A novel method to calculate the anomaly score of movement variability of repetitive tasks

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Abstract
This study proposes a new calculation method for the anomaly score of repetitive tasks based on singular spectrum transformation (SST) that accounted for a long-term history of human motion. To validate the efficacy of the proposed method, the calculated anomaly score was compared with movement variability computed by a traditional method and to its SST-computed score. Eleven male participants performed repetitive lightweight material handling tasks under different work conditions and an electromagnetic tracking system measured their working posture. Movement variability and anomaly score on the shoulder and elbow joints were calculated based on measured working postures. The movement variability on the elbow flexion angle increased with time. In contrast, the anomaly score of the elbow flexion angle decreased with time, but shoulder flexion and inner rotation angles showed increased scores with the passage of time. These findings are similar to those of previous studies that stated that movement variability increased from redundant degrees of freedom available for performing multi-joint movements; this occurred due to the development of muscle fatigue on the shoulder joint from performing repetitive tasks. On comparing this to the anomaly scores calculated by conventional SST, it was observed that the score computed by the proposed method reflected the whole trend of human motion in repetitive tasks and did not depend on local problems in working posture. Therefore, it was concluded that the new method of calculating the anomaly score is more suitable to detect changes in movement variability in repetitive tasks.

KEYWORDS
anomaly detection, human motion analysis, movement variability, repetitive tasks, working posture

1 | INTRODUCTION

Manual work is an important aspect of the industrial sector and is dependent on the human capability of adaptation and learning to produce high-quality and customized products (Forsman, Hasson, Medbo, Asterland, & Engström, 2002). Owing to increasing automation in modern workplaces, manual work now primarily consists of repetitive tasks with low physical workloads (Mathiassen, 2006). Muscle fatigue may be caused by performing repetitive tasks and is a risk factor for the development of musculoskeletal disorders (MSDs; Hansson et al., 2000; International Organization for Standardization, 2014; Kinali, Kara, & Yildirim, 2016). Muscle fatigue...
causes changes in movement variability and decreases the capability of humans to perform a smooth and controlled motion (Cortes, Onate, & Morriss, 2014; Yang et al., 2018). To prevent MSDs in repetitive tasks, the current recommended ergonomic intervention is to decrease the similarity of working motion, that is, to increase movement variability (Mathiassen, 2006).

The effect of movement variability on preventing MSDs in repetitive tasks has been reported by several previous studies, for example, workers exhibiting a larger movement variability showed a low occurrence of muscular fatigue and pain (Fallia, & Farina, 2007; Madeleine, & Madsen, 2009) and a faster rate of recovery from injury (Moseley & Hodges, 2006). These studies suggested that the risk of developing MSDs decreased by performing repetitive tasks with larger movement variability (Madeleine, 2010; Mathiassen, 2006).

Several studies evaluating movement variability have been reported, which include methods based on approximate or sample entropy (Madeleine and Madsen, 2009), nonlinear dynamics (Stergiou & Deckler, 2011), angle-angular velocity phase plots (Wagner, Pfusterschmeid, Klou, von Duvillard, & Müller, 2012), and goal equivalent manifolds (Cusumano & Dingwell, 2013; Sedighi & Nussbaum, 2017). Longo, Meulenbroek, Haid, and Fedoroff (2018) reported that principal component analysis (PCA) is a suitable method for detecting movement variability and identifying changes in postural configuration. However, these methods cannot evaluate the time-varying movement variability.

Anomaly detection is useful for identifying variations in working posture in a time series. Singular spectrum transformation (SST; Ide & Inoue, 2004) or singular spectrum analysis (SSA; Moskvina & Zhigljavsky, 2003) detect the change-point in a time series without assuming a prior distribution, which is useful in predicting time-varying movement variability. Previous studies in the ergonomic and physiological fields utilized SST or SSA to remove noise electroencephalograms and electrocardiograms (Maddirala & Shaik, 2016; Mourad, 2019), estimate gait (Jarchi et al., 2014), and detect the signal onset in EMG recordings (Vaisman, Zariffa, & Popovic, 2010). Conventional SST can detect unexpected changes or identify the change-point in human motion during work. Conventional SST compares the present and past patterns of human motion but limits the past-compared pattern to a part of a task in the time series. Therefore, conventional SST may not be able to evaluate the variation of working posture, which gradually changes with time in long-term repetitive tasks. In other words, conventional SST cannot display a long-term history of human motion in repetitive tasks done over long periods.

This study proposes a new method to calculate the anomaly score based on the type of SST that depicts a long-term history of human motion in repetitive tasks. This study measures the working posture in repetitive lightweight material handling tasks and calculates the movement variability and the anomaly score accordingly. To validate the efficacy of the proposed method, the calculated anomaly score is compared with the movement variability computed by a traditional method and to its score computed by conventional SST.

## 2 | MATERIALS AND METHODS

### 2.1 | Outline of SST

SST proposed by Ide and Inoue (2004) is a method that converts an original time series into a new time series based on the change-point score. Consider a time series \( T = \{ x(1), x(2), \ldots, x(t), \ldots, x(N) \} \) and its consecutive subsequence with window length \( M \) as \( \{ x(t-M), \ldots, x(t-2), x(t-1) \} \). When a column vector corresponding to its consecutive subsequence is defined as \( s(t-1) = (x(t-M), \ldots, x(t-1))^T \), the two types of Hankel matrix, the trajectory matrix \( X(t) \) and the test matrix \( Z(t) \) are defined as follows:

\[
X(t) \equiv [s(t-n), \ldots, s(t-2), s(t-1)],
\]

\[
Z(t) \equiv [s(t+L+M-1), s(t+L+M), \ldots, s(t+L+M+k-1)].
\]

The trajectory and test matrices represent the past and present patterns of human motion, respectively. \( L \) is a nonnegative constant used to determine the relative position between the trajectory matrix and the test matrix, and is called lag.

The anomaly score is defined as the difference between two principal subspaces \( U(t) \) and \( Q_m(t) \), which are the trajectory matrix and test matrix of principal subspaces at time \( t \), respectively. \( U(t) \) and \( Q_m(t) \) are defined as follows:

\[
U(t) \equiv [u_1(t), u_2(t), \ldots, u_m(t)],
\]

\[
Q_m(t) \equiv [q_1(t), q_2(t), \ldots, q_m(t)].
\]

where \( u_i(t), q_m(t) \) are left singular vectors obtained via singular value decomposition (SVD) on \( X(t) \) and \( Z(t) \). \( r \) and \( m \) are the numbers of left singular vectors taken from a left singular matrix obtained via SVD. Anomaly score \( \alpha(t) \) at time \( t \) is calculated as follows:

\[
\alpha(t) = 1 - \|U(t)^T Q_m(t)\|_2.
\]

As shown in Equation (5), the anomaly score \( \alpha(t) \) is limited to the range \( 0 < \alpha(t) < 1 \). A smaller \( \alpha(t) \) indicates a slight difference between the two patterns, whereas a larger \( \alpha(t) \) indicates a larger difference.

### 2.2 | Proposal for a new calculation method of anomaly score at \( t \)

To determine the differences in the working posture among different tasks, the correct selection of the trajectory matrix is essential. In the calculation for change-point score using SSA, the trajectory matrix is defined as the matrix that represents all the data and extracts major data patterns from it (Hassani, 2007). However, the selection methods of the trajectory matrix have some problems, for example, the trajectory matrix may include unnecessary movement patterns when...
comparing task-to-task working postures. The calculated anomaly score differs widely when major motion patterns are extracted in different periods from the whole human movement. Therefore, it is important to evaluate the long-term history of human motion in repetitive tasks for long periods to achieve the correct anomaly score. To consider a more long-term history of human motion, this study proposes a new calculation method of anomaly scores $a(t)$ at time $t$ as follows:

$$a(t) = \frac{\sum_{i=1}^{N} 1 - \|U_i(t-(i-1)L)Q_{an}(t)\|_2}{N},$$

(6)

where $N$ represents the quotient when time $t$ is divided by lag $L$. Note that $L$ is required to match with the representative value of the time of a single task extracted from the sequential task.

3 | EXPERIMENTAL DESIGN

3.1 | Participants

In this experiment, 11 healthy, right-handed male students without any self-reported upper limb disorders were recruited. All participants provided written informed consent after they were briefed about the research protocol, which follows the principles outlined in the Declaration of Helsinki and was approved by the Research Safety Ethics Committee of Tokyo Metropolitan University. The mean ± standard deviation of participants’ age, height, and weight were 23.1 ± 1.5 years, 1,732 ± 42 mm, and 67.4 ± 9.0 kg, respectively. The mean ± standard deviation of participants’ hand length, forearm length, and upper limb length were 185 ± 11, 441 ± 17, and 740 ± 27 mm, respectively.

3.2 | Experimental condition and procedure

In the experiment, the participants sat on chairs and moved light ball-shaped objects (diameter = 35 mm, weight = 8 g) for 10 min. Participants performed two types of tasks: Task A and Task B. Task A was to move the objects from a basket on the left to another basket on the right. Task B was to move the objects from a basket placed farther away to another basket nearby.

The participants were instructed to sit in a chair and maintain an anatomical position at the beginning of the experiment. After maintaining the position for 5 s, the participants were requested to move the objects to the instructed basket at a free pace. Participants orally answered subjective workload questions pertaining to their right upper limb using the Borg CR10 scale (Borg, 1998) every 20 s while performing the task. After performing the task for 10 min, participants maintained the anatomical position for 5 s. The effect of residual fatigue on their work motion was eliminated by providing sufficient rest before the next task. Participants rested for a minimum of 3 min after performing the task in each experimental condition. Subsequently, participants were asked whether any discomfort or fatigue remained in the right upper limb. When participants stated that they had no remaining discomfort, the next experimental condition was performed. If participants still had discomfort or fatigue in the right upper limb, the resting time was extended until the discomfort or fatigue was resolved.

3.3 | Measured data and analysis

3.3.1 | Working posture measurement and movement variability estimation

An electromagnetic tracking system (trakSTAR, Ascension Technology) was used to obtain the three-dimensional position and orientation of the lower back, chest, right upper limb, right forearm, and right hand at a sampling frequency of 50 Hz. For each of these body segments, electromagnetic receivers were placed in the manner described in a previous study (Bouvier, Durprey, Claudon, Dumas, & Savescu, 2015), as shown in Figure 1. Subsequently, the joint angles between the trunk and right upper limb were calculated by applying a measured orientation of the body segment into three-dimensional rigid-link models.

The movement variability was estimated with MATLAB R2019a (MathWorks, Inc.) based on an equation for the standard deviation on vector lengths of the normalized angle-angular velocity cycle, as reported by Wagner et al. (2012). The normalized angle and angular velocity were calculated as follows:

$$\theta_{\text{norm}} = \frac{2\theta - (\theta_{\text{max}} + \theta_{\text{min}})}{\theta_{\text{max}} - \theta_{\text{min}}},$$

(7)

$$\omega_{\text{norm}} = \frac{2\omega - (\omega_{\text{max}} + \omega_{\text{min}})}{\omega_{\text{max}} - \omega_{\text{min}}},$$

(8)

where $\theta_{\text{max}}$ and $\omega_{\text{max}}$ depict the maximum angle and angular velocity in each task, respectively, while $\theta_{\text{min}}$ and $\omega_{\text{min}}$ depict the minimum angle and angular velocity in each task, respectively. Angular velocity was calculated from the time-series data of joint angles in the experiment. Vector length of the normalized angle-angular velocity phase angle was calculated as follows:

$$\lambda = \sqrt{\theta_{\text{norm}}^2 + \omega_{\text{norm}}^2}.$$  

(9)

**FIGURE 1** Electromagnetic receiver placement on participants for working posture measurement.
In this study, movement variability at time t was defined as the standard deviation of \( \lambda \) over the last 20 s of work performed. Besides this, the movement variability at the beginning of the experiment, when the participants had maintained the anatomical position, was calculated independently. The intersubject mean and standard deviation of movement variability were calculated for each task condition.

### 3.3.2 | Calculation of anomaly score using SST

SST calculated the anomaly score of each joint angle with MATLAB R2019a (MathWorks Inc.) using the following parameters: \( M = 50 \), \( L = 75 \), \( n, k = M/2 \), and \( r, m = 3 \). \( M, n, \) and \( k \) were defined as such because the observed task time per a single task was 1.5 s (Hassani, Heravic, & Zhigljavsky, 2009; Kugiumtzis, 1996). The value for \( L \) reflects a basic time required to complete a single task. To validate the efficacy of our proposed method, the calculated anomaly score was compared with its score computed using two types of trajectory matrices selected by traditional methods. In this paper, we have referred to the two types of trajectory matrices as “whole trajectory matrix” and “extracted trajectory matrix,” respectively. The whole trajectory matrix represents human motion in the whole task. The extracted trajectory matrix extracts human motion patterns between 10 and 20 s after the beginning of the experiment.

To describe the trend of anomaly score with time elapsed, the median of its score at \( t \) was calculated from the history of its score until \( t \). Subsequently, the average time variance of anomaly scores was calculated for 11 participants.

### 3.3.3 | Estimation of the pace of work

To estimate the pace of work, the time taken to pick up lightweight, ball-shaped objects was estimated based on the positions and velocities of the right wrist using MATLAB R2019a (MathWorks Inc.). The pace of work was defined as the interval between the current pickup action and the one immediately preceding it. Subsequently, the median of the pace of work was calculated per 100 s under each task condition, following which the mean of the pace of work was calculated for 11 participants.

### 3.3.4 | Subjective evaluation

To clarify the subjective workload during the task, participants orally described their subjective experiences of workload on their right upper limbs using the Borg CR10 scale (Borg, 1998) at 20-s intervals while performing tasks. The median rating of subjective workload was then calculated for 11 participants.

### 3.3.5 | Statistical analysis

To clarify the effect of muscle fatigue caused by repetitive tasks on the movement variability, anomaly score, pace of work, and subjective evaluation, the final score in each evaluation index was analyzed using analysis of variance (ANOVA). A one-way ANOVA was used for the statistical analysis of results for movement variability, subjective evaluation, and the pace of work. The experimental factor was the task type. In addition, one-way ANOVA was used for the statistical analysis of anomaly score results under each calculation method. The experimental factor was the calculation method for anomaly scores. In all statistical analyses, the significance level was set at 5%, and the statistical analysis package in Origin Pro 2020 (OriginLab Corporation) was used.

### 4 | RESULTS

#### 4.1 | Movement variability

Figure 2a–d shows the average movement variability in each task for 11 participants. The movement variability was larger at the beginning of the task for all joint angles. The movement variability of the shoulder abduction angle under both tasks was constant in the whole task, and the main effect of task type was not significant \( F(1, 21) = 1.663; \ p = .212 \). The movement variability of the shoulder flexion angle remained constant throughout each task and was slightly larger in Task B than in Task A; however, the main effect of task types was not significant \( F(1, 21) = 1.477; \ p = .238 \). The movement variability of the shoulder inner rotation angle was constant in Task A but decreased with time in Task B. The ANOVA results showed that the main effect of the task type was significant at the movement variability of the shoulder inner rotation angle \( F(1, 21) = 4.666; \ p = .043 \). The movement variability of the elbow flexion angle increased with time and was larger in Task B than in Task A; however, the main effect of task type was not significant \( F(1, 21) = 3.001; \ p = .099 \).

#### 4.2 | Anomaly score

##### 4.2.1 | Anomaly score in Task A

Figure 3a–d shows the average anomaly score in Task A for 11 participants. The anomaly score of most joint angles increased at the beginning of the experiment, which was a result of the participants maintaining an anatomical position and the existence of a larger difference in the working postures than in the postures during the repetitive tasks. Therefore, the focus was on the trend of anomaly score at 100 s from the beginning of the task.

For the shoulder abduction angle, the anomaly score calculated by the proposed method and the whole trajectory matrix were
FIGURE 2  Mean movement variability in each task condition for each joint angle: (a) shoulder abduction, (b) shoulder flexion, (c) shoulder inner rotation, (d) elbow flexion angle.

FIGURE 3  Mean anomaly score in Task A for each joint angle: (a) shoulder abduction angle, (b) shoulder flexion angle, (c) shoulder inner rotation angle, (d) elbow flexion angle. Legends in the figure show the three types of calculation method for anomaly score which is using the whole trajectory matrix (whole), using extracted trajectory matrix (extracted), and using the proposed method.
constant. The proposed method anomaly score was larger than the score calculated by the whole trajectory matrix. The anomaly score of shoulder abduction calculated by the extracted trajectory matrix increased with time. For the shoulder flexion angle, the anomaly score increased with time when calculated by the extracted trajectory matrix and the proposed method; however, the proposed method score was larger than the matrix score. The ANOVA results showed that the main effect of the calculation method was significant \[ F(2, 32) = 3.752; \, p = .035 \].

The anomaly score of the shoulder flexion angle that was calculated using the whole trajectory matrix remained constant with time. The ANOVA result showed that the main effect of the calculation method was significant \[ F(2, 32) = 3.885; \, p = .032 \].

The time variance of the anomaly score of the shoulder inner rotation angle decreased when calculated using the whole trajectory matrix, slightly increased when using the extracted trajectory matrix, and remained constant when calculated by the proposed method. However, the ANOVA result showed that the main effect of the calculation method was not significant \[ F(2, 32) = 0.296; \, p = .746 \].

For elbow flexion angle, the anomaly scores calculated using the whole and extracted trajectory matrices were constant in the overall task, while the anomaly score calculated by the proposed method decreased with time. The ANOVA result showed that the main effect of the calculation method was significant \[ F(2, 32) = 47.890; \, p < .001 \].

4.2.2 | Anomaly score in Task B

Figure 4a–d shows the average anomaly score in Task B for 11 participants. The trend of anomaly scores at 100 s from the beginning of Task B was examined in the same way as for Task A.

For the shoulder abduction angle, the anomaly score remained almost constant in the overall task when calculated by the proposed method and the two trajectory matrices; however, the score of the proposed method was greater than both matrices scores. The ANOVA result showed that the main effect of the calculation method was significant \[ F(2, 32) = 27.590; \, p < .001 \].

For the shoulder flexion angle, the anomaly score calculated by the proposed method, and the extracted trajectory matrix increased slightly with time. The anomaly score calculated by the proposed method was larger than the score calculated with the extracted trajectory matrix. The anomaly score of the shoulder flexion angle remained almost constant in the overall task when calculated by the whole trajectory matrix. The ANOVA result showed that the main effect of the calculation method was significant \[ F(2, 32) = 6.300; \, p = .005 \].

For the shoulder inner rotation angle, the anomaly score calculated by the proposed method was larger than the score calculated by both trajectory matrices, and the score increased with time. The anomaly score calculated using the whole trajectory matrix remained almost constant in the overall task. The anomaly score calculated using the extracted trajectory matrix slightly increased with time.

![FIGURE 4](image-url)

**FIGURE 4** Mean anomaly score in Task B for each joint angle: (a) shoulder abduction angle, (b) shoulder flexion angle, (c) shoulder inner rotation angle, (d) elbow flexion angle. Legends in the figure show the three types of the calculation method for anomaly score which is using whole trajectory matrix (whole), using extracted trajectory matrix (extracted) and using the proposed method.
However, the ANOVA result showed that the main effect of the calculation method was not significant \( F(2, 32) = 1.911; p = .165 \).

For the elbow flexion angle, the anomaly score decreased with time when calculated by the proposed method and by the whole trajectory matrix. The anomaly score calculated by the proposed method was larger than the score calculated with the whole trajectory matrix. The anomaly score of the elbow flexion angle slightly increased with time when calculated using the extracted trajectory matrix. The ANOVA result showed that the main effect of the calculation method was significant \( F(2, 32) = 73.708; p < .001 \).

### 4.3 | Pace of work

Figure 5 shows the mean of the pace of work under each task condition. In Task A, the mean pace of work in the latter half of the tasks decreased compared with the mean in the first half of the tasks. In Task B, the mean pace of work in 100 s was equal to that in 600 s; however, the mean pace of work in 600 s was lower than that in 300 s. When the final score was compared with the maximum value during tasks, the final score in Task A decreased by approximately 0.15 s from the maximum value; in Task B, the final score decreased by approximately 0.08 s. However, the ANOVA result showed that the main effect of the task type was not significant \( F(1, 21) = 0.115; p = .738 \).

### 4.4 | Subjective evaluation

Figure 6 shows the median value of the subjective workload on the right upper limb and its increase ratio. The rate at which the workload increased with time and the final score of the subjective workload were larger in Task B than in Task A. The subjective workload in Task A remained constant after 400 s from the beginning of the task. The plots of increase ratio under each task condition were linearly approximated, and the increased ratio of subjective workload on the right upper limb decreased with time under both task conditions. The ANOVA result showed that the main effect of the task type was significant \( F(1, 21) = 4.938; p = .038 \).

### 5 | DISCUSSION

#### 5.1 | The validity of estimating movement variability using the proposed method

When the proposed method was used, the anomaly score of the shoulder flexion angle and of the shoulder inner rotation angle increased with time in Task A and Task B, respectively. Moreover, the anomaly score of the elbow flexion angle decreased with time in both task conditions. On the other hand, when calculations were performed using the traditional method (Wagner et al., 2012), the movement variability of the elbow flexion angle increased with time in both task conditions, while those of the shoulder joint angles were constant or decreased with time. The trend of anomaly scores when the proposed method was used did not agree with the trend of movement variability calculated by the traditional method. Srinivasan and Mathiassen (2012) reported that movement variability increased when redundant degrees of freedom were available for performing multi-joint movements. Moreover, several studies have reported that movement variability increased with the development of muscle fatigue in the shoulder while performing repetitive tasks (Fuller,
Lomond, Fung, & Côté, 2009; Srinivasan & Mathiassen, 2012). The subjective workload shown in Figure 6 increased with time in both task conditions. The relationship between the anomaly score of the shoulder, as calculated by the proposed method, and the subjective workload agrees with the trend reported by several previous studies, which show increasing movement variability of the shoulder with the development of muscle fatigue. Moreover, the increased ratio of the subjective workload, as shown in Figure 6, decreased with time under both task conditions. The relationship between the anomaly score of the shoulder from the proposed method and the increase ratio of the subjective workload suggests that increases in movement variability of the shoulder prevent an increase of muscle fatigue in repetitive tasks. This finding agrees with those of a previous study that also reported that increases in movement variability effectively prevented MSDs in repetitive tasks (Mathiassen, 2006).

In contrast, the trend in movement variability estimated by the traditional method did not agree with the findings of several previous studies, and movement variability in the elbow flexion angle increased with time in both task conditions. The minimum and maximum value of the joint angles and angular velocities were used to calculate the movement variability following the method developed by Wagner et al. (2012). The time required for a single task decreases as the proficiency with which participants repetitively perform a task increases (Adler & Clark, 1991). In our findings, the pace of work decreased in the latter half of the tasks (Figure 5). Therefore, the relationship between movement variability of the elbow flexion angle and the pace of work suggests that the increase in movement variability was caused by increasing the variation of angular velocity. Srinivasan, Samani, Mathiassen, and Madeleine (2015) reported that movement variability decreased as the pace of work in repetitive motions increased. Regarding the relationship between the anomaly score of the elbow flexion angle and the pace of work, the trend obtained by the proposed method agrees with the finding of a previous study (Srinivasan et al., 2015) that movement variability decreases as the pace of work increases. The results of the proposed method showed that, as muscle fatigue began to develop during repetitive tasks, the anomaly score of the shoulder joint and of the elbow joint increased and decreased, respectively. This suggests that the movement of the shoulder joint changes with time. Similarly, a previous study reported that increases in movement variability effectively prevented MSDs in repetitive tasks (Mathiassen, 2006). Thus, the results of the proposed method suggest that the movement of the shoulder joint differs from that of the elbow joint in terms of decreasing the effect of muscle fatigue during repetitive tasks.

Longo et al. (2018) suggested that PCA is a suitable method for detecting motor variability and identifying changes in postural configuration. Compared with PCA, SVD can generally be considered as an equivalent method of mathematical processing. Therefore, the proposed method, which is based on SVD, can be considered as an effective method for detecting changes in movement variability. Moreover, because the proposed method corresponds to time series data, it may be a more suitable method for detecting the time variance of movement variability in repetitive tasks. When the extracted trajectory matrix was used, the anomaly score of the shoulder abduction angle increased with time. In contrast, the anomaly score calculated by our proposed method remained almost constant in the whole task, which is in line with the score obtained when the whole trajectory matrix was used. In other words, the anomaly score calculated by our proposed method reflected the complete trend of human motion during repetitive tasks and was not influenced by local problems in working posture. Therefore, these findings suggest that our method is a more suitable method for detecting changes in movement variability in repetitive tasks over a long period of time.

5.2 Limitations

To determine the physical workload and muscle fatigue of workers based on the variation of movement variability, the calculated anomaly score is required to be identified based on the particular threshold value which took into account the specific ergonomic problem. Its threshold value is required to be associated with the traditional method for evaluating muscle fatigue; for example, the maximum endurance time (El Ahrache, Imbeau, & Farbos, 2006) and the theoretical model based on the motor units of muscle fibers (Liu, Brown, & Yue, 2002; Xia & Frey-Law, 2008). These methods are as general as the chosen model-based muscle fatigue evaluation, but this method has some issues that require resolution. The maximum endurance time may underestimate muscle fatigue when the fatigue nonlinearly changes with time. Rashedi and Nussbaum (2015) showed that measuring low to moderate levels of muscle fatigue is required to apply the muscle fatigue model proposed by Xia and Frey-Law (2008) in various conditions. To propose the threshold value based on the index for muscle fatigue, further investigation is required to clarify the relationship between the proposed method and the muscle fatigue model in high-frequency tasks with the low physical workload, such as the tasks assigned to the subjects in this study.

6 Conclusion

This study proposed a new method for calculating the anomaly score based on SST, which accounted for a more long-term history of human motion during the performance of repetitive tasks. To validate the efficacy of the proposed method, the calculated anomaly score was compared with the movement variability computed by a traditional method and to the corresponding score computed by conventional SST. When the anomaly score was calculated by the proposed method, the score of the shoulder flexion angle in Task A and of the shoulder inner rotation angle in Task B decreased with time, while the score of the elbow flexion angle decreased with time. These results of the proposed method differ from the trend of movement variability calculated by a traditional method; however, they are in agreement with the findings of several previous studies. When the anomaly score calculated by the proposed method was
compared with the same score calculated by conventional SST, our
results showed that the score of the proposed method reflected the
whole trend of human motion in long-term repetitive tasks and was
not affected by local problems in working posture. Future studies are
necessary to verify our findings and provide further evidence for the
validity of our proposed method. These findings have far-reaching
implications for research into the development of a suitable method
for evaluating anomaly scores and, eventually, for the practical ap-
lication of reducing the manual load on industrial workers.

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