Prolonged Sitting Detection for Office Workers Syndrome Prevention Using Kinect

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***Abstract*—This research has focused on detection of prolonged sitting of office workers by performing data mining classification on the real-time skeleton data stream captured by a single Kinect camera set up in an office worker's work station area. The system classifies the input stream into sequences of *stills* or *moves*. The performance of several classification methods such as decision tree, neural network, naive Bayes, and k-Nearest Neighbors are compared in order to acquire the optimal classifier. The proposed system can effectively monitor the user's postures with 98% accuracy and give the user real-time feedback based on the three levels of healthy in ergonomics. In addition, the proposed work includes development of an alerting device using a microcontroller, and provision of data visualization for a daily summary report.**

Keywords—Health and Medical Informatics; Ergonomics; Office Workers Syndrome; Kinect Camera; Human Gesture Recognition; Classification

I. Introduction

Office workers syndrome is a group of symptoms resulting from prolonged sitting and/or improper sitting habits, causing body pain and disrupting the nervous system [1]. This syndrome has become commonplace among office workers due to their lengthy computer work sessions. It is recommended that while sitting at work, people should perform body movements frequently and take breaks at certain intervals. Even though many people may already know the risk of prolonged sitting, it is not easy for them to be aware of their prolonged sitting while concentrating on their work. It is clear that some tools are needed to help monitor sitting habits and to promptly alert users when an unhealthy pattern is detected.

In this work, we have explored ergonomics and technologies for health monitoring. After comparing potentials among several technologies, we believe that an effective and efficient office workers syndrome monitoring system could be developed using a Kinect camera. We propose the system which obtains input gesture data from Kinect's real-time skeleton data stream. Then, the system analyzes the user's posture patterns and provides real-time feedback based on the model of health in ergonomics. Although office workers syndrome may be caused by both prolonged sitting and improper sitting postures, detection of prolonged sitting is the main focus of this work.

II. Literature Review

A. Health Monitoring Technology

According to surveys of health monitoring technology [2, 3], in the past, health monitoring was done mainly by family caretakers or paid services from healthcare providers. Consequently, information technology was applied for automated health monitoring systems in order to reduce costs without sacrificing quality of care.

Traditional health monitoring systems such as wearable or ambient intelligent device-based systems were primarily used for people with special needs. Wearable systems were complex and uncomfortable, with constant problems of faulty data synchronization and power supply shortage. Ambient intelligence, which required setup of multiple devices, proved costly and expensive.

As image processing technologies became popular, there were more camera-based systems. However, there were problems with accuracy and difficulty in the complex algorithms required for low-level image processing.

With the release of the Kinect camera and its open source drivers in late 2010 [4, 5], there has been a growing trend of using Kinect for health monitoring research. The Kinect camera is a low-cost, gesture-based gaming device that is already used in many households. It solved a privacy problem because its real-time skeleton tracking system could detect human movements without the need on the developer's part to store and process raw images. Therefore, development of health monitoring solutions using Kinect is much simpler and cheaper. With these advantages of Kinect, it has become an effective and practical solution platform in posture and gesture recognition including the platform of our system.

B. Office Workers Syndrome

"Office Workers Syndrome" is not an actual medically-diagnosed syndrome; it is a group of symptoms commonly found in office workers caused by unhealthy work habits. This syndrome results in musculoskeletal pain, headaches, aching arms, wrists and fingers, numbness of wrists or feet, eye strain, and dry eyes. It may also be due to a chronic underlying illness, such as arthritis or neuritis [1].

1) Prolonged Sitting

Health risks from prolonged sitting have been pointed out in several studies [6, 10]. Prolonged sitting time and lack of body movement have been strongly associated with obesity, abnormal glucose metabolism, type-II diabetes, metabolic syndrome, cardiovascular disease and cancer. Longer sitting time resulted in higher risk of heart attack or other cardiac events, as well as the risk of death. It has been concluded that even if one exercises almost every day, there is no benefit if the person sits the rest of the day.

In order to prevent the risk of disease from prolonged sitting, experts recommend practices such as "dynamic sitting" and "micro-breaks". Office workers have been encouraged to develop good work habits.

C. Ergonomics

1) Micro-Breaks

Taking frequent micro-breaks during work is suggested to ensure a healthy level of musculoskeletal system activity, and to prevent ergonomic injury.

The recommended times for taking micro-breaks are different across multiple studies, as follows:

- OSHA [11] suggests that employers encourage workers to change their positions frequently. Micro-breaks of 3 to 5 minutes should be taken every 20-30 minutes. And after 2 hours of moderate computer work, there should be a 10-15 minute break.
- Stanford Environmental Health & Safety [12] suggests that continuous computer use or repetitive lab tasks last for 30 minutes maximum before taking a short break for 2 minutes or performing another task. And for micro-breaks, 30 seconds to 1 minute should be taken every 10 minutes.
- Liebenson [13] mentions that if one gets up every 20-30 minutes, a long micro-break is not required; otherwise, breaks and exercise should be taken every 30 minutes.
- Canada's Ministry of Labor [14] mentions that shorter but more–frequent breaks were more effective in reducing discomfort, compared to working for long periods of time and taking longer breaks. The ministry encourages workers to take frequent breaks of about 5 minutes every hour.

D. Related Works

In 2005, Jaimes and Liu [15] introduced a system for tracking sitting behaviour. It was claimed as the first camera-based system which made use of a web-camera and a microphone. The system worked by letting the user decides what "good" postures are; the system recognized them and would sound an alarm if the postures were not good ones.

In 2009, Tessendorf et al. [16] developed a system using pressure sensor mats for monitoring sitting behaviour in an unsupervised manner. The core of their research was autonomous comparison of pressure data, frame-by-frame. The system could provide feedback to users of how long they remained still in the same posture, and quantify their risk of developing lower back pain.

In 2011, Schrempf et al. [17] developed an intelligent office chair using four force transducers. The research promoted dynamic sitting, encouraged users to move frequently, and discouraged staying in the same posture for a long time.

In 2012, Hong et al. [18] introduced a mobile system called SEPTIMU. By using only sensors embedded in earphones, the system could monitor how long users remained in a single posture, and give feedback based on the model of health in ergonomics.

In 2013, Uribe-Quevedo et al. [19] proposed a Kinect-based system of seat tracking for correcting computer work postures. The system was successful in tracking both position and orientation.

III. Proposed System

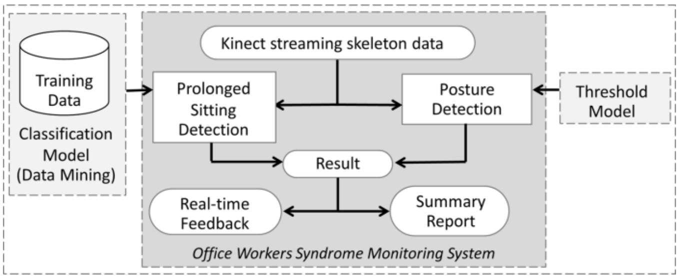
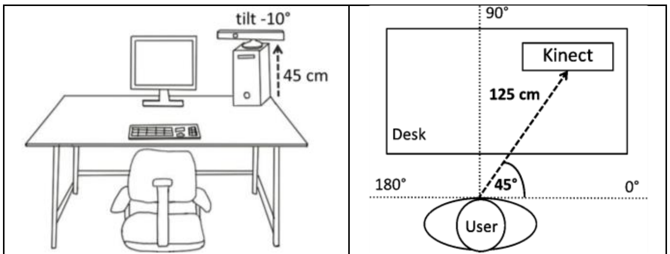


Fig. 1. System Overview Architechture.



View from behind. View from above.

Fig. 2. Recommended Setup.

A. System Overview

Our proposed system consists of two main features, which are prolonged sitting detection and posture detection. Kinect video clips were collected from volunteers and used as a training data set for building a classification model for detection of prolonged sitting. Posture detection was done by the threshold model as seen in Fig. 1. The system's recommended setup is shown in Fig. 2.

The proposed system reads streaming data from Kinect skeleton tracking, and provides real-time feedback from the prolonged sitting and posture detection to users. The proposed system can also generate a daily summary report, notifying the ergonomic health level of the user's daily sitting behaviour.

B. Other Issues

1) Customization

Default thresholds (e.g. the expected time to work before taking a break) are based on widely-recognized medical research; however, the system allows the user to adjust the system default configuration. The user can set the threshold or turn on/off the alarm sound.

2) Privacy

Only skeleton data, health risk level records, dates, times, and camera setting information are kept with the system. Skeleton data can be played back. The system does not keep raw RGB images, to preserve users' privacy.

IV. Prolonged Sitting Detection

The proposed system performed detection of prolonged sitting by initially building various classifiers. The data set was trained, tested, and cross-validated in several workflows with different combinations of techniques to find the optimal classifier. This optimal classifier was then applied in the final prototype system development. All steps are shown in Fig. 3.

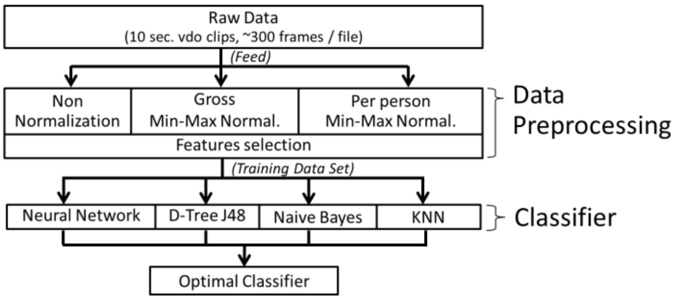


Fig. 3. Model building for prolonged sitting detection.

A. Data Collection

Video clips (raw data files) were collected from 28 volunteers (16 males, 12 females); the mean age of volunteers was 34.57 ± 12.83 years, and the mean height was 167.14 ± 8.63 centimetres in various body shapes. Video clips were divided into chunks of data called "feeds", representing a collection of skeleton data of a user's postures in 10 seconds. There were 1,326 feeds; each feed contained 31 attributes (see Fig. 4a) and had approximately 300 frames, and the 31 attributes consisted of time and 3D vector of 10 body joints (see Fig. 4b). An entire feed (each instance) was labelled a class whether it was sitting *still* or having a significant *move*. This data set is available at [20].

The *still* class implies that a user does not have significant body movement in a given period of time. If this state is continuous, the user is in a state of prolonged sitting. The *move* class implies that a user does have some significant movement (e.g. exercising, stretching) in a given period of time. This breaks up a prolonged sitting period and reduces the risk of office workers syndrome.

{ *Time, Head_x, Head_y, Head_z, ..., HandRight_z* }

a) Attributes in a feed.

{ *Head, ShoulderCenter, ShoulderLeft, ShoulderRight, ElbowLeft, ElbowRight, WristLeft, WristRight, HandLeft, HandRight*}

b) Ten body joints.

Fig. 4. Attributes used in data collection.

B. Data Pre-processing

There were 1,326 feeds collected (663 *Still*, 663 *Move*). In each feed, Euclidian distance between each pair of consecutive frames (movements within 0.033 seconds of each other) was calculated for all body joints, using (1).

$$J_{Dist_{(1,2)}} = \sqrt{\left(J_{X_2} - J_{X_1}\right)^2 + \left(J_{Y_2} - J_{Y_1}\right)^2 + \left(J_{Z_2} - J_{Z_1}\right)^2} \quad (1)$$

Where J is a single joint of body (e.g. *Head*, *ShoulderCenter*), J_{Dist} is a Euclidian distance between two adjacent frames.

After all Euclidian distances were calculated; we performed Min-Max normalization using (2) over J_{Dist} to equalize the scale of data. Min-Max normalization was done in two ways: Gross Min-Max normalization (GMM) and Per person Min-Max normalization (PMM).

GMM used the minimum and maximum values among all 1,326 feeds. On the other hand, PMM was done one-by-one for each volunteer; it used the minimum and maximum values among all feeds only from a specific volunteer (~48 feeds).

$$J'_{Dist} = \frac{J_{Dist} - J_{Dist_{Min}}}{J_{Dist_{Max}} - J_{Dist_{Min}}} \quad (2)$$

Features were extracted by calculating variance (*V*), maximum (*Max*), average (*Avg*), 75th percentile (*P75*), and 90th percentile (*P90*) of J'_{Dist}. However, both *P75* and *P90* were less useful compared to *Avg*. Thus they were left out as irrelevant attributes. This resulted in a training data set with attributes as shown in Fig. 5.

{ *Head_Dist_V, Head_Dist_Max, Head_Dist_Avg, ..., HandRight_Dist_Avg* }

Fig. 5. Attributes in a training data set.

C. Feature Selection

Feature selection is the process of selecting the minimum set of candidate attributes in a training data set (Fig. 5) for classification. Feature selection was done using two techniques, as follows:

1) D-Tree, Optimal Decision Nodes

Decision tree [22] achieves optimality in data splitting by testing the most important attribute in classifying class label. The attribute in a higher level of the decision tree is considered to have more predictive power than the lower-level attribute node.

2) Boxplot

Boxplot is a technique used for exploratory data analysis. In this work, boxplot is used to determine the significant attributes which can separate class labels clearly.

D. Classification Methods

Sets of features (results from feature selection) were processed through 4 classification methods:

1) Decision Tree (D-Tree)

Decision tree [22, 23] is used to classify data from class label, which yields output as a flowchart-like tree structure. In this work, a decision tree algorithm called J48 (in WEKA data mining tool) was used to classify human gestures as a set of decision nodes and leaf nodes. Each leaf node showed a class outcome label (*Move* or *Still*).

2) Neural Network

In this work, the neural network for classification is multi-layer perceptron (MLP) [22, 23], a feedforward neural network with one or more layers between input and output layer. This type of network uses a back propagation algorithm in its learning.

3) Naive Bayes

Naive Bayes [22, 23] is a simple probabilistic classifier based on applying Bayes' theorem with a naive assumption of independence between every pair of features. The nodes in a Bayesian model are created from the given training data.

4) k-Nearest Neighbors (KNN)

KNN [22, 23] is a non-parametric lazy learning algorithm that predicts objects' values or class memberships based on the *k* closest training examples in the feature space. KNN algorithm is amongst the simplest of all machine-learning algorithms: an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its *k* nearest neighbors. In this work, we set *k* equal to 5.

V. POSTURE DETECTION

When the system starts up, the user has to register the system "Base Posture" which is then used to calculate the change in the user's postures. The threshold model (a rule-based algorithm with a threshold value) is used to detect postural changes when the user stands or walks out for a break.

A. Sit-Stand Detection

Sit-Stand detection involves detection of whether the user stands up or sits down, using heights (*Y)* of *Head* joint and *ShoulderCenter* joint.

The system decides that the user is standing up when

$$ShoulderCenter_{Y_{Current}} > Head_{Y_{Base}} \tag{3}$$

The system decides that the user is turning left when

$$ShoulderCenter_{Y_{Current}} \leq Head_{Y_{Base}} \tag{4}$$

B. Break Detection

Break or Walkout detection is done by the calculation using ranges (*Z)* of *ShoulderCenter* joint. The system decides that the user is taking a break if the range is more than 1 meter from the base posture range when he or she originally sits.

VI. ALARM AND REPORT

According to literature reviews on ergonomics, we have introduced the leveling system for justifying the state of health risk. Moreover, novel ways for providing system feedback and reports are also introduced in this work.

A. Health Risk Level

Three levels of health risk are introduced. The health risk level works by using the counter called "risk score".

- *Lv0* or *Green* : healthy state
- *Lv1* or *Yellow* : caution state
- *Lv2* or *Red* : unhealthy state

1) Risk Score for Prolonged Sitting

(1) The risk score is in the range of [0, 240].

(2) The risk score is added by 1, every 30 seconds of sitting still.

(3) The risk score is subtracted by 12, every 30 seconds of body movement or standing up.

(4) The risk score is reset to 0, when walking-out is detected.

(5) Health risk level is *Lv1* when a score is more than 40.

(6) Health risk level is *Lv2* when a score is more than 60.

This scoring system works as follows:

- The user should begin to think about taking a short rest when they have worked for 20 minutes.
- It is risky for health to work more than 30 minutes continuously.
- Using the 12:1 ratio, the user should take a rest and exercise for 30 seconds every 6 minutes, or 5 minutes every hour, or 10 minutes every 2 hours.
- If the user takes a rest for 10 minutes by exercising or walking out for a break, the health risk is reset to *Lv0*.

B. Real-Time Feedback

On office workers syndrome monitoring, the system can provide feedback to the user (immediate feedback from posture detection and feedback with 10-second buffer time from prolonged sitting detection). This task can be done by using simple pop-up messages or via an alerting device.

1) Monitor Screen and In-App Alarm

The user can see results of the prolonged sitting and posture detection on a monitor screen in the application (Fig. 6). The application alerts the user based on the health risk level (e.g. showing a pop-up message, suggesting that the user take a break when health risk level is *Lv1*, generating an alarm sound when health risk level is *Lv2*).

2) Alerting Device

We have developed an alerting device called "Pos-Monitor" using a microcontroller. This device includes an 8-pin LED light, 16 x 2 character LCD monitor, and a buzzer, as shown in Fig. 7.

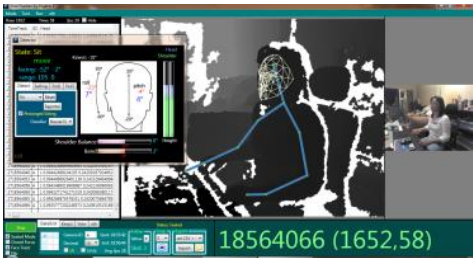
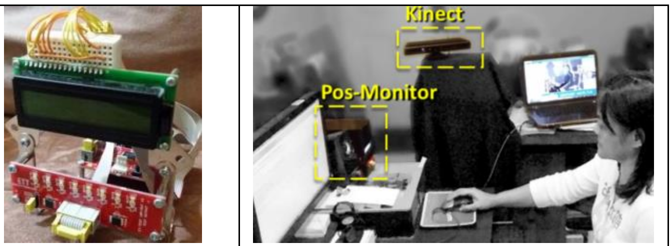


Fig.6. Monitoring Screen.



Pos-Monitor without a case. Pos-Monitor is placed next to the monitor.

Fig.7. Pos-Monitor.

Instead of using a monitor screen and an in-app alarm, Pos-Monitor is an alternate user interface of the system, which provides the following warnings:

- LED lights indicate how long the user has been in a state of prolonged sitting (e.g. when 4 out of 8 LEDs are turned on, this means the user has continuously worked for 60 minutes).
- LCD monitor shows a message suggesting that the user have a break after working for 20 minutes.
- LED lights blink to draw the user's attention to the suggestion on the LCD monitor when health risk level reaches *Lv1*.
- The buzzer generates an alarm sound when health risk level reaches *Lv2*.
- The device will automatically sleep when the user walks out for a break, and it will wake up and greet the user when he or she comes back.

The objective of Pos-Monitor is to provide a user-friendly interface to help users be aware of their posture without interrupting their work. Pos-Monitor allows users to have an easy way to receive feedback from the system. This desktop device costs about $30.

C. Daily Summary Report

Visualization is used to generate a daily summary report. Colors (green, yellow, and red) are used to indicate the health risk levels as seen in Fig. 8. Reports can zoom-in and zoom-out over a given time frame.

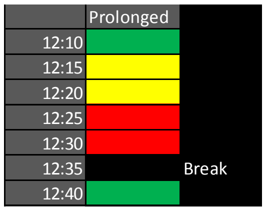


Fig.8. Daily summary report; time frame = 5 minutes.

VII. Experiment and Results

A. Feature Selection

By performing D-Tree using all attributes, we found that the five attributes at highest-level decision nodes are:

{*ElbowLeft_Dist_Avg*, *ShoulderRight_Dist_Avg*, *ShoulderLeft_Dist_V*, *HandLeft_Dist_Max*, *WaistRight_Dist_Avg* }

From boxplot visualization, it was found that differences between *still* and *move* classes were clearest in:

{*ElbowLeft_Dist_Avg*, *ElbowRight_Dist_Avg* }

With the guideline from previous methods, we created several sets of features with different combinations of recommended attributes.

B. Classification Method

For each set of features, we performed three types of normalization and process through four classification methods. Training and testing were done using the 10-fold cross validation.

As the final result, we found that optimal accuracy was achieved when the set of features was:

{*Head_Dist_Avg*, *ElbowLeft_Dist_Avg*, *ElbowRight_Dist_Avg*}

Elbows were the most important attributes resulting from the feature selection, so *ElbowLeft* and *ElbowRight* were the main consideration. In addition, the *Head* joint was added in order to track the upper body, because the user sometimes moved his or her head while the elbows remained still.

The accuracy shown in Tab. 1 is favored, and there is no significant difference in the processing time across different classification methods; for best real-time performance, the simplest method should be selected.

Table 1: Classification accuracy rate of prolonged sitting detection using { *Head_Dist_Avg*, *ElbowLeft_Dist_Avg*, *ElbowRight_Dist_Avg*}.

Method	**Normalization**		
	Non	**GMM**	**PMM**
D-Tree	98.11%	* 98.04%	97.66%
Bays	98.19%	98.19%	95.17%
KNN (K5)	96.83%	98.27%	96.08%
NN	98.04%	98.04%	96.00%

Various normalization methods were done in order to deal with the different body sizes of the users. If PMM was selected, the system had to learn minimum and maximum values for each specific user. On the other hand, if GMM was selected, the system could use minimum and maximum values from the training data set of all user subjects. GMM likely promotes more robustness.

From Tab. 1, D-Tree was selected for the reason that it is interpretable. As a result, the classifier in this research was built using { *Head_Dist_Avg*, *ElbowLeft_Dist_Avg*, *ElbowRight_Dist_Avg* } by performing GMM normalization and D-Tree classifier with 98.04% accuracy.

C. Posture Detection

Both Sit-Stand detection and Break detection achieve a 100% accuracy rate as long as the skeleton data can be tracked by Kinect camera.

VIII. Conclusions and Future work

We have presented the system for monitoring office workers in order to prevent office workers syndrome. The Kinect camera is used as an input device. Detection of prolonged sitting is done by data mining classification, and posture detection is done by threshold model. A health risk leveling system is introduced; an alerting device has been developed using a microcontroller, as well as visualization for providing a daily summary report.

From system usability testing of our prototype by 10 volunteers, all users were satisfied; they found this system useful and friendly without interrupting their work. However, we found the shapes and the materials of tracked objects also affected system performance (e.g. noise increased when tracking a person with long curly hair or persons wearing satin clothes).

For future work, machine learning can be used for noise detection and reduction. The system should be extended to detect more postures (e.g. pitch, leaning, twisting) and provide more detailed feedback.

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