Development of Intelligent Bed Robot System

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Abstract: In this paper, an Intelligent Bed Robot System (IBRS) is proposed, that is a special bed equipped with robot manipulator. To assist a patient using IBRS, pose and motion estimation process is fundamental. It is designed to help the elderly and the disabled for their independent life in bed without other assistants. For this purpose, we use the pressure sensor distributed mattress for detecting the change of motion on the bed. Using that data, we control the robot arm to move to the appropriate position and serve to the user. In addition, we can estimate the user's intention based on the change of pressure and use those data to control the robot arm guide.

Keywords: Intelligent bed robot system, pressure sensor distributed bed, pose and motion estimation

1. INTRODUCTION

The increase in the life span of many elderly people means that there are more demands for aids to support them in normal life. It is a fact that the general improvement in living conditions has increased the number of elderly persons (over 60 years old) [1]. It is increasingly important that robots assist humans at home because of the forthcoming aging society problem.

Usually, one third or a quarter of life is spent for being in bed. Especially, peoples who need care usually spend the whole day for being in bed. If their movements are measured and evaluated quantitatively, not only robots can assist humans properly, but also theses data can be used for a health monitoring and an evaluation of rehabilitation progress.

Body movements are very important for humans to live. Moving the body makes humans take adaptive behaviour to the outside world. It is said that physical conditions and mental conditions are buried in the body movements, because humans often move their bodies when they are in good health, but move rarely their bodies when they are in bad health. Therefore, it is thought that physical and mental conditions can be estimated by measuring the body movements.

Body movement can be classified by its size [2]. Fig. 2 shows the classification of body movement. The existence means only whether the human exists or not. The posture is a static pose. The articular movement means a dynamic motion such as twisting or bending motions. The body movement can be categorized into a gross movement and a slight movement. The gross movement is mainly produced by skeletal muscle. The slight movement is mainly produced by cardiac muscle or smooth muscle. Under the pulse, it includes small convulsion or internal organs' movements.

A measuring system that has sensors attached to a human body directly is usually for the body movement or posture estimation. There is the system that can recognize postures using accelerometers [3]. Although this system can measure the body movement or posture accurately, many sensors must be attached to the body to measure accurate movements. Since attaching many sensors to the body produces mental burdens and restricts person's activities, it is difficult to measure unaffected body movements. In order to measure unaffected body motions, sensors need to be attached not to the body but to an environmental side as a bed.

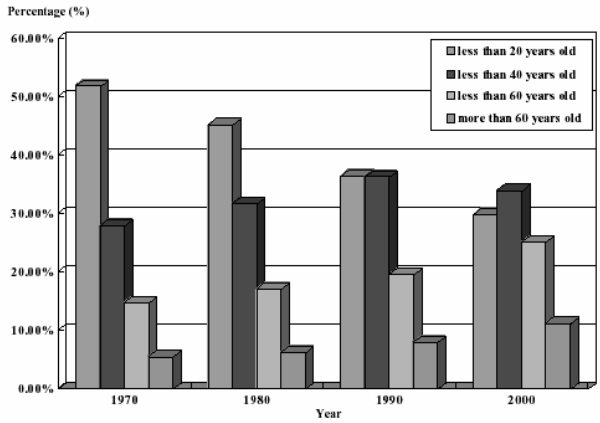

Fig. 1 The census of Korea [1] from 1970 to 2000. This figure shows the population of elderly people (more than 60 years old) is increasing gradually.

Many researches are performed for body motion tracking by using video [4], [5], [6]. However, it is difficult for these systems using video camera to extract motion features because the body is lost of sight in a quilt. Static charge sensitive bed is famous for monitoring the body movements in bed. It can measure respiration, a heart rate and twitch movements [7]. Temperature sensors distribution bed can measure gross movements such as body turns [8]. Pressure sensor distributed bed is applied in many researches [2]. Harada et al. [2] has applied Pressure sensor distribution bed to estimate the body posture. His approach was based on the body model. This approach estimated the subtle posture and motion between main lying postures (supine and lateral posture). Since the body model had lots of model parameter determined, it takes lots of calculation time to determining the posture.

In our system, the control of manipulator is performed from the result of patient's posture and motion estimation. Therefore, short calculation time is required to control the manipulator based on posture estimation. In this paper, we propose the IBRS, which is capable of estimating the patient's posture and motion on bed in real-time and supporting the patient using manipulator. Section 2 briefly introduces the research background for designing IBRS and the proposed system. In Section 3, is described. Experimental results and conclusion are followed in Section 4 and 5.

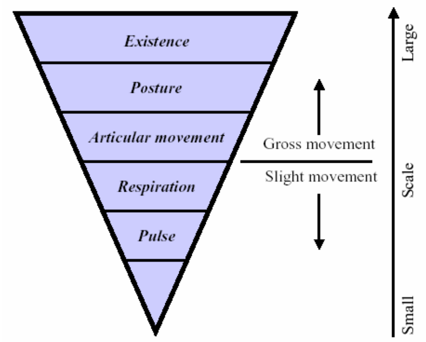

Fig. 2 Body movement classification [2]

2. SYSTEM DESCRIPTION

Most previous researches have a focus on the system which can monitors the patient's posture and motion on bed. In this paper, we will propose the robotic system, which can actively help the patient using robotic manipulator. While there exists the patient on the bed, the pressure sensors monitor his posture and motions. When he moves on the bed, the robotic manipulator can support his body.

Before we design an intelligent bed robot system, we conducted a survey of patients' opinion on IBRS at a rehabilitation center and hospitals in Korea. At the survey, we made a questionnaire focused on activities in bed, the functionality of IBRS, and difficulties in doing something without assistant. The survey said that people with motor difficulties in their legs need assistant in doing body movement for posture change or taking a ride on a wheel chair. They also answered a robot system supporting the stability of body posture during movement would be helpful.

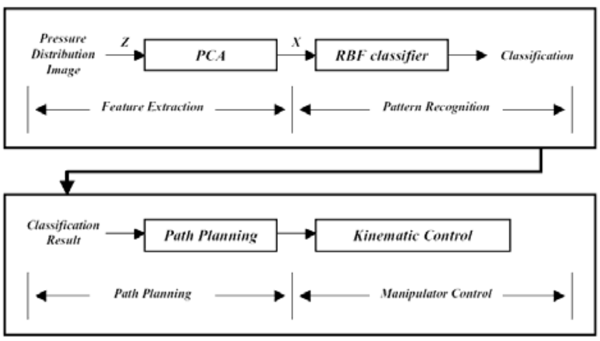

Fig. 3 The system architecture for IBRS.

2.1 Pressure sensor distributed bed

In order to realize unrestraint estimation of gross and slight movements, we distributed pressure sensors over a bed surface. Vertical motions against the bed surface can be estimated by measured pressure and horizontal motions can be estimated by the positions of the pressure sensors.

Force Sensing Resistor is applied as a pressure sensor. The FSR is a thin film sensor, which is made from piezoresistive polymer. The resister value of the FSR decreases in proportion to applied force on the active surface. Measurement range of force is up to 10kg/cm^2. The size of pressure sensor pad is 1900x800x12mm. A spatial interval is 70mm to vertical direction and 50mm to horizontal direction. This sensor pad is divided into three modules in order to correspond to reclining beds.

Fig. 4 Pressure sensors distribution bed.

A pressure sensor control box can select one of the pressure sensors and read the selected pressure sensor's value. There are so many pressure sensors to get pressure values at one time, so the pressure sensor control box scans pressure sensors one by one by using the multiplexers, reads one of pressure sensors' values and transmits this sensor's value to the computer. Pressure distribution is measured as a pressure distribution image. Sampling frequency of the images is 10Hz. Its resolution is 10 bit. By using these pressure distribution images, posture and gross movement estimation are realized. We can estimate lying human's body posture and motion by using measured pressure distribution with the proposed algorithm.

2.2 Supporting manipulator

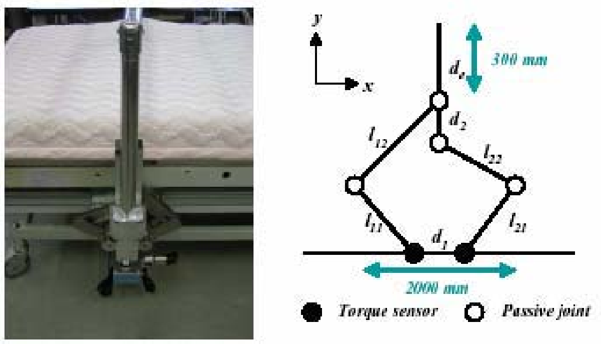

Fig. 5 Supporting manipulator.

The mechanism consisted of the actuated arms and two torque sensors, each of which was attached to the moving platform. A 50W DC motors were used as the actuator. Two passive arms were also attached to an upper link via passive revolute joints. This manipulator is built on the moving platform, which is actuated by another 50W DC motor. This supporting manipulator can sense the subtle motion on the fixed position of the moving platform and help the patient to move another position on bed. In addition, the mobile platform can move between ends of bed, so that the manipulator can reach and serve the whole area on the bed. Torque sensors can measure the 2-dimensional user intention.

3. POSE AND MOTION ESTIMATION

The mass of the body and the force produced by the muscle generate the pressure on the FSR sensors attached on the mattress.

Normally, RBF neural networks are widely used for function approximation and pattern recognition wherein the pattern dimension in this application is usually small. However, the pressure distribution image in our system has a high dimensional property. The pressure distribution image has 336 features (equal to the number of FSR sensors).

Due to the high redundancy present in the pressure distribution image vector, principal component analysis (PCA) was used to reduce the dimensionality of data. PCA is a multivariate statistical technique that can be used to calculate the principal directions of variability in data and to transform the original set of correlated variables into a smaller set of uncorrelated variables. The new uncorrelated variables are linear combinations of the original variables. These principal components represent the most important directions of variability in a dataset.

PCA is an optimal representation criterion in the sense of mean square error; however, it does not consider the classification aspect. To improve the classification performance, one should combine PCA with some classification criterion, such as RBF classifier.

3.1 Principle Component Analysis (PCA)

Let a pressure distribution image Z_i be a two-dimensional m_w x m_h array of intensity values. An image may also be considered as a vector of dimension m (= m_w x m_h). Denote the training set of n pressure distribution images by $Z = (Z_1, Z_2, \ldots, Z_n) \subset R^{m \times n}$, and we assume that each image belongs to one of c classes. Define the covariance matrix as follows:

$$\Gamma = \frac{1}{n}\sum_{i-1}^{n}(Z_i - \bar{Z})(Z_i - \bar{Z})^T = \Phi\Phi^T \tag{1}$$

where $\Phi=(\Phi_1, \Phi_2, \ldots, \Phi_n) \subset R^{m \times n}$ and $\bar{Z} = (1/n)\sum_{i=1}^{n} Z_i$.

Then, the eigenvalues and eigenvectors of the covariance Γ are calculated. Let $U = (U_1, U_2, \ldots, U_r) \subset R^{mxr}$ ($r < n$) be the r eigenvectors corresponding to the r largest eigenvalues. Thus, for a set of original of pressure distribution images $Z \subset R^{m \times n}$, their corresponding eigenimage-based feature $X \subset R^{r \times n}$ can be obtained by projecting Z into the eigenimage space as follows:

$$X = U^T Z \tag{2}$$

3.2 RBF neural network

An RBF neural network can be considered as a nonlinear mapping: $R^r \rightarrow R^s$.

Let $P \in R^r$ be the input vector and $C_i \in R_r$ ($1 \leq i \leq u$) be the prototype of the input vectors. Usually, the Gaussian function is preferred among all possible radial basis functions because it is factorizable. The output of each RBF unit is as follows:

$$R_i(P) = \exp\left[-\frac{\|P - C_i\|^2}{\sigma_i^2}\right] \quad i = 1,\ldots,u \tag{3}$$

where $\|\cdot\|$ indicates the Euclidean norm on the input space, and σ_i is the width of the ith RBF unit. The jth output $y_j(P)$ of an RBF neural network is

$$y_j(P) = \sum_{i=0}^{u} R_i(P) \times w(j,i) \tag{4}$$

where $R_0 = 1$, w(j,i) is the weight or strength of the ith receptive field to the jth output and w(j, 0) is the bias of the jth output.

3.3 Hybrid learning

Hybrid learning is used for the adjustment of RBF parameters. The adjustment of RBF parameters is a nonlinear process while the identification of weight $w(i,j)$ is a linear one. A hybrid-learning algorithm combines the gradient paradigm and the linear least square (LLS) paradigm to adjust the parameters.

Let r and s be the number of inputs and outputs respectively, and suppose that u RBF units are generated. For any input P_i, the jth output y_i of the system is

$$Y = WR \tag{5}$$

Given $R \in R^{u \times n}$ and T = (T1, T2, …, Tn) $T \in R^{s \times n}$, where n is the total number of sample patterns, T is the target matrix with exactly one ``1" per column that identifies the processing unit to which a given exemplar belongs. Then, find an optimal coefficient matrix W* ∈ Rs x u such that the error energy $\tilde{E}^T \tilde{E} = (T - Y)^T (T - Y)$ is minimized. This problem can be solved by the LLS method.

$$W^* = T(R^T R)^{-1} R^T \tag{6}$$

where R^T is the transpose of R, and $R^+ = (R^T R)^{-1} R^T$ is the pseudo-inverse of R.

Here, the parameters (centers and widths) of the prototypes are adjusted by taking the negative gradient of the error function E^c

$$E^c = \frac{1}{2}\sum_{k=1}^{s}(t_k^c - y_k^c)^2 \quad c = 1,2,\ldots,n \tag{7}$$

where $y^c{}_k$ and $t^c{}_k$ represent the kth actual output of RBF classifier and the target output at the cth pattern, respectively. By the chain rule, the error rate with respect to center C and width σ can be derived from (7) as follows:

$$\Delta C^c(i,j) = -\xi_1 \frac{\partial E^c}{\partial C^c(i,j)} = -\xi_1 \frac{\partial E^c}{\partial y_k^c}\frac{\partial y_k^c}{\partial R_j^c}\frac{\partial R_j^c}{\partial C^c(i,j)}$$
$$= 2\xi_1 \sum_{k=1}^{s}(t_k^c - y_k^c)\cdot w^c(k,j)\cdot R_j^c \cdot \frac{P(i,l) - C^c(i,j)}{(\sigma_j^c)^2}$$
$$i=1,2,\ldots,r,\ j=1,2,\ldots,u \tag{8}$$

$$\Delta\sigma_j^c = -\xi_2 \frac{\partial E^c}{\partial \sigma_j^c} = -\xi_2 \frac{\partial E^c}{\partial y_k^c}\frac{\partial y_k^c}{\partial R_j^c}\frac{\partial R_j^c}{\partial \sigma_j^c}$$
$$= 2\xi_2 \sum_{k=1}^{s}(t_k^c - y_k^c)\cdot w^c(k,j)\cdot R_j^c \cdot \frac{\|P_c - C^j\|^2}{(\sigma_j^c)^3}$$
$$j=1,2,\ldots,u \tag{9}$$

where $\Delta C^c(i,j)$ is the central error rate of the ith input variable of the jth prototype at the cth training pattern, $\Delta\sigma_j^c$ is the width error rate of the jth prototype at the cth pattern, $P(i, l)$ is the ith input variable at the lth training pattern and ξ is the learning rate, v

4. EXPERIMENTAL RESULTS

Figure 6 shows the developed system, which has pressure sensor distributed bed and two robotic arm.

Mainly four kinds of postures on the bed (supine, right lateral, left lateral and sitting posture) are considered in this paper. These postures were used for body posture estimation.

Fig. 6 Intelligent bed robot system

In our system, discrimination that the current patient's posture belongs to the posture class is more important than the fact such as opening degree of legs. The patient's motion and intension are estimated from changes between the posture classes. The proposed algorithm was applied to estimate pose and motion.

Figure 7 shows the postures to be estimated. In our research, 93.6% success rate was obtained.

5. CONCLUSION

In this paper, the unrestraint human pose and motion estimation system using the pressure sensor distribution bed was described. This system is thought to be used for analyzing the body pose and motion, assisting the patient with robotic manipulator. Furthermore, it can be used for a health monitoring and evaluation of rehabilitation progress and so on.

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(a) supine (b) right lateral (c) left lateral (d) sitting

Fig. 7 Postures to be estimated.

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