A Swarm of Wearable Sensors at the Edge of the Cloud for Robust Activity Recognition

Yashaswini Prathivadi, Carl Sechen, Roozbeh Jafari
Electrical Engineering Department
University of Texas at Dallas
{yxp120330, cms057000, rjafari}@utdallas.edu

ABSTRACT

Wearable computers intelligently combine data from motion sensors placed at various locations on body with the aim to recognize human activities for the applications of healthcare and wellness. Many activity recognition algorithms for wearable computers exist today. To ensure the effectiveness of the recognition algorithms, the sensors typically have to be worn with a known orientation, since patterns of interest or templates for signal processing would be generated for that orientation. If worn in a disparate orientation, activity recognition algorithms will likely fail. We propose a technique that enables the activity recognition algorithm to function properly irrespective of the orientation of the nodes. This will provide a unique opportunity to assure the effectiveness of the recognition algorithms even when the sensors accidentally move or are misplaced. More importantly, this will enable the notion of reusing data generated in the past potentially by other users, and when the sensors are worn differently. This will eliminate the need for training the system every time it is deployed on a new user for the first time. This feature will be extremely attractive for the swarm of wearable computers capable of generating vast amounts of data. The notion of data reuse will be empowered by performing the proposed technique in the cloud infrastructure or on the wearable computers in real-time.

Keywords

Wearable motion sensors, Movement templates, Swarm of sensors, Cloud computing

1. INTRODUCTION

Activity recognition based on wearable motion sensors has several applications in healthcare, sports fitness and wellness assessment. The sensors provide data that is not only valuable for real time health monitoring but also in enabling effective longitudinal studies that uses recorded, long-term and non-reproducible data (*e.g.*, for the study of neurodegenerative diseases like Parkinson's disease).

Several commercial wearable sensors are available, such as the *fitbit Flex*, the *Jawbone Up*, and the *Misfit Shine*. These health monitoring devices can show the calorie expenditure, calorie consumption, distances walked and so forth. However, they cannot perform precise activity recognition. Several solutions already exist which perform activity recognition using dynamic time warping (DTW) [1], hidden Markov models [2], or statistics-based feature extraction techniques [3]. However, these classical methods have limitations on their effective use.

These limitations and their severity are elucidated by the following example: Joe has been diagnosed with Parkinson's disease. His doctor would like to study his movement patterns and their changes over the past 10 years to determine the onset of the disease and its progress. This could help him treat Joe and also identify similar symptoms in others and hence initiate their treatment early on. Joe was using a few wearable motion sensors and his movement data from the past 10 years have been collected. However, the sensor orientation is not known. His movement patterns now range over different orientations of the sensor for potentially the same movement. In this scenario, the classical method using DTW would not be able to perform activity recognition effectively on the data due to the following limitation:

Limitation 1: the templates needed for activity recognition are only generated for one orientation of the sensor [4]. *The sensors have to be always worn in that orientation for effective activity recognition. Alternatively one could generate and retain many templates for the same movement, but for different orientations of the sensor. This greatly slows activity recognition and requires significant computational and storage capabilities*.

Also, as the disease progressed, Joe's movement patterns changed and the data collected by his sensor now represents these varied movement patterns which the classical method using DTW was not trained to detect due the following limitation:

Limitation 2: templates cannot be generated or updated over time for changes in movement patterns due to the variations in physical capabilities of the body caused by age, progression of diseases, etc. Retraining all of the sensors for new templates for the movements takes considerable time which diminishes the ease of use and the user friendliness of the device.

The requirement is for Joe to have the freedom to wear the sensor anyway he chooses to and still meaningfully use the data thus generated. We propose an approach that addresses this requirement.

2. APPROACH

The objective for our novel approach is:

To detect movements irrespective of the orientation in which the user wears the sensor.

We addressed this objective by using advanced signal processing techniques to convert the sensor data that was in a different orientation, to the orientation in which the template was created. This technique further enables the notion of movement data reuse, generated for movements performed by a diverse group of users. These movement data can be used as templates to recognize the same movements done by any other user and do this without any dependency on the sensor orientation.

The concept of reuse of data also helps in finding similarities between movements of different individuals and more importantly in finding anomalies in the movements of the same individual which may indicate the onset of a disease. This feature has great value in early diagnosis of diseases.

The feature of reusing the data available will also facilitate the notion of eliminating training when sensors are worn for the first time for new users. In other words template generation for new movements can be performed on-the-fly without any user intervention required or specified time allotted for it.

These applications are further empowered by the notion of a swarm of sensors that has an ability to produce significant amount of data representing different movements over a diverse set of users within the swarm. The infrastructure of cloud computing further enables the swarm of sensors to be well connected and provides a unique platform for their collective and coordinated functioning in real time by providing computing and communication resources. Fig. 1 illustrates this concept.

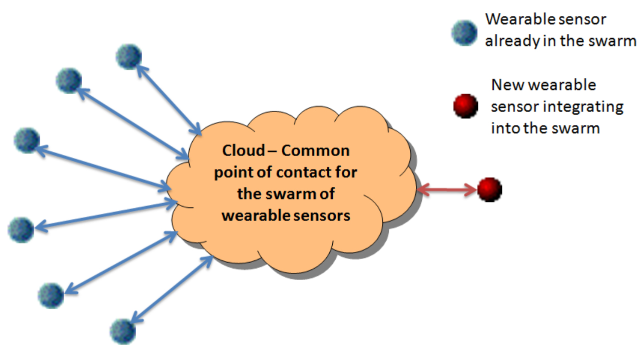
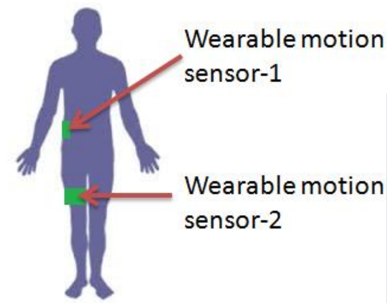


Figure 1. Swarm of wearable motion sensors at the edge of the cloud

3. EXPERIMENTAL RESULTS

For proof of concept, a database of the movements shown in Fig. 2 was built from the readings taken from several subjects all in the same age group ranging from ages 20 to 30 for simplicity. The subjects wore two motion sensors: one on the thigh and another on the waist as shown in Fig. 2 in any random orientation chosen by them.



Num	Movement
1	Sit to stand
2	Stand to sit
3	Sit to lie
4	Lie to sit

Figure 2. Table of movements and locations of wearable motion sensors

All the movement data were treated as templates. Thus there were many templates from different users for all the movements in Fig. 2 and all for various orientations. Data from eight orientations of the nodes were incorporated. A new subject was then asked to perform the same movements but with a new sensor orientation. Our new advanced signal processing techniques were then employed for orientation transformation along with using signal processing based on DTW. All the movements performed by this new user were recognized using the movement templates from the database. The precision and recall rates were 100% for all movements.

4. REFERENCES

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