin{cases} \overline{b_j^k} - \mu\Delta\overline{b_j^k} \text{ if } \left|\Delta\overline{b_j^k}\right| \le 30\%.\overline{b_j^k} \\ \overline{b_j^k} \end{cases}$$

$$W_j^k = \begin{cases} W_j^k - \mu\Delta W_j^k \text{ if } \left|\Delta W_j^k\right| \le 30\%.W_j^k \\ W_j^k \end{cases}$$

$$\overline{W_{ij}^k} = \begin{cases} \overline{W_{ij}^k} - \mu\Delta\overline{W_{ij}^k} \text{ if } \left|\Delta\overline{W_{ij}^k}\right| \le 30\%.\overline{W_{ij}^k} \\ \overline{W_{ij}^k} \end{cases} \quad (26)$$

Where k = 1, 2 and μ is the learning rate of the neural network controller.

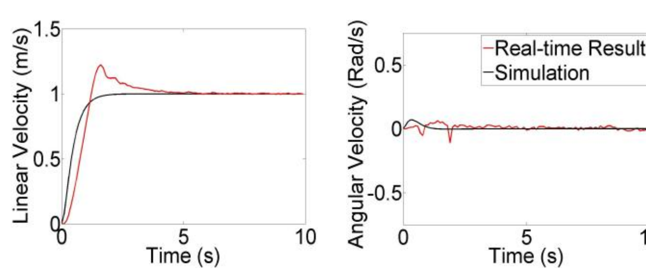
B. Pre-training process for neural network controller

To guarantee the optimal performance of two closed-loop systems, a pre-training process may be applied. The purpose of the pre-training is to find relatively optimal weights for the neural controller which improves convergence speed.

IV. Results and Discussions

A. Decoupled PI control

The simulation and real-time results of decoupled PI controllers are shown in Fig.6. Labwindows software with real-time module was used to implement control tasks for the hospital bed system in a real environment. The sampling time is set at 100ms.



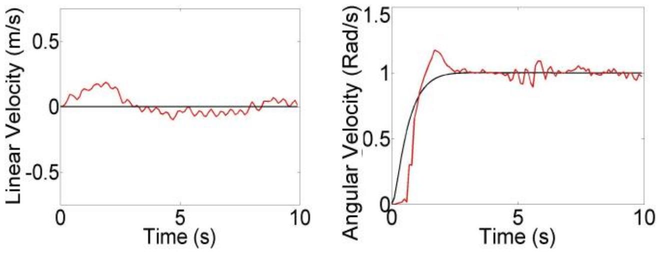


Fig.7 Simulation and real-time results of the decoupled PI controller

B. Advanced Neural Network control

The neural network structure (4,3,1), which has 4 input nodes, 3 hidden nodes and 1output node, is applied in this experiment. The learning rate (μ) is chosen as $\mu = 0.0002$ and the gains for the fixed feedback controllers are chosen as K_1 = 0.4 and K_2 = 0.1. We tested the hospital bed on the cement surface. Fig.8 shows the obtained real-time results.

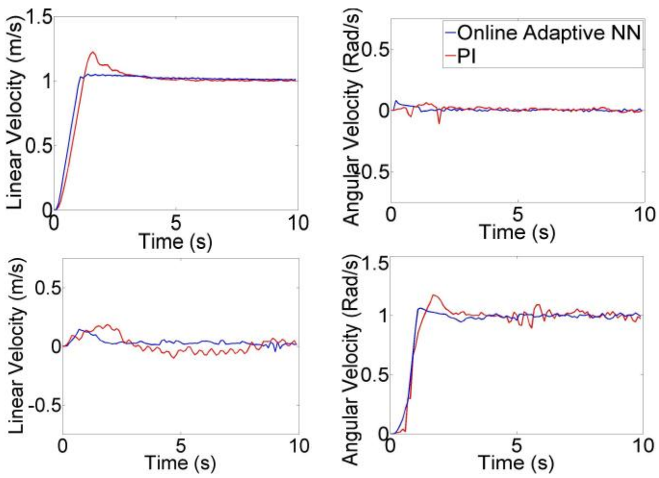


Fig.8 Real-time responses of the online adaptive NN and PI controllers

C. Experiment with patient loading

In order to confirm the system performance under condition of system uncertainty, we conducted the result-time experiment with the hospital bed carrying an 80kg patient. The Fig.9 show the comparative results obtained by PI control method and our proposed neural network control method.

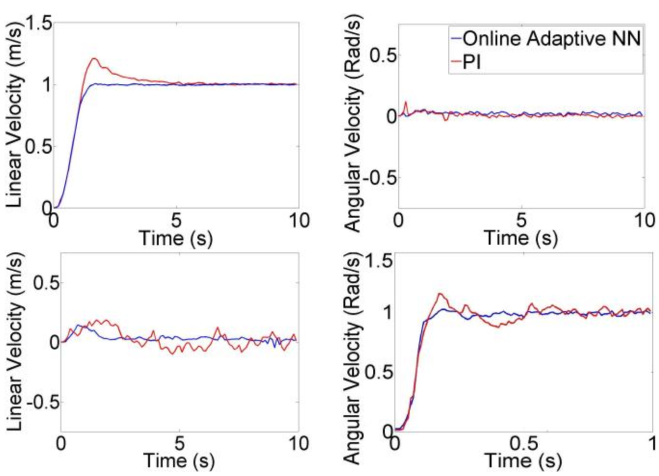


Fig.9 The hospital bed with patient loading in the real environment

The closed-loop responses of the elements G_{12} and G_{21} indicate that the system has been decoupled efficiently.

D. Discussions

The results in Fig.7 show that TDD significantly reduced the coupling effect of the hospital bed system. Compared to two PI controllers, better performance (Ts<4[s] and no overshoot) of the overall system was achieved by two pre-trained neural network controllers. The performance of the system is also confirmed in real-time implementation as shown in Fig.8. The system uncertainty effect is substantially reduced as shown on the last real-time experiment (Fig.9 results).

V. Conclusion

In this study, we have shown a new approach to the research area of the hospital bed. As various uncertain factors impact the hospital bed system when it performs in the real environment, it is retreated as a linear multivariable system with uncertainties. By combining decoupling technique with adaptive neural network control approach, our proposed control strategy transforms a multivariable control problem into single variable control problems. Both simulation and real-time experiment confirm that the desired performance of the overall system has been achieved even under condition of system uncertainties.

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