Extraction of Cognitive Index for Dynamic Parameter in Human Motion

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ABSTRACT
Human motion is affected by some dynamic parameters, which represent the interaction between the body and the environment. Human can estimate the scale of the dynamic parameter from observation of motions. In this paper, a method to extract adaptive components in the motion is proposed. This method provides precise reconstruction of behavior using the adaptive components. However, it is not proven that these reconstructed behaviors affect people to perceive the dynamic parameters properly. A method to estimate the cognitive scale of the dynamic parameter and a method to extract the characteristic components necessary for perception are also proposed. The proposed methods have been applied to loading motion. Those results have suggested that the extracted characteristic components, that is the cognitive index, are not identical with the adaptive components. It was found that motions reconstructed on the basis of the cognitive indices lead to appropriate perceptions of the dynamic parameters.

Categories and Subject Descriptors
H.4 [**Information Systems Applications**]: Miscellaneous

General Terms
Theory

Keywords
Feature extraction, Motion analysis, Adaptive components, Cognitive index, Cognitive scale

1. INTRODUCTION
Human body motions are thought to be governed by several order parameters that describe how the environment interacts with the body itself. To take walking as an example, some of these parameters are speed, ground slope and the friction coefficient. In this paper, the parameters that describe an environment that exerts an interaction on the subject are called "dynamic parameters" while the components of motion changes corresponding to changes in the dynamic parameters are called "adaptive components." It is reported that human can cognize the scale of the dynamic parameter just from the observation of human body motions which includes adaptive components [1, 2].

In pantomime, a mime remains silent but encourages audience members to imagine non-present things on the stage with him or her, just by using body motions to interact with imagery items. Fujikura et al. assert that pantomime is not in fact an accurate reproduction of actual motions, but in reality consists of actions that exaggerate those motion characteristics that best stimulate the imagination of the onlookers. They said "Mimes emphasize the essence of the motion to a certain degree in order to ensure that the most important aspects of the situation they are portraying are cognized by the audience. They do this continually, which enables them to conceal the vagueness of the details" [3]. Thus, if we consider cognitive indices of motion in terms of the formation principles of mime, it is possible that a faithful reproduction of the adaptive components of motions, one that includes all the details, would actually have a negative impact on cognition of the dynamic parameters by an audience.

The purpose of this research is to clarify the indices used for recognizing information that is not explicit in motions. We propose a method for extracting adaptive motion components via motion capture or other methods that could then be used to make reproductions in both computer graphics (CG) and robot actions that correspond to changes in dynamic parameters. This paper also proposes a method for extracting the cognitive scales of dynamic parameters along with the motion components that function as the cognitive indices. After applying this method to a human body engaged in a lifting motion, we show that the cognitive indices for dynamic parameters do not match the adaptive components. It will also be shown that it is impossible to accurately identify dynamic parameters in motions that are reconstructed based on the adaptive components, but that it is possible to correctly identify dynamic parameters in motions reconstructed based on cognitive indices extracted with our proposed procedure.

BODYNETS 2013, September 30-October 02, Boston, United States

DOI 10.4108/icst.bodynets.2013.253668

2. EXTRACTION OF ADAPTIVE COMPONENTS OF MOTIONS

Motions change due to interactions with the environment. Changes in motion induced by changes in dynamic parameters are called the "adaptive components" of the motion. Generally speaking, there exist multiple environmental dynamic parameters, and their influences on motions are not independent. If just one of the multiple dynamic parameters imposing order on the environment is varied while the other parameters are held constant, the adaptive component induced by that parameter can be extracted. Let us suppose that the dynamic parameter s is varied in e ways:

$$s_1 < s_2 < \cdots < s_e \tag{1}$$

There will be differences in the trials of a single individual's motions even when there have been no changes in the individual's environment. Therefore, adaptive components are extracted over n trials ($n > 1$) in order to avoid the influence of these variations. The motion of the entire body during the j-th trial for dynamic parameter s_i is represented by the column vector $\boldsymbol{a}_{s_i}^j$ ($j = 1, 2, \cdots n$). Here, for the column vector $\boldsymbol{a}$ representing full body motion, the time series data for the posture angles of all the main body joints have been arranged vertically, just as with Reference [4]. The time span required for each motion, from beginning to end, varies with the trial. Therefore, using the data with the longest time span for the motion as standard, the time series length for all of the data was normalized by second-order interpolation and other methods.

$\boldsymbol{a}_{s_i}^j$ normalized to the data length N was drawn up in columns, yielding

$$D_E = \left(\boldsymbol{a}_{s_1}^1\ \boldsymbol{a}_{s_1}^2 \ldots \boldsymbol{a}_{s_1}^n\ \boldsymbol{a}_{s_2}^1\ \boldsymbol{a}_{s_2}^2 \cdots \boldsymbol{a}_{s_e}^n\right) \tag{2}$$

The singular value decomposition of matrix D_E is expressed as

$$D_E = U_E \Sigma_E V_E^T \tag{3}$$

Using previous results published in the literature [4], similar components $\bar{\boldsymbol{a}}$, which are independent of dynamic parameters and variation in trial results, are described as

$$\bar{\boldsymbol{a}} = \sigma_{E_1} \bar{v}_{E1} U_E \tag{4}$$

where $\bar{v}_{E1}$ is the mean value for the components in the first column of matrix V_E.

The motion data $\boldsymbol{a}_s^j$ of a certain dynamic parameter s is distributed in an N-dimensional space about some central point along with scatter due to the variations in trial results. Changes in the dynamic parameters cause both a shift of the central point of the motion data distribution and a change in the scatter from the variations in trial results. Of these changes, the adaptive components of the motion correspond to "the shift of the central point of the motion data distribution." Thus, the motion data are categorized into e classes on the basis of the magnitude of dynamic parameters. Here, we conceive index $J(W)$

$$J(W) = \frac{|W^T S_B W|}{|W^T S_W W|} \tag{5}$$

of the linear transformation of the motion datum $\boldsymbol{a}$, $\boldsymbol{z} = W\boldsymbol{a}$. We then seek the linear transformation W^* which satisfies

$$W^* = \arg\max_W J(W) \tag{6}$$

where S_B is the between-class variance and S_W is the within-class variance:

$$S_B = \sum_k n_k \left(\bar{\boldsymbol{a}}_k - \bar{\boldsymbol{a}}\right)\left(\bar{\boldsymbol{a}}_k - \bar{\boldsymbol{a}}\right)^T \tag{7}$$

$$S_W = \sum_{i=1}^{e}\sum_{j=1}^{n}\left(\boldsymbol{a}_{s_i}^j - \bar{\boldsymbol{a}}_{\boldsymbol{s_i}}\right)\left(\boldsymbol{a}_{s_i}^j - \bar{\boldsymbol{a}}_{\boldsymbol{s_i}}\right)^T \tag{8}$$

n_k is the number of data points belonging to class k. $\bar{\boldsymbol{a}}$ and $\bar{\boldsymbol{a}}_k$ represents the mean of all samples and the mean of the motion data belonging to class k, respectively. W^* represents a linear transformation that provides mutual separation between the data of each class, and corresponds to adaptive components of motion. W^* is determined by solving a generalized eigenvalue problem. However, S_W is singular, so D_E is found by reducing the dimension of the matrix by PCA [5].

The motion data are categorized into two classes determined by the size of the dynamic parameters. When Equation (6) is solved, W^* is an N-dimensional vector. W^* indicates the direction of maximal change of the dynamic parameters. The W^* found in this way is defined as the adaptive component $\boldsymbol{r}_E$. We propose the projection component $p_{s_i}^j$, in the direction of adaptive component $\boldsymbol{r}_E$ of each motion data $\boldsymbol{a}_{s_i}^j$.

$$p_{s_i}^j = \boldsymbol{r}_E{}^T \boldsymbol{a}_{s_i}^j \tag{9}$$

The sign of $p_{s_i}^j$ corresponds to one of the two classes it is divided into, and $|p_{s_i}^j|$ indicates the magnitude of the contribution of the adaptive component of the motion.

3. EXTRACTION OF COGNITIVE INDICES OF MOTIONS

3.1 Animations employed for cognition experiments

In this paper, we obtain cognitive indices for the magnitude of dynamic parameters from CG animations that are created based on motion data where a single dynamic parameter varies while all other parameters are kept constant. Here again, the dynamic parameters s will be varied in e ways, as in Equation (1). The motions of the entire body for each dynamic parameter s_i are represented by column vector $\boldsymbol{a}_{s_i}$. Here, as in Reference [4], for the column vector $\boldsymbol{a}$ representing the motions of the entire body, the time series data for the posture angles of the main body joints are arranged vertically.

When the dynamic parameters of motion are identified by visual observation, the items used as indices can include the subject's muscle tension, facial expression, and so on. However, these items can change independently of changes in dynamic parameters. Therefore, in order to eliminate such influences, a CG skeleton model of the body was created from the motion data and the cognitive indices of dynamic parameters were extracted by observing motions based on this CG model in this study.

3.2 Extraction of cognitive scales

A cognitive scale of dynamic parameters related to visual observation of the motion is obtained via a cognitive experiment during which a pair of motions is presented and subjects are asked only about the relative magnitude of the dynamic parameters of those motions. The pairwise comparison method poses a light burden on the subjects and boasts high reproducibility. In this study, Thurstone's Pairwise Comparison method [6] was employed to calculate the cognitive scale of dynamic parameters in visual observation of motions. More specifically, a cognitive experiment was conducted in which the CG animations of two different dynamic parameters were selected from a number of CG animations created based on actual motion data $\boldsymbol{a}_{s_i}$. These were presented to the subjects, who then evaluated the dynamic parameter's magnitude relation of the paired animations. The size and resolution of the presented CG animations, as well as the view directions of the skeleton model were the same for all experiments. The motions of the s_i and s_j dynamic parameters were pairwise compared, and the selection rate q_{ij} was calculated as the proportion of subjects stating that $s_i < s_j$. It is then clear that

$$q_{ji} = 1 - q_{ij} \tag{10}$$

The interval scale in the observation of the dynamic parameter is obtained using Thurstone's Paired Comparison based on matrix Q, whose components are q_{ij}. This interval scale is defined as the cognitive scale of the dynamic parameter. In Thurstone's Pairwise Comparison, the selection ratio q_{ij} is substituted into the inverse function z of the cumulative distribution function of the standard normal distribution. Because of this, for motion pairs on which all the subjects have agreed, we obtain values of $z(1) = \infty$ and $z(0) = -\infty$, and the calculation results diverge. In order to eliminate this issue, we make the following adjustment: we define $z(1) = c > 0$, $z(0) = -c$, where c is a large enough number to overwhelm the value of z. In the results given in this paper, we set $c = 4$.

3.3 Extraction of cognitive indices

The cognitive scales for the dynamic parameters of the motions determined from the animations made using the motion data $\boldsymbol{a}_{s_i}$ for the dynamic parameters s_i $(i = 1, 2, \cdots, e)$ are represented as y_i. With $\boldsymbol{r}_O$ being an N-dimensional column vector, we get:

$$y_i = \boldsymbol{r}_O^T \boldsymbol{a}_{s_i} \tag{11}$$

Superscript T indicates the vector transpose. Here, $\boldsymbol{r}_O$ represents a linear transformation of the motion data $\boldsymbol{a}_{s_i}$ into the cognitive scales y_i for the dynamic parameters, and represents the variable components of the motions corresponding to the cognitive scale. Accordingly, $\boldsymbol{r}_O$ is an index for cognition of dynamic parameters of the motion. In this paper, $\boldsymbol{r}_O$ is called a "cognitive index" of the dynamic parameter.

Drawn up $\boldsymbol{a}_{s_i}$ in columns, we have

$$A_O = (\boldsymbol{a}_{s_1}\ \boldsymbol{a}_{s_2} \cdots \boldsymbol{a}_{s_e}) \tag{12}$$

Employing matrix A_O and y_i arranged vertically as vector $\boldsymbol{y}$, Equation (11) then takes the form

$$\boldsymbol{y} = A_O^T \boldsymbol{r}_O \tag{13}$$

A_O^T is an $e \times N$ matrix. N is the product of the number of measured sites of the human body, the dimension of attitude representation, and the sampling numbers. In general, $N > e$. Therefore, we cannot determine uniquely the N-dimensional column vector $\boldsymbol{r}_O$ based on Equation (13). In such cases, we can use a pseudo-inverse matrix to satisfy Equation (13) and find the solution that minimizes $|\boldsymbol{r}_O|$. If we use the pseudo-inverse matrix $(A_O^T)^+$, for A_O^T, then we obtain

$$\boldsymbol{r}_O = (A_O^T)^+ \boldsymbol{y} \tag{14}$$

Here, the singular value decomposition of matrix A_O is described as

$$A_O = U_O \Sigma_O V_O^T \tag{15}$$

U_O and V_O are orthogonal $N \times N$ and $e \times e$ matrices, respectively. Σ_O is a matrix whose non-diagonal elements are 0, while the elements on the diagonal are the non-negative singular values $\sigma_{O_i} (i = 1, 2, \cdots, e)$. Here, $\sigma_{O_1} \geq \sigma_{O_2} \geq \cdots \geq \sigma_{O_e}$. Since

$$(A_O^T)^+ = U_O \Sigma_O^+ V_O^T \tag{16}$$

$$\Sigma_O^+ = \begin{bmatrix} \mathrm{diag}(1/\sigma_{O_1}, 1/\sigma_{O_2}, \cdots, 1/\sigma_{O_E}) \\ O_{(N-e)\times e} \end{bmatrix} \tag{17}$$

The cognitive indices $\boldsymbol{r}_O$ of the dynamic parameters can be expressed as

$$\boldsymbol{r}_O = U_O \Sigma_O^+ V_O^T \boldsymbol{y} \tag{18}$$

Based on Equation (18), Equation (13) was solved by reducing the dimension of both the motion data $\boldsymbol{a}_{s_i}$ and $\boldsymbol{r}_O$ using the column vector U_O, that is, the left singular vector of A_O. Here, since the first left singular vector of A_O represents similar components of $\boldsymbol{a}_{s_i}$ [4], it does not contain perceptible data about the dynamic parameters. Generally speaking, the first singular value σ_{O_1} is larger than the higher singular values. Thus, we can ignore the contribution of the first left singular vector from Equation (18) and write the cognitive index $\boldsymbol{r}_O$ as

$$\boldsymbol{r}_O = U_O \hat{\Sigma}_O^+ V_O^T \boldsymbol{y} \tag{19}$$

$$\hat{\Sigma}_O^+ = \begin{bmatrix} \mathrm{diag}(0, 1/\sigma_{O_2}, \cdots, 1/\sigma_{O_e}) \\ O_{(N-e)\times e} \end{bmatrix} \tag{20}$$

4. APPLICATION TO LIFTING ACTION

4.1 Gathered motion data

The motion examined in this study was that of a human's lifting of a load in both arms. One of the dynamic parameters was the mass of the lifted object. The load had an unvarying shape and size while the motion data were taken. It was a cuboid cardboard box 509 mm long, 399 mm wide and 398 mm high. Its mass was varied by changing the number of weights in the box. Each weight had a mass of 2 kg. The motion started at a crouching body position, bent at the waist and knees, and ended with the lift completed and the body standing upright and stationary. Since the posture changes over a range exceeding 90 degree in this motion, we cannot avoid consideration of the effects of the singularity when expressing this with Euler angles. Therefore, the unit quaternions were used to represent the posture instead. Data were taken from three trials of this motion at each mass.

Loading motion was measured using inertial measurement units. A commercial inertial measurement unit, MTx, which is developed by Xsens Technology [7], was used in our experiments. On a sensor unit, three gyros, three accelerometers and dimensional magnetic field sensors are installed. Measurements obtained from the sensors are fused to determine the sensor unit's posture by use of Kalman filter technique. All sensor units were synchronized and the measurement rate of the posture was 50 Hz. Measurement data were sent to a personal computer through Bluetooth communication. As shown in the left figure of Figure 1, sensor units were placed on head, shoulders, upper arms, lower arms, waist, thighs, lower thighs, and feet. The right figure of Figure 1 is a picture of a subject equipped with sensors units.

4.2 CG animations displayed in cognition experiment

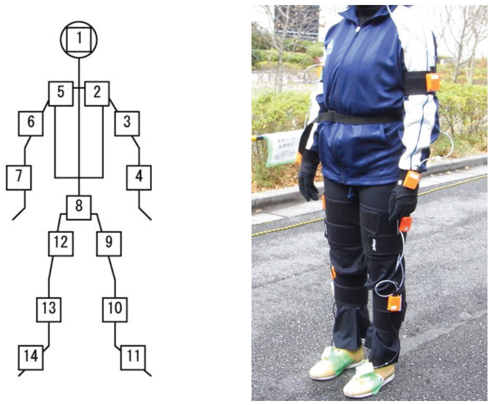

Figure 1: A subject equipped with sensor units and the unit installed location

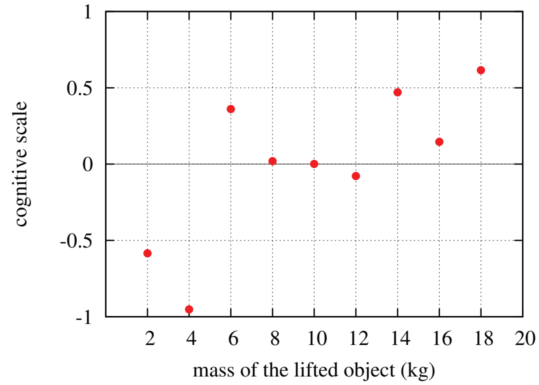

Figure 2: Cognitive scale of loading motion

In order to eliminate the effects of factors such as its tilting on cognition, the CG animations did not show the load. The CG animation pairs created based on the gathered motion data were shown side by side on a single 37-inch display. The subjects viewed the animation while seated on a chair placed 1.5 m front of the display. The animation showed a skeleton model, viewed from the left side as it moved in the sagittal plane. The motion data durations were normalized so that the playback times were all the same. The playbacks were also timed to be perfectly synchronized. The subjects were then asked to identify which of the CG animation pair had larger dynamic parameters. They were given 15 seconds to reply. The animation pair was replayed repeatedly during the reply time. All of the animations were displayed together in pairs. While the order of display was set randomly, all the subjects saw the pairwise animations in the same order.

4.3 Results of extraction of cognitive scale of dynamic parameters

A cognitive experiment was conducted using CG animations created based on the motion data of the same individual. The weight totals increased in 2 kg increments from 2 to 18 kg, so the number e of dynamic parameters was nine. The experiment involved showing each animation pair to 22 subjects (20 adult males and two adult females) who were asked to differentiate the sizes of the dynamic parameters. After the experiment had been completed, the subjects were also asked to write free descriptions of the aspects they had considered in order to determine the relative magnitude of the dynamic parameters.

Figure 2 shows the cognitive scales of the dynamic parameters found in the cognitive experiment. The horizontal axis is the dynamic parameter values of the animations and the vertical axis is the cognitive scale. The bigger cognitive scale is, the bigger the judged dynamic parameter is. In this case, a motion of bigger cognitive scale is judged to be that with a heavier object. As can be seen in this figure, there were many points of contradiction in the magnitude relationships in the extracted cognitive scales and the actual dynamic parameters. This indicates that cognition of the magnitude of dynamic parameters by the observation of motion does not necessarily match completely the actual magnitude of the dynamic parameters.

4.4 Results of extraction of cognitive indices of dynamic parameters

The cognitive indices $\boldsymbol{r}_O$ were calculated using the cognitive scales in Figure 2. It is difficult to see $\boldsymbol{r}_O$ directly as changes in motions of the body, so the similar component of the motion and the constant parameter k_O are employed to synthesize the reconstructed motion $\boldsymbol{a}_{kO}$, based on the adaptive components, as follows:

$$\boldsymbol{a}_{kO} = \bar{\boldsymbol{a}} + k_O \frac{\boldsymbol{r}_O}{|\boldsymbol{r}_O|} \tag{21}$$

where k_O is a scalar parameter called intensity coefficient. The magnitude and the sign of k_O is the degree of emphasis and the direction of the cognitive indices $\boldsymbol{r}_O$, respectively. Figure 3 presents the reconstructed motion using a skeleton model. The upper portion of Figure 3 shows the motion reconstructed when $k_O > 0$ and the lower portion, when $k_O < 0$. In the motion reconstructed with $k_O > 0$, the change is undertaken with the elbow extended once and then re-bent between the 20% and 40% time points. No change over time in the head posture was seen during this period, and it can be seen that the head remained nearly vertical, slightly bent back. The process in Figure 3 can be interpreted as resulting from the following: The arms were not strong enough to sustain the weight of the load at the outset of lifting, so the body is pulled toward the load; the subject then "puts more muscle" into lifting. As a result, this change component seems to lead to the cognition that the dynamic parameter is large.

In contrast, the process differed in the reconstructed motion when $k_O < 0$. We can see that the elbows remained bent, and that the head posture remains bent forward and did not change over time. This change can be interpreted as resulting from the fact that the arms were strong enough to hold the load from the beginning of the motion at this time, and simply continued lifting the load. As a result, this change component seems to lead to the cognition that the dynamic parameter is small. In the survey conducted after the experiment, the subjects said that their criteria for judging that the dynamic parameter was large were straining movement at the outset of lifting, jerking movements with the elbows, and bending back of the neck at the outset of lifting. The extracted cognitive indices correspond to these results from the survey.

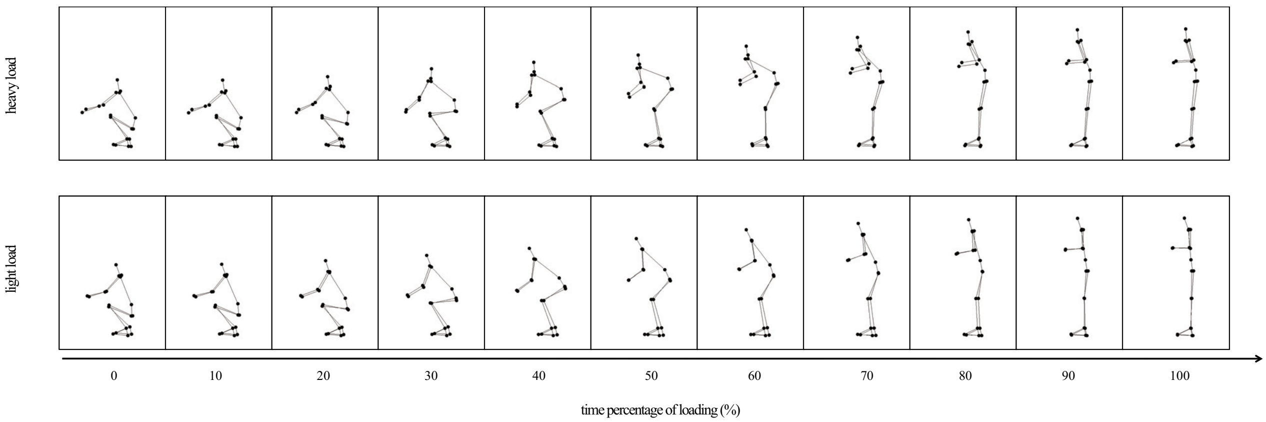

Figure 3: Visualization of cognitive index by skeleton model

Figure 4 shows the changes in posture indicated by the extracted cognitive indices $\boldsymbol{r}_O$. The horizontal and vertical axis of the figure represents the parts of the body and the time percentage of loading, respectively. 0 % is the start of the motion and 100 % the end. The darker the color, the greater the change in posture of that part at that time. For comparison, Figure 5 shows the changes in posture expressed by the adaptive component $\boldsymbol{r}_E$ in the same motion data. We can see with $\boldsymbol{r}_E$ that the head showed its greatest angular changes during the $30 \sim 70\%$ time span. In the same way, there were variations over time in the power applied at the legs during the angular changes; these were quite marked in the $20 \sim 80\%$ time span, while we also see that there was little change over time in power with changes in the arms.

In contrast, with the cognitive index $\boldsymbol{r}_O$, the changes in the angle of the head were very small. Although there were large changes during the $30 \sim 70\%$ time span, these time-based changes were somewhat small in comparison to the adaptive components. Not only were the overall changes in leg posture angle small, the time-based changes were small as well, with the largest change seen in the left arm. In particular, we can see that the left forearm changed during the $0 \sim 50\%$ time span, while the upper left arm showed changes after 50%. These results show that the $\boldsymbol{r}_E$ of the adaptive components is different from the cognitive indices $\boldsymbol{r}_O$, not only spatially, but also in the time region.

4.5 Verification of extracted cognitive indices

An experiment in cognition of dynamic parameters of reconstructed motions was conducted in order to confirm that the extracted cognitive indices $\boldsymbol{r}_O$ are important motion components for cognition of the dynamic parameters. For comparison, just as in Equation (21), we made the reconstructed motions $\boldsymbol{a}_{kE}$ using adaptive components $\boldsymbol{r}_E$. $\boldsymbol{a}_{kE}$ is described as

$$\boldsymbol{a}_{kE} = \bar{\boldsymbol{a}} + k_E \boldsymbol{r}_E \tag{22}$$

where for the adaptive component $\boldsymbol{r}_E$, $|\boldsymbol{r}_E| = 1$. As well as k_O appeared in Equation (21), k_E is a scalar parameter called degree of emphasis. $\boldsymbol{a}_{kO}$ emphasizes motion components for cognition of the dynamic parameters, while $\boldsymbol{a}_{kO}$ emphasizes the motion change corresponding with the change of the dynamic parameters. Six motions were reconstructed with k_E and k_O =± 1, ± 2 and ± 3. A seventh standard motion was defined with $k_E = k_O = 0$, i.e. , composed of only $\bar{\boldsymbol{a}}$, and CG animations were created for each of these seven. A cognitive experiment was then conducted to distinguish the sizes of the dynamic parameters using animation pairs of the reconstructed motions. A total of 23 subjects (21 adult males and two adult females) watched the animations. After the experiment had been completed, the subjects were asked to write free descriptions of the aspects they had considered in order to judge the relative magnitude of the dynamic parameters.

Figure 6 shows the cognitive scale for dynamic parameters obtained from the experiment results. These have been parallel shifted so that the cognitive scale of the standard motion is 0. The solid and dashed lines in the figure represent the cognitive scale for the motions $\boldsymbol{a}_{kE}$ and $\boldsymbol{a}_{kO}$ reconstructed from the cognitive indices and the adaptive components, respectively. The emphasis of the motion characteristics k_E and k_O are on the horizontal axis and the cognitive scale of the dynamic parameters is on the vertical axis. From Figure 6, we see that the cognitive scale of the dynamic parameters increase monotonically with an increase in both k_E and k_O for positive values of those variables. Thus, the motion observer can see that the increase in cognitive scale for the cognitive index $\boldsymbol{r}_O$ was greater than that for the adaptive component $\boldsymbol{r}_E$. This shows that the reconstructed motions $\boldsymbol{a}_{kO}$ based on the cognitive index $\boldsymbol{r}_O$ resulted in more accurate cognition of the appropriate dynamic parameters.

Turning to the situation when $k_E < 0$, we see that the cognitive scale of the dynamic parameters increased with decrease of k_E. Reconstructed motions based on adaptive components with $k_E < 0$ correspond to motions with small dynamic parameters. In other words, the details presented here contradict the cognitive results. This indicates that even if motion is reconstructed on the basis of adaptive components, it does not lead to adequate cognition of dynamic parameters. We can also see that since the cognitive indices were not negative, in this case, if motions are reconstructed using the adaptive components, the dynamic parameters were perceived to have increased more than the standard motions. In contrast, motions reconstructed on the basis of the cognitive indices while $k_O < 0$ showed negative cognitive indices, and the motion observer can see that the dynamic parameters were perceived as smaller than the standard motions. When $k_O \geq -2$, the cognitive scale of the dynamic parameters decreased monotonically with a

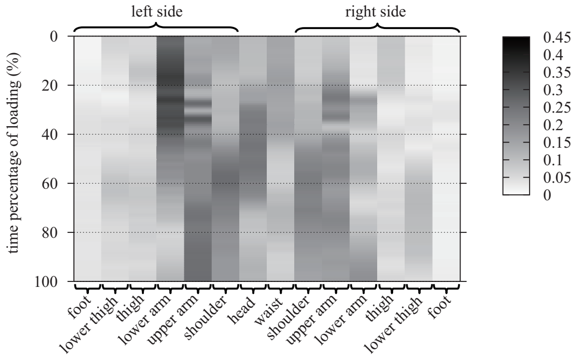

Figure 4: Posture angle of each part of body (cognitive index)

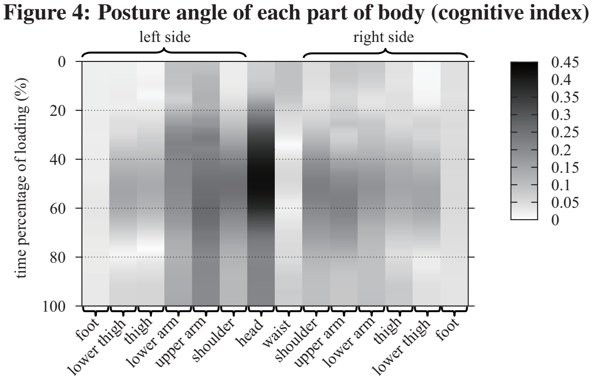

Figure 5: Posture angle of each part of body (adaptive component)

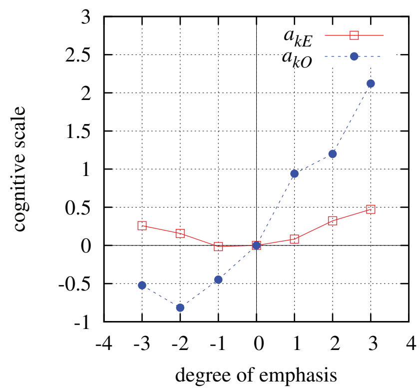

Figure 6: Comparison of cognitive scale between the adaptive component and the cognitive index

decrease in k_E, but the cognitive index when $k_O = -3$ recovered to about the same level as when $k_O = -1$. In other words, the presented details contradict the cognitive results. The reason for this was probably exaggerated emphasis of the cognitive indices, which caused them to diverge further from the standard motions.

Comparing the rate of increase of the cognitive scale in the two domains $-2 \le k_O \le 0$ and $0 \le k_O \le 3$, we see that the increase was larger when $k_O \ge 0$. This indicates that recognition of dynamic parameters based on cognitive indices was not consistent, and that there was distortion. Specifically, this shows that with lifting motions, it is harder to cognize when the load is light than when it is heavy.

The above results show that the cognitive indices extracted using Equation (19) are key motion components for accurate cognition of the dynamic parameters of motions.

5. CONCLUSION

We proposed a method for extracting adaptive motion components that correspond to changes in dynamic parameters. This paper also presents a method for extracting the cognitive scale and cognitive indices of dynamic parameters in observed motions of a human body. An interval scale for distinguishing the sizes of dynamic parameters perceived was developed based on a cognition experiment employing CG animations containing information only related to changes in the posture of a skeleton model of a human body as it performed a lifting action, which was employed as a cognition scale. A procedure for finding the motion components that reflect the extracted cognitive scale in terms of the cognitive indices of changes in dynamic parameters was demonstrated. Application of the proposed procedure to the lifting motion showed a lack of consistency between the adaptive components appearing in response to changes in the dynamic parameters and the motion components corresponding to cognitive indices. It was found that the posture changes caused by the adaptive components and the cognitive indices are dissimilar not only spatially, but also in terms of time region. It was also found that motions reconstructed on the basis of the extracted cognitive indices lead to perceptions that appropriately reflect sizes of the dynamic parameters, while motions reconstructed on basis of adaptive components lead to incorrect dynamic parameter perceptions.

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