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Joint Angle Estimation System for Rehabilitation Evaluation Support

Junya Kusaka, Takenori Obo, Janos Botzheim, Naoyuki Kubota
Graduate School of System Design, Tokyo Metropolitan University
6-6 Asahigaoka, Hino, Tokyo, 191-0065 Japan
kusaka-junya@ed.tmu.ac.jp, { takebo, botzheim, kubota}@tmu.ac.jp

Abstract— **In this research, we propose a methodology for getting joint angles by Kinect sensor for rehabilitation evaluation support. We measure the motion of the arm of a patient with hemiplegia before and after the rehabilitation, and estimate the range of the motion by using genetic algorithm and neural network. The range after the rehabilitation is bigger than before the rehabilitation. Based on this result, our methodology is able to evaluate the change of the motion before and after the rehabilitation for patients with hemiplegia.**

I. INTRODUCTION

Recently, the number of elderly people is increasing in the aging society. In addition, the number of hemiplegia patients with the aftereffects of Cerebral Vascular Disorder (CVD) increase, too. Hemiplegia is paralysis that may occur in patients who have a neurological disorder [1]. Until now it has been thought that it is impossible to recover from hemiplegia. Recently, it turned out that motion measurement, motion analysis, and rehabilitation support are very important and necessary for patients [2-3]. Although it is really ideal, when these tasks are performed by therapists, however the number of therapists is not enough in the current situation. Hemiplegia is evaluated by Brunnstrom Stage (BS). BS is an evaluation criterion of hemiplegia, which classifies six stages of paralysis [4]. Nevertheless BS is not suitable for an exact hemiplegia evaluation because of the width between stages. In addition, therapists cannot evaluate the progress of the symptom quantitatively, since they evaluate a reaction of the muscular contraction. Thus, it is necessary to measure the range before and after the rehabilitation of joint angles for quantitative evaluation support. The range of the motion (ROM) measurement is often used for evaluation of the movement [5] and it is suitable for a quantitative hemiplegia evaluation. However since the therapist measures joint angles, it will take much time and effort. The definition of the range of joint angles is based on the ROM index.

The motion capture is often used for movement analysis of the person [6-10], however, there are two problems in the motion capture. On one hand, it needs the setting of the surface marker. On the other hand, it is expensive. Therefore, we use 3D distance image sensor to measure human motions.

In this paper, we focus on a methodology for obtaining joint angles by Kinect sensor for rehabilitation evaluation support. We considered that these joint angles could help assess the improvement of upper limb movement of the patient. At first, we use the 3D distance image sensor to measure human motions. In order to perform motion analysis, we need the history of joint angles of human poses. We can solve the inverse kinematics by using relative position data, but the estimation quality is not good owing to the measurement noise of the 3D distance image sensor. Therefore, we propose an estimation method of time series of 3D human pose by using Genetic Algorithm (GA) and Neural Network (NN). Finally, we show experimental results, and discuss the effectiveness of the proposed method.

This paper is organized as follows. Section II explains Kinect sensor, and discusses the positional precision using Kinect sensor. Section III proposes a methodology for obtaining joint angles by Kinect sensor. Section IV shows experimental results of the proposed method, and Section V summarizes the paper.

II. MOVEMENT MEASUREMENT

A. Kinect Sensor

Figure 1 illustrates Kinect sensor. This 3D distance image sensor can measure the distance from the device like a camera in real-time. This device includes a 3D distance image sensor, microphones, an RGB camera, an accelerometer, and a tilting-up mechanism. It can be connected to host PC through USB.

Furthermore, the built-in processor estimates the physical joint parts using the information obtained from the sensor and builds skeleton data and tracks the skeleton in real time. This function is called a joint automatic detection function which can obtain the skeleton data of the person as depicted in Fig. 2. Kinect sensor directly provides 3D information without any markers [11].Table I shows the specification of Kinect sensor [12].

B. Positional Precision

In this subsection, we compare the estimation to the depth data, which are the raw data of the Kinect sensor in order to evaluate the precision of the estimation of the joint position.

The depth data are the data of the depth sensor as shown in Fig. 3. We compare the hand position of skeleton data to the depth data when the person performs flexion, extension, abduction, horizontal flexion, and horizontal extension of the shoulder, and flexion and extension of the elbow. In addition, Table II shows the error of the joint position. From Table II we can see that the maximum error of the joint position is approximately 40 mm. When we estimate the joint angles, this error is considered as not so big.

There is an occlusion when we measure the patient's movement (Fig. 4). However, occlusion as shown in Fig. 4 occurs for the skeleton data when the person performs the flexion of the shoulder as presented in Fig. 5. Figure 6 shows the change of the arm length at the time of the flexion of the shoulder. Since the position of the wrist is near to the hand, it is thought that the noise of the length of the hand is the biggest in case of occlusion.

In this study, we create a 3D human model that defines the link length of the arms beforehand to solve the problem mentioned above (Fig. 7). Next, each joint position acquired by Kinect sensor is approximated to the joint position of the 3D human model. We calculate each joint angle from the result by solving inverse kinematics. In addition, we use Open Dynamics Engine (ODE) which is a physical calculation engine for the construction of the 3D human model [13].

Fig.1. Kinect sensor

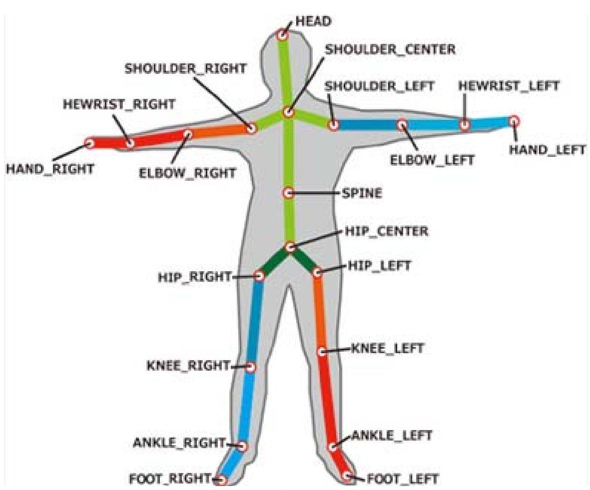

Fig.2. Joint positions

TABLE I
SPECIFICATION OF KINECT SENSOR

Size	282×72×72 [mm]
Horizontal field of view	57 [deg]
Vertical field of view	43 [deg]
Physical tilt range	±27 [deg]
Measuring range	1.2 – 3.5[m]
Resolution	320×240, 640×480 [pixel]
Frame rate	30 [fps]

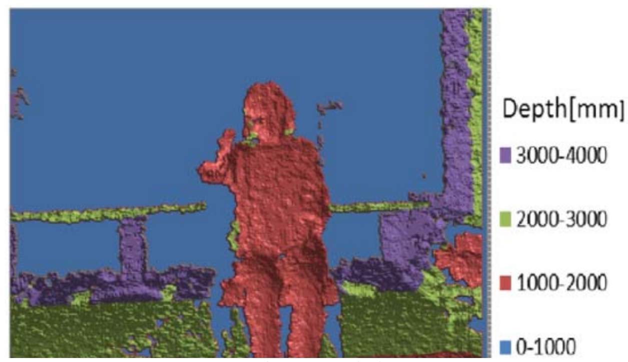

Fig.3. Depth data

TABLE II
ERROR OF THE JOINT ANGLES

Point	Movement	Error			
		x	y	z	3 axes
Shoulder	Flexion	5.21	-4.05	9.77	11.78
	Extension	-3.24	-31.53	16.78	35.86
	Abduction	19.1	-6.98	33.73	39.39
	Horizontal Flexion	-2.84	-15.8	4.62	16.7
	Horizontal Extension	1.55	-4.64	28.88	29.29
Elbow	Flexion	15.42	-14.56	16.05	26.6

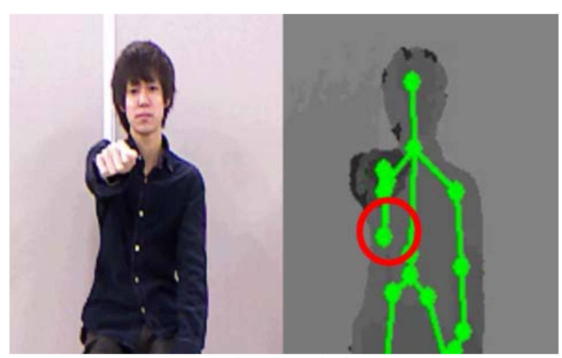
Fig.4. Occlusion

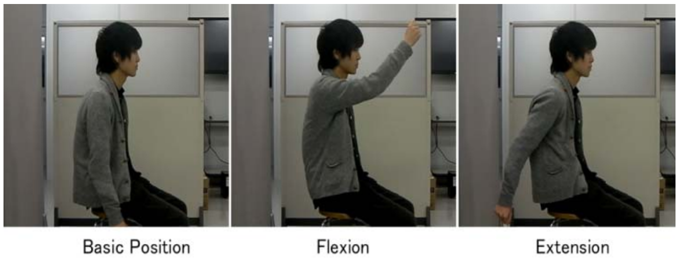

Fig.5. Movement of flexion and extension

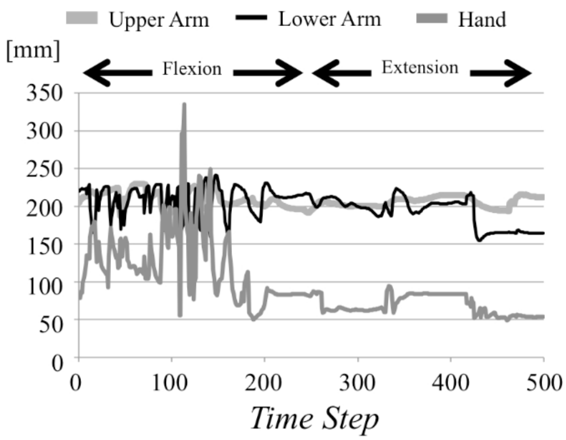

Fig.6. Change of arm length

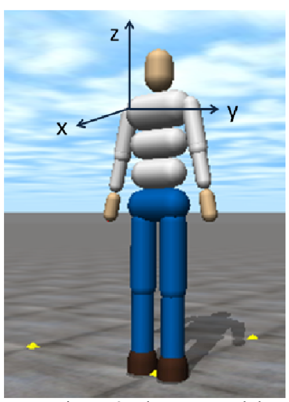

Fig.7. 3D human model

III. Joint Angle Estimation

A. Proposed System Using 3D Model

In this paper, we propose the optimization methodology of the joint angles using the 3D human model. Figure 8 illustrates a conception diagram of the systems. First, we measure the movement of arms and acquire the 3D joint positions. Second, the joint angle of each movement is estimated from the joint positions by using steady-state genetic algorithm (SSGA) [14-16]. Finally, the joint angle generated by GA is learned using feed-forward neural network (NN), and a model is built to estimate the joint angle from each joint position. We suggest how to estimate the joint angle of the arms by integrating GA with NN.

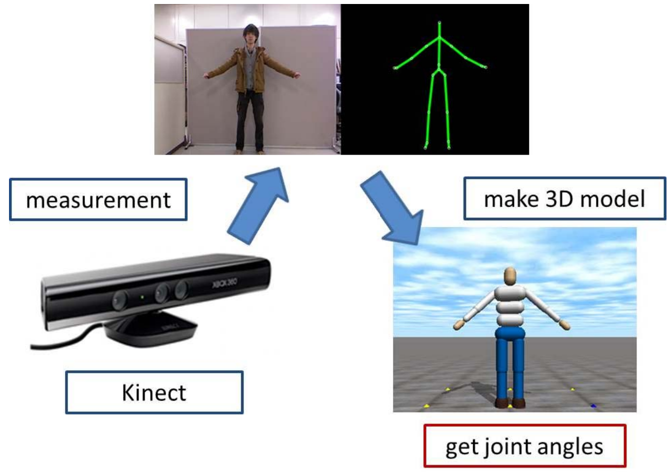

Fig.8. Proposed system

B. Joint Angle Estimation

In this subsection, we propose a method of 3D human pose estimation by using steady-state genetic algorithm. We assume the posture of human arm is composed of 6 degrees of freedom (DOF); $\theta = (\theta_0, \theta_1, ..., \theta_5)^T$, because the 3D distance image sensor can measure only the position of human hand, wrist, elbow, and shoulder (Fig.9). In order to perform motion analysis, we need the history of joint angles of human poses. We can solve the inverse kinematics by using relative position data, but the estimation quality is not good owing to the measurement noise of 3D distance image sensor. Therefore, we propose an estimation method of time series of 3D human pose by using SSGA, which can obtain feasible solutions with less computational cost, but the poses of a patient include specific features or structures.

Therefore, if we can collect various types of 3D human pose sequences, we can extract features of human motion patterns. In this paper, we apply a feed-forward neural network (NN) [17-19].

Figure 10 shows the architecture of 3D human pose estimation and learning by SSGA and NN. Here, SSGA plays the role of the search in the inverse kinematics, while NN plays the role of the memory of motion patterns in the inverse kinematics. In addition, the forward kinematics model evaluates the quality of a 3D human pose. First, a time series of human motions are measured by 3D distance image sensor, and the position of each body part in the measured motions is estimated:

$$\mathbf{P}_m = \left(\mathbf{p}_{m,1,1}, \mathbf{p}_{m,1,2}, ..., \mathbf{p}_{m,k,t}, ..., \mathbf{p}_{m,K,T_m}\right) \qquad (1)$$

$$\mathbf{p}_{m,k,t} = \left[x_{m,k,t} \ \ y_{m,k,t} \ \ z_{m,k,t}\right]^T,$$

where $\mathbf{p}_{m,k,t}$ is the position of the k-th body part of the m-th motion at discrete time step t; K is the total number of body parts; T_m is the total time steps of the m-th human motion. In this paper, since we focus on the human right arm motions, $\mathbf{p}_{m,1,t}$, $\mathbf{p}_{m,2,t}$ and $\mathbf{p}_{m,K,t}$ are defined as the position of elbow,

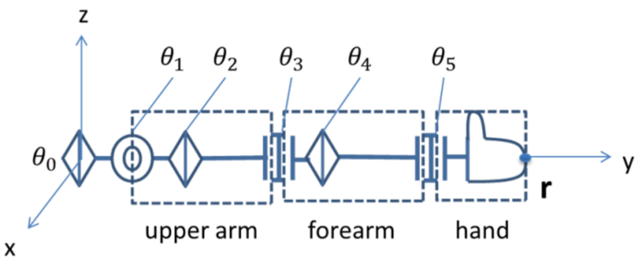

Fig.9. Model of arm

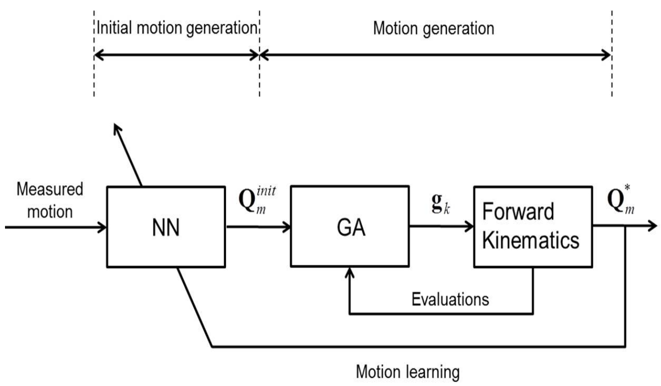

Fig.10. Architecture of GA and NN

wrist, and hand of right arm (K=3), respectively. Next, NN makes outputs its corresponding poses:

$$\mathbf{Q}_m^{init} = \left(\mathbf{q}_{m,1}, \mathbf{q}_{m,2}, \ldots, \mathbf{q}_{m,t}, \ldots, \mathbf{q}_{m,T}\right)$$
$$\mathbf{q}_{m,t} = \left[q_{m,1,t} \;\; q_{m,2,t} \cdots \; q_{m,D,t}\right]^{\mathrm{T}}, \tag{2}$$

where D is the degrees of freedom. Next, we obtain the positions ($\mathbf{P}_m^{init}$) of body parts calculated by forward kinematics model using the time series of poses. The difference between two series of positions are calculated by

$$E = \left\| \mathbf{P}_m^{init} - \mathbf{P}_m \right\|. \tag{3}$$

At the same time, SSGA generates initial candidate solutions of trajectories according to the outputs from NN. Small normal random value is added to each input to NN in order to generate various candidate solutions. Finally, SSGA outputs the best trajectory ($\mathbf{Q}_m^*$), and simultaneously, the NN is trained by the back-propagation algorithm using $\mathbf{Q}_m^*$.

C. Human Pose Estimation by Genetic Algorithm

We apply Genetic Algorithm (GA) to estimate the joint position. We use GA to generate candidate solutions of each joint angle and search solutions. A candidate solution is composed of numerical parameters corresponding to the joint angles $\mathbf{q}_{m,t}$:

$$\mathbf{g}_i = \left(\theta_{i,1}, \theta_{i,2}, \theta_{i,3}, \theta_{i,4}, \theta_{i,5}, \theta_{i,6}\right) \tag{4}$$

where $\theta_{k,h}$ is the h-th joint angle of the k-th candidate solution. The worst individual is updated using adaptive mutation:

$$\theta_{worst,h} = \begin{cases} \theta_{rand,h} + (0.05 + f_i \cdot \gamma) \cdot N(0,1) & \text{if } \mathrm{U}(0,1) < \lambda \\ \theta_{best,h} + (0.1 + f_i \cdot \gamma) \cdot N(0,1) & \text{otherwise} \end{cases} \tag{5}$$

where θ_{rand} is a random individual; θ_{best} is the best individual; γ is a constant; λ is a constant, N(0,1) is a normal random number, U(0,1) is a uniform random number. Fitness is calculated by

$$f_i = \sum_{j=1}^{S} \left(\alpha_j \left\| \mathbf{p}_j^{GA} - \mathbf{p}_j \right\| + \beta \right) \tag{6}$$

where f_i is the i-th fitness; S is the number of joints; α_j is weight coefficient; β is penalty term; $\mathbf{p}_j^{GA}$ is the position of body parts calculated by forward kinematics model using obtained angles, and $\mathbf{p}_j$ is the position measured by the Kinect sensor. As above, this problem is a minimization problem to minimize the fitness.

D. Human Pose Learning by Neural Network

We apply a neural network (NN) to learn human motion patterns, because human motion patterns include specific features and structures. The number of layers of NN in this study is 3 (l=3). The output of the i-th neuron in the l-th layer can be calculated recursively as follows:

$$y_i^l = f\left(z_i^l\right) = f\left(\sum_{j=0}^{n_2} w_{j,i}^l \cdot x_j^l\right) = f\left(\sum_{j=0}^{n_2} w_{j,i}^l \cdot f\left(\sum_{k=0}^{n_1} w_{k,j}^{l-1} \cdot x_k^{l-1}\right)\right) \tag{7}$$

where x_j^l is the j-th input in the l-th layer, (j=1,2,$\cdots$, n_2; k=1,2,$\cdots$, n_1); $w_{j,i}^l$ is the weight parameter from j-th to i-th neuron; $w_{0,i}^l$ is threshold and $x_0^l = -1$ to simplify the equation; $f(\cdot)$ is a sigmoidal function. The error function is defined as

$$E_p = \frac{1}{2} \sum_{i=1}^{o} \left(y_{p,i}^* - y_i^l\right)^2, \tag{8}$$

where $y_{p,i}^*$ is the teaching signal of i-th output of p-th data; o is the number of outputs (o=n_3). We can train and update weight parameters by using the generalized delta rule:

$$w_{j,i}^l \leftarrow w_{j,i}^l + \Delta w_{j,i}^l = w_{j,i}^l - \eta \frac{\partial E_p}{\partial w_{j,i}^l}. \tag{9}$$

If the l-th layer is the output layer (l=3), the partial derivative with respect to $w_{j,i}^l$ is derived by the chain rule:

$$\frac{\partial E_p}{\partial w_{j,i}^l} = \frac{\partial E_p}{\partial y_i^l} \frac{\partial y_i^l}{\partial z_i^l} \frac{\partial z_i^l}{\partial w_{j,i}^l} = -\left(y_{p,i}^* - y_i^l\right) f'\left(z_i^l\right) x_j^l. \tag{10}$$

Here the error signal in the output layer based on back-propagation algorithm is defined as

$$\delta_i^l = -\frac{\partial E_p}{\partial z_i^l} = -\frac{\partial E_p}{\partial y_i^l} \frac{\partial y_i^l}{\partial z_i^l} = \left(y_{p,i}^* - y_i^l\right) f'\left(z_i^l\right). \tag{11}$$

Then, the weight is updated according to

$$\Delta w_{j,i}^{l} = -\eta \frac{\partial E_p}{\partial w_{j,i}^{l}} = \eta \delta_i^l x_j^l \tag{12}$$

where η is a learning rate. If the (l-1)-th layer is a hidden layer, the partial derivative with respect to $w_{k,j}^{l-1}$ is further derived by the chain rule:

$$\frac{\partial E_p}{\partial w_{k,j}^{l-1}} = \frac{\partial E_p}{\partial z_i^l} \frac{\partial z_i^l}{\partial x_j^l} \frac{\partial x_j^l}{\partial z_j^{l-1}} \frac{\partial z_j^{l-1}}{\partial w_{k,j}^{l-1}} = -\sum_{i=1}^{o} \delta_i^l w_{j,i}^l f'\left(z_j^{l-1}\right) x_k^{l-1}. \tag{13}$$

Furthermore, the error signal in the (l-1)-th layer is defined as:

$$\delta_j^{l-1} = -\frac{\partial E_p}{\partial z_j^{l-1}} = \sum_{i=1}^{o} \delta_i^l w_{j,i}^l f'\left(z_j^{l-1}\right). \tag{14}$$

The weight is updated according to

$$\Delta w_{k,j}^{l-1} = -\eta \frac{\partial E_p}{\partial w_{k,j}^{l-1}} = \eta \delta_j^{l-1} x_k^{l-1}. \tag{15}$$

The inputs to NN are the position of a pose based on the position of shoulder at discrete time step t,

$$\mathbf{X}_{m,t} = \left(\mathbf{p}_{m,1,t}, \mathbf{p}_{m,2,t}, \mathbf{p}_{m,3,t}\right), \tag{16}$$

where $\mathbf{p}_{m,1,t}$, $\mathbf{p}_{m,2,t}$ and $\mathbf{p}_{m,3,t}$ are the position of elbow, wrist, and hand (K=3), respectively; p=t and P=T_m in the learning algorithm. The outputs from NN are joint angles of right arm composed of 5 DOF; $\mathbf{q}_{m,t}^{*}$ are generated by SSGA. This means the trained NN can approximately solve the inverse kinematics using position data of a human right arm.

IV. Experiment

A. Preliminary Experiment

In this subsection, we discuss the precision of the joint angle estimation using the methodology that we suggested. Table III shows the basic axis of the movement to measure. In addition, we discuss the precision by comparing the result of angle gauge to the joint angle that we estimated. Table IV presents the parameter setting. We set the parameters so that the error is smaller than 10 degrees. The error of 10 degrees is considered to be satisfactory for the error, which arises even if therapists actually use an angle gauge.

TABLE III
BASIC AXIS OF THE MOVEMENT

Point	Movement	Base Axis	Motion Axis
Shoulder	Flexion	Normal axis to floor	Humerus
	Extension		
	Abduction	Normal axis to floor	Humerus
	Adduction		
	Horizontal Flexion	Normal axis to sagittal plane	Humerus
	Horizontal Extension		
Elbow	Flexion	Humerus	Radius
	Extension		

TABLE IV
PARAMETER SETTING

α_0	0
α_1	0.2
α_2	0.3
α_3	0.5
β	100
γ	0.001
λ	0.333

TABLE V
ERROR BETWEEN ANGLE GAUGE AND KINECT SENSOR

Point	Movement	Angle gauge [deg]	Kinect sensor [deg]	Error[deg]
Shoulder	Flexion	0	3.47	3.47
		60	65.56	5.56
		90	80.09	9.91
		120	129.88	9.88
	Extension	30	25.41	4.59
	Abduction	60	69.15	9.15
		90	80.16	9.84
		120	128.5	8.5
	Horizontal Flexion	60	55.31	4.69
		120	118.46	1.54
	Horizontal Extension	30	21.32	8.68
Elbow	Flexion	60	26.14	33.86
		120	80.09	39.91

In a shoulder joint, Table V shows that the error is smaller than 10 degrees without the flexion of the elbow. However, in the future we need to improve this system in order to decrease the error related to the elbow angle.

B. Experimental Method 1

In order to examine the effectiveness of the proposed method, we measured the motion of the arm of a patient with hemiplegia before and after the rehabilitation. We focus on showing the joint angle quantitatively. Figure 11 presents the experiment environment. Kinect sensor is installed in the position which was about 1.8m away from the patient's front. The patient performs the flexion, extension, abduction, horizontal flexion and horizontal extension of the shoulder, and the flexion and extension of the elbow sitting on a chair before and after the rehabilitation (Fig. 12). In addition, we use each joint position that we measured, to visualize the movement in the 3D human model. Finally, we examine the usefulness of the system from the provided result.

C. Experimental Results 1

Figure 13 shows the change of the joint angle in the flexion of the shoulder, which was estimated using the proposed method. Table VI shows the joint angle before and after the rehabilitation in each movement. We were able to show the change of the joint angle quantitatively. In this experiment, the measurement method of the joint angle was classified according to each movement, but for the comparatively slight hemiplegia independent motion is also difficult, and the person performs a synergic movement.

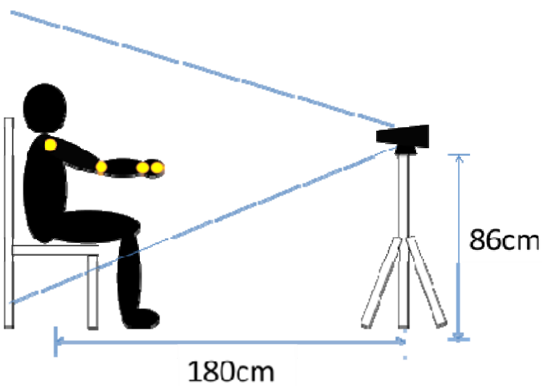

Fig.11. Experiment environment

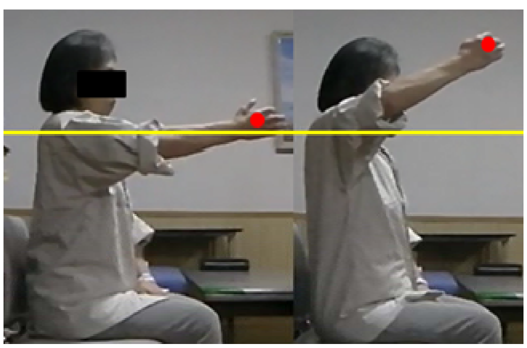

Fig.12. Before and after the rehabilitation

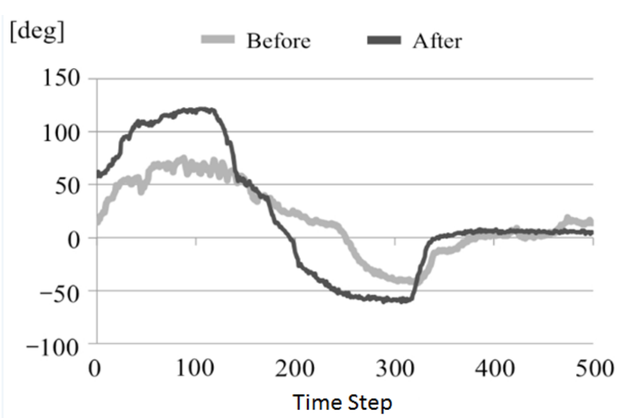

Fig.13. Change of the flexion of the shoulder

TABLE VI
JOINT ANGLE IN EACH MOVEMENT

Point	Movement	Range of Angle	
		Before	After
Shoulder	Flexion	75.54 [deg]	121.92 [deg]
	Extension	43.03 [deg]	60.98 [deg]
	Abduction	69.37 [deg]	77.08 [deg]
	Adduction	0.0 [deg]	0.0 [deg]
	Horizontal Flexion	99.27 [deg]	108.41 [deg]
	Horizontal Extension	33.88 [deg]	28.29 [deg]
Elbow	Flexion	144.95 [deg]	149.94 [deg]
	Extension	0.0 [deg]	0.0 [deg]

D. Experimental Method 2

Seven elderly people carried out for 5 days gymnastics in this experiment, and we measured the maximum joint angle every day. We checked the validity of the system by comparing the observations with changes in the maximum angle of the flexion and abduction of the shoulder and the flexion of the elbow. Experimental environment is the same as shown in Fig. 11.

E. Experimental Results 2

Figure 14 and 15 show the graph of the changes in the maximum angle of the flexion and abduction of the shoulder and the flexion of the elbow of the elderly people A-B.

In this experiment for five days, we have hardly seen a big change in each maximum joint angle (Fig. 14-15). Other subjects also showed similar results. However, the improvement of the operation was shown by the observation. Therefore we need to do long-term experiment.

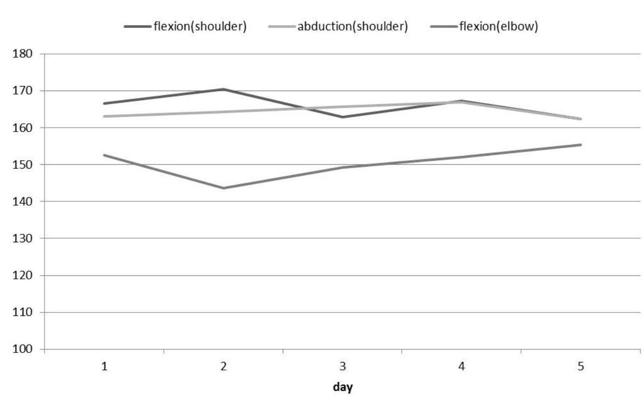

Fig.14. Change of the joint angle of elderly people A

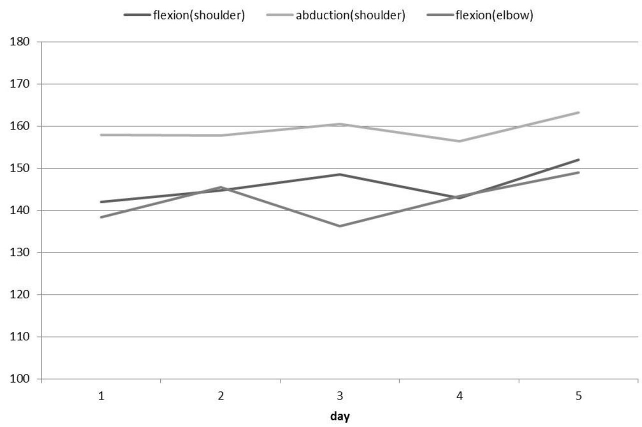

Fig.15. Change of the joint angle of elderly people B

V. Summary

This paper proposed a measurement system of human motions based on 3D distance image sensor for rehabilitation. First, we described a human motion analysis method based on genetic algorithm and neural network. The experimental result shows the effectiveness of the proposed method. However, in the future it is necessary to conduct experiments with more subjects and for longer term.

Acknowledgment

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References

[1] J. C. Wall and G. I. Turnbull, "Gait asymmetries in residual hemiplegia," Archives of physical medicine and rehabilitation vol.67, no.8, pp.550-553, 1986.

[2] S. F. Szekeres, M. Ylvisaker, and S. B. Cohen, "A Framework for Cognitive Rehabilitation Therapy, Community Re-entry for Head Injured Adults," Boston: Butterworth-Heinemann, pp. 87-136, 1987

[3] Y. Toda, Y. Kodai, E. Hiwada, and N. Kubota, "Human Motion Tracking for Cognitive Rehabilitation in Informationally Structured Space Based on Sensor Networks," Proc. of 2011 IEEE International Conference on Fuzzy Systems, pp.1459-1465 ,2011

[4] M. Akay. M. Sekine, T.Tamura, Y.Higashi, and T.Fujimoto "Fractal dynamics of body motion in post-stroke hemiplegic patients during walking," Journal of neural engineering vol.1, no.2, pp.111-116, 2004.

[5] V. L. Graham, G. M. Gehlsen, and J. A. Edwards, "Electromyographic evaluation of closed and open kinetic chain knee rehabilitation exercises," Journal of athletic training vol.28, no.1 , pp.28-30, 1993

[6] T. Molet, R. Boulic, and D. Thalmann, "A Real Time Anatomical Converter For Human Motion Capture," Proc. 7h Eurographics Int. Workshop on Animation and Simulation, Springer-Verlag, Wien, pp.79-94, September 1996.

[7] N. Miller, O. C. Jenkins, M. Kallmann, and M. J. Mataric, "Motion Capture from Inertial Sensing for Untethered Humanoid Teleoperation," Proc. Of the IEEE-RAS International Conference on Humanoid Robotics, Santa Monica, CA, pp.547-565, Nov, 2004

[8] V. Ganapathi, C. Plagemann, D. Koller, and S. Thrun, "Real Time Motion Capture Using a Single Time-Of-Flight Camera," Computer Vision and Pattern Recognition (CVPR), pp.755-762, 2010

[9] H. Zhou, H. Hu, H. Liu, and J. Tang, "Classification of Upper Limb Motion Trajectories using Shape Features," IEEE Transactions on Systems, Man and Cybernetics, Part C, vol.42, no.6, pp. 970-982, 2012.

[10] A. Aristidou and J. Lasenby, "Real-time marker prediction and CoR estimation in optical motion capture," The Visual Computer vol.29, no.1, pp.7-26, 2013.

[11] Q. Zhang, X. Song, X. Shao, R. Shibasaki, and H. Zhao, "Unsupervised skeleton extraction and motion capture from 3D deformable matching," Neurocomputing, vol.100, pp.170-182, 2013.

[12] http://www.xbox.com

[13] Open Dynamics Engine, http://ode.org

[14] G. Syswerda, "A Study of Reproduction in Generational and Steady-State Genetic Algorithms, Foundations of Genetic Algorithms," Morgan Kaufmann, pp. 94-101 , 1991

[15] M. Mitchell, *An Introduction to Genetic Algorithms*. The MIT Press, 1996

[16] D. Whitley and J. Kauth, "GENITOR: A different Genetic Algorithm," in Proc. of the Rocky Mountain Conference on Artificial Intelligence, Denver, pp. 118-130, 1988.

[17] N. Kubota, J. Botzheim, and T. Obo, "Human Motion Tracking and Feature Extraction for Cognitive Rehabilitation in Informationally Structured Space," Proc. of the 9th France-Japan & 7th Europe-Asia Congress on Mechatronics and the 13th International Workshop on Research and Education in Mechatronics (REM), Paris, France, pp. 464-471, 2012.

[18] R. Hecht-Nielsen, *Neurocomputing*. Addison-Wesley, 1990.

[19] J. Botzheim, T. Obo, and N. Kubota, "Human Gesture Recognition for Robot Partners by Spiking Neural Network and Classification Learning," Proc. of Joint 6th International Conference on Soft Computing and Intelligent Systems and 13th International Symposium on Advanced Intelligent Systems (SCIS & ISIS 2012), pp. 1954-1958, Kobe, Japan, 2012.