Arm motion analysis using genetic algorithm for rehabilitation and healthcare

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ABSTRACT
The world population is quickly aging. With an aging society, an increase in patients with brain damage is predicted. In rehabilitation, the analysis of arm motion is vital as various day to day activities relate to arm movements. The therapeutic approach and evaluation method are generally selected by therapists based on his/her experience, which can be an issue for quantitative evaluation in any specific movement task. In this paper, we develop a measurement system for arm motion analysis using a 3D image sensor. The method of upper body posture estimation based on a steady-state genetic algorithm (SSGA) is proposed. A continuous model of generation for an adaptive search in dynamical environment using an adaptive penalty function and island model is applied. Experimental results indicate promising results as compared with the literature.

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1. Introduction

The aging of population is on the rise. In this regards, it is predicted that patients with brain damage are also rising. In general, the following steps in a rehabilitation process for brain injury is done: (i) acute care and neurosurgery, (ii) post-acute rehabilitation, (iii) community-based rehabilitation, and (iv) longer-term community support [1]. The rehabilitation process starts to quickly reduce impairment and preventing secondary complications. The post-acute rehabilitation reduces disabilities and improves daily activities in regaining mobility and independence, for activities of daily living (ADL) [2]. Basic ADLs include self-care tasks such as showering, dressing, eating, functional mobility, personal hygiene and grooming. The community-based rehabilitation deals with the extended ADL (EADL) [3] such as social integration and returning to work or study. This has made home-care rehabilitation more important than ever.

In rehabilitation, arm motion analysis is crucial as a number of daily activities are directly related to arm movements. If the arm motion analysis is applied regularly to the rehabilitation and diagnosis, a set of desired functional tasks can be established. Ideally, the team should consist of specialists from multidisciplinary rehabilitation, based on the patient needs. However, there is a lack of trained specialists currently. The therapeutic approach and evaluation methods are typically based on their experience, which can be a problem of quantitative evaluation. Therefore, a systematic approach based on integration of information technology, robotics and mechatronics, and intelligence can support the therapists comprehensively using measurements, data collection, motion analysis, persona update, persona analysis, program planning support, and rehabilitation support [4–9].

Various methods have been proposed to detect and track postures and angles of arm joints [10]. These approaches are divided into two groups: non-visual based system [11–13] and visual based system [14,15]. The non-visual based system includes goniometer, accelerometer, and electromyography (EMG) sensor. Goniometer is a tool to measure the angular change on systems of a single degree of freedom. It is however inappropriate to detect movements with multiple degrees of freedom and the measurement depends on a therapist’s visual estimation. An accelerometer is compact and lightweight, hence being frequently used in portable devices. Such sensors however have a problem of drift that can lead to serious integration errors of the estimation. EMG sensors have been applied to the tracking system for its size, sampling rate, and lack of occlusion. Being used in many applications, these sensors are very sensitive to postural changes.

The visual systems include optical marker, X-ray stereophotogrammetry, and magnetic resonance imaging (MRI). Motion
capture system, where the markers are attached with human body can provide high accuracy joint tracking. X-ray and MRI images enable the measurements of internal movements under the skin. These systems however are too expensive and big for nursing homes. In recent years, various sorts of 3D image sensors have been released in the market, some at low-cost. Such sensor devices have the software to detect human movements such as skeleton tracking, hand tracking, and face tracking. As such, many researches have applied such sensors to human behavior analysis in various fields.

In our previous work [16], we developed a posture measurement system using Kinect sensor. The sensor has a built-in processor for human skeleton tracking. However, since the skeleton model is updated in every frame, the length between two joint points varies with postural change and self-occlusion. Hence, an intelligent technique is required to find optimal joint angles corresponding to the measured human posture.

In this paper, we propose a method of upper body posture estimation using a kinematic model and steady-state genetic algorithm (SSGA). SSGA is an evolutionary optimization method using selection, mutation, and crossover operators [17]. Since SSGA is a simplified model, it is an easy implementation in real-time processing. We also develop a rehabilitation support system for upper body motion analysis with a 3D image sensor and physics engine. In the system, the trajectory of estimated joint angles is shown in a graphic form, and the measured motion pattern is represented by the kinematic model in the virtual space. The main contribution in this paper is the development of an advanced estimation method to find an appropriate solution of human posture in a dynamic environment, caused by postural change and self-occlusion. Joint angle estimation calculated from the skeleton model extracted by Kinect sensor has been discussed in [18-21]. The effectiveness of Kinect sensor usage was examined in terms of the accuracy, and comparing it with other measurement systems. Moreover, the functional potential of Kinect sensor for rehabilitation application was found according to the substantiative experiments. These works indicated that the sensor has the acceptable capability for measuring upper arm joint angles. However, in these works, it is noted that the tracking of movement that partial bodily parts are occluded can lead to the vast loss of the precision. Much of the difficulty arises in the uncertainty of difference between property of personal motion and disturbance caused by postural change and self-occlusion. The tracking could be improved if the properties were predefined, but the issue is very difficult technically. In this paper, we compare our proposed method with related works in order to show the advantages of our method. We consider some intelligent techniques for the genetic search to solve the problem, such as how to adaptively reduce the influence of the dynamic environment for the genetic search, and how to avoid a premature convergence and local minimum in order to solve the underspecified problem.

The organization of this paper is as follow. Related works are first presented in Section 2. Section 3 details the developed measurement system. The proposed method of arm motion analysis is explained in Section 4. Experimental results are discussed in Section 5. Concluding remarks and future research directions are given in Section 6.

## 2. Related works

In this section, a literature review on the related works is presented. A summary of the works is presented in Table 1. Various motion capture systems have been developed and applied to rehabilitation research [22]. The technology is precise, but a disadvantage is that the markers are cumbersome and uncomfortable for the patients. In addition, the systems are relatively expensive and typically housed at large medical facilities. With the recent advancements in depth sensors, 3D image sensors have often been used as a solution [23]. In particular, the Microsoft Kinect sensor which was developed as a human interface for gaming can provide a low-cost human motion analysis.

Some researchers in the field of rehabilitation have compared the Kinect sensor with motion capture systems in terms of the tracking accuracy [24]. In [25], it is pointed out that the motion tracking system implemented into Kinect sensor struggled with occlusion caused by postural changes. Other researchers applied Kinect sensor to virtual reality (VR) and game-based exercise systems for rehabilitation. A visual based system for cognitive assessment and rehabilitation is proposed in [26]. In [27], a stroke rehabilitation system for the upper limbs, developed as an interactive virtual environment with a humanoid robot is presented. In these works, the sensor was used not as a precise measurement system but as an innovative system to easily obtain human postural information in real time. In this paper, we focus on a method to improve the accuracy of body posture estimation, based on the motion tracking system embedded into Kinect sensor.

Various types of body posture estimation methods based on Kinect sensor have been also used in the robotics field. A method of full-body pose imitation for a humanoid is proposed in [28]. 20 DOF joint angles of a person are calculated based on the position data obtained. The angle was directly derived from the direction vector of two joint points. In [29], inverse trigonometric functions and cosine formula is applied to calculate the joint angular configuration. These works showed the interesting results, however, the position data basically includes noise depending on postural change and self-occlusion. Therefore, it is difficult to apply inverse kinematics based on geometric approach.

A robotic kinematic model is used in [30], in which the scale of body structure is predefined. An error function is defined to evaluate the similarity of posture between a person and kinematic model [30]. The Levenberg–Marquardt algorithm (LMA) was used to reduce the error and estimate the optimal joint angles. The effectiveness of their proposed method using the similarity function is discussed. However, as for many fitting algorithms, the LMA finds only a local minimum, which is not necessarily the global minimum. Furthermore, in [31,32], Kalman Filter and a kinematic model are utilized to generate the parameter of kinematic model from the noisy data obtained from Kinect sensor. Kalman Filter has the ability to minimize the mean square error of the estimated

<table>
<thead>
<tr>
<th>Table 1 Summary of the related works.</th>
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<tbody>
<tr>
<td>Ref.</td>
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<tr>
<td>[20]</td>
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<td>[32]</td>
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<tr>
<td>[33]</td>
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<tr>
<td>[14]</td>
</tr>
</tbody>
</table>
parameters if all noise is based on Gaussian distribution. However, in the linearization of nonlinear system, the estimation based on Gaussian random variable struggles against large error in the true posterior mean and covariance. Hence, Unscented Kalman Filter (UKF) is applied to the nonlinear problems in the joint angle estimation. This approach addresses the problem by using a deterministic sampling approach. UKF was used to generate the matrix of angular velocity and smoothness of motion in [31,32]. However, in these approaches, the solution to the inverse kinematics is derived based on a conventional geometric approach to calculate Euler angles for each joint. Despite of the fact that UKF can only be applied to models driven by Gaussian noises, this was not discussed.

As a related methodology, we can consider Particle Filter to find a set of optimal joint angles [33]. Particle Filter is a Monte Carlo methodology to produce the posterior probability density function, and can be applied to non-Gaussian model. Although the inverse kinematics problem is an underspecified, Particle Filter can provide non-unique solutions. On the other hand, to calculate the posterior probability density function based on Monte Carlo methodology, the computational cost of Particle Filter is much higher than that of the Kalman filters. An accurate dynamic model is required to calculate the probability distribution. Hence, in this paper, we apply genetic search as a multi-point searching method.

In our previous work [16], we proposed an optimization method to estimate human posture using SSGA and kinematic model. SSGA can find a set of joint angles of the kinematic model corresponding to human posture measured by the 3D image sensor. However, as the objective function was based on just the error of similarity, the previous method sometimes suffered from influence of occlusion. To avoid the problem, we applied a neural network (NN) as a predictive model. It is a hybrid method based on neuro-genetic approach. As a result, the method can improve the accuracy of the estimation. In this method, the learning phase of NN is important to improve the precision, but it is difficult to design the learning structure in advance because features of human movement vary among individuals. Therefore, we propose a new method based on SSGA with adaptive penalty function and island model to improve the previous works.

3. Posture measurement system

In this section, we detail the 3D image sensor and posture measurement and analysis. The details are given in the following sections.

3.1. 3D Image sensor

The Microsoft Kinect sensor is used as a 3D image sensor. The specification of the Kinect is shown in Table 2. The 3D image sensor can measure distances from the device in real-time. The Kinect sensor includes a 3D image sensor, microphones, an RGB camera, an accelerometer, and a tilting-up mechanism. It is connected with the host computer through USB. The Kinect sensor has a built-in processor to extract human posture. The Kinect for Windows SDK 1.8 was used in the system. Fig. 1 shows an example of human posture extraction by using skeleton model. The skeleton model is
Table 2
Specification of Kinect sensor.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size</td>
<td>262 × 72 × 72 mm</td>
</tr>
<tr>
<td>Horizontal field of view</td>
<td>57 deg</td>
</tr>
<tr>
<td>Vertical field of view</td>
<td>43 deg</td>
</tr>
<tr>
<td>Physical tilt range</td>
<td>±27 deg</td>
</tr>
<tr>
<td>Measuring range</td>
<td>1.2–3.5 m</td>
</tr>
<tr>
<td>Resolution</td>
<td>320 × 240, 640 × 480 pixel</td>
</tr>
<tr>
<td>Frame rate</td>
<td>30 fps</td>
</tr>
</tbody>
</table>

Fig. 3. Link length of skeleton detected by Kinect sensor during shoulder flexion and extension.

To solve the mentioned problem, a kinematic model is used. The kinematic model is based on the human body structure, as shown in Fig. 4. In our approach, the joint angles are estimated by matching the kinematic model with the actual human posture. This is an optimization problem that we should define and solve. The kinematic model is built by using Open Dynamics Engine (ODE) to visualize the arm movement. The user is able to monitor the trajectory of arm movement through the kinematic model.

4. Arm motion analysis

Based on details from Section 3, the arm motion analysis is given in detail in this section. In the following subsections, inverse kinematics is first presented, followed by postural estimation based on genetic algorithm.

4.1. Inverse kinematics

The upper body of skeleton model detected by the Kinect sensor is composed of 11 joints, as shown in Fig. 1. It comprises of “HEAD”, “SHOULDER_CENTER”, “SHOULDER_RIGHT”, “ELBOW_RIGHT”, “WRIST_RIGHT”, “HAND_RIGHT”, “SHOULDER_LEFT”, “ELBOW_LEFT”, “WRIST_LEFT”, “HAND_LEFT”, and “SPINE”. The position of each joint point in measured motion is estimated:

\[
q_i = \left[ q_{i,0} \quad q_{i,1} \quad q_{i,2} \right]^T
\]

where \(q_i\) is the position of the \(i\)th joint of body part. Based on a geometric approach to inverse kinematics [27,29], we can calculate a set of joint angles represented in Fig. 4. The kinematic model has 3 trunk joints and 4 joints in one arm, which is given as follows:

\[
\Theta = (\phi_1, \phi_2, \phi_3, \theta_1, \theta_2, \theta_3, \theta_4)
\]

where \(\phi_1, \phi_2\) and \(\phi_3\) are the trunkal joint angles, \(\theta_1, \theta_2\) and \(\theta_3\) are the shoulder joints angles, and \(\theta_4\) is the elbow joint angle. To obtain the joint angles of upper limb, we have to detect the trunk posture first. The joint angles of torso are calculated by

\[
\phi_1 = \arctan \left( \frac{q_{SC,0} - q_S,0}{q_{SC,2} - q_S,2} \right)
\]

\[
\phi_2 = \arctan \left( \frac{q_{SR,2} - q_S,2}{q_{SR,1} - q_{SL,1}} \right)
\]

\[
\phi_3 = \arctan \left( \frac{q_{SR,0} - q_S,0}{q_{SR,1} - q_{SL,1}} \right)
\]

where \(q_{SC}, q_{SR}, q_{SL}\) and \(q_S\) are the position vector elements of “SHOULDER_CENTER”, “SHOULDER_RIGHT”, “SHOULDER_LEFT”, and “SPINE”, respectively.

The joint angles of shoulder can be calculated based on the coordinates of shoulder and elbow. In case of the right arm, the angles of shoulder flexion-extension and abduction-adduction are derived from

\[
\theta_1 = \arctan \left( \frac{\|q_{ER,0} - q_{SR,0}\|}{\|q_{ER,2} - q_{SR,2}\|} \right)
\]

\[
\theta_2 = \arctan \left( \frac{\|q_{ER,2} - q_{SR,2}\|}{\|q_{ER,1} - q_{SR,1}\|} \right)
\]

where \(q_{ER}\) is the position vector elements of “ELBOW_RIGHT”. Elbow flexion is the angle between the upper arm and lower arm measured on the plane defined by shoulder, elbow, and wrist points. The joint angle is given by

\[
\theta_4 = \arccos \left( \frac{\|q_{SR} - q_{ER}\|^2 + \|q_{ER} - q_{WR}\|^2 - \|q_{SR} - q_{WR}\|^2}{2\|q_{SR} - q_{ER}\|\|q_{ER} - q_{WR}\|} \right)
\]

3.2. Posture measurement and analysis by the Kinect sensor

The data of joint positions obtained from the Kinect sensor is applied to the angular estimation. If accurate data of joint coordinates can be acquired, we can use inverse kinematics to derive the joint angles. However, since the sensor estimates the joint positions in every frame, each link length of the skeleton differs from frame to frame. Fig. 2 shows a human posture of shoulder flexion and extension, while Fig. 3 represents the transition of arm lengths measured by Kinect sensor: upper arm, lower arm and hand. In the figures, the person slowly raised his right arm above his head first (shoulder flexion). After that, the person slowly lowered his right arm and pulled his arm back (shoulder extension). Here, the link lengths vary depending on the change of human posture. Especially in the flexion motion, the length of upper arm changes enormously because the shoulder position is covered by the lower arm and the hand. This is a self-occlusion problem.
where $\mathbf{q}_{\text{WR}}$ is the position vector of “WRIST_RIGHT”. Finally, the external and internal rotation at shoulder is calculated as follows:

$$
\theta_1' = \arctan\left(\frac{q_{\text{WR},0} - q_{\text{SR},0}}{q_{\text{WR},2} - q_{\text{SR},2}}\right),
$$

(9)

$$
\theta_2' = \arctan\left(\frac{|q_{\text{WR},2} - q_{\text{SR},2}|}{|q_{\text{WR},1} - q_{\text{SR},1}|}\right),
$$

(10)

$$
q_{\text{WR},0}' = |\mathbf{q}_{\text{SR}} - \mathbf{q}_{\text{WR}}| \sin(\theta_1' - \theta_1),
$$

(11)

$$
q_{\text{WR},1}' = |\mathbf{q}_{\text{SR}} - \mathbf{q}_{\text{WR}}| \sin(\theta_1' - \theta_1),
$$

(12)

$$
\theta_3' = \arctan\left(\frac{q_{\text{WR},1}}{q_{\text{WR},0}}\right).
$$

(13)

where $q_{\text{WR},0}'$ and $q_{\text{WR},1}'$ are the position vector elements of “WRIST_RIGHT” in coordinate system of elbow joint.

The upper body posture can be estimated by using the geometric approach. However, the joint position data is very sensitive to self-occlusion and postural change. In Section 5, we compare the proposed method with the geometric approach, and discuss the effectiveness of the proposed method.

4.2. Postural estimation based on genetic algorithm

Evolutionary computation (EC) has been applied to various types of optimization problems [34]. EC has three different historical streams: genetic algorithm (GA) [35], evolutionary programming (EP) [36], and evolution strategy (ES) [37]. GA has mainly been applied to combinatorial problems [17,38,39]. The main genetic operator is a crossover, and the fitness proportional selection such as a roulette wheel selection is used as a selection strategy. In order to renew the population, there are two major kinds of generation models. The first one is discrete generation model, and the second one is continuous generation model.

In this paper, we have to consider dynamic environments where there are various types of noise factors in the time-series data. The optimization method should be easily implementable in real-time processing, and the optimal solution should be adaptively found in the dynamic environments. Therefore, we apply a steady-state genetic algorithm (SSGA) as a continuous model of generation. Fig. 5 shows an overview of the processing flow.

A candidate solution is composed of numerical parameters corresponding to the joint angles as:

$$
\mathbf{g}_t = (\theta_{1,t}, \theta_{2,t}, \theta_{3,t}, \theta_{4,t}, \gamma_{t,1})
$$

(14)

where $\theta_{ij,t}$ is the $j$th joint angle of the $i$th candidate solution at time $t$, and $\gamma_{ij,t}$ is the scale ratio.

In the SSGA, only the worst candidate is replaced with a candidate solution generated by crossover and mutation. The former is elitist crossover that a new individual is generated by combining genetic information between an individual selected randomly and the worst one, and the latter is adaptive mutation that a new individual is given by

$$
\theta_{\text{worst},j} = \theta_{c,j} + \left(\alpha \frac{|f_{\text{best}} - f_{\text{worst}}|}{f_{\text{best}} - f_{\text{worst}}} + \beta\right)N(0, 1)
$$

(15)

where $c$ is number of the selected individual, $\alpha$ is a coefficient value, $\beta$ is an offset value, and $N(0, 1)$ is a normal random number. The adaptive mutation can perform local search and global search, because the normal random number is multiplied by a coefficient calculated based on the fitness value of selected individual. In the above crossover and the mutation, the worst candidate is removed in each generation. The searching processes are repeated until the terminal condition is satisfied.

The objective is to minimize the difference between actual human posture and posture of the kinematic model. To achieve the objective, the fitness value of candidate solution is calculated by

$$
f = e_i + \sum_{k=1}^{K} p_{\text{GA}}^k \left| \mathbf{p}_{m,k,t} - \gamma_{s,t} \mathbf{p}_{m,k,t} \right|
$$

(16)

$$
e_i = \sum_{k=1}^{K} \left| \mathbf{p}_{m,k,t} - \gamma_{s,t} \mathbf{p}_{m,k,t} \right|
$$

(17)

$$
\lambda_k = \left[1 - \exp\left\{ -\frac{(\theta_{k,t} - \theta_{\text{best},k,t-1})^2}{\sigma_d}\right\}\right] \times \left[1 - \exp\left\{ -\frac{(\theta_{k,t} - \omega_{\text{best},k,t-1})^2}{\sigma_v}\right\}\right]
$$

(18)

where the fitness value function is composed of error function $e_i$ and penalty $\lambda_k$. Here, $K$ is the number of upper limb joints ($K = 4$), $\mathbf{p}_{m,k,t}^\text{GA}$ is the position of the joints calculated by forward kinematic
model using the candidate solution, $p_{j,k,t}$, is the position measured by the Kinect sensor at time $t$, $v_k$ is the coefficient value of the penalty, and $\theta_{j,k}$ is an angle velocity of the $k$th joint. The error function denotes the sum of distance between the joint positions of the kinematic model and the ones of a person. Moreover, the penalty is represented as the sum of correlation values between the difference of each joint angle between two configurations of time $t$ and $t - 1$ and the difference of each angle velocity. Therefore, this optimization problem results in a minimization problem. In Eq. (16), the coefficient value $v_k$ should be defined properly, however it is difficult to predefine the coefficient value $v_k$. Hence, the adaptive coefficient value is applied as follows:

$$v_k = \bar{\hat{e}} + \frac{\hat{\lambda}_k}{\sum_{j=1}^{n} \lambda_j^2}$$

where $\bar{\hat{e}}$ and $\hat{\lambda}_k$ are averaged values of error and penalty in the current population, respectively.

In order to improve the random search, we applied an island model depicted in Fig. 6. In the island model, it has been argued that having multiple subpopulations helps to preserve genetic diversity because each island can potentially follow a different trajectory through the search space [40,41]. The general process of island model is based on migration selection and replacement. We use $k$-means algorithm as a clustering method to divide the population into several groups. In this way, the genetic search is conducted within each local cluster. In the migration, the best individual in all of the populations is transferred to a subpopulation which has the worst individual, replacing the worst individual. The migration occurs based on probability varying with the iteration step. The probability linearly increases in the search process. In Section 5, we compare the proposed method with SSAG without the adaptive penalty function as a previous method.

5. Experimental results

The experimental results are presented in this section. The proposed method was implemented in a measurement system, made up of a Kinect sensor with a host computer with an Intel i5 2.4 GHz processor. The sampling interval of Kinect sensor is approximately 30 ms. The sensor was set at 2 m away from a person. The host computer had a 3D simulator based on ODE to visualize human movement using the kinematic model.

To discuss the effectiveness of the proposed method, we conducted two experiments. In the first experiment, the accuracy of joint angles estimated by the proposed method is compared with results of a previous method and goniometer measurement. In the second experiment, we evaluate the human posture tracking performed by the proposed method. We introduce some developed systems for rehabilitation support as an application of the proposed method.

5.1. Accuracy comparison

The first experiment was conducted using measurements of static arm posture. We focus on the range of motion in shoulder and elbow joints: shoulder abduction, extension, flexion, external and internal rotations, and elbow flexion. Subjects of the experiment are made up of 6 normal males and 3 normal females. Fig. 7 shows measured data of depth image and skeleton frames. The data sets of each posture are composed of 150 data samples, in which the static postures for 5 s are recorded. Table 3 shows the parameter setting for the proposed method. The number of population and islands is 50 and 5, respectively and the maximum number of iterations in each frame is 1000. In this experiment, we compared

![Island model](image1)

Fig. 6. Island model.

![Arm postures in the experiment](image2)

Fig. 7. Arm postures in the experiment.
Table 3  
Parameters for the proposed method.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
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</thead>
<tbody>
<tr>
<td>Population size</td>
<td>50</td>
</tr>
<tr>
<td>Number of islands</td>
<td>5</td>
</tr>
<tr>
<td>Maximum iteration steps</td>
<td>1000</td>
</tr>
<tr>
<td>Coefficient: α</td>
<td>1.0</td>
</tr>
<tr>
<td>Offset: β</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Table 4  
Angle estimation results [deg].

<table>
<thead>
<tr>
<th>Posture</th>
<th>Goniometer</th>
<th>Geometric approach</th>
<th>Proposed method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shoulder abduction</td>
<td>60</td>
<td>57</td>
<td>57</td>
</tr>
<tr>
<td></td>
<td>90</td>
<td>78</td>
<td>82</td>
</tr>
<tr>
<td>Shoulder extension</td>
<td>30</td>
<td>24</td>
<td>25</td>
</tr>
<tr>
<td>Shoulder flexion</td>
<td>60</td>
<td>64</td>
<td>60</td>
</tr>
<tr>
<td></td>
<td>90</td>
<td>89</td>
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</tr>
<tr>
<td></td>
<td>120</td>
<td>123</td>
<td>122</td>
</tr>
<tr>
<td>Shoulder external rotation</td>
<td>60</td>
<td>44</td>
<td>56</td>
</tr>
<tr>
<td>Shoulder internal rotation</td>
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<td>53</td>
<td>55</td>
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<tr>
<td>Elbow flexion</td>
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<td>48</td>
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<tr>
<td></td>
<td>90</td>
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<tr>
<td></td>
<td>120</td>
<td>114</td>
<td>116</td>
</tr>
</tbody>
</table>

Bold values are closer to measured value.

The proposed method to the geometric approach for inverse kinematics as mentioned in Section 4.1.

Table 4 shows the experimental result of angle estimation. The estimated joint angles are the average values in the subjects. Most of the joint angles estimated by the proposed method are closer to the actual value measured by goniometer. Generally, it is said that goniometer measurement has a margin of error of ±5 degrees in rehabilitation. Therefore, the estimated angles should be within 5 degrees of the actual measurement values. While the geometric approach does not provide the adequate results, the proposed method can improve the estimation and give the sufficient results in most of the posture.

5.2. Human posture tracking

In the second experiment, we applied the proposed method to joint angle estimation in continuous motion measurement. The
parameter setting for the proposed method is the same as in the first experiment. Fig. 8 shows the monitoring interface implemented in the developed system. The trajectory of joint angle is visualized graphically on the interface, and measured motion data is represented by the kinematic model that can perform imitative motions corresponding to actual human motions.

To discuss self-occlusion problems, we conducted an experiment for comparing the proposed method with the geometric approach for inverse kinematics. Fig. 9 shows examples of misdetection caused by self-occlusion, and Fig. 10 depicts the trajectory of measured arm length during shoulder flexion and elbow flexion motions. In the figures, the arm lengths vary infinitely at (A) and (B) when the elbow is occluded by the hand.

Figs. 11 and 12 represents the comparison results of joint angle estimation in the shoulder flexion and elbow flexion, respectively. In the figures, while the estimation method based on geometric approach is susceptible to changes in arm length, the proposed method can reduce the influence of misdetection and improve the
tracking accuracy. This indicates the proposed method based on kinematic model and genetic search is an effective way to deal with the self-occlusion problem.

Next, we conducted another experiment to compare the proposed method to SSGA without adaptive penalty function and island model, as in the previous method. Here, we measured 3 types of motions: (i) shoulder flexion/extension, (ii) shoulder abduction, and (iii) elbow flexion and shoulder external/internal rotation. The maximum number of generations in the previous method is 5000.

Fig. 13 shows the comparative results of joint angle estimated during shoulder flexion and extension motions. The figure shows the trajectory of joint angles generated by the previous method, and illustrates the tracking result performed by the proposed method. This indicates the method converged on a local minimum because the inverse kinematics problem is basically underspecified. Fig. 14 shows the trajectory of measured arm length during shoulder flexion and extension. In the SSGA, the population was stochastically generated based on the best individual at previous frame in the video sequence. Although the continuous generation model was used, it was difficult for the previous method to adaptively find an appropriate solution in a dynamic environment where the arm lengths change continuously. The proposed method on the other hand can remove the outliers and improve the accuracy of joint angle estimation. Here, it can be assumed that the penalty function is effective in removing outliers, and the island model sustains genetic diversity to avoid convergence on a local minimum. Figs. 15 and 16 show the estimation results during shoulder abduction and elbow flexion and shoulder external/internal rotation, respectively. In these experiments, we obtained results similar to that of shoulder flexion and extension.

Another comparative experiment was then conducted in order to discuss the effectiveness of island model. In this experiment, we considered the effect of the number of islands on the estimation.

![Fig. 13. Comparative results of angle estimation in shoulder flexion and extension.](image1)

![Fig. 14. Trajectory of measured arm length during shoulder flexion and extension.](image2)

![Fig. 15. Comparative results of angle estimation in shoulder abduction.](image3)
Table 5 shows the settings of the number of islands and the maximum number of iteration steps. The number of islands and iteration steps in each case are designed to equalize the computational costs.

Table 6 shows the average of obtained fitness values. It can be seen from cases 1 to 5, the average value is reduced by increasing islands. Here, the value in case 5 is the least. On the other hand, from cases 6 to 10, the fitness values increase with the increasing islands. That is due to the increase of genetic diversity can inhibit the convergence of fitness value. As seen in the results, the island model can improve the accuracy of genetic searching to detect appropriate joint angles according to continuous motions.

5.3. Application for rehabilitation support

From the experimental results, we showed the proposed method can improve accuracy of joint angle estimation. In this paper, the aim is to apply the proposed method to applications in rehabilitation support. As an example, Fig. 17 shows a developed system for visualizing range of motion. Red and blue balls are represented as the trajectory of elbow and hand positions, respectively. In the rehabilitation process, quantitative evaluation of range of motion is one of the most important tasks. The visualization system can provide not only numerical data but also visual information of
motion patterns. Furthermore, we have developed a motion analysis system based on virtual reality (Fig. 18). In the system, head posture of kinematic model is synchronized with that of a person by using head postural data detected by the Kinect sensor. The system can provide some rehabilitation task to the person in virtual space. Using this system, therapists can simultaneously conduct the measurement, analysis, and evaluation of motion patterns.

6. Conclusions
In this paper, a method of upper body posture estimation using a kinematic model and SSGA with an adaptive penalty function and island model has been proposed. First, the difficulty of the joint angle estimation is detailed and compared with the other related methods. Next, the necessity of the proposed genetic approach is given. The SSGA was applied as a continuous generation model to estimate arm joint angles of the kinematic model corresponding to actual human postures. In addition, an island model is applied to preserve genetic diversity for the genetic search in dynamic environment. Comparative results are shown and effectiveness of the proposed method is discussed, in which the measurement was for normal individuals. In the experiment of static posture measurement, we noted that the proposed method has a smaller margin of error than a conventional geometric approach, and that the result meets the necessary standards for the actual measurement. Moreover, in the experiment of posture tracking, the proposed method reduced the effect of the outliers caused by the postural change and self-occlusion. These indicate that the proposed method is an applicable way for joint angle measurement during tracking of basic arm motions, and that the genetic approach can be a solution to the problems mentioned in Sections 1 and 2. In the future, we will extend this work to measure actual patients in the future to further evaluate the effectiveness of the proposed method. In addition, a rehabilitation program implemented into the system will be worked on.

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References

Table 5
Parameter settings for proposed method in second experiment.

<table>
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<th></th>
<th>Case 1</th>
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<th>Case 3</th>
<th>Case 4</th>
<th>Case 5</th>
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<tbody>
<tr>
<td>$%$ of islands</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
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<tr>
<td>$%$ of iteration</td>
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<td>2500</td>
<td>1666</td>
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<td>1000</td>
</tr>
<tr>
<td>$%$ of islands</td>
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<tr>
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<td>714</td>
<td>625</td>
<td>555</td>
<td>500</td>
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Table 6
Fitness values of SSGA with island model in each motion.

<table>
<thead>
<tr>
<th></th>
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<th>Case 2</th>
<th>Case 3</th>
<th>Case 4</th>
<th>Case 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motion (i)</td>
<td>0.0348</td>
<td>0.0311</td>
<td>0.0353</td>
<td>0.0139</td>
<td>0.0139</td>
</tr>
<tr>
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<td>0.0121</td>
<td>0.0064</td>
<td>0.0343</td>
<td>0.0065</td>
</tr>
<tr>
<td>Motion (iii)</td>
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<td>0.0125</td>
<td>0.0125</td>
<td>0.0125</td>
<td>0.0126</td>
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<tr>
<td>Average</td>
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<td>0.0186</td>
<td>0.0180</td>
<td>0.0202</td>
<td>0.0110</td>
</tr>
<tr>
<td></td>
<td>Case 6</td>
<td>Case 7</td>
<td>Case 8</td>
<td>Case 9</td>
<td>Case 10</td>
</tr>
<tr>
<td>Motion (i)</td>
<td>0.0139</td>
<td>0.0142</td>
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<td>0.0143</td>
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<tr>
<td>Motion (ii)</td>
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<td>0.0067</td>
<td>0.0069</td>
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<td>0.0070</td>
</tr>
<tr>
<td>Motion (iii)</td>
<td>0.0127</td>
<td>0.0128</td>
<td>0.0130</td>
<td>0.0132</td>
<td>0.0134</td>
</tr>
<tr>
<td>Average</td>
<td>0.0111</td>
<td>0.0112</td>
<td>0.0113</td>
<td>0.0114</td>
<td>0.0116</td>
</tr>
</tbody>
</table>

Fig. 18. Rehabilitation support in virtual reality.