Journal of Korea Multimedia Society Vol. 14, No. 12, December 2011(pp. 1517-1527)

Posture Symmetry based Motion Capture System for Analysis of Lower-limbs Rehabilitation Training

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ABSTRACT

This paper presents a motion capture based rehabilitation training system for a lower-limb paretic patient. The system evaluates the rehabilitation status of the patient by using the bend posture of the knees and the weight balance of the body. The posture of both legs is captured with a single camera using the planar mirror. The weight distribution is obtained by the Wii Balance Board. Self-occlusion problem in the tracking of the legs is resolved by using k-nearest neighbor based clustering with body symmetry and local-linearity of the posture data. To do this, we present data normalization and its symmetric property in the normalized vector space.

Key words: Virtual Rehabilitation, Human Motion Capture

1. INTRODUCTION

Clinicians who work with paretic rehabilitation focus on correcting functional disorders for brain damaged or paretic patients. In that case, rehabilitation training needs to force the leg muscles of the patient to exercise. Typical examples for this purpose of exercise are knee bending, walking and weight shifting. Clinicians recommend that the patients reiterate the knee bending with the weight shifting for paretic or hemi-paretic rehabilitation [1,2].

This paper presents a rehabilitation training system for a paretic patient. We attach four infra-red markers on each leg of the patient and track them with a single camera, with a planar mirror installed to capture both legs' posture simultaneously. This system configuration gives a practical advantage by reducing its working dimension. However the system may loss some marker due to self-occlusion. The weight distribution, another important measure for the paretic rehabilitation, is captured by a pressure sensor. To solve the self-occlusion problem, we propose a leg pose estimation based on the k-Nearest Neighbor (k-NN) algorithm. For subject independence, the posture data is mapped into the normalized vector space in which the posture of both legs is represented by four unit vectors in 3D space and the weight distribution is divided by the whole weight of the patient. The data has symmetry and locally linearity in the normalized vector space.

The proposed system is used to prescribe proper exercise for the patient after analyzing the patients' functional condition by comparing their movement with the standard movements.

2. RELATED WORKS

Rehabilitation training systems are mainly cate-

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Receipt date : Oct. 31, 2011, Revision date : Dec. 28, 2011
Approval date : Dec. 28, 2011
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※ This work was supported by Republic of Korea Dual Use Program Cooperation Center(DUPC) of Agency for Defense Development(ADD).

gorized into two groups. One is the virtual experience based system like game therapy [3-12], and another one is motion capture based athletic therapy [1,2,13,14].

2.1 VR based Rehabilitation

Traditionally the medical rehabilitation systems use mechanical instruments to train the patient. Nowadays, however, many clinical methods are proposed by using VR systems with a simple controller for reaction and feedback to virtual environment on the rehabilitation training system. *Theragame* is a home-based rehabilitation game which runs on a PC with a webcam [3]. The game needs combination of motor and cognitive abilities of the patients. With this system, the participants can achieve athletic enhancement, but still have limitation to grasp an actual condition of patients' disorder, because the system uses abstracted motion flow data for training. Huang's research is very similar to *Theragame* for neuromotor rehabilitation, but more expanded human motion behaviors to adapt on virtual environment (VE) contents [4]. This work shows the importance of patients' actual motion connected to virtual experiences by using recordable electric signals from multiple electronic sensors. Holden's research presents the possibility and importance of the VE based tele-rehabilitation system [5]. This system allows a therapist in a remote location to conduct treatment sessions using a VE based motor training system, for a patient who is located at home.

Recently, the limelight methods in the clinical field use commercial devices for console games such as SONY Playstation3™ and Nintendo Wii™. Especially Wii gaming console controllers such as remote, nun-chuk and balance board are very popular to use by medical therapists because of its easy access from market. The controllers consist of various kinds of sensors which are composited on a single device and comparatively light weight. Wii controller based rehabilitations are usually played to enhance their functional or mental disadvantages [6-9]. In the case of several works, Wii balance board is used for human balancing and mobility rehabilitation [10-12]. The above works intend to enhance the patients' standing posture, gait speed, walking endurance and balancing on the variable conditions, but the weight information is used for playing games without sensing actual motion of the patients.

2.2 Motion Capture based Rehabilitation

In the existing human motion capture systems, various sensing technologies such as optical or non-optical systems are used [13,14]. Non-optical systems use mechanical, inertial, or magnetic apparatus for capturing human motion. These approaches guarantee high-rate accuracy and real-time sensing of motion data. However, they are hard to setup in terms of instruments and expensive to use. Optical systems utilize data captured from multiple cameras to triangulate the three-dimensional position of a subject. This method is cheaper than non-optical systems to establish the motion capture environment, but very complicated to calculate the result.

A typical example of a full-body motion capture based rehabilitation system is the *CAREN* [15]. This system uses optical and magnetic sensors to register human body movements in real-time. However, the system is hard to replace the training space for various disorder symptoms and very expensive for personal use. Previous researches for the treatment of paralysis using simplified motion capture are proposed [1,2]. Their system considers joint angle measurement of the knee by tracking infrared markers which are attached on the leg. However, this system captures only one side of the patients for hemi-paretic rehabilitation. In order to capture both legs, we need two cameras installed perpendicularly to each side of legs so that the system dimension is big and the marker position is processed in the 2D image space. Moreover, their

Fig. 1. An example of weak-point of 2D based measuring method.

system has to place the camera almost precisely perpendicular to the leg's side. This is the limitation of 2D image based approach that occur measuring error in recognition of knee's angle from view-point changing of the observing camera. [Fig. 1] shows an example of the visible change of legs by change of view-point.

3. SYSTEM CONFIGURATION

In this paper, we try to enhance the Jung's works by defining some geometrical constraints and adopting computer vision approaches to track both legs in 3D space [1,2]. The system uses two kinds of sensors. The posture data of both legs is captured by a webcam, whose IR-cut filter is removed. The weight balance data is obtained by Nintendo's Balance Board connected to a PC with Bluetooth module. For the system installation, we use a planar mirror sufficient to cover the patient's lower limbs, and four IR-LEDs are attached on the corner of the mirror for the camera calibration. The camera should be facing the planar mirror, but its position is not limited on the space as shown in [Fig. 2].

The system consists of three main parts; camera calibration, training space initialization and posture management as shown in [Fig. 3]. In the calibration, the external camera parameters with respect to the mirror are estimated by using four corners

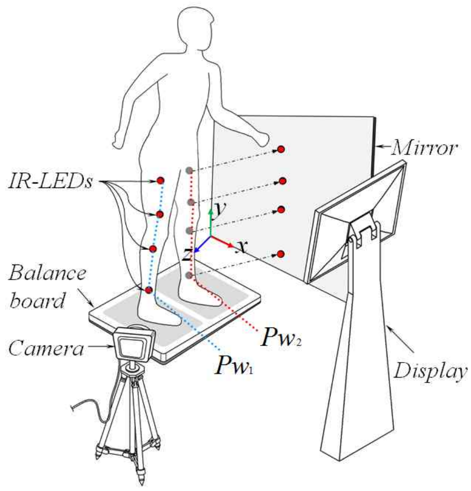


Fig. 2. Installation of the motion capture based rehabilitation training system.

of the mirror. We obtain the patient's weight and the distance between a pair of markers on the legs from the initial standing posture of the patient. We also estimate the foot positions from the weight distribution. For the initialization of the training space, the camera and its virtual camera are reflected by the mirror works meaning a setup of the multiple cameras. In the posture management, the system estimates the leg posture by data fusing the position of markers and weight distribution.

3.1 Camera Calibration

The camera calibration has two steps; back-

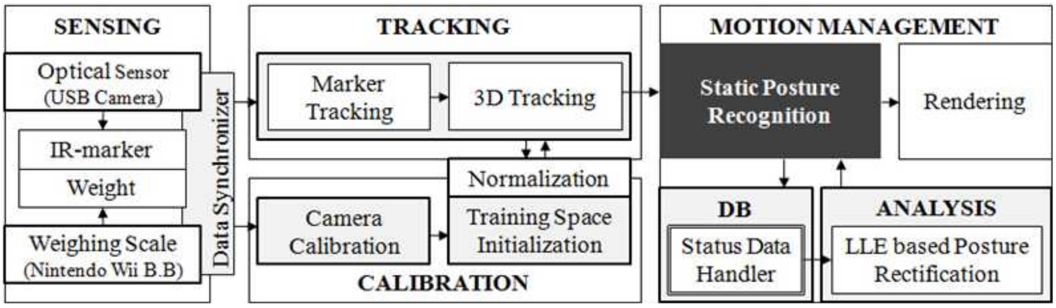


Fig. 3. Overview of the system work flow.

ground modeling and camera pose estimation. In the background modeling, the system computes the brightness distribution at each pixel from the n-frames of the empty scene. The system also makes a reference image that has ideal background information. The highly bright areas in the reference image are used to eliminate the false detections of the IR-LED markers and detect the actual pixel candidates of the markers in real-time. The positions of the markers are defined by the connected component labeling [16] and each labeled blob has own index and its trajectory is estimated by the spatial proximity.

To setup the camera in the 3D world coordinate, we have to calculate the camera pose toward to real-world mirror plane. For this, we calibrate the camera projection matrix by common way in the projective geometry. In order to estimate the camera pose, we use four-point method [17] with the

markers attached on the corners of the mirror. The pose of the virtual camera reflected by the mirror is estimated by a vanishing points based method [18]. We already know the length of the IR-markers, and then we can get the relative camera pose to the plane by four IR points by using the above method. The camera projection matrix represent P can decomposed by the camera intrinsic parameter K, the rotation matrix R and translation vector t. By computing the projection matrix, we can exactly locate the mirror plane on the world coordinate toward to the real camera as [Fig. 5].

With above process, we obtain the extrinsic camera parameters of the real camera P_{real} and the virtual camera as shown in [Fig. 4]. The transformation between two cameras is defined as

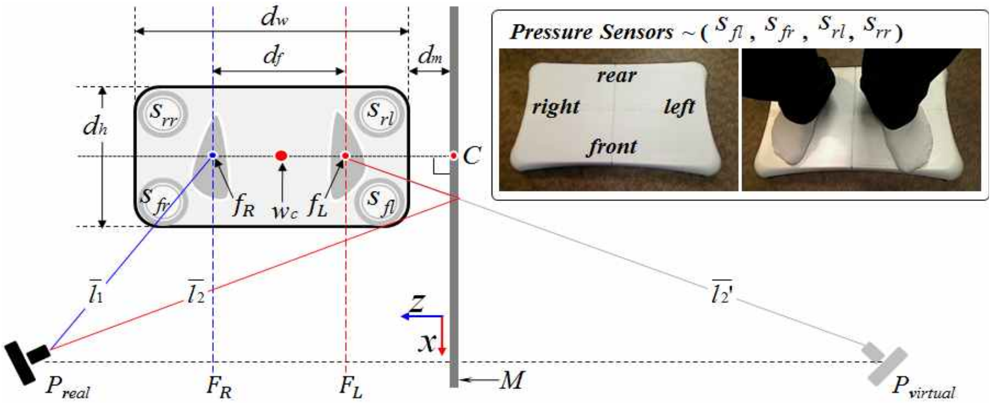


Fig. 4. The illustration of the training space with a single camera and the planar mirror (left), and the setup example of the Wii balance board (right).

$P_{virtual} = D_M \times P_{real}$. The distance from the mirror to the camera is computed by $d = n_x t_x + n_y t_y + n_z t_z$, where $\boldsymbol{t} = [t_x, t_y, t_z]^T$ is the translation vector of the real camera and $\boldsymbol{n} = [n_x, n_y, n_z]^T$ is the normal vector of the mirror plane. Using these notations, the reflection transformation for the mirror plane is given by D_M as follows,

$$D_M = \begin{bmatrix} I - 2\boldsymbol{n}\boldsymbol{n}^T & 2d\boldsymbol{n} \\ 0^T & 1 \end{bmatrix}.$$

3.2 Training Space Initialization

After the camera calibration, we initialize the training space. We already know the positions of the camera and the Balance Board with respect to the mirror plane. The most important process in the space initialization is to estimate the footprint positions of the patient to calculate the 3D position of the markers attached on both the legs. After the patient steps the right foot first, the system calculates the z-distance of the right foot f_R as,

$$f_R = \left(\frac{w_R - w_L}{w_R + w_L} + 1 \right) \times \frac{d_w}{2} + d_m,$$

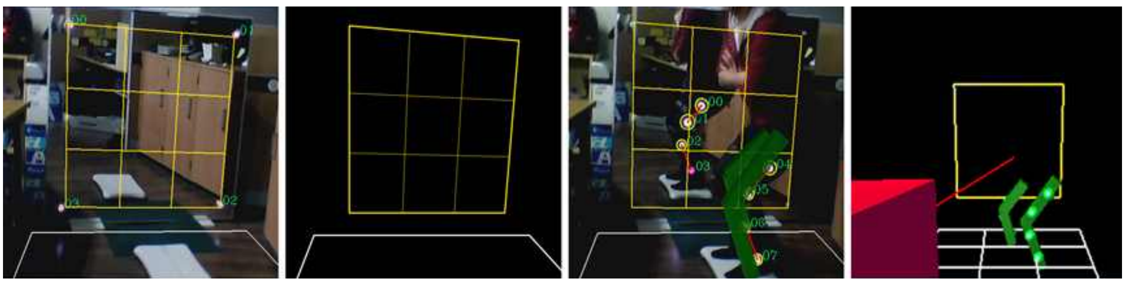
where $(s_{fl}, s_{fr}, s_{rl}, s_{rr})$ is the pressure sensor values, $w_R = s_{fr} + s_{rr}$, $w_L = s_{fl} + s_{rl}$ and d_w is the width of the sensor board. After the patient steps feet, the weight center of the body w_c is obtained similarly to the center of right foot f_R. The center of left foot f_L is also calculated from w_c and f_R by using the symmetry of the body weight. We assume that the leg markers at the initial standing posture are on the plane F_R and F_L as illustrated in [Fig. 4]. With the geometric configuration of the footprint support planes F_R or F_L, the two dimensional marker position is transformed into the three dimensional data. The markers of each leg will be on the ray $\overline{l_1}$ or $\overline{l_2}$, and the corresponding 3D points are the intersection points of the rays with the footprint support planes as shown in [Fig. 4]. Finally, we initialize the training space from the above process as shown in [Fig. 5].

3.3 Data Normalization with Posture Symmetry

The rehabilitation status of the patient is represented by the marker positions and the weight distribution, but the data is dependent on the dimension of the patients and the foot location on the weight board. The normalization of the data assures a robust common vector space without depending on the patients. Before the normalization of the weight distribution, we remove its bias by shifting the weight center into the center of the board. The shift vector $\Delta\omega$ is obtained as,

$$\Delta\omega(x,y) = (2W_p \frac{w_{cx}}{d_w}, 2W_p \frac{w_{cy}}{d_h}),$$

where (d_w, d_h) is the dimension of the Balance



(a) (b) (c) (d)

Fig. 5. An example of the initialized training space in 3D world coordinate by calibrated camera pose; (a) and (b) shows the result of the four point based camera pose estimation on the corner points of the planar mirror, (c) shows the result with augmenting the graphical objects on the current scene, and (d) is the graphical result to visualize the tracked 3D leg's marker position and calibrated camera(red box).

Board, and (w_{cx}, w_{cy}) is the current center of the weight, and W_p is the patient's weight. The normalized feature vector is defined by

$$f=(\overrightarrow{L_{rt}},\overrightarrow{L_{rb}},\overrightarrow{L_{lt}},\overrightarrow{L_{lb}},s_{fl},s_{fr},s_{rl},s_{rr})\in F,$$

as shown in [Fig. 6(a)], where $\overrightarrow{L_i}$ represents the unit vectors of the pairs of the markers on both legs and s_d represents the weight distribution divided by the whole weight of the patient. The legs can move according to the physical limitation of the limbs. This fact makes the obtained features form a specific distribution as depicted in [Fig. 6(b)]. In the feature vector space, the closely positioned feature vectors represent the similar pose. Moreover we motivated by the motional characteristics to solve the loss of data in the symmetry between both side of human body movement. [Fig. 7] shows the symmetry relationship of each side of leg movement. Then, we also added the reflected version of a sampled feature vector that is defined as,

$$f_R=(\overrightarrow{L_{lt}},\overrightarrow{L_{lb}},\overrightarrow{L_{rt}},\overrightarrow{L_{rb}},s_{fr},s_{fl},s_{rr},s_{rl})\in F_R.$$

The normalization should be done before the recording to the database for the stable posture data. Because of this consideration related to restoration process, we can refine the lost or unstable data and calculate the posture information while the patient's movement in the training space.

3.4 Posture Recognition and Refinement

The recognition process of the patient's movement offers a method to diagnosis the patient's status. To recognize the patient's posture for the movement of legs, the system detects and calculates the leg's position and angle of knees at the same time. For the recognition of both legs, we use the marker's position and angle on the 3D training space. There are two groups of vectors to support both legs and we can simply find an angle θ for each angle of knee by cross-product with each side of vectors.

Sometimes, the markers are occluded by the other leg or not detected depending on situations. Our system contains a method to estimate position of occluded markers using the symmetry of human body. We employed k-NN algorithm [19] and recover the position of makers that are occluded by other parts of human body. The following equation shows the formulation by k-NN based similarity

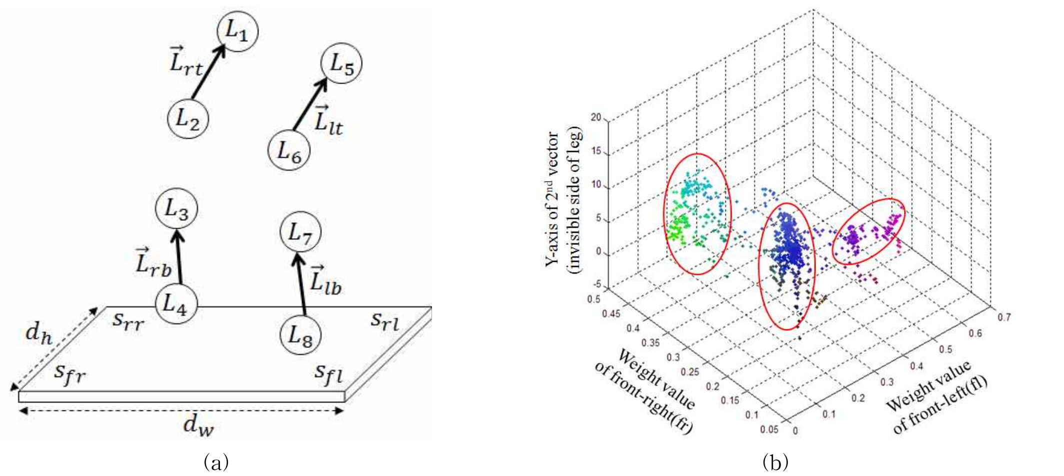


Fig. 6. (a) is the illustration of the posture vector definition and (b) shows the feasibility of the k-NN based classification to solve the self-occlusion problem by well-clustered posture data on the specific vector space.

analysis for our problem.

$$x_s = \{\overrightarrow{leg_{lt}}, \overrightarrow{leg_{lb}}, s_{fl}, s_{fr}, s_{rl}, s_{rr}\} \in X_S,$$

$$y_s = \{\overrightarrow{leg_{rt}}, \overrightarrow{leg_{rb}}\} \in Y_S$$

$$x_t = \{\overrightarrow{leg_{lt}}, \overrightarrow{leg_{lb}}, s_{fl}, s_{fr}, s_{rl}, s_{rr}\} \in X_t,$$

$$y_t = \{\overrightarrow{leg_{rt}}, \overrightarrow{leg_{rb}}\} \in Y_t$$

The target feature vector, y_t, consists of positions of markers on the mirror plane occluded. Other elements are used as sampled data to calculate weights for linear combination. X_S and Y_S are obtained from both sampled data set F and reflected opposite side of sample data set F_R. The nearest neighbors are obtained by measuring $L2$ distance between $x_s \in X_S$ and x_t. The linear weights are calculated using the cost function by,

$$\epsilon(W) = \left| x_t - \sum_{j=0}^{K} w_j x_j \right| ,$$

where $x_j \in X_S$, $\Sigma_{j \in K} w_j = 1$, and K is the set of neighbors. Finally, the reconstruction of y_t is represented by $y_t = \Sigma_{j \in K} w_j y_j$. [Fig. 9] shows the result of the recovered angle for the occluded marker. This estimation is simple and fast enough to use as real-time speed.

4. EXPERIMENTAL RESULTS

The experimental approach of our method is to achieve a measuring method to obtain the posture of both legs with the symmetrical human body motion as shown in [Fig. 7]. There are five motion cycle to observe the motion status of both legs. We can see these motions are changing similarly in terms of the knee angle and weight distribution of both legs in every cycle.

Fig. 8 shows the robustness of our system by changing the camera's view point. The center of the graph is a position perpendicular to the mirror-plane from the camera. This graph shows the measured angle error grows on both side of center with respect to image angle. However, with our

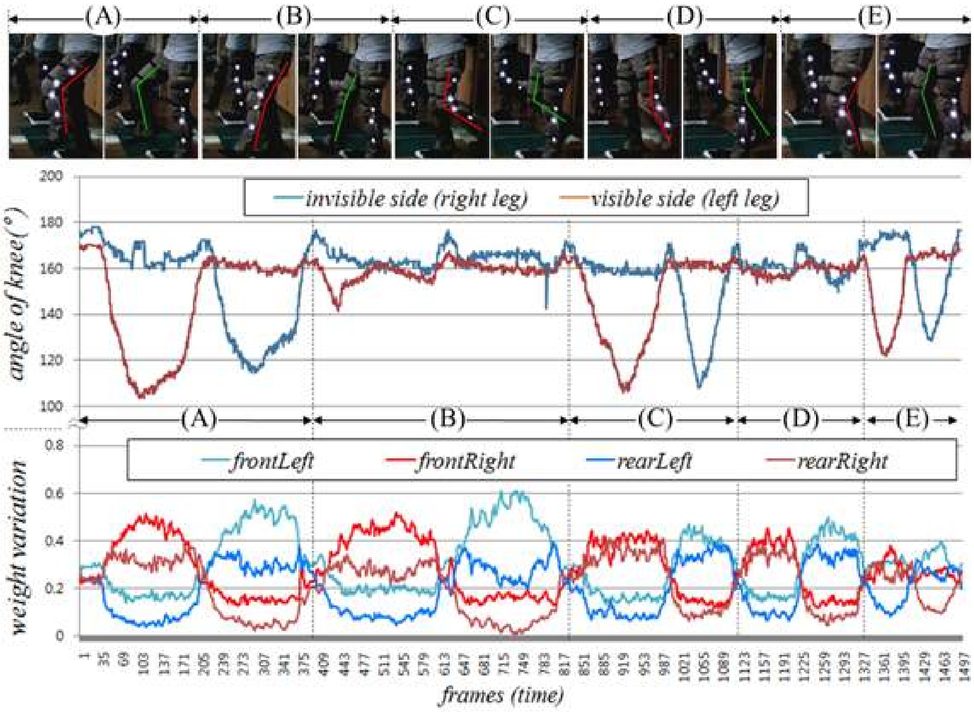


Fig. 7. The result of both legs symmetry characteristics in each motion (A), (B), (C), (D), and (E).

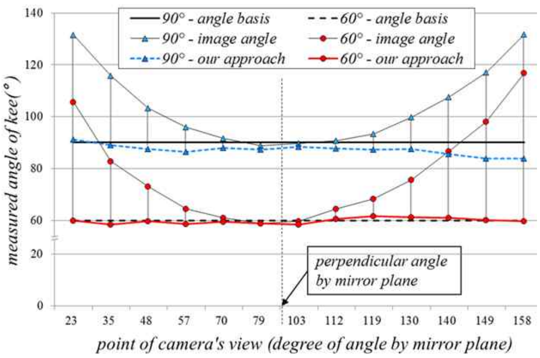


Fig. 8. The comparison result of the 3D based method (our approach) with the 2D based measurement.

method, the amount of error is considerably smaller.

Fig. 9. represents the estimated result by using k-NN based method when the marker is invisible on the scene due to self-occlusion or change of camera's viewing angle. In this experiment, we used only visible side of detected markers with weight distribution to estimate the opposite leg's occluded markers from the trained data including motion symmetry. When compared to the observed data, the estimated data have a jitter, sometimes. However, in the practical use of this system, one or two invisible markers should be recovered by higher accuracy than this.

In Fig. 10, the virtual red graph at the left-bottom side of each picture shows the change of weight distribution by shifting trainee's weight for the posture changing. And also, this figure shows the tracking status of the labeled each IR markers for each change of leg's posture. In the training situation, sometimes, some marker has occluded by the other leg like as third picture. Such like this situation, we called self-occlusion.

Fig. 11. represents the posture of the legs. We draw the result on the three-dimensional space by using OpenGL library to visualize the status of both the legs including change in knee angle and camera view-point for different motion. These kinds of results are very helpful to analysis the patient's status of the rehabilitation training for both the clinicians and patients. The abundant-view of the patient's training state is very useful to observe and understand the patient's specific disadvantage, and moreover, clinicians can establish the care plan for proper rehabilitation training.

Fig. 9. The graph compares the k-NN based estimated posture result with the ground-truth by observed camera without angle consistency.

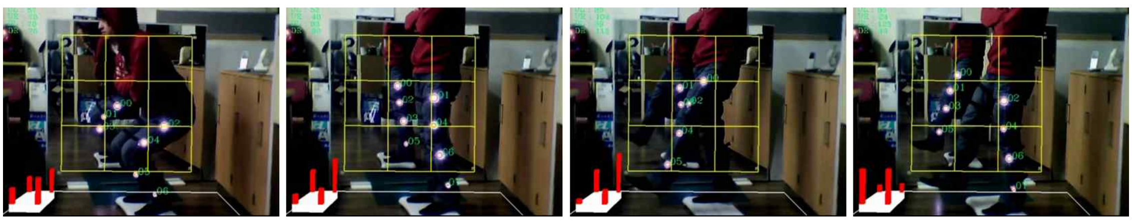


Fig. 10. Each picture shows the change of weight distribution and the tracking result for attached IR markers with labeling.

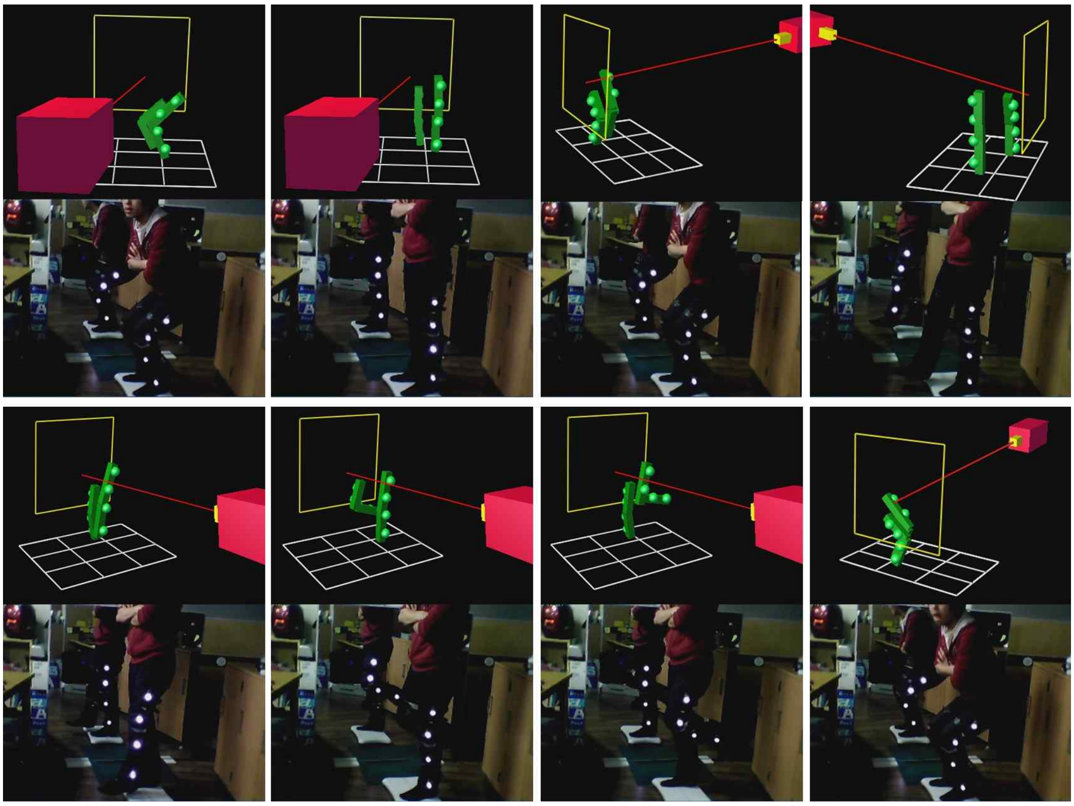


Fig. 11. The series of the captured posture result that represented by 3D green object on the training space (top) for the real trainee's pose (bottom) with various 3D view point.

5. CONCLUSION AND FUTURE WORK

In this paper, the observation of patient's leg motion has been presented by using motion tracking with single camera and mirror. The result of this study demonstrate the motion capture based rehabilitation training for lower-limb paretic patients and for a small number of patients who are traumatic brain injury. The people with lower limb paretic disorder need to observe the range of movement in the angle of knees. This system presents an elaboration upon a training process to enhance the patients' insufficient functional movement, which makes us recognize and analyze both legs' motion information measured in our system.

This ongoing attempt is the first step towards a home-based rehabilitation system and shows a considerable potential of motion capture based rehabilitation training. It also satisfies the requirements that get a proper result of calculated motion information and easily setup the training space anywhere at lower cost. However, it is needed to test the system in usability by using the plentiful data set. In the next studies for enhancement of this system, we need more case studies to examine its usability with more clinical population. And our future works will consider the less requirement of equipment, and pursue more simple and stable installation of the training environment for patient's convenience.

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