WatChair: AI-Powered Real-time Monitoring of Sitting Posture and Corrective Suggestions using Wearable Motion Sensor System

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***Abstract*—The majority of the population around the globe spend a considerable portion of their days seated. This fact can be associated with several factors, such as the circumstances of most of the current jobs and the prevalence of the use of computer systems. One could argue that this knowledge indicates that the impacts of maintaining proper posture while sitting can be observed more than before. Therefore, it is critical to be able to observe, correct, and control our sitting posture throughout the day. Monitoring and correcting our short-term and long-term sitting habits over time can lead to significant improvement in our physical well-being. In this work, we propose WatChair, an AI-powered remote subject monitoring system that assists in short-term sitting posture recognition, activity-level tracking, long-term monitoring, and providing corrective suggestions. Our platform consists of a small wearable component, an application, and a cloud-based back-end. Our framework has been evaluated in practice, and the results of empirical validation and the user-friendliness questionnaire points to a simple, accurate, and user-friendly system for remote sitting posture monitoring. This framework also presents an adaptable solution for general dynamic posture recognition and tracking using wearable systems based on motion sensors.**

***Index Terms*—mobile health, remote health monitoring, machine learning, ehealth**

I. Introduction

The sedentary lifestyle has caused people to spend a considerable portion of their lives seated. The act of sitting has the potential to cause severe short-term and long-term health problems if not done correctly. An example of such problems is the feeling of pain and discomfort in the neck and back area [1]–[3]. Most studies have indicated a strong connection between the sitting posture in performing different activities with outcomes including health status and eating, claiming that controlling it and maintaining proper sitting posture can help the subjects [4], [5]. As simple as sitting as an activity might seem, it has also been known for its impacts on certain types of decision-making, such as online grocery shopping [6].

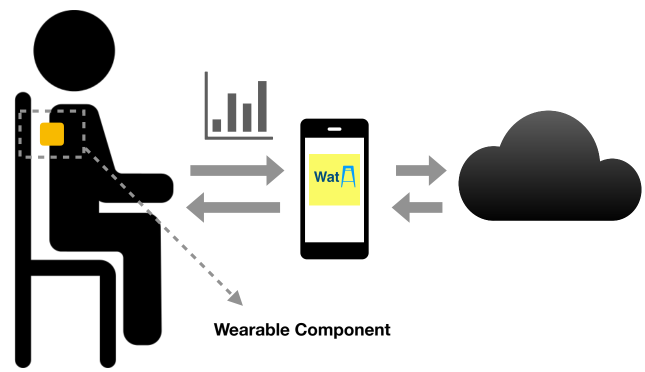

Fig. 1. The system architecture of WatChair platform

For the reasons mentioned above, remote monitoring of sitting posture and attempting to correct it over time is an exciting area of research. This stems from the fact that a convenient and thorough solution for this problem is invaluable as it has the potential to improve the quality of life for many people.

In this work, we introduce WatChair, a platform for continuous monitoring of sitting posture that aids subjects with corrective suggestions. This work attempts to bring a smooth remote monitoring experience to the subjects while attempting to keep the cost and intrusion associated with the data acquisition system as low as possible. This is done by focusing on providing more efficient solutions to the software-related aspects of the problem. Our system will monitor the sitting posture, recognize different sitting posture patterns, and help the subject with a thorough report of the statistics of their sitting posture throughout the day. It also provides them with their history of sitting information, assisting them with easy progress tracking.

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This article is structured as follows: In section II, a review of the previous works that are related to sitting habit monitoring is presented. Our system is introduced in section III, and it is followed by the discussion of experiments and results in section IV.

II. Related Works

Remote monitoring of the human body, postures, and activities is an important area of mobile health research. Many researchers and companies have been working on developing utilities and analytical solutions to monitor, understand, track, and leverage the information related to body posture. These solutions assist subjects in improving physical activities, ranging from general posture to particular therapeutic exercises [7], [8].

There have been numerous research works focusing on monitoring sitting as an important daily activity. These works were mostly focused on analyzing the sitting posture to better fathom its transitions and variations throughout the process of sitting [9], [10]. The system in [11] is designed for sitting behavior tracking and analysis. This work has utilized many stretchable sensors and pressure sensors to prepare a thorough sensor-driven system. Their main contribution is their sitting behavior recognition using neural networks and dynamic time warping.

The system proposed in [12] with the objective of helping mitigate the impacts of poor sitting posture such as pain and discomfort in the back and neck. Their system is based on multiple motion sensors, and it is close to our approach in terms of low cost and affordability. Their system differentiates between sitting, lying, walking, and standing postures. Their framework's main components are cardboard, test pole, and dynamic measure units (DMU) that include accelerometer, gyroscope, and magnetometer.

The framework proposed in [13] follows a different objective of monitoring floor sitting postures. This work proposes the use of a number of pressure sensors in a system to achieve this objective.

A personalized transportable folding device is utilized in [14] to assist with maintaining a better sitting posture while eating. Their results led to the empirical validation of the hypothesis that improving the sitting posture while eating can help with the mitigation of the adverse effects of dysphagia.

The use of sensor-augmented and specialized chairs is also investigated in the literature [15]. In [16], the authors have proposed a system based on a chair embedded with pressure sensors to differentiate between the three main sitting postures of leaning forward, reclining backward or neutral sitting. In terms of the sitting postures that this system attempts to recognize, this work bears considerable similarity to ours. Nevertheless, there is no need for any other circuitry besides a single motion sensor in our approach. A similar grouping of sitting postures can be found in [17] as well. Another work in which a chair is augmented with a large number of electrical sensors is [18]. In a different approach, [19] uses a pressure mat for sitting posture recognition. A sensor-augmented cushion is also used in [20] and [21] for sitting posture detection, which serves as an approach similar to the previously mentioned works.

The work in [22] uses feedback mechanisms for posture correction. The system in [22] is composed of a Kinect device for extracting body landmarks and helping the user by providing feedback, urging them to maintain proper posture. Several other Kinect-based approaches focused on finding unhealthy sitting postures [23]–[26]. In [27], authors combine the information obtained from Kinect with smartwatches to improve the resulting detections. As the sitting posture recognition is especially important for remote health monitoring of elderly patients, a similar work focused on Kinect-based posture recognition for the elderly is presented in [28].

Our contributions in this study and the main differences compared to the mentioned works are as follows:

- The recognition scheme in this work focuses on linking the sensory data to discrete classes corresponding to essential proper and improper sitting postures. The mobile application utilizes the machine learning algorithm and interacts with a single wearable device to associate every time window with the corresponding status and stores the relevant information in the cloud database. It provides the statistics on the short-term evaluation of the subject's posture and activity while seated and shows corrective suggestions. In addition, it reads and visualizes the historical data on the subject's sitting habits, which can help in tracking long-term progress.
- The proposed algorithm is compatible with small sampling frequencies, which leads to a significant reduction in battery consumption on the wearable device and improves the usability of the framework.
- The mobile application provides an easy to use interface to interact with for users and developers. It allows custom labeling for developers, enabling gathering data on custom postures, and storing the data in the cloud database for further analyses.
- The analytical approaches are verified in a Python-based research framework. Our current inference engine for sitting posture recognition is composed of pre-processing steps and linear support vector machine instances, which are implemented in the mobile application as well.
- The experimental setup and the empirical results on our cohort indicate the effectiveness of this system for posture tracking and correction while the subject is seated. As shown in the literature, this can lead to the prevention of complications in short-term and long-term health conditions.

III. Proposed System

The overall architecture of WatChair is depicted in Figure 1. The first part of the system is a simple wearable component, which includes the motion sensors that we are interested in monitoring. This component would be located on the subjects' back and between the arms and used for sampling data points

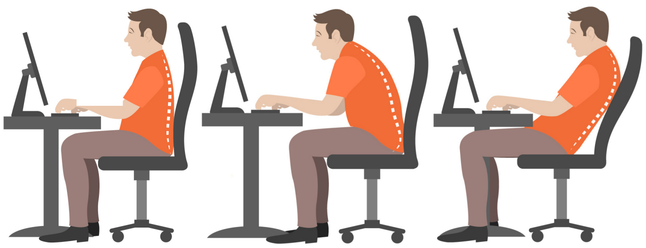

Fig. 2. Three main postures for sitting habit monitoring [29]

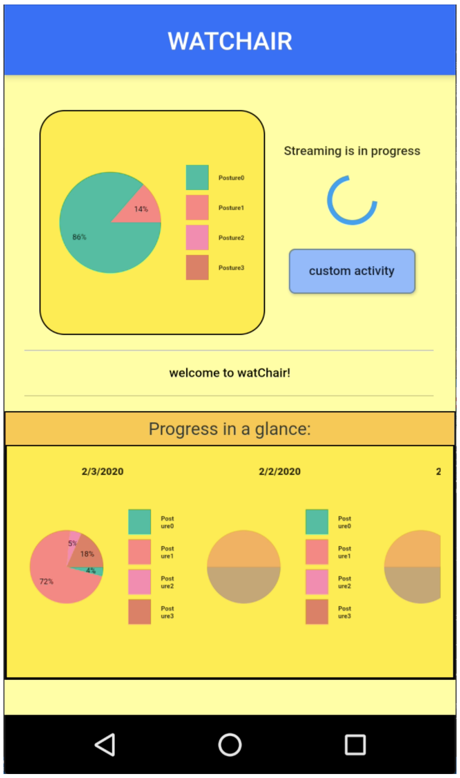

Fig. 3. The main interface of our application is shown in this figure.

and transmission. The system obtains its electrical power from a coin battery inside it, and given the frequency of reading, here, there is no need for frequent battery replacement.

This wearable component interacts with an android device using the WatChair app. Upon running the application, if the device is in range, the connection is maintained, and the process of data acquisition, recognition, and transmission to our cloud back-end begins.

The application provides a user-friendly interface between the board, the cloud back-end, and the subject. The user can observe long-term and short-term information about their pattern of sitting and score their seated behavior accordingly. This framework renders it possible to fine-tune the models as more data is gathered in the cloud database. In this work, we attempted to evaluate the performance of a general model with no need for per person calibration. Nevertheless, this framework can be used with ease to provide each user with separate user-calibrated models as well.

In what follows, the details of our approach and the components of this framework are elaborated upon.

A. Data

The main and only sensory part of this framework is composed of affordable, portable, and widely available MetaTracker boards [30]. These boards are widely used when motion sensors are to be utilized for evaluating physical readiness, an example being training pilots [31].

The single wearable component of this platform is placed on the subject's back and between the arms, which can be easily done using a strap or cord. The main component for the effective tracking of sitting habits is posture recognition. The main three postures that our platform focuses on recognizing are depicted in Figure 2 [32], and empirical results indicate that the data acquired from this location is mostly sufficient for making such determination. In addition, the sensor alignment can be automatically determined, and the system is flexible in terms of small displacements in using the wearable component.

The wearable component uses a Lithium battery, and in our framework, there is no need for frequent battery replacement. This is due to the fact that our framework is focused on seated posture and is compatible with low-frequency sensor readings. This property and being equipped with 2.4 GHz Bluetooth Low Energy chips enables us to maintain a smooth connection route between the wearable component and the app.

The mobile application then handles the data-related routines, including cloud storage, analytics, and transmission.

B. Application

Another essential component in our system is WatChair's mobile application. Upon launching the application, it writes the configuration necessary for the motion sensors, such as the frequency of sampling, and issues the start command for the wearable component. The information then can be monitored continuously using the app's interface, as depicted in Figure 3.

Afterward, the information is continuously retrieved, filtered, and pushed to our cloud database. For the back-end database, we are using Google Cloud Firestore as a NoSQL database composed of documents and collections. The application builds a communication channel to the Firebase instance in order to efficiently perform the transactions. These transactions include pushing the gathered data to the cloud database, an instance of Cloud Firestore, and reading the historical information for updating the visualizations in the app.

Please note that the related intervention information regarding how to correct the posture is also presented in the application, providing the subject with a more in-depth understanding of how to proceed regarding the given personalized posture correction information.

The quality of the application was surveyed through a usability questionnaire developed according to the Usefulness, Satisfaction, and Ease of use questionnaires in [33], [34]. This questionnaire was given to the subjects in our study,

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with the idea of receiving feedback on the application as the main component in this framework. It has scored 9.9/ 10.0, indicating the easiness of using and getting familiar with it.

Machine Learning: The machine learning component of WatChair is composed of an inference pipeline that directly links sensor readings to different sitting postures and characteristics. The trained model weights are used in the application to enable efficient use and effortless alterations in the future. The relevant sensor readings that come from motion sensors (mainly, the three-axis sensors of accelerometer and gyroscope) are buffered and transmitted to the application. In our experiments, we considered the time window of 60 seconds; therefore, the seated behavior of the subject for every minute is represented and used by the model for evaluation. The findings are then stored with the timestamps to help with the progress review.

The recognition pipeline is designed using Support Vector Classification which enables differentiating between the labels using one-vs-all classifiers. The training objective uses hinge loss and is as follows:

$$\min_{\theta,b} \frac{1}{2}\theta^T\theta + C\sum_{i=1}^{N} \max(0, y_i(\theta^T\phi(x_i) + b))$$

In the above formula, θ and b are the single model parameters which are trained, and ϕ is the linear kernel. The Support Vector classification with a linear kernel is chosen so the model complexity could fit the problem well, and the trained model could be easily implemented and used in the mobile application as well.

IV. Experiments

To obtain a dataset for our analyses, we have asked 6 subjects in the age range of 24-27 to participate in this study. For gathering the training data regarding each type of sitting behavior, a picture was shown to the subjects depicting such behavior. They were then asked to perform as they usually do in such a posture. While performing their normal activities (e.g., working with their laptops, writing), a sufficient amount of data could be gathered along with the supervision signals.

Our analytical platform is implemented in Python3.6, and using Google Cloud SDK, and Sci-Kit learn machine learning library enables us to retrieve the information from our cloud database and perform the corresponding analytical investigations. For evaluation purposes, several experiments were done, and in each experiment, the data from one subject was used as the test set while the model was trained on the rest.

The empirical results indicate that our model is able to recognize and distinguish between our three main pre-defined sitting postures accurately. The micro and macro average F1-Score for our current model over the three sitting postures are 72.12% and 75.09%, respectively.

The normalized confusion matrix for the predictions is shown in Table I. These results suggest that the system exhibits accurate performance, even though the flexibility of the system in terms of the positioning of the wearable component can potentially add to the error level. As another example, ”Slouching” data, which can be argued as the main posture of interest, has been efficiently captured.

TABLE I
MICRO-AVERAGED CONFUSION MATRIX FOR EVALUATING OUR MODEL USING LEAVE-ONE-SUBJECT-OUT SCHEME - EACH ROW CORRESPONDS THE PREDICTIONS FOR A GROUNDTRUTH LABEL

	Upright	**Leaning Back**	**Slouching**
Upright	0.65	0.22	0.14
Leaning Back	0.05	0.64	0.31
Slouching	0.02	0.0	0.98

This work aimed to propose an accurate and efficient pipeline to perform monitoring without the need for per-person calibration. However, it is understandable that in specific use-cases (e.g., certain disabilities, the cohort of elderly), the addition of per-person calibration to improve the performance further might be necessary. In such cases, labeled data can be easily obtained and analyzed using WatChair’s interface. This will enable the data analysis and preparations for such cases to take place with ease.

To use the model in the mobile application as well, this inference engine was implemented in Java and is included in the application to perform continuous recognition and update the cloud database accordingly.

V. Conclusion

We presented WatChair, an AI-powered remote monitoring framework for short-term and long-term tracking of sitting habits and proposing corrective suggestions. The effectiveness of this system in performing this task is then empirically validated. Given the critical health impacts of improper sitting habits, this low-cost and affordable system, combined with accurate machine learning inference, can improve user behavior while seated and therefore help prevent medical complications that are associated with improper sitting.

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