MONITORING WORKSPACE ACTIVITIES USING ACCELEROMETERS

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ABSTRACT

In this paper, we describe a physical activity classification system using a body sensor network (BSN) consisting of cost-sensitive tri-axial accelerometers. We focus on workspace activities (different motions and sitting postures). We use a Naive Bayes classifier and show that we can train the system simply and systematically. For each task, we find a set of features that separate the corresponding activities.

Index Terms— Activity classification, Naive Bayes classifier, Accelerometers.

1. INTRODUCTION

Physical activity monitoring (PAM) systems comprised of on-the-body accelerometers are effective tools for monitoring physical activity with medical, athletic training, and general health applications. In this paper we used a PAM system for monitoring people at their workplace.Accelerometer systems have already proven their effectiveness for the physical activity classification necessary for health monitoring, successfully classifying basic physical activities including walking, jogging, and going upstairs and downstairs [1]. In this project we demonstrated that our PAM system is capable of utilizing a personalized training set easily acquired by the user in a clinical setting. We also investigated the effect of training set duration on overall classification accuracy. Previous research has used pressure sensors embedded in a worker's chair for seated posture classification [2] [3], and video surveillance has been used to classify standing, sitting and lying down postures [4]. However, there has been little research concentrated on workspace activity and seated posture classification with accelerometers. These sensors are less costly for mass production than chairs equipped with embedded sensors and less invasive than video surveillance. Workplace activities that are of interest for classification in our system include walking, standing, sitting, sitting posture, and seated movements such as shaking ones leg or twisting in a chair. Studies have shown that too much sedentary behavior, such as sitting at a computer during the work day, is detrimental to health so much so that it leads to increased risks of cardiovascular disease, despite regular participation in moderate to intense exercise [5]. It has also been shown that bad workplace posture can result in widespread physical pain [6]. Fidgeting and restlessness, such as shaking ones leg and twisting in a chair, are both symptoms of anxiety, and thus the monitoring of such activities could potentially provide insight into the stress level of workers [7] [5]. With the tri-axial accelerometers used in this work, employers and employees will be able to monitor exactly how much time they are spending in sedentary positions, whether or not they have proper posture when sitting, and to what extent they are exhibiting anxious physical behaviors. This data will be able to be used as a guideline for altering their behaviors for the preservation and improvement of their health.

2. THE SYSTEM ARCHITECTURE

2.1. System Components

Our system consists of tri-axial wireless and wearable Gulf Coast Data Concept X6-2mini accelerometer sensors. The sensors continually collect data in the X, Y, and Z directions once removed from a USB port, at a selected rate of 160Hz.

2.2. Training Data Collection

Sensors are placed on the user in specified locations (knees, chest). When collecting a training set, an easily recognizable signature (such as jumping or leaning back and forth five times) is performed before each activity. Each activity is performed for the same amount of time and its occurrence and duration is recorded, facilitating the ease of labeling the data. The orientation and location of each sensor is also recorded in order to remain consistent between data collection sessions. The workspace activities performed are walking, standing, sitting, sitting with the back reclined 85-95, sitting with the back reclined 115-125, sitting while slouching, shaking one leg while sitting, crossing one leg while sitting, swiveling in a chair, and sliding in a chair away from and towards a desk.

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2.3. Scripted/Testing Data Collection

Sensors are placed in the same locations and with the same orientations as they are in training data collection. The same activities are performed but in a natural, un-planned manner. An observer (or the user) records the activities that the user performs so that the data can be labeled appropriately, creating ground truth for classification. In a deployed system, this recording would not be necessary as we would rely on the classifications, presuming they yield sufficiently accurate statistics.

2.4. Data Analysis

For the classification, we used a Naive Bayes classifier [8] over a feature space. The features were calculated over a window of 4 seconds. The features were: mean, maximum value, and frequency energy. This was done on several levels first by classifying sitting, walking, and standing, and then within sitting, classifying the postures and movements.

3. EXPERIMENTS AND RESULTS

The activities classification preformed were structured into three levels. The first classification level comprised of walking, sitting, and standing, the second of seated posture, and the third of seated movements: twisting in the chair, shaking the leg, sliding to and from the desk, and crossing legs. From these data the frequency, max, min, mean, and standard deviation values were extracted on the three levels of classification. Splitting the classification into several levels has advantages for (1) producing a model that is physically understandable, and thus leading to information that is more useful in advising subjects on how to change their behavior (e.g., degree of slouch, take more breaks, etc.), and (2) reducing training time, since each decision is low-dimensional. We chose the Naive Bayes classifier [8] because it is simple and it worked well.

On the first level (walking, sitting, and standing) an accuracy of 99.5% was achieved as seen in Fig. 1. For the posture, where the angle of the back was measured, the accuracy was 99.6%, as seen in Fig. 2. On this level, two types of proper posture [9] were classified; reclined at 120 degrees, and upright at 105 degrees and many types of slouching were classified as improper. For the various movements while sitting, an accuracy of 96.5% was obtained, as seen in Fig. 3.

True Class	Classification			
	Unknown	Walk	Stand	Sit
Unknown	5.2632	40.3509	15.7895	38.5965
Walk	0	100	0	0
Stand	0	1.0929	98.9071	0
Sit	0	0.4651	0	99.5349

Fig. 1. Walking, sitting, and standing classification statistics.

True Class	Classification			
	Unknown	Proper Reclined	Proper Upright	Improper
Unknown	0.5464	25.1366	59.5628	14.7541
Proper Reclined	0	98.4962	1.5038	0
Proper Upright	0	0	100	0
Improper	0	0	0	100

Fig. 2. Sitting posture classification statistics.

True Class	Classification				
	Unknown	Twist	Shake	Cross	Slide
Unknown	0.6342	1.0571	20.9302	67.6533	9.7252
Twist	0	100	0	0	0
Shake	0	0	97.3684	0	2.6316
Cross	0	0	0	92.6829	7.3171
Slide	0	2.7778	0	0	97.2222

Fig. 3. Sitting motions classification statistics.

3.1. Training Data Set Duration

An integral part of our PAM system is the training data set, the set of data that the classifier bases its classifications on. In order to determine the optimum amount of time for which each activity should be performed in the training data set, a single set of data was broken up into subsets of time intervals. One time interval was dedicated as the testing data set, while the other time intervals length was varied and dedicated as the training data sets. The same testing data set was tested against each of these training data sets, and the overall accuracy for each training data set length was recorded. For walking, standing, and sitting classification, it was found that 2 minutes was an adequate training interval, as seen in Fig. 4. For seated posture classification it was found to be 2 minutes, as seen in Fig. 5. For seated motions it was found to be 15 seconds, as seen in Fig. 6.
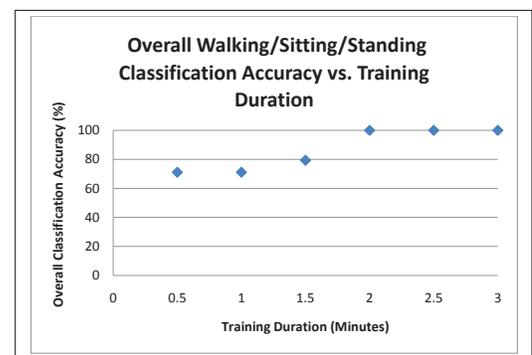

Fig. 4. Overall classification accuracy of walking, sitting, and standing as a function of training duration.
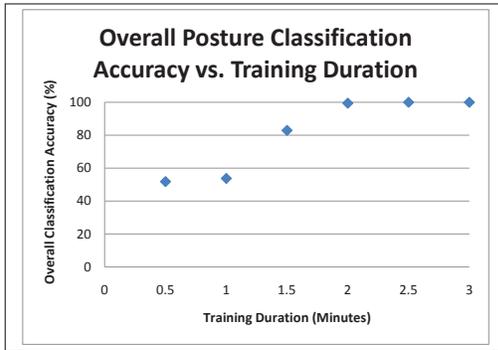
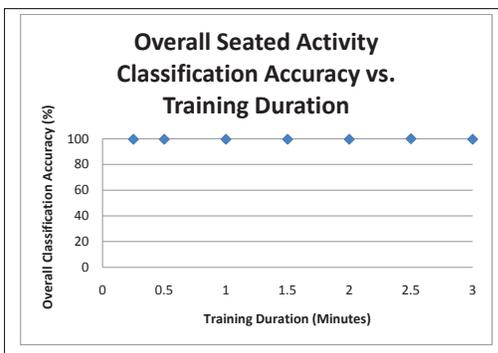**Fig. 5**. Overall classification accuracy of seated posture as a function of training duration.

Fig. 6. Overall seated motion classification accuracy as a function of training duration.

4. CONCLUSION

We have presented a system that can accurately classify daily life activities in the work place. The systematic and simple method of training that has been developed is key. The procedures developed and results obtained allow, with research on basic activities as a foundation, for the monitoring of work place physical activity. Subjects who have expressed pain or discomfort in their body would be enabled with such a system to track their daily movement and posture without any disruption to their daily life.

Further work in two main areas is desired, expanding on posture and feature selection. We have only studied the posture of the back; whether the subject is sitting at a proper angle or slouching. However, there are many aspects to posture and proper physical motion in the workplace, such as how long subjects stare at a computer monitor, the angle of the knees, whether the subject's feet are flat on the floor, the level of the arm rest, etc. With more data collected in these areas, the applications of the system would be even greater. Another interest is in feature selection. There are many possible features to compute, and many possible sensor positions. Further analy-

sis on the best features and combination of features is needed. There are also more feature selection algorithms that could be investigated, such as giving features weights that reflect their ability to differentiate between activities. In the future, we would like to test this system on various subjects for longer periods of time to gain a wider data pool for pattern analysis.

5. REFERENCES

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