Context-Aware Posture Analysis in a Workstation-Oriented Office Environment

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Abstract. Among current research trends, correction of the sitting posture is attracting growing attention. Most office workers suffer several health problems during their work. The two greatest causes of health problems in the office environment are simple things. The first is poor sitting posture. Sitting with poor posture in front of a computer for hours causes cumulative damage. The second is an inappropriate workstation environment. The workstation environment is related to good sitting posture. For example, if the desk is too low, the user has to lean forward to look at the display. To address this problem, we propose a sitting posture recognition system that can recognize both human posture and the context of the workstation environment. The proposed system has three components. First, skeleton tracking is used to create a sideways view of the human skeleton. The skeleton model in this research is used to measure the joint angles of the human body. Second, we detect information on objects using a proposed workstation environment tracking system. Three types of features are used to filter the objects from the depth image. Finally, we compare the overall information with a standard sitting posture in a model-matching component. Experimental studies showed that the system can provide the necessary information for analyzing the human posture. A physician or user can apply this information to achieve correct sitting posture or prevent health problems in the office using the provided results.

Keywords: Sitting posture recognition, skeleton model, workstation environment tracking.

1 Introduction

Office syndrome is a serious problem that is common in office workers, who spend about 6 h/day working at a desk. A study by the American Cancer Society [1] found that sitting in front of a computer for long periods of time can lead to poor health outcomes. For example, men who sit for more than 6 h/day have a 20% higher death rate than those who sit less than 3 h/day. Moreover, an improper sitting posture can also cause several conditions such as inflammation of the muscles, back pain, or shoulder pain. Thus, recognition of the user's ergonomics

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while sitting plays an important role in correcting the sitting posture to improve the user's health.

Among current research trends, the analysis of human posture in a workstation-oriented office environment is attracting growing attention. Kikugawa et al. [2] proposed a system for interrupting poor posture when a user is performing a video display terminal task. In their approach, the distance between the user and the display is used to identify poor posture, and then the user is notified by means of a blur effect on the PC's display. Mu et al. [3] presented a sitting posture surveillance system based on image processing technology. In their approach, the face's location and size were used to detect the sitting posture. Although several research works have proposed sitting posture recognition systems, the limitations of existing research leave room for improvement; for instance, when only the upper body is considered, a system cannot recognize poor sitting posture that involves crossing the legs.

To address this problem, the primary goal of this research is to provide a human sitting posture profile and context awareness at the workstation to analyze human posture. To achieve our goal, three components are established in this research. First, we propose a skeleton tracking method. Nine joints on the human body are detected to identify the ergonomics of sitting. Second, workstation environment tracking is developed for recognizing the objects in the workstation space. Information about the desk height, chair height, and distance between the user and the display is considered in terms of the human sitting posture. Finally, all of the observed information is evaluated according to the standard for the ergonomics of sitting. The benchmark for analyzing the ergonomics of sitting is based on that of the U.S. Occupational Safety & Health Administration (OSHA) [4]. The system developed in this study can provide the user's sitting profile to enhance understanding of good and poor sitting posture so that the user can correct poor sitting posture using the provided information.

2 Related Works

A wide range of methods for recognizing human posture has been introduced. However, two main sensing approaches are commonly used for posture classification. The first is a sensor-based approach, and the second is a vision-based approach.

In the sensor-based approach, various types of sensors have been used to capture human motions. The most commonly used sensor in posture classification is the force sensor, which is generally attached to an object to which mechanical force is applied, such as a chair, sofa, or bed. Huang [5] proposed a sitting posture detection and recognition method using the force sensor. Seven force sensors were attached to a chair to recognize four types of sitting posture. Sitting posture classification systems with force sensors have also been studied [6, 7]. Other types of sensors are also used in posture classification. Wongpatikaseree et al. [8] proposed a posture classification system using ultrasonic sensors. Three types of human posture (standing, sitting, lying down) were observed. In their research, ultrasonic sensors were attached to the human body, and the height data for each sensor were extracted to classify the human posture.

The concept of the vision-based approach is to use an image processing technique to extract the human posture from an image. This approach uses primarily a visual sensing device, such as a high-resolution camera or a Kinect camera, to collect image or video files. Liao et al. [9] proposed a vision-based walking posture analysis system. In their approach, four features were extracted from the images: the body line, neck line, center of gravity, and gait width. Along the same lines, Kaenchan et al. [10] also presented a technique for analyzing the walking posture using Kinect cameras. Three Kinect cameras were used to capture the walking posture, and the resulting multiple skeletons were combined into one final skeleton for analyzing the walking posture. In addition, a sitting posture surveillance system was also presented in [3]. The details of the sitting posture, such as the face's location and size, were extracted from the images to identify poor sitting posture.

3 System Architecture

In this research, we propose a sitting posture recognition system for recognizing and analyzing the human sitting posture. The system architecture is designed as shown in Fig. 1. To obtain data, the Kinect camera [11] is used as the main device for recording the depth image. The depth image is sent to two components: the skeleton tracking and workstation environment tracking components. The main task of the skeleton tracking component is to create the human skeleton model in the sitting posture and then analyze the relationship between body parts by measuring the angles of body joints. The workstation environment tracking component tracks the objects around the workstation using three proposed features. Next, the results from the first two components are sent to the model-matching component, which analyzes the ergonomics of sitting on the basis of the benchmark, which is provided by OSHA. Consequently, the results are plotted in graphs, and then a physician or user can determine the cause of the poor sitting posture using the provided results.

4 Skeleton Tracking

Tracking the human skeleton is not a new technique in posture recognition. Several studies attempted to recognize the human posture using a skeleton model. However, in this research, we developed a skeleton model to classify the human sitting posture in a different way. The entire body as seen from a side perspective is used to create the skeleton model. In the skeleton tracking component, we set up the Kinect camera, which gives a 640×480 image at 30 frames per second (fps) with a depth resolution of a few centimeters, next to the user to record the depth image in sideways. Each control point in the image is defined by a position (x, y, z) expressed in skeleton space. Figure 2 illustrates the axes of the coordinates (x, y, z) of the Kinect camera.

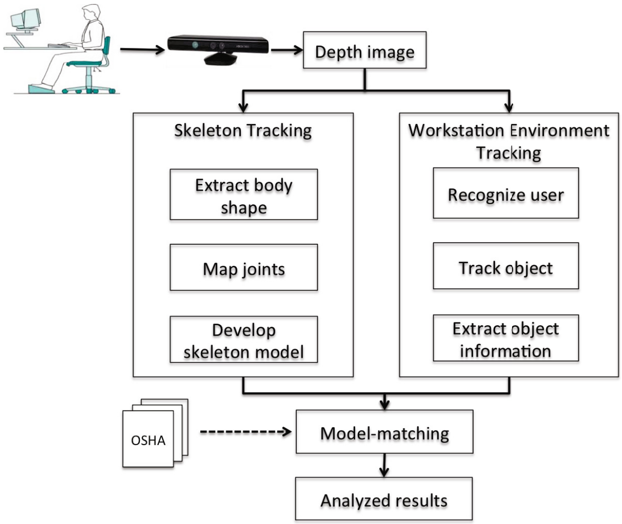


Fig. 1. System architecture

To realize the skeleton model in this research, the main body and shape are extracted from the depth image. Then, this shape information is used to label each joint on the human body. Because we use only one Kinect camera placed to the right of the user, the Kinect camera will label only the joints on the right side of the body. The major joints of a human skeleton are modeled as nine control points (head, center of shoulders, right shoulder, right elbow, right wrist, spine, center of hip, right hip, and right knee), as shown in Fig. 3.

Although we can recognize the sitting posture using the proposed skeleton model, we cannot guarantee that the recognized posture is correct or incorrect. Thus, the skeleton tracking component not only creates the skeleton model, but also measures the angles between joints. These angles can indicate the correct sitting posture. For example, the hip angle should be 90 ° but should not be more

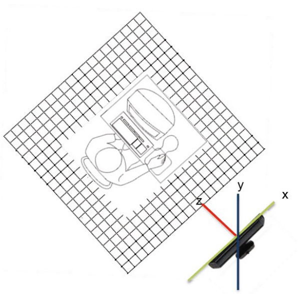
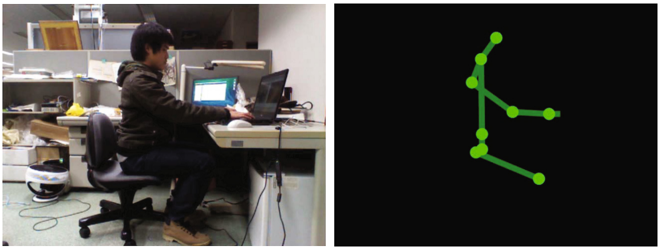


Fig. 2. Axes of coordinates of Kinect camera



(a) (b)

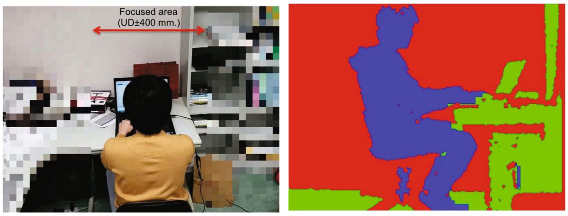
Fig. 3. (a) RGB image in sideways (b) stick skeleton model in sideways

than 120°. In this research, we determine two angles: the hip angle and elbow angle. The hip angle is the most important element of human body posture. The position in three dimensions (x, y, z) of three control points (spine, center of hip, and right hip) are used to calculate the hip angle. Further, the elbow angle is also an important piece of information that we have to consider because improper positioning of the shoulder and forearms can lead to shoulder pain. The positions of the right shoulder, right elbow, and right wrist are detected for measuring the elbow angle. In addition, height differences between two body parts are also investigated to check the correct sitting posture. For instance, the height of the knee joint should be the same as that of the hip joint, whereas the forearms should be straight and parallel to the floor. Examples of the results of skeleton tracking will be described in more detail in Sect. 7.

5 Workstation Environment Tracking

Because the skeleton model alone cannot identify the correct sitting posture accurately, other information might help the user or physician to determine the cause of poor sitting posture. Workstation environment information can be used to analyze the cause of poor sitting posture. For example, the seat height should be adjusted to support the knee and prevent swelling of the leg; in addition, if the position of the armrest is too low, it can lead to shoulder pain because the user has to lean to the side to rest one forearm. Regarding context-awareness at the workstation, it has been proposed that users practice ergonomic principles while working at computers [12]. However, only a few research works propose a practical system that uses context-awareness in ergonomics research. In this research, the context will be analyzed to help the user achieve a good workstation environment.

To extract the information on the workstation environment, the system recognizes the user and then measures the distance between the user and the Kinect camera, called the user distance (UD). Next, the system will define the focus area based on the UD, as shown in Fig. 4. Green indicates the objects, which are located UD $\pm$ 400 mm from the camera. Blue represents the user, and Red denotes the objects, which are placed in the other ranges.



(a) (b)

Fig. 4. (a) Focused area, (b) focused area in depth image

In this section, we attempt to extract three pieces of information from the workstation environment: the desk height, chair height, and distance between the user and the display. Three features are used to filter these three objects in the workstation environment, as illustrated in Table 1. The pixel matching technique is adopted for filtering the desired objects. First, the desk feature size (25×10) is used to recognize the desk in the depth image in Fig. 4(b). The pixels that are consistent with the desk feature size are represented in green; otherwise, the pixels are red, as shown in Fig. 5(a). Second, the extent of the color is adopted in the chair feature for detecting the chair object. The first three lines in the chair feature should be blue, and overall this feature should be about 80% to 90% blue. Figure 5(b) illustrates an example of chair recognition, where the chair object is represented in blue. Finally, to recognize the monitor, the system uses the UD information to filter the objects that are located at the same distance as the user. Then, the monitor feature is used to recognize the monitor, as shown in Fig. 5(c), where green indicates the monitor, and the user is identified in blue.

Table 1. Features for extracting objects

Objects	**Feature size**	**Condition**
Desk	25×10 pixels	Green (100%)
Chair	25×25 pixels	Blue (80%-90%) Note: First three lines of feature should be blue
Monitor	7×15 pixels	Green ($\geq$20%) Note: First and last pixel of feature should be green

6 Model-Matching

The model-matching component analyzes the results from the first two components. The benchmark for analyzing the ergonomics of sitting is based on that of OSHA [4]. OSHA provides a basic design for sitting posture and the workstation environment. Several points need to be considered when setting up a computer workstation. In this research, evaluation checklists are established for analyzing

(a) (b) (c)

Fig. 5. (a) Desk recognition result, (b) chair recognition result, (c) monitor recognition result

Table 2. Checklist for sitting posture

Working postures (Consider these points when evaluating sitting posture)	
Human body	**Condition**
Wrist and forearms	Roughly parallel to the floor
Elbow	$90 - 120^{\circ}$
Hip	$90 - 120^{\circ}$
Thigh	Roughly parallel to the floor

the human sitting posture and the workstation environment, as illustrated in Tables 2 and 3.

To analyze the results, a rule-based technique is adopted for matching the information obtained from the first two components. Using the results of the matching process, the system can explain why the user has poor sitting posture by plotting the results in graphs, as described in more detail in the next section. The physician can use this information to diagnose the cause of conditions such as back pain, shoulder pain, or eyestrain.

7 Experimental Results

7.1 Experimental Setup

To analyze the human sitting posture, the sitting posture recognition system, which has the three main components described above, was implemented in C# using the Microsoft Kinect SDK library. In this experiment, the Kinect camera was set to operate at 30 fps and was located to the right of the user. In the experiment, we asked only that the examinee perform computer tasks for 1 hour, without further instruction. The examinee was free to use any sitting posture during the experiment.

7.2 Results

Figure 6 demonstrates the recognition results of the system after 1 hour. First, Figure 6(a) and 6(b) illustrate the elbow and hip angles, respectively. The blue

Table 3. Checklist for workstation environment

Workstation Environment (Consider these points when evaluating workstation objects	
Object	**Condition**
Desk	Height should generally be between 50-72 cm.
Chair	Height should be approximately at knee level.
Monitor	User should view the monitor from a distance of at least 50 cm.

line indicates the angle in degrees, whereas the red lines indicate the range of suitable angles, which is defined in Table 2. Second, Figure 6(c) presents the distance between the user and the display, where the blue line represents the distance in centimeters, and the red lines indicate the normal range of distances, which is defined in Table 3. Finally, Figure 6(d) and 6(e) show the difference in height between two body parts. This value is used to check whether the forearm and thigh are parallel to the floor (which is indicated by a value of 0).

From the results, we found that the relationships among parts of the human body affect the ergonomics of sitting. Three sitting postures were identified in the experiment, as shown in Fig. 7.

1. **Leaning forward**
   Normally, this sitting posture can happen easily when the user is typing on the keyboard and is highly attentive to the work. The user tends to sit close to the display by leaning the body forward, as shown in Fig. 7(a). On the basis of the graphs, the system can recognize this posture using the relationships among four data points (elbow angle, hip angle, distance between user and display, and height difference between elbow and wrist). A good example of detection of this sitting posture appears between 10 and 20 min. The angles of the elbow and hip are below the threshold angle, and the distance between the user and the display is small. Further, the forearm will be forced to tilt because the body is too close to the computer, so the height difference between the elbow and the wrist increases. Consequently, this posture will cause the user to suffer from neck pain, shoulder pain, or eyestrain because the main body is not in a straight line, and the upper body is bent toward the front edge of the chair.
2. **Leaning backward**
   The observation suggests that sitting while leaning backward normally occurs after the user has focused on the work for a long time. The user tends to relax his back against the backrest by leaning backward. Thus, the lower back is not supported by the backrest. In the experiment, the system recognized this posture between 35 and 43 min. The distance between the user and the display was increased because the user leaned backward against the backrest. At the same time, the angle of the elbow is greater than usual because the user has to stretch his arm to type on the keyboard, as illustrated in Fig. 7(b). In this posture, the user might experience tension in the upper

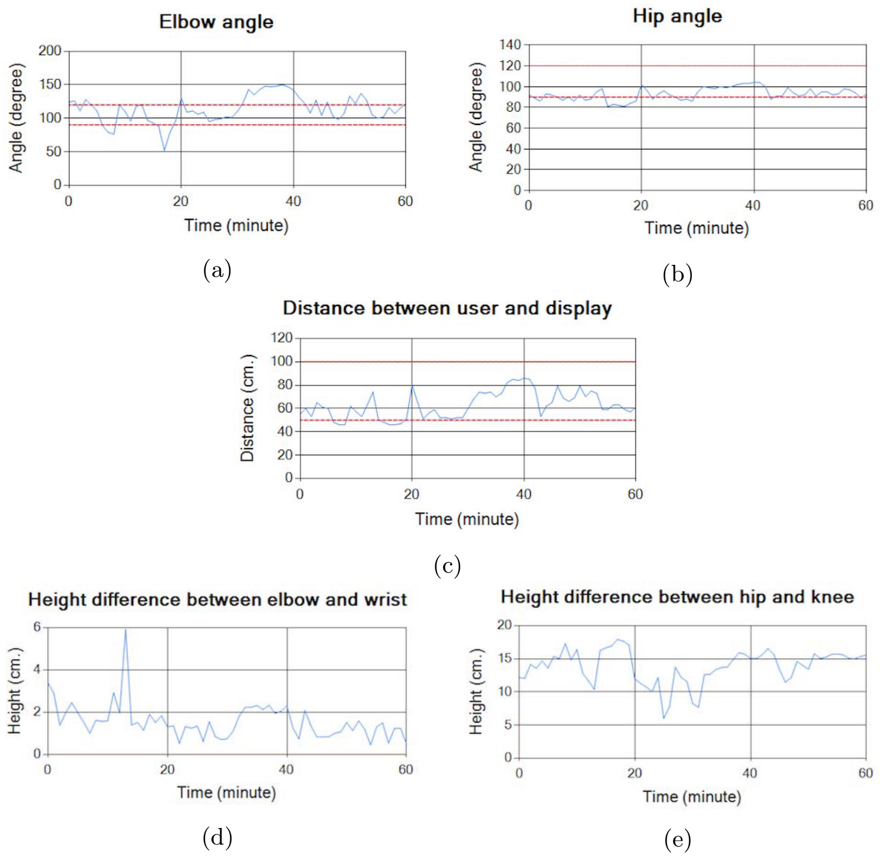
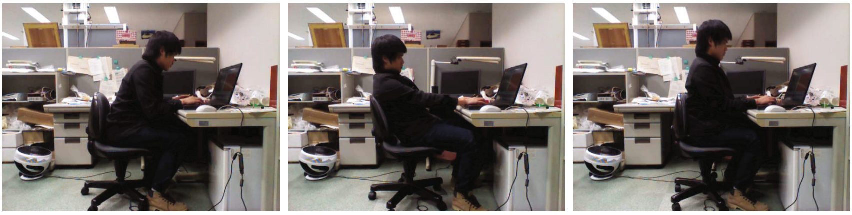


Fig. 6. (a) Elbow angle, (b) hip angle, (c) distance between user and display, (d) height difference between elbow and wrist, (e) height difference between hip and knee

or lower back or the shoulder because the lower back is not supported by the backrest, and the keyboard is too far from the main body.

3. **Correct posture**
   The correct posture is a comfortable working posture in which the joints are naturally aligned. In this posture, the user sits with a neutral pelvis; the forearms are straight, in-line, and roughly parallel to the floor, and the elbows remain close to the body and are bent at an angle of $90 - 120\,°$. Further, the user is upright or leans back slightly. The results indicate that from about 55 to 60 min, the user tended to sit properly. All of the data were consistent with the benchmark, except for the height difference between the hip and knee. Unusual results also appeared in this period of time, which are described in more detail in the next section.

In addition to the results from the skeleton tracking component, we need to consider the workstation environment because good sitting posture is not



(a) (b) (c)

Fig. 7. Three sitting postures: (a) leaning forward, (b) leaning backward, (c) Correct posture

possible without a good workstation environment. Moreover, because we cannot design a good workstation environment that fits every person, it is necessary to establish an appropriate environment for the individual. Thus, we observed three pieces of information: the desk height, chair height, and position of the display. Because most of the workstation environment objects are not moved often, the system will recognized the objects and average the results over 1 hour. Table 4 shows the real positions of the objects and the average results of these three pieces of information in 1 hour.

Table 4. Results of workstation environment tracking

Data	Real position	Recognized position
Desk height	70 cm	77.776 cm
Chair height	50 cm	56.63 cm
Distance between user and display	60 cm	62 cm

7.3 Discussion

As described in Sect. 2, most studies have attempted to recognize the sitting posture using only the human upper body information. Sometimes, however, the use of this information alone cannot guarantee that the user has a proper sitting posture. For instance, using only the distance between the user and the display, the system cannot identify a good sitting posture because a suitable distance does not mean that the user is sitting correctly. The user might be sitting within the distance range but leaning forward or backward. This research aims to solve this problem by capturing the human posture using the entire body in sideways view. The system can perceive the relationship between body parts for identifying good sitting posture.

Although our proposed system can provide the necessary information to the user or physician to analyze the sitting posture, there are several limitations in this research. The first is the recognition accuracy. When the Kinect camera is placed to one side, the skeleton cannot be tracked accurately. The results for the height difference between the hip and knee in Fig. 6(e) are an excellent example.

We found that the height of the knee joint was underestimated compared to the real position. The evidence of this is shown in Fig. 3(b) Consequently, recognizing the human posture in sideways view with a single Kinect camera might not yield accurate results. Using multiple cameras from different angles might provide more accurate recognition results.

In addition, the area between the Kinect camera and the workstation environment is absolutely clear space. It does not have any objects to block the view of the camera, so it is easy to track objects in this environment. Therefore, an intelligent image processing algorithm should be improved or developed to remove objects in real offices that block the view of the Kinect camera.

8 Conclusion and Future Work

In this paper, we proposed a sitting posture recognition system that detected both the entire human body in sideways view and provided context-awareness in the workstation area. This differs from other research that used only the upper body to recognize human sitting posture. Our proposed system can provide the necessary information for identifying good sitting posture. A skeleton model in sideways was created to measure the angles of joints on the human body. Nevertheless, the skeleton model alone cannot determine good sitting posture, and other information should be considered. In this research, three objects (the desk, chair, and monitor) were detected using three proposed features. This information plays an important role in setting up a good workstation environment. In addition, all of the observed results will be evaluated using the standard for the ergonomics of sitting provided by OSHA. With the results of this research, the user or physician can perceive the true cause of poor sitting posture and also prevent health problems such as back pain, shoulder pain, or eyestrain by correcting the sitting posture using the provided information.

Although our proposed system can provide the necessary information for analyzing the human posture, it requires more intelligent techniques for improving the recognition accuracy. For example, a multiple camera technique can be adopted in this research to improve the ability to recognize the features of images in sideways view. Moreover, other objects in the workstation environment, such as the keyboard, mouse, or footrest, need to be tracked.

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