A novel target following solution for the electric powered hospital bed based on Laser Range Finder

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***Abstract*— The paper proposes a novel target following solution for an electric powered hospital bed. First, an improved real-time decoupling multivariable control strategy is introduced to stabilize the overall system during its operation. Environment laser-based data are then collected and pre-processed before engaging a neural network classifier for target detection. Finally, a high-level control algorithm is implemented to guarantee safety condition while the hospital bed tracks its target. The proposed solution is successfully validated through real-time experiments.**

I. INTRODUCTION

Conventionally, hospital beds have been operated in hospital environments through manual pushing by professional hospital staffs. This is the main cause of increasing physical injuries and workload for healthcare workers. In recent years, many transportation systems have been developed to solve this problem. These developments include a bed transfer system [1] or a combination of a bed mover and a patient transfer apparatus [2]. These systems not only reduce effectively the risk of transportation in hospital environments but also simplify the task of moving beds or patients between wards. However, it is still challenging to develop an intelligent hospital bed, which could automatically be guided in hospital environments.

Surprisingly, not many publications have been specifically devoted to design this type of intelligent hospital beds. In our previous work [3], we presented a new assistive patient mobile system, an intelligent hospital bed, which followed an autonomous robot. In this paper, we extend our research to develop an advanced target tracking solution for this intelligent hospital bed.

This project consists of three stages, target detection method, high-level control strategy and low-level controller design. Various approaches have been employed to detect the target such as multiple sensors system[4] , camera fusion [5] or laser range finder (LRF) [6] . Among them, LRF is widely utilized because it equipped with high resolution and good reliability. In [7], Eui-Jung proposed a target detection algorithm using Support Vector Data Description (SVDD). However, the computation of this technique is very expensive and complex. An artificial Neural Network has been studying for many years to solve complex identification problems. The advantage of a Neural Network (NN) is that the algorithm could be generalized to solve various problems. Instead of improving SVDD algorithm, a NN classifier is applied in our solution.

In literature, several target tracking methods are applied on wheelchairs or various types of mobile robot. In terms of control strategy for these systems, many studies have been presented to improve the high level control problem whereas little research has concerned about the low-level control task. As the hospital bed is usually very heavy, the performance of the hospital bed depends highly on coupling effects and its dynamics model. It is necessary to implement an advanced low-level controller to stabilize the bed system while it transports.

In this study, we develop a novel target following solution for the intelligent hospital bed. Our proposed method focuses on two main problems: target detection algorithm and low-level controller design. For the first problem, we develop a classifier to detect the target based on a Neural Network with three features. In the next problem, an Improved Decoupling Multivariable Control (IDMC) strategy is designed to guarantee the stability of the overall system. In order to achieve desired performance, a decoupling technique known as Triangular Diagonal Dominance (TDD) [8] is firstly utilized to convert the multivariable system to series of single variable systems. Then based on [9, 10], a Neural Network control method strategy is designed for each independent scalar system.

The structure of our study is organized as follows. In section II, a novel target following solution is presented in detail. Real-time experimental results and discussions of the proposed approach are shown in Section III. Finally, a conclusion can be found in Section IV.

II. A NOVEL TARGET FOLLOWING SOLUTION FOR THE HOSPITAL BED SYSTEM

In our proposed solution, we focus firstly on the design of an improved decoupling multivariable control method for the low-level system of the hospital bed. A target detection algorithm based on a neural network is then developed to classify the target and non-targets. Finally, we implement a high-level control strategy to track the target with the desired safe distance.

A. Improved Decoupling Multivariable Control

To design a low-level controller, the hospital bed model system is regarded as a linear multivariable system with uncertainties. Two steps are required to construct the controller. The structure of the improved decoupling multivariable control strategy is presented in Fig.1.

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Step 1: Decoupling procedure using TDD technique

In this step, a decoupling procedure is applied to reduce the multivariable control problem to series scalar control problems. As mentioned in [10], the nominal dynamic model $G_{nom}(s)$ of the hospital bed can be obtained and simplified as:

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

After utilizing the TDD technique, the decoupling transfer function matrix is obtained as:

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

Based on [11], we try to diagonalize the triangular matrix $P_{nom}(s)$ by choosing the pre-compensator $E(s)$ as follows:

$$E(s) = \begin{bmatrix} 1 & 0 \\ -\frac{0.827(s+1.54)}{s+11.17} & 1 \end{bmatrix} \quad (3)$$

Then, the diagonalized model of the electric powered hospital bed can be obtained in the simplified form:

$$P_D(s) = P_{nom}(s).E(s) \quad (4)$$

$$P_D(s) \approx \begin{bmatrix} \frac{1}{(1+0.8s)(1+0.1s)} & 0 \\ 0 & \frac{7.25}{(s+1.54)(s+10)} \end{bmatrix} \quad (5)$$

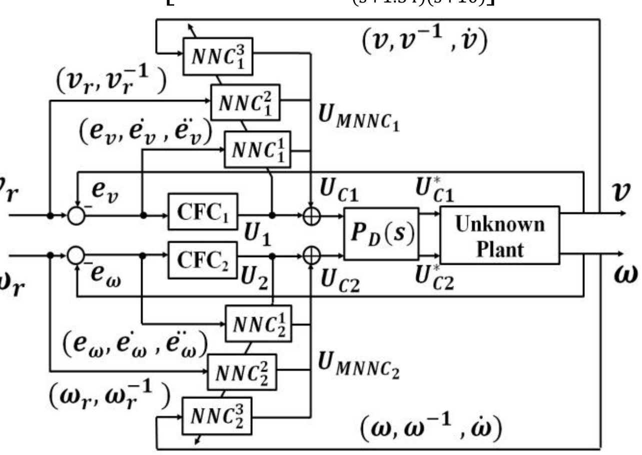

Fig. 1. Improved decoupling multivariable control strategy

Step 2: A modification of Neural Network control design via Feedback Error Learning

After being decoupled, the hospital bed system is decomposed into two independent single variable systems, linear velocity (v) loop and angular velocity (ω) loop. Based on [9, 12], we modify the neural network structure via Feedback Error Learning control strategy for each velocity loop. In our proposed approach, the structure of three neural networks is adopted to improve the ability of learning the inverse model. The output of the conventional feedback controller (CFC) is utilized to train all partial neural networks. The set of NN inputs is divided into appropriate smaller sets for each NN. The set of input for each neural network is given by:

$$X_1^1 = [e_v, \dot{e_v}, \ddot{e_v}]^T \quad X_1^2 = [v_r, v_r^{-1}]^T \quad X_1^3 = [v, \dot{v}, v^{-1}]^T$$
$$X_2^1 = [e_\omega, \dot{e_\omega}, \ddot{e_\omega}]^T \quad X_2^2 = [\omega_r, \omega_r^{-1}]^T \quad X_2^3 = [\omega, \dot{\omega}, \omega^{-1}]^T$$

where $(.)^{-1}$ denotes for output values at time $(n-1)$. The output of multiple neural networks is given by the following equation:

$$U_{MNNC_k} = \sum_n \left(\sum_j W_{kj}^n f\left(\sum_i X_{ki}^n W_{kij}^n + b_{kj}^n\right) + b_k^n\right) \quad (6)$$

where $f(\cdot)$ denotes the activation function of the hidden layer. Defining the cost function as follows:

$$E_1 = \frac{1}{2}(v_r - v)^2 = \frac{1}{2}{e_1}^2 \quad (7)$$

$$E_2 = \frac{1}{2}(\omega_r - \omega)^2 = \frac{1}{2}{e_2}^2 \quad (8)$$

In the proposed control scheme:

$$U_{C_k} = U_k + U_{MNNC_k} \quad (9)$$

where U_k is the output of CFC. To train the neural networks, we apply the chain rule:

$$\begin{aligned} \frac{\Delta E_k}{\partial W_{kj}^n} &= \delta \frac{\partial E_k}{\partial e_k} \frac{\partial U_{MNNC_k}}{\partial W_{kj}^n} \\ \frac{\Delta E_k}{\partial b_k^n} &= \delta \frac{\partial E_k}{\partial e_k} \frac{\partial U_{MNNC_k}}{\partial b_k^n} \\ \frac{\Delta E_k}{\partial W_{kij}^n} &= \delta \frac{\partial E_k}{\partial e_k} \frac{\partial U_{MNNC_k}}{\partial W_{kij}^n} \\ \frac{\Delta E_k}{\partial b_{kj}^n} &= \delta \frac{\partial E_k}{\partial e_k} \frac{\partial U_{MNNC_k}}{\partial b_{kj}^n} \end{aligned} \quad (10)$$

Depending on the conventional feedback controller utilizing, $\delta = \frac{\partial e}{\partial U_{MNNC}}$ is obtained from equation (10). By adding the momentum factor β, the updating rules of weights and bias are given by:

$$\Delta W_j^n(n+1) = (1-\beta)\delta f\left(\sum W_{ij}^n X_i^n + b_j^n\right) + \beta \Delta W_j^n(n)$$
$$\Delta b^n(n+1) = (1-\beta)\delta + \beta \Delta b^n(n) \quad (11)$$
$$\Delta W_{ij}^n(n+1) = (1-\beta)\delta f'\left(\sum W_{ij}^n X_i^n + b_j^n\right) W_j^n X_i^n + \beta \Delta W_{ij}^n(n)$$
$$\Delta b_j^n(n+1) = (1-\beta)\delta f'\left(\sum W_{ij}^n X_i^n + b_j^n\right) W_j^n + \beta \Delta b_j^n(n)$$

B. *Target detection algorithm*

From the laser range finder attached on the hospital bed, raw environment data are acquired and pre-processed. Background data subtraction process is implemented for filtering the raw data, obtained data are then clustered by adopting foreground data clustering algorithm. To identify which cluster denoting for the target, we adopt a neural network classifier. This neural network has a multilayer feed-forward neural network structure with one input layer, one hidden layer and one output layer. Based on [3], three features W, G, H of each cluster are utilized as inputs of the neural network. *Tansig* is the hyperbolic tangent sigmoid transfer function used for hidden layer and output layer. The output layer has one node, which indicates the target or the non-targets.

To speed up the convergence of the back propagation learning method, the ANN is trained by the Levenberg-Marquardt (LM) algorithm, which is effective and popular training algorithm. To measure the performance of the classification results, sensitivity and specificity are used and given as follows:

$$Sensitivity = \frac{TP}{TP+FN} \tag{12}$$

$$Specificity = \frac{TN}{TN+FP} \tag{13}$$

where TP (True Positive) is the number of target events which are correctly classified as target; FN (False Negative) is the number of target events which are wrongly classified as non-target; TN (True Negative) is the number of non-target events which are correctly classified as non-target; FP (False Positive) is the number of non-target events which are wrongly classified as target [13].

C. High level control strategy

To track the target, a high-level control strategy is required to ensure the target be always in front of the bed system with a desired safe distance. The linear velocity of the bed system is adopted to control the distance between the target and the bed system while the angular velocity of the hospital bed is utilized to adjust the angle between the direction of target and the direction of the hospital bed with respect to the hospital bed local coordinate. A typical proportional controller may be suitable for our application. Two proportional controllers are developed for our solution to control the linear velocity and angular velocity. The following equations describe the proportional controllers applied to the hospital bed system:

$$v = K_v(D_a - D_d) \tag{14}$$

$$\omega = K_\omega(\varphi_a - \frac{\pi}{2}) \tag{15}$$

where K_v is the proportional linear velocity control gain, K_ω is the angular velocity control gain, D_a, D_d denote the actual distance between the hospital bed and the target and the desire tracking distance, respectively. φ_a is defined in Figure.2.

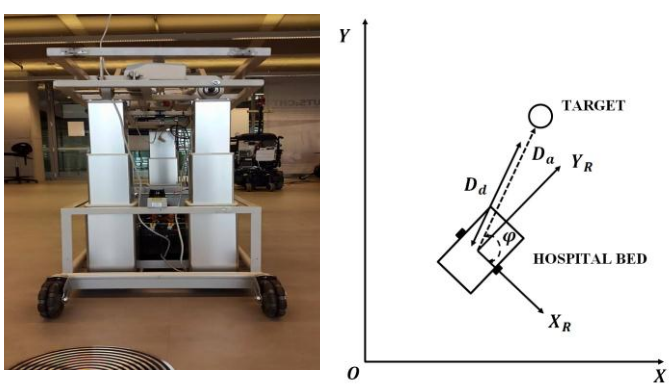

Fig. 2. The hospital bed with laser range finder (a), The hospital bed and the target for tracking (b)

III. Real Time Experimental Results

The purpose of transportation in the hospital bed is the transferring of patient between wards. For the autonomous navigation approach, the hospital bed takes time to build the global map and localize the destination. Moreover, it is not able to avoid the case of wrong destination. Comparison with the target following solution, the hospital bed is able to follow nurse (the target) who knows exactly the destination of the transportation. From the theory of our proposed solution, the hospital bed has the ability of tracking different types of target working as a navigator such as a nurse or an autonomous robot. Inheriting our previous work [3], we utilize an autonomous robot (Turtlebot), chosen as the target. All configurations of the hospital bed are maintained from the previous work. In this study, our work focuses on improving the target detection method and guaranteeing the stability of the bed system while it follows the Turtlebot. Therefore we perform three experiments to evaluate our proposed solution. Fig.3 shows the hospital bed following the Turtlebot in the real-time environment.

A. Neural Network Classifier

In the first experiment, six different static targets, including a trash can, a recycle bin, a carton box, human legs, a flower pot and a warning column, are used for data collection procedure. Using laser range finder attached on the hospital bed, 2250 samples, 750 samples for Turtlebot and 1500 samples for other target have been collected. These samples contain three features W, G, H. These features are then used as inputs for the neural network training task. The overall data set consists of a training set, validation set, and testing set, which are randomly selected with proportions of 35%, 35%, and 30% out of overall data, respectively.

Fig. 3. The hospital bed follows the Turtlebot

TABLE I. RESULT OF NEURAL NETWORK CLASSIFICATION

METHOD	TRAINING		VALIDAITON		TESTING	
	Sens	Spec	Sens	Spec	Sens	Spec
NN-LM	93.45	92.18	92.43	88.64	92.41	89.8
NN-SCG	91.83	88.56	92.16	90	91.13	88.81
NN-RP	91.3	90.26	86.13	89.49	90.58	90.26
NN-GDX	91.63	89.12	90.03	89.52	89.38	86.85

For the comparison of the performances, three other training algorithms, gradient descent with momentum (GDX), resilient back propagation (RP) and scaled conjugate gradient, were also utilized to train the neural network model in order to compare their performances with the proposed Table I presents the results of training algorithms in terms of classifying the Turtlebot and other objects.

B. *Improved Decoupling Multivariable Controller*

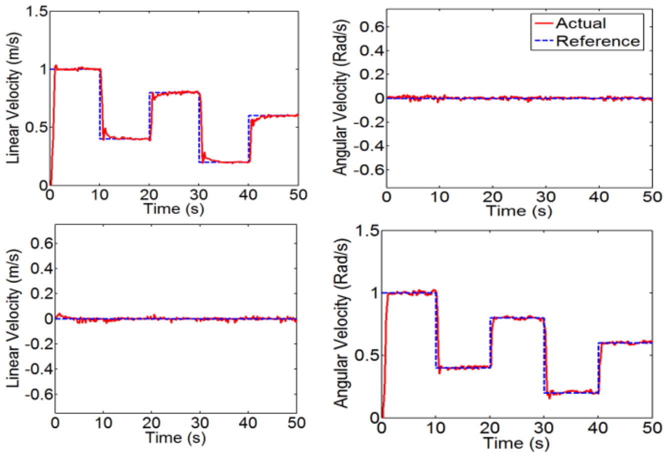

Figure. 4. The Improved Decoupling Multivariable control strategy

In the second experiment, we test the speed tracking performance of the hospital bed. We also evaluate the ability of eliminating the coupling effect of the improved decoupling multivariable control strategy. Firstly, the angular velocity of the hospital bed is constant at $\omega = 0$ (rad/s) while the linear velocity is changed with the order: $v = 1$(m/s), 0.4(m/s), 0.8(m/s), 0.2(m/s) and 0.6(m/s) each t = 10s. Then this process is repeated with the angular velocity. Clearly, the coupling effects are suppressed as shown in Fig.4.

C. *Tracking performance*

In the final experiment, the Turtlebot moved with varying direction in the real environment to show the tracking performance of the hospital bed. Fig.5 shows the obtained trajectory tracking results.

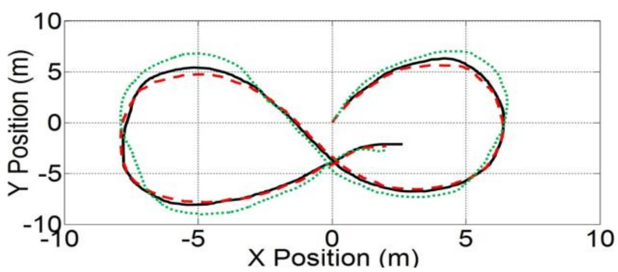

Fig. 5. Target following of the hospital bed

The black line presents the Turlebot path while the green dot line denotes for the path of the hospital bed with the conventional low-level controller. The dash line (red) presents for the hospital bed path with utilizing the improved low-level control strategy

Discussions

Table I illustrates that LM algorithm procedures the best classification in which the training results of 93.45% sensitivity and 92.18% specificity are gained and the testing set leads to 92.41% sensitivity and 89.8% specificity. As shown in Fig.4, uncertainties and external disturbances of the hospital bed are effectively eliminated. The speeds tracking results shown this Fig.4 also indicate that desired performance of the low level of the hospital bed is achieved. In Fig.5, even though the Turtlebot moved in a curve path, the hospital bed is able to track the target with minimum error. The obtained results confirm that the new neural network controllers perform better than the conventional controllers.

IV. Conclusion

In this paper, we have proposed a novel target tracking solution for a hospital bed system. The first contribution is the advanced target detection based neural network classification. The second contribution is the development of the advanced low-level control algorithm for the hospital bed. Utilizing the proposed target tracking solution in real time, we have shown that low-level control strategy plays an important role in applications of transportation for the hospital bed.

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