Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

Marker-Based Monitoring of Seated Spinal Posture Using a Calibrated Single-Variable Threshold Model

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Abstract— **This work, as part of a larger project developing wearable posture monitors for the work environment, seeks to monitor and model seated posture during computer use. A non-wearable marker-based optoelectronic motion capture system was used to monitor seated posture for ten healthy subjects during a calibration exercise and a typing task. Machine learning techniques were used to select overall spinal sagittal flexion as the best indicator of posture from a set of marker and vector variables. Overall flexion data from the calibration exercise were used to define a threshold model designed to classify posture for each subject, which was then applied to the typing task data. Results of the model were analysed visually by qualified physiotherapists with experience in ergonomics and posture analysis to confirm the accuracy of the calibration. The calibration formula was found to be accurate on 100% subjects. This process will be used as a comparative measure in the evaluation of several wearable posture sensors, and to inform the design of the wearable system.**

I. Introduction

POOR seated posture is an increasingly significant source of back problems. Although good seated posture is rare in regular computer users, no means currently exists to monitor posture and provide the user biofeedback in real time. A major reason for this is the unavailability of a simple, wearable means of long-term monitoring spinal posture in the working environment. The research presented in this paper describes the first part of a larger project which seeks to develop a wearable posture monitor for use in the workplace. Specifically, this paper is focused on the exploratory investigation of the important parameters in seated posture, and the development of a simple, calibrated, single-variable threshold model of seated spinal posture.

II. Background

A. Seated Posture and Musculoskeletal Disorder

Computer work has long been associated with musculoskeletal disorders of the upper extremity [1]-[3]. Workplace design, working postures, long hours of computer work and prolonged periods of holding a static posture are some of the ergonomic factors shown to be related to an increased risk of developing work related upper limb and neck disorders [2]-[7]. The prevalence of work related upper extremity musculoskeletal disorders reported in the United States has increased dramatically during the past two decades. In 1982, they accounted for 18% of all reported occupational illnesses in the USA; in 2002, that number had increased to 66% [8].

Many ergonomic studies have focused on the postural effects of changing parts of the computer workstation such as the display height, and/or keyboard height as well as other interventions [9]. Despite widespread acceptance that work related upper limb musculoskeletal disorders among computer users can be prevented by posture modification [10] or ergonomic interventions like specific hardware (eg. adjustable chairs, forearm supports, alternative input devices), there exist very few reliable, objective and accurate methods of continually monitoring posture in the work environment to ascertain whether or not these modifications or interventions are successful.

B. Measuring Seated Posture

An extensive literature review by Li and Buckle [11] examines current techniques for assessing physical exposure to work-related musculoskeletal risks, with emphasis on posture-based methods. This review shows an extensive range of data collection methods, including self administered questionnaires, electromyography, inclino-meters, goniometry, electro-goniometry, professional observations, physical examinations and three-dimensional kinematics. Of the available assessment techniques, 3D kinematic systems offer the most direct and detailed motion capture data, as they alone are capable of quickly recording with a great deal of precision the simultaneous movement of a large customizable set of body landmarks, without significant discomfort for the subject.

C. Wearable Body Monitoring

Three-dimensional kinematic motion capture offers a very detailed record of body movement. It is also among the least invasive and most comfortable body monitoring techniques, requiring only that markers be adhered lightly to the skin. Compared with techniques such as intra-

Manuscript received April 3, 2006. This work was supported in part by the University College Dublin under grant BS123456, and in part by Science Foundation Ireland under grant number 03/IN.3/I36.

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muscular electromyography (which requires the insertion of needles directly into muscle tissue), it is a fast and easy method of detailed body motion capture. However, none of the existing clinical body monitoring techniques allows the long-term monitoring of a user in their actual work environment, nor do they provide the user with real-time biofeedback.

A long-term field analysis of seated posture thus requires that the user be fitted with a simple, easy-to-use, wearable posture monitor that requires neither alteration of the work environment (to include cameras, etc.) nor the use of a computationally complex data processor. Toward that end, the research described here utilizes a three dimensional motion capture system to develop a calibrated, single-variable threshold model for seated spinal posture, and evaluates the accuracy of that model on a set of ten users completing a typing task. The marker-based system will be used as a comparative standard in future evaluation of simple wearable sensor-based posture monitors.

III. METHODS

A. Equipment

The Coda Cx1 (Charnwood Dynamics Ltd, UK), a three-dimensional motion measurement and analysis system was used to record spinal flexion and extension in the sagittal plane during a three minute typing task. The Coda CX1 scanner contains three pre-aligned solid-state cameras which track the position of a number of active markers (infra-red LEDs) in real-time.The Coda Cx1 scanner was located directly behind the subject, with a video camera (for the purpose of visual analysis) placed at 90 degrees to record a side profile of each subject as they completed the task. The dorsal positioning of all markers removed the chance of occlusion, thus only one camera was required to capture all movement data.

B. Marker Location

The marker set used was an adaptation of a marker set used by Frigo *et al.* [12] specifically designed for their study of spinal movements. Markers were placed on bony landmarks C7, T4, T7, T10, T12, L2, and L4 with each marker corresponding to the spinous process of the vertebra underneath (Figure 1). The shoulder girdle was identified by markers on the medial aspect of the left and right spines of scapulae.

Vector angles were created in the Coda analysis software using data from the marker points, to allow analysis of movement in individual areas of the spine, and to monitor the overall movement of the spine in the sagittal plane. Vectors were created between each landmark (eg. C7-T4, T4-T7, T7-T10, T12-L2 and L2-L4). Overall flexion was measured using the angle between vector C7-T7, and vector T7-L4, thus encompassing the whole range of spine included in the marker set.

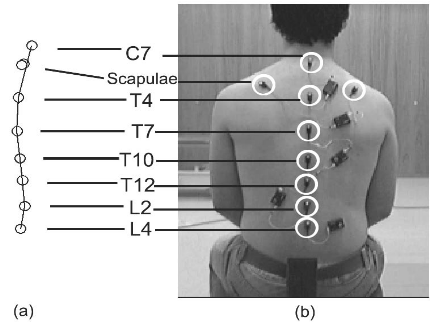

Fig. 1. Marker locations on the back (a) and on the corresponding stick figure (b). White circles added for clarity, markers are within each circle.

C. Protocol

Subjects were seated on a backless desk chair in front of a laptop computer. Seat height was adjusted such that he/she could place both feet on the floor and the angle of elbow flexion was greater than 90 degrees. Ten subjects each completed a calibration exercise and a three minute typing task, with their hands on the keyboard for the duration of both tasks. The calibration exercise established the outer limits of spinal flexion in the sagittal plane. Subjects first sat for 5 seconds as straight and tall as possible, in a hyper-extended position, then flexed into a full "slump" position (without forward flexion at the hip), which was held for 5 seconds, after which the hyper-extended position was repeated. Finally, subjects relaxed into "good seated posture" i.e., with their torso and neck approximately vertical and in line, maintaining the natural curves of the spine (thoracic kyphosis at T6/7, lumbar lordosis at L3/4), thighs approximately horizontal, and lower legs vertical [13], as illustrated in Figure 2(a). Subjects were advised to maintain this posture as they completed a typing task. All positions and movements were demonstrated by a qualified physiotherapist, and subjects practiced each movement prior to testing. A standardized typing package, TypingMaster (Typing Master, Finland Inc.) was used to display text for the subject to copy for three minutes. The same laptop computer and desk were used for all subjects.

D. Population

Subjects included in the study were ten physically fit postgraduate students, seven males and three females, at the School of Physiotherapy and Performance Science, University College Dublin, with a mean age of 24.4 yrs.

IV. ANALYSIS

A. Developing the Model

Initially, all vector data from the calibration tests (between-landmark vectors and overall flexion vector) were manually labelled "good" or "bad" for each data point. This labelled data was used to train a J48 decision-tree machine learning classification algorithm [14] for each dataset. J48 was used in this case to determine the best indicator (or set of indicators) of posture from the set of vector indicators. In this phase the objective was to identify the simplest means of measuring posture that would at the same time provide the required level of accuracy. The overall flexion vector was found to be the most consistent indicator across the user group. As this vector alone provided 100% accuracy in cross-validation for all test subjects, no additional data were used in the model.

It is important to note that in this case the simplest posture model was sought. Other posture variables, such as neck flexion or shoulder elevation or abduction, were not evaluated. Similarly, a more complex model of spinal curvature is of course possible, but in the anticipated application the simplest possible accurate model is optimal.

Because of the simplicity of the model, machine learning techniques were no longer necessary. Using a trial-and-error method of visual analysis, a threshold identification procedure was identified. The relaxed good seated posture data for each subject from the calibration exercise was averaged into an “average good” value. To this was added 10% of the total range of motion (identified by the minimum and maximum values from the calibration exercise), to yield the threshold value for each subject.

B. Applying and Evaluating the Model

The posture threshold for each subject was then applied to the data from the typing test. Overall flexion values that fell below the threshold were considered “good” posture, and above the threshold were considered “bad”. Stick figures and video stills were extracted for each data point where the subject’s posture crossed the threshold (i.e., went from good posture to bad posture) to check the similarity of all threshold values, and for the minimum and maximum flexion values for both the calibration exercise and the typing task, to contextualize each subject’s range of motion and typing posture. Video and stick figures were subjected to expert visual analysis to check that the threshold was indeed an accurate representation of the shift from good to bad posture.

V. RESULTS

A. Seated Posture

As an exploratory investigation, this study yielded several interesting observations about seated spinal posture during computer use. Most significant was the inability of many subjects to maintain good posture, even when instructed to do so. No subject maintained good posture throughout the entire task, and two of the ten test subjects never regained good posture after the start of the typing task. Figure 2 shows this behaviour in one subject. Figure 2(a) shows the threshold posture, and Figure 2(b) and (c) show the minimum and maximum flexion values during his typing task. As illustrated, his minimum curvature during the task is visibly greater than the identified threshold curvature.

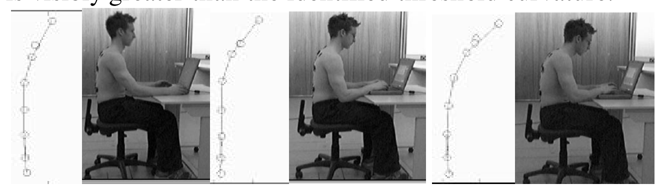

Fig. 2. Example threshold (a) and typing task minimum (b) and maximum (c) flexion. Subject does not regain threshold or “good” posture during the typing task.

This inability to maintain posture was observed even though all subjects were aware that good seated posture was the objective of the exercise, and were monitored in a laboratory environment where they were observed and videotaped throughout the testing period.

B. Calibration of Model

Range of flexion for each subject was distinct, as was the threshold value, as seen in Figure 3. Example results from the calibration test are shown in Figure 4.

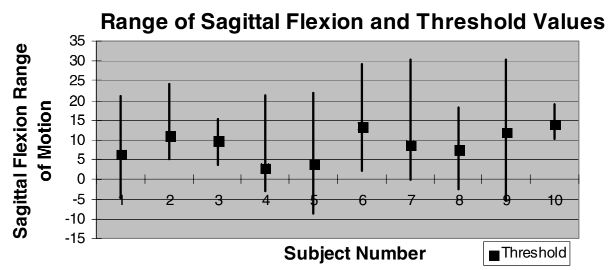

Fig. 3. Range of sagittal flexion and threshold flexion values for each subject.

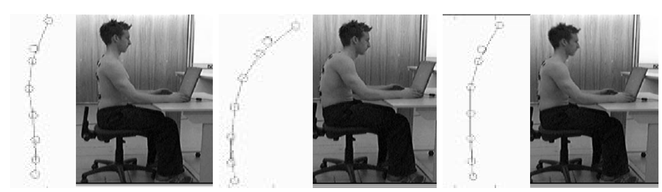

Fig. 4. Example minimum (a) maximum (b) and threshold (c) sagittal flexion during calibration exercise.

C. Accuracy of Model

Due to the simplicity of the model used, the posture recorded for each crossing of the calculated threshold was not always identical. The threshold was calculated using only one vector variable, and spinal curvature is comprised of several different component vectors, thus the model used was a very simplified model of spinal posture.

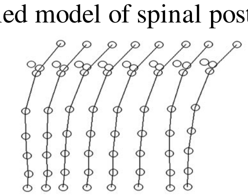

Fig. 5. Example threshold postures for one subject over the course of the entire typing task.

Figure 5 shows the variation in threshold posture for one subject: while the threshold postures are not identical, they are very similar and safely within the tolerance limits of this subject's threshold "good" posture. Based on the expert visual analysis, the threshold determined by the process described above was accurate in ten of ten subjects.

VI. Discussion

Paramount to the evaluation of the results of this study is the intended application of this exploratory research. The anticipated system will use the threshold established in this work to remind the user to resume correct posture. As this application requires considerably less precision than other possible posture-monitoring scenarios (such as a medical or therapeutic monitoring of a specific spinal problem), the simplified posture model developed provides an adequate representation of spinal curvature.

The exploratory investigation described here illuminated many influencing variables to be examined in the development of the anticipated wearable device. Since overall flexion proved more reliable than other smaller vectors in accurately predicting spinal posture across subjects, the wearable sensor must be similarly capable of capturing full spinal flexion (vs. a smaller portion of spinal flexion). Based on this investigation, a single flex sensor may be capable of providing enough posture information to accurately provide biofeedback to the user. However, a similar investigation of the influence of shoulder curvature may also provide a more complete model of seated posture. Future work will consider this variable.

The wide variance in sagittal range of flexion and threshold posture values confirmed the importance of calibrating the system to each individual user. As evidenced, the "good" normal posture displayed by each subject was not necessarily considered anatomically perfect, but rather represents the individual subjects' personal best. Many individuals experience difficulty in attaining "perfect" posture, thus calibrating a biofeedback device to the anatomically ideal posture would result (for some subjects) in an impossible-to-please device, and a dataset that ignores relative improvements. In the proposed application, a regularly re-calibrated wearable device would be able to track both the user's performance in maintaining their personal best posture, but also the gradual long-term changes in their threshold posture resulting from feedback, training, or ergonomic interventions.

Although there exists a wide variance in threshold posture and range of sagittal flexion across the user population, the actual range of flexion for each user can be relatively small. As seen in Figure 4 and Figure 6, the minimum, maximum, and threshold values can be (while definitely distinct) fairly similar in appearance. Since most traditional methods of evaluating posture involved the visual evaluation of a live subject or a still picture [11], a precise value of "perfect" posture is nearly impossible to pinpoint. And because the actual range of motion is not very large in physical space, in fact the range of values that can be classified as "good" posture represents a considerable portion of total range of motion. This may perhaps explain the effectiveness of such a simple model for posture classification.

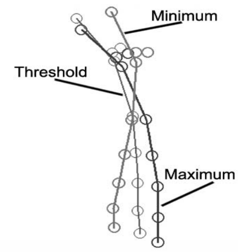

Fig. 6. Minimum, maximum, and threshold flexion for one subject.

VII. Conclusion

The results of this investigation of seated spinal posture using a marker-based motion capture system indicate that the single-variable model developed here has the potential to translate very easily into the wearable domain. The model developed utilizes simple, easy to capture information that is possible to replicate using only one wearable flex sensor. The exploratory investigation conducted here also reinforces the hypothesis that most users consistently assume poor seated posture, and find it very difficult to maintain good posture while occupied in a typing task, which points to a clear need for the proposed wearable biofeedback device.

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