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Ergonomic Assessment Method of Risk Factors for Musculoskeletal Disorders Associated with Sitting Postures

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Musculoskeletal disorders (MSDs) are associated with sitting postures. The assessment and prevention of risk factors for workplace exposure are indispensable aspects of reducing the occurrence of MSDs. This paper proposes an ergonomic assessment method of risk factors for MSDs associated with sitting postures in the actual working conditions. A Kinect sensor with the RULA method was primarily used to collect the data and evaluate the relevant postures. The results obtained were compared with the evaluation results by a human expert. Additionally, we verified the capability and effectiveness of this method. A program system for human joint recognition and acquisition was implemented. The results indicated that the Kinect joint data is generally accurate and can adequately complete the RULA evaluation table. The results from the front and right-hand side obtained by the Kinect were consistent with the results of the expert evaluation, and no significant difference was observed between them ($p > 0.05$). However, when the participants faced the Kinect, the sensor performed better, and the evaluation result was more accurate. A high consistency was observed between the evaluation results obtained from the front and the expert (proportion agreement index = 0.65, Cohen's kappa = 0.77). Only a slight consistency was observed between the evaluation results obtained from the right-hand side and the expert (proportion agreement index = 0.41, Cohen's kappa = 0.08). This research created a new ergonomic method for the risk assessment of MSDs associated with sitting postures. The combination of theory and practice is crucial in the risk assessment of sitting postures in workplaces.

Keywords: Sitting posture assessment; ergonomics; RULA; Kinect.

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1. Introduction

Musculoskeletal disorders (MSDs) are very common in the workplace. The Global Burden of Disease recorded a high prevalence of MSDs in workers during their working years; MSDs are the primary cause of occupational disability (18.5%).[24] According to a survey, the back and neck are the most uncomfortable parts for sedentary people.[26] In addition, the prevalence rate of shoulder pain among computer users was among the top three of various MSDs.[15] In a previous study, Collins and O'Sullivan observed that the prevalence rates were the highest in the neck (58%), shoulder (57%) and lower back (51%), based on a questionnaire of 852 university office workers.[6] Similarly, people with discomfort in these parts of the body primarily work in a sitting posture. Therefore, observing the movement of these joints during work is critical to the study of office ergonomics. Additionally, conducting an ergonomic assessment of work-related risk factors for MSDs is essential.[2]

Ergonomic risks in the workplace negatively affect the health and quality of life of workers and the economic benefits of employers.[23] Therefore, it is very important to study the sedentary behavior. Many studies[1,10] show that the longer the people keep sitting, the more uncomfortable they feel. Arippa *et al.*[1] showed that passive indicators of musculoskeletal discomfort may appear as early as 42.5 min after sitting in a healthy population of office workers. An ergonomic assessment of the postures adopted during work is essential to exploring and avoiding the risk factors of work-related MSDs (WMSDs). Therefore, ergonomics experts and many scholars have used various methods and tools to investigate work postures and identify the potential MSD risk factors. These methods can be divided into three categories depending on the accuracy and precision of the data collection and measurement techniques: self-report, direct measurement and observational method.[7,13] The self-report methods include questionnaires, checklists, rating scales and interviews. Although these methods have the characteristics of easy implementation, wide application and low cost, they are not reliable, and they are easily affected by subjective factors; this may result in biased interpretation or perception errors.[27] The direct measurement methods rely on sensors that are directly connected to the subject to measure the target variables as the subjects work, but they are generally more expensive, invasive and time-consuming.[11] Directly installing sensors on subjects, which is difficult to achieve in a practical working environment, may cause discomfort and affect their working behavior.[7] The observation method is generally a direct observation of workers as they work. It has many advantages, such as being simple to use, applicable to a variety of work scenarios and being of low cost when investigating a large number of subjects. In a previous study, Roman-Liu[22] provided a detailed review of the most common observational assessment methods, such as OWAS, revised NIOSH, rapid upper limb assessment (RULA), OCRA, REBA, LUBA and EAWS. Chiasson *et al.* compared eight different methods, including OWAS, to determine the risk factors of WMSDs.[4] However, the data collection used by these methods has many limitations. Generally, the posture data are collected and analyzed by subjective observation or estimation of the people's joint angle in an image or video. Moreover, experts must conduct a time-consuming assessment, which can be easily affected by observation errors, the reliability of the evaluator and other factors; therefore, the accuracy of joint-point estimation is affected.

The observation method based on time sampling is relatively reliable. It can analyze the duration of body position as a risk factor and measure it as the relative frequency of occurrence of various risk levels. However, the analysis frequency or risk over time requires the use of devices with high sampling rates. With the development of existing technology and devices, it has become a realizable technology for calculating the joint angles and tracking the motion of humans. A low-cost distance sensor such as Microsoft Kinect can be used to collect data at a very high frequency. According to previous studies,[21] the Kinect device has been proved to be a highly reliable posture analysis tool, which can minimize the impact caused by joint angle error.

RULA is one of the most popular methods of observation in ergonomics.[14] It is a rapid-analysis simple method primarily used to evaluate static posture. The primary limitation of RULA is related to the reliability of the rates; however, it is simple, easy to calculate and does not require prior knowledge of biomechanics or ergonomics. The RULA score quantifies the exposure of postures to the risk factors of MSDs and is primarily for estimating the joint angles of the upper limb, trunk and neck. Each joint angle is related to a joint score according to a predefined angle range. Finally, a final grade score and the suggestions are obtained using these joint scores. Traditional data collection is obtained by subjectively observing the projection angle in a video or image. Because this method is based on an isolated key posture (frequently the worst-case posture), it focuses on evaluating static posture. To overcome this limitation, the design of a method of continuous evaluation of human motion will provide new relevant information for evaluating potential MSD risks such that it can effectively assist RULA through computer processing and Kinect sensors.

Previous studies analyzed the accuracy of kinematic data provided by Kinect. As a three-dimensional motion capture system in the working environment, the accuracy of Kinect is slightly lower than that of more expensive equipment, but it is sufficient to capture human skeleton joints for ergonomic evaluation in the working scene.[5,9,29] In recent years, many scholars have conducted extensive research in the field of ergonomic evaluation by using Kinect. For example, Otto *et al.* evaluated the applicability of Kinect in EAWS ergonomic assessments using a Kinect bone tracker and redirection system extended by a multi-depth camera tracking algorithm.[16] However, they only evaluated the nine working postures specified by EAWS; therefore, Kinect has certain limitations in ergonomic evaluations. Plantard *et al.*[19] evaluated the reliability of the inverse dynamic method based on modified Kinect skeleton data and its potential use in estimating joint torque and force in chaotic environments. The results demonstrated that Kinect could provide reliable joint torques in an unobstructed environment. In addition, an evaluation method based on a virtual human model was proposed. Under the limited pose and sensor arrangement, the results of the virtual human model were consistent with those of actual objects.[18] These results implied that the Kinect sensor is a highly reliable tool for pose analysis, particularly for indexes based on the calculation of angle thresholds; this can minimize the effects of joint angle errors. As a low-cost, easy-to-configure and unmarked depth information acquisition device, Kinect is a good option for measuring human posture because of its accuracy, efficiency, cost-effectiveness and noninvasiveness. The introduction of Kinect into the research of ergonomics can simplify the process of human modeling and ergonomic simulations, and it can provide statistical and analytical data for ergonomic evaluation by obtaining the key joint points of the human body. However, most of the current research is based on whole-body postures. Using estimated joint positions, the global coordinate system was established to calculate the joint angles using the ISB recommendations.[28] In addition, the evaluation research on relatively important WMSDs caused by sitting postures has seldom been conducted. This study used Kinect to evaluate the working posture based on the sitting posture.

This research aims to develop a computational method to evaluate the risk factors of human MSDs in the actual working environment. Taking the sitting posture of office employees as an example, this paper explores the risk degree of the sitting posture for work-related musculoskeletal diseases. The secondary aim of this study was to test the reliability of the assessment when workers are not facing the sensors. In this study, we used a Microsoft Kinect V2 sensor to identify the sitting position of people at work in real-time. Thus, we could obtain the spatial coordinate data of the joint, calculate the joint angle using the method described in this paper and complete the RULA score grid. The results were compared with those evaluated by the RULA expert. The aim was to determine the accuracy of the evaluation results of the skeletal information obtained using this method in the evaluation of the risk factors of MSDs related to sitting posture. Moreover, we verified whether the evaluation results obtained from the front and the side were consistent and determined whether the Kinect device is suitable for obtaining the information required by the method.

In the following sections, the RULA method is briefly introduced and discussed in Sec. 2. The data obtained by the sensor can be transformed into data that can be used in the RULA method. Then, the experimental setting is presented, which describes the calculation method of human joint angle, and the research method of using Kinect bone data under high-frequency sampling to calculate the information required for the RULA score. After this, the experimental results and the data explanation are presented in Sec. 3, followed by the summary of the main contributions of this paper with the discussion of the limitations of the research being discussed in Sec. 4. In Sec. 5, the paper is concluded with the conclusions and prospects for future research.

2. Material and Methods

2.1. *Participants*

Nine healthy laboratory workers (two women and seven men, age: 24.1 ± 0.5 years, height: 173 ± 2 cm, mass: 63.9 ± 3.5 kg) without MSDs participated in the study as the subjects of data collection and observation. All participants frequently used a seated posture in their daily work. In this study, their normal working posture was also considered as the posture for analysis and research. In addition, we recruited a RULA expert, who has a deep understanding of the RULA method and extensive practice experience and could accurately complete the assessment of postures.

2.2. *Experiment protocol*

2.2.1. *RULA method*

The RULA method[14] is a rapid method of screening a working population to determine the exposure of workers to risk factors for work-related upper limb diseases. With this method, the exposure degree of risk factors is evaluated using a human posture map and three scoring tables. The first two tables provide the posture scores for each part of the body and are related to the joint angle interval of each joint (e.g. in the [0, 10] interval, the neck joint flexion is 1 point). Subsequently, each score is adjusted according to the frequency of operation and force load on the limbs. The third table uses the previous score as input and provides a large score (1–7). The estimated risk grade of injury due to musculoskeletal loading ranges from 1 to 7, indicating the interventions required to reduce the risk of injury:

(1) Grand-score range 1–2: The posture is acceptable if it is not maintained or repeated for long periods.
(2) Grand-score range 3–4: Further investigation is required, and changes may be required.
(3) Grand-score range 5–6: Investigation and changes are required soon.
(4) Grand-score 7: Investigation and changes are required immediately.

The assessment was designed to be conducted rapidly and with minimal equipment or change to the working environment and with minimal disruption to those under observation. However, the limitation is that other factors that affect RULA scores, such as the load on the arm and the type of muscle used, are not assessed.

2.2.2. *Experimental procedure*

During the experiment, a Kinect sensor (V2, model 1656, Microsoft Corporation, Redmond, WA, USA) was placed in front of the participants. The horizontal distance between the Kinect sensor and each participant was approximately 75 cm. Another one was placed on the right-hand side of the participant at a horizontal distance of approximately 100 cm. The height and tilt angle of Kinect could be adjusted according to the height of the participant to capture the upper body and upper limbs of the participant. Kinect sensors can monitor the user's body movements in real-time, enabling the simultaneous recording of three-dimensional coordinates of all joint points tracked by Kinect with an average sampling frequency of 30 Hz. A video camera will be placed to assist experts in ergonomic evaluation in the process of the experiment. Experts need to evaluate part of the joint information of the experimenter in the video, including bending degree, loading, frequency, etc. This information will be finally calculated into RULA scores. Then, the data obtained by the expert was imported into an Excel table for use to compare with the results obtained by Kinect. All the experimenters used the most habitual sitting posture in daily life for the experiment. The task of the experiment is to read a book (Fig. 1). Each participant performed work tasks twice for 5 min each. Use Kinect to record the front and side data of participants during each task. The expert also observes the working actions of participants and records relevant data. Therefore, we developed a customized application program to obtain joint data by using the interface provided by Microsoft Kinect SDK 2.0. In terms of algorithm implementation and graphics

Fig. 1. Examples of the experimental task. All participants are experimented according to the specified tasks and the Kinect is used to obtain musculoskeletal data during their reading.

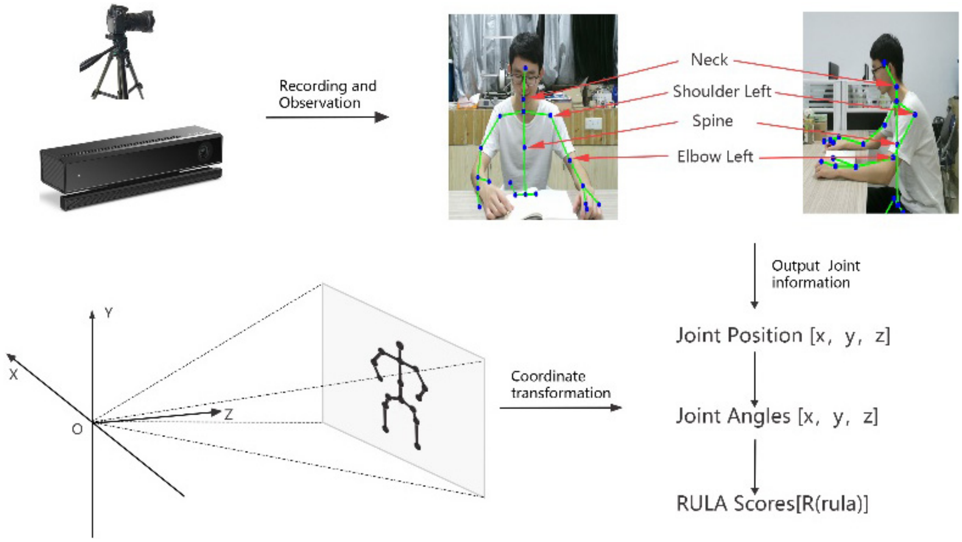

Fig. 2. Illustration of the experimental procedure. The Kinect is set up to obtain joint points, all the joint points obtained are output and used to calculate the joint positions, angles and then the RULA scores.

display, a C++ program and OpenCV, a cross-platform computer vision library based on the BSD license (open source), were used to acquire, store and process data.

Figure 2 shows the flow of the experiment. First, we used the data obtained by Kinect to calculate the angle of each joint. Second, we used the joint angles to calculate the RULA grand scores of the participants from the front and the right-hand side to make a risk assessment for posture. In addition, the expert independently evaluated each body part required by the RULA method on-site and calculated the RULA score; we used video records to review the results. In this experiment, we defined our Hypothesis 1 as RULA grand scores calculated using Kinect data agreeing with different observational perspectives on the front or right of the participants. Meanwhile, the results calculated by Kinect were compared with the RULA scores of the expert. Therefore, we defined our Hypothesis 2 as RULA grand scores calculated by Kinect data agreeing with those obtained by the RULA expert.

2.3. *Data collection and process*

In this subsection, we describe a method to calculate the joint angle based on the joint position estimated by the Kinect skeleton tracking technology. When the participant appears in the field of view of Kinect, the joint of the participant can be recognized and the corresponding coordinate position can be obtained. In contrast to the spatial coordinates of the depth image, the camera coordinate system is a three-dimensional spatial coordinate system with the sensor as the origin, and the unit is meter (m). The collected joint position information is input into the computer, and it will process the joint position information. The angle of the relevant joint will be calculated by the obtained sitting position information, and the total score of the corresponding working posture is calculated according to the RULA method.

2.3.1. *Joint angle definition*

The Kinect skeleton tracking technology establishes the coordinates of each joint of the human body by processing the depth data. It can determine each part of the human body as well as its positions. The position coordinates of each joint point are represented by (x, y, z). In this study of sitting posture, we focused only on the changes in joint points of the upper limbs. Because the regular parameters were evaluated using the geometric angles between joints, we defined the joint angles of some sitting positions (Fig. 3).

We defined that the body vector is the vector connecting the SpineMid (from Windows SDK nomenclature) to the SpineShoulder. The flexion/extension of the body was measured by calculating the angle between the body vector and the vector perpendicular to the horizontal plane.

The inclination of the neck was measured by calculating the angle between the line passing through the middle of the shoulder and neck and the line projected on

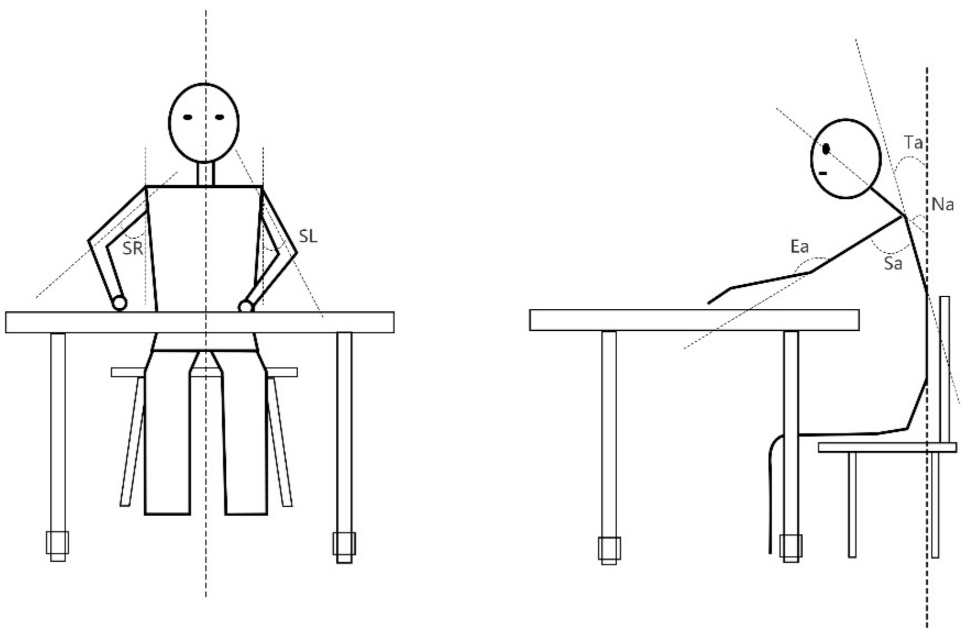

Fig. 3. Definitions of sitting joint angles. The definitions of the angles of the trunk, neck, arm and other joints from the front and the right-hand side are illustrated in the figure as SR (right arm, front), SL (left arm, front), Ta (trunk, right-hand side), Na (neck, right-hand side), Sa (upper arm, right-hand side) and Ea (lower arm, right-hand side).

the trunk plane. In other words, the neck flexion was calculated by the projection of the neck vector on the YOZ plane in the local trunk coordinate system.

For shoulder adduction/abduction, we computed the angle between the horizontal vector parallel to the X-axis and perpendicular to the body vector and the vector connecting the SpineShoulder and the shoulder. For the shoulder flexion/extension, the angle between the vectors connecting the SpineShoulder and the neck and between the spine of the shoulder and shoulder was calculated. (The angle between the vector of ShoulderMid and shoulder and the XOZ plane could also be calculated).

To determine the flexion/extension of the upper arm, we calculated the angle between the shoulder-to-elbow vector and the XOY plane in the coordinate system. For upper arm abduction, we evaluated it by calculating the angle between the shoulder-to-elbow vector and the vector corresponding to the projection on the plane through the trunk. For flexion/extension of the lower arm, we computed the angle between the elbow-to-wrist vector and the XOY plane. The abduction of the lower arm was evaluated by calculating the angle between the elbow-to-wrist vector and the vector corresponding to the projection on the plane through the trunk.

Additionally, we used the same method to calculate the flexion/extension and adduction/abduction of the upper and lower arms on the right-hand side. The difference was that the coordinate system is required to be transformed accordingly. The angle between the vector and XOY plane became the angle between the vector and the YOZ plane.

Although we improved the methods of joint detection and angle calculation, owing to the effect of detection accuracy and observation method, the accuracy was still not sufficient to detect some important parameters of joints, such as wrist and neck twists. In addition, for the calculation of the joint angle, we had to ensure the accuracy of the acquired joint data. To a certain extent, the accuracy of the joint angle determines the accuracy of the RULA grand score, thus affecting the ergonomic evaluation of the working posture. Therefore, ensuring the accuracy of the data was an important aspect of this study.

2.3.2. *Data accuracy*

Owing to the effects of occlusion, light and other factors, particularly with the movement of the body, Kinect loses some joint information or recognizes wrong joint information; this significantly affects the recognition of sitting posture. Filtering and excluding the joint-point coordinate information with large errors was one of the keys to improving the accuracy of the calculation. The coordinate information of each joint of the tracked object was output to the file in sequence with the frame as the time unit. Each joint had a corresponding output file; thus, the classification of the neck, shoulder, arm and other joints was automatically realized.

First, Kinect has a high sampling rate, which can output many sets of coordinate information in the observation time. Generally, the pose of participants did not change dramatically in a short time. Therefore, for the same pose sensor, multiple sets of joint coordinate information were detected and output at this time. We divided all the data output from the same joint into groups with $t = 30$ frames. First, we excluded the data with obvious errors; subsequently, we averaged the data of each group to reduce the overall error of the data.

Second, the joint motion is generally continuous, and the speed of the joint is limited at a certain time. If the speed of the joint exceeds a certain range, it means that the position of the acquired joint has a large deviation in a short time. First, assuming that joint A moves at a constant speed or remains in each frame, we can obtain the coordinate information of the Kth and $(K-1)$th frames of the joint in this coordinate system. If the time interval between the two frames is t, the speed of joint A in the Kth frame is (V_x, V_y, V_z). Similarly, the velocity of joint A at the $(K-1)$th frame can be calculated, and the velocity threshold value is set as (v_x, v_y, v_z). According to the previous frames, we can estimate that the velocity of joint A at the Kth frame is (V'_x, V'_y, V'_z). The real-time speed of joint A should satisfy the requirements of $(V_x, V_y, V_z) \in (V'_x \pm v_x, V'_y \pm v_y, V'_z \pm v_z)$. Otherwise, such joint information is not credible.

2.3.3. *Joint angle calculation*

After obtaining the three-dimensional coordinates of the human skeleton data, we calculated the angles between joints. The commonly used method to calculate the angle is analytic geometry, but it also introduces the problem of boundary conditions. Thus, we had to consider various special scenarios. Therefore, we used the space vector method to calculate the angle, and it effectively avoided the above problems. First, the joint position coordinates in the Kinect coordinate system required conversion to the coordinates in the computer world coordinate system. Overall, the calculation method is relatively simple. From the translatability and directionality of vectors, we can deduce that any two noncoincident coordinate points $A(x_1,\ y_1,\ z_1)$ and $B(x_2,\ y_2,\ z_2)$ in the Kinect coordinate system can be transformed into a mathematical coordinate system after transformation. For the composed vector $\mathbf{AB}$, we can consider that it is derived from the origin of the coordinate axis, and the transformation formula is as follows:

$$\mathbf{AB} = (x_2 - x_1, y_2 - y_1, z_2 - z_1). \tag{1}$$

According to the above principle, the calculation of the human joint angle can be transformed into the calculation of the space vector angle (Fig. 4). For the calculation of the elbow joint angle, the upper and lower arms can be considered as two vectors, and the angle calculation method in three-dimensional space can be expressed as follows:

$$\mathbf{ES} = (S_x - E_x, S_y - E_y, S_z - E_z), \tag{2}$$

$$\mathbf{EH} = (H_x - E_x, H_y - E_y, H_z - E_z), \tag{3}$$

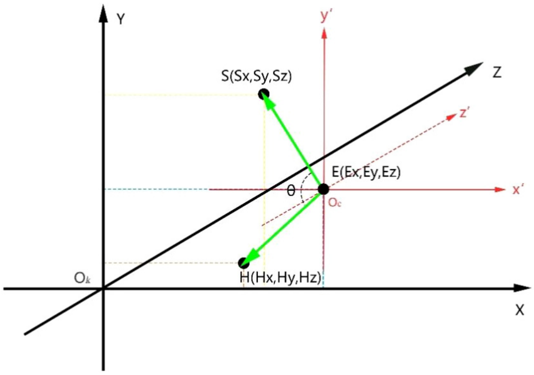

Fig. 4. Coordinate conversion and angle calculation diagram. E, H and S represent elbow, shoulder and hand, respectively. θ is the angle of the arm. According to the coordinates of E, H and S, two vectors **ES** and **EH** can be obtained using Eq. (1). After determining the angle according to the vector direction and calculation formula (4), it can be used for subsequent RULA score calculation.

Table 1. Description of joint angles and the RULA standard.

Evaluation of Parts	Joint Description	RULA Score Assessment Value
Neck flexion/ extension	N_a : Angle between the vector **NH** and the XOY plane	$1 : N_a \in (0° - 10°)$ $2 : N_a \in (10° - 20°)$ $3 : N_a > 10°$ $4 : N_a < 0°$
Neck side-bending	N_s : Angle between the vector **NH** and the YOZ plane	$0 : N_s \in (0° - 10°)$ $1 : N_s > 10°$
Trunk side-bending	T_s : Angle between the trunk vector and the YOZ plane	$0 : T_s \in ()$ $1 : T_s > 10°$
Trunk twisting	T_t : Angle between the shoulder vector **SS** and the YOZ plane	$0 : T_t \in (0° - 10°)$ $1 : T_t > 10°$
Shoulder adduction/ abduction	S_a : Angle between the vector of the shoulder–SpineShoulder and the YOZ plane	$0 : S_a \in (0° - 10°)$ $2 : S_a > 10°$
Upper arm flexion/ extension	E_s : Angle between the vector of the shoulder–elbow and the XOY plane	$1 : E_s \in ()$ $2 : E_s \in (20° - 45°)$ $3 : E_s \in (45° - 90°)$ $4 : E_s > 90°$
Upper arm adduction/ abduction	E_f : Angle between the vector of the shoulder–elbow and the YOZ plane	$1 : E_f \in ()$ $2 : E_f > 10°$
Lower arm flexion/ extension	E_w : Angle between the vector of the elbow–wrist and the XOY plane	$1 : E_w \in (60° - 100°)$ $2 : E_s \in (0° - 60°)$ or $E_s > 100°$
Lower arm adduction/ abduction	E_{wf} : Angle between the vector of the elbow–wrist and the YOZ plane	$1 : E_{wf} \in ()$ $2 : E_{wf} > 10°$

$$\cos\theta = \frac{\mathbf{ES}\cdot\mathbf{EH}}{|\mathbf{ES}||\mathbf{EH}|}. \tag{4}$$

As the sine of the angle between the line and the plane is the absolute value of the cosine of the angle between the line direction vector and the plane normal vector, we can also calculate the angle between the line and the plane using the space vector method. The above method can be used to calculate other joint angles.

2.4. *Data analysis*

The analysis of the data was performed using Microsoft Excel 2007 and the Statistical Package for the Social Sciences (SPSS). Using the calculated joint angles, we calculated the RULA scores of the evaluated parts. To facilitate the calculation, we simplified the RULA method into a mathematical language (Table 1).

We compared the RULA score calculated using the Kinect data with the score obtained from expert evaluation and calculated the proportion agreement index P_0 and unweighted Cohen's kappa (k) to represent the consistency strength between samples, as proposed by Diego-Mas and Alcaide-Marzal.[8] This was conducted to complete the comparison between the method and human expert evaluation results and test our hypothesis.

3. Results

Using the above principle and method of calculating joint angle, we developed a program to obtain the position of the upper limb joint and calculate the joint angle. For the data obtained from front and right-hand side views, the joint angle was calculated and compared, and the RULA score of the adopted posture was calculated through the joint angle.

Figure 5 shows the proportion agreement index P_0 of the RULA scores. We used these values to evaluate the correlation of using this method with various observation perspectives and the difference between single joint evaluations and to explore the feasibility in the actual work scene. It is generally believed that $P_0 \in (0, 0.2)$ which indicates that the correlation between the two variables is very low. $P_0 \in (0.2, 0.4)$ indicates that the correlation between the two variables is low. $P_0 \in (0.4, 0.6)$ indicates that the correlation between the two variables is medium. $P_0 \in (0.6, 0.8)$ indicates that the correlation between the two variables is high. $P_0 \in (0.8, 1)$ indicates that the correlation between the two variables is very high. The average of P_0 from the eight joints was 0.31, P_0 ranged from 0.03 to 0.61 and six of the eight joints were lower than 0.4. It can be proved that the data obtained from the front is inconsistent with the data observed from the side. The P_0 value of the trunk is the largest. It is proved that different perspectives have little impact on their RULA score. The reason is that the spatial coordinates of the neck, spine and hip can be obtained from both the front and side observations. Therefore, compared with other joints, it is less difficult to obtain.

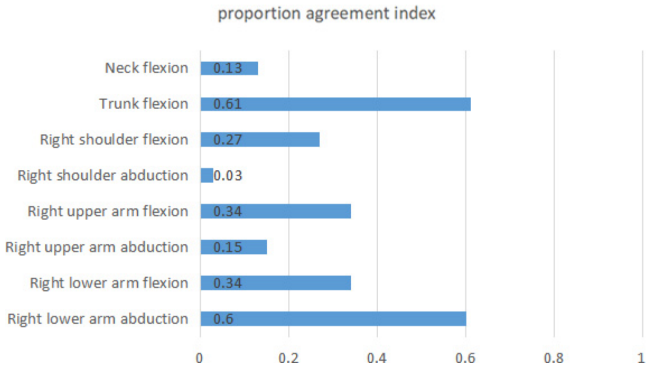

Fig. 5. Results of the correlation test. The x-axis in the figure indicates the correlation between the RULA scores obtained from the front and the right-hand side. The RULA scores of different joints are obtained from front observation and side observation, and the correlation of RULA scores is calculated.

As Table 2 shows, at a significance level of $\alpha = 0.05$, the variance analysis (the full name is single-factor ANOVA) was used to study the difference in the observed and calculated RULA grand scores from the right-hand side and front. The table indicates that the front RULA grand samples did not exhibit significance for all right RULA grand samples ($p > 0.05$); this meant that they exhibited consistency and no difference. We can conclude that our hypothesis was consistent with the actual scenario. The observed and calculated RULA grand scores using Kinect from the front or right-hand side did not have significant differences; this meant that the evaluation results from different perspectives were consistent, enabling us to confirm Hypothesis 1. Therefore, the difference between the two was more owing to chance variation rather than the inconsistency between our assumptions and the overall reality.

Furthermore, for each subject, we studied the effects of the evaluation results from the front and right-hand side and the RULA scores reported by the expert on the whole ergonomic evaluation method. Figure 6 shows the RULA grand scores for the front and the right-hand side compared with expert evaluation as a baseline. The results indicated that there is no significant difference between the scores from the front and the expert evaluation.

We used the two-dimensional contingency table (Table 3) to evaluate the consistency between the expert manual scoring results and the RULA grand scores calculated using the Kinect data. These results indicated a "substantial" agreement between the front grand scores and the expert evaluation and only a "slight"

Table 2. Significance test of RULA grand scores of Kinect data obtained from the front and the right-hand side.

	α	F-Value	p-Value	Null Hypothesis
RULA grand score	0.05	0.354	0.571	Accept

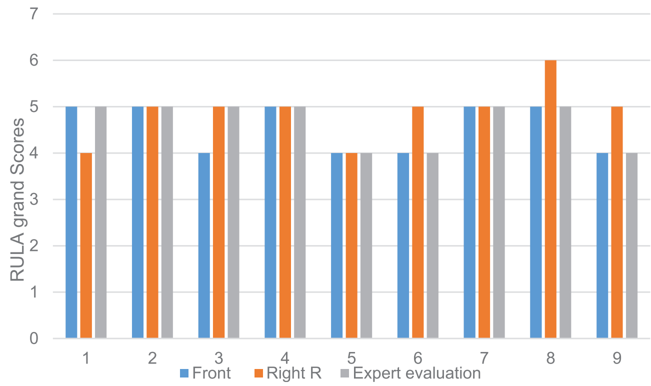

Fig. 6. Comparison of results between the RULA scores and the expert evaluations. RULA scores are calculated from the Kinect data collected from the front and the right-hand side.

Table 3. Observed agreements between the Kinect data and the expert observations, linear weighted Cohen's kappa and z-test results.

View Angle	P_0	Cohen's Kappa	Agreement	z-Value	p-Value	Null Hypothesis
Front	0.65	0.77	Substantial	2.37	< 0.05	Reject
Right	0.41	0.08	Slight	0.28	0.777	Accept

agreement between the right grand scores and the expert evaluations in the Landis–Koch scale.[12]

To validate the statistical significance of these results, we tested the null hypothesis that the observed agreement was accidental, by referring to the value of the critical ratio z for tables of the standard normal distribution. Rejecting the null hypothesis ($p < 0.05$) of the consistency between the results of the expert and front observation enabled us to confirm Hypothesis 2: Using Kinect to observe and calculate RULA grand scores from the front observation is consistent with the result obtained manually by the RULA expert. In contrast, by accepting the null hypothesis ($p = 0.777$), we verified the consistency between the expert and observation results from the right-hand side using Kinect. Simultaneously, we confirmed that the results evaluated using Kinect from the front were better than those observed from the right-hand side.

As Table 4 shows, to explore the relationship between the RULA grand scores calculated using the Kinect data and the observations of the expert, we computed P_0 and the strength of agreement on a sample-to-sample basis, as expressed by the linear weighted Cohen's kappa. The results of the RULA grand scores and kappa index exhibited a strength of agreement from slight to substantial. A more noticeable result was that the kappa index of RULA grand scores observed from the right-hand side was low; this indicated that the consistency with the expert evaluation results was poor. Thus, we can conclude that the error was relatively small when observation was

Table 4. RMSE of the RULA score, P_0 and Cohen's kappa index between RULA scores being computed using the Kinect data and expert observations in actual work conditions.

	RMSE (RULA Score)	P_0	Kappa (k)
Score C Front (upper limb)	0.88	0.27	0.20
Score C Right (upper limb)	0.67	0.41	0.08
Score D Front (neck, trunk)	0.47	0.46	0.60
Score D Right (neck, trunk)	1.15	0.62	0.09
Front RULA Grand Score	0.33	0.65	0.77
Right RULA Grand Score	0.67	0.41	0.08

conducted from the front and there was a stronger consistency with the expert evaluation results in this case.

4. Discussion

4.1. *Primary contributions*

This paper aims to propose an ergonomic evaluation method for the risk factors of human MSDs in actual work conditions. The method uses the Kinect skeletal data to estimate the RULA scores, enabling the joint angles and RULA grand scores to be calculated according to the limited Kinect skeletal data, and complete the evaluation of the risk factors of MSDs related to the sitting posture. In contrast to considering the whole-body working posture in the workplace as the primary research objective, the data obtained using Kinect were used to verify the ergonomic evaluation method in the laboratory and in actual working conditions.[20] Moreover, research on the risk assessment of MSDs related to sitting postures is relatively lacking. Most studies[1,10] have been conducted to evaluate sitting posture by calculating the scores through the method of oral or questionnaire. To make an intensive study of the sitting posture, this paper creates a new perspective for such ergonomic assessment research. The combination of Kinect and RULA can effectively and objectively achieve ergonomic evaluation.

To evaluate the method, we used expert evaluation results as the standard and compared them with the observation results of the Kinect sensor. The primary aim was to analyze and evaluate the feasibility of using the Kinect sensor to observe working postures and using the RULA score to assess the MSD risk levels. The Kinect sensor and its SDK have demonstrated effectiveness and acceptable accuracy when used in computerizing the observational ergonomic assessment metrics. The results show that the consistency between the data obtained from the front and the data obtained from the side is very low (Fig. 5). Generally, ergonomic experts have only limited information to evaluate the joint angles. Additionally, we observed the differences among experts when evaluating the same posture. If more experts participated, the variability would have increased slightly, which would also result in better results for our method. Pavlovic-Veselinovic *et al.*[17] proposed a computer-based expert system (SONEX). The SONEX rule base has over 140 questions, the knowledge base includes over 200 risk factors and around 500 possible answers can be generated. It can be considered that MSDs are evaluated in the form of a questionnaire, and the results are not objective enough. The method of this paper is based on real-time bone data, calculates the joint angle and evaluates it using the RULA method. For individuals, it can be quantified by specific values and as an "expert" to evaluate human posture.

Cai *et al.*[3] considered that the acquisition of musculoskeletal data using Kinect in different locations will be different. This inspired us to research from different perspectives. Due to different experimental settings, the results are also different. This research shows that the Kinect sensor was placed at the central site of a subject with an orientation of around 30–45° for upper limb functional tasks, which can achieve the best result. The experimental setting of this paper is to do book reading, and there is no need to make too much comparison on the requirements of perspective. The comparison of the front and right-hand side is enough to explain. So, our research determined the degree of consistency between the observations agreed upon by a human assessment expert and those obtained using the Kinect sensor. We observed and evaluated them from two completely different perspectives: the front and the right-hand side. The results indicated that the data obtained using Kinect and evaluated using the RULA method were consistent with the evaluation results of the expert. Among them, two, four, five and seven subjects used Kinect to calculate RULA grand scores from the front and right-hand side views, which were consistent with the evaluation results of the expert (Fig. 6). However, when the posture of the operator involved high ergonomic risk, the results obtained from the front had the same score as the expert, but the results from data from the right observation obtained higher RULA grand scores (+1). This also indicated that when an operator faced the sensor, the sensor performed better. Xu *et al.*[30] placed the Kinect on the front, 15° to the left and 30° to the left to obtain the data. The results show that the error obtained by placing it on the front is the smallest. In this experiment, Kinect is placed on the front and right-hand side, which is similar to the results obtained by Xu *et al.*

Overall, when using Kinect to observe from the right-hand side, the ergonomic risk was overestimated, but the same score was obtained by the expert when observing from the front. Moreover, the error of the calculated joint angle was smaller when observing from the front, and the degree of consistency between the calculated RULA grand scores and expert evaluation results was stronger.

4.2. *Limitations and possible research developments*

First, the experimental environment contained controlled lighting conditions and no occluded objects; these are the best-operating conditions of the Kinect V2 skeleton tracking algorithm.[25] This means that Kinect has limitations in estimating joint positions owing to clutter or occlusion.[20] Occlusion primarily comes from two aspects: self-occlusion, which causes the inner part of the human body to be occluded, or a joint recognition error due to the bending or approximate position of the joints; the other is external occlusion, which may result in the occlusion by some structures, such as tables, chairs, clothes, etc. By using the method of correcting and reducing the effects of these objects, we can partially overcome this limitation. Because the effects caused by the occlusion of the subject cannot be eliminated in the experiment, the data acquisition of the primary joint points will have errors or even mistakes. This scenario is more noticeable when observing human posture from the right-hand side. More specifically, it is reflected in the measurement of the shoulder and limb flexion/extension. In the calculation results, the MAE and RMSE of the results obtained from the right-hand side were higher, and the kappa consistency index (right RULA grand score = 0.08, front RULA grand score = 0.77) was lower. Second, the RULA grand scores recorded and calculated by the expert were considered evaluation standards. Experiments require Kinect to obtain data with high accuracy in an actual working environment. Because we only used Kinect as the sensor to obtain the data on human joints in this study, we cannot guarantee the accuracy of the data obtained by Kinect. Therefore, we must perform numerous calculations in the data authenticity test to exclude unreliable joint information and attempt to improve the authenticity and accuracy of the data; this means that we must test each joint information of each frame. However, this will require much computation and time. Third, the scope of this study had some limitations. Although the work with a sitting posture is not a highly cyclical, variational and repetitive task, its working posture is relatively fixed during computer use. However, for other tasks, such as light-duty assembly tasks, the repetitive operation of the human body's working posture must be conducted periodically. In these light assembly tasks, we require further study on whether the Kinect sensor can accurately evaluate the effect on human MSDs when placed at different viewing angles. Additionally, this method must be tested over a wider range. Finally, when using this method to evaluate the working posture of the human body, the effects of individual and psychological factors were not considered. The default value was also used in the force or load score, which may have affected the RULA assessment results but did not change the final RULA score.

We will explore methods for observing human posture and obtaining joint points in future research, including directly obtaining the joint points of the body from the input image, and collecting data without using depth sensors and low-cost noninvasive wearable devices. By training a deep learning model and neural network, we can obtain necessary information such as joint points, improve the accuracy of recognition and accelerate the development of ergonomic evaluation systems.

5. Conclusions

This paper presents an ergonomic evaluation method for evaluating the risk factors of human MSDs in actual work conditions and summarizes the ability and limitations of the method. This paper demonstrates that Kinect can be used as a useful motion capture tool for ergonomic evaluation. In most of the results of this research, the accuracy was sufficient for application to ergonomic evaluation methods. The research used the RULA grand score calculated by the expert as a benchmark and compared it with the results calculated using the data obtained when the participants faced and did not face the Kinect. The results indicated no significant difference between the results of using Kinect from the front and right-hand side views and the evaluation results of the expert, but the consistency between the evaluation results obtained from the front and the expert was higher. Moreover, we observed differences between various perspectives and joint angles. Placing the Kinect sensor in front of the participants resulted in fewer errors and better performance than placing it on the side. The results provided some reference and basis for the study of the relationship between sitting posture and MSDs; for example, neck forward, shoulder adduction/abduction and trunk forward will result in higher risk levels. Therefore, these are the risk factors for MSDs which should be avoided in workplaces.

Therefore, the ergonomic evaluation method proposed in this paper provides simple and easy-to-use Kinect skeleton data to measure human body joint angles, and it can provide more accurate data. Combining the RULA method can effectively aid in assessing MSD risk factors. In addition, it can be applied to actual work environments and promote the development of ergonomic methods based on vision.

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