Activity Recognition with mobile devices

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Abstract*—This document is a discussion on the topic activity recognition focusing on Human Activity Recognition (HAR) using mobile device accelerometers. Existing studies and papers are therefore examined and the different approaches of data collecting and processing are illustrated. For this work no separate experiments were carried out. However advantages and disadvantages of existing studies like activity recognition using a single tri-axial accelerator or using a set of multiple accelerators placed on different parts of the body are compared. What's more also current as well as future possibilities of HAR concerning the health and sports sector are reflected. As pattern detection of different human gestures is a complex task, we concentrate on just on some main activities like walking, jogging, sitting, standing, ascending stairs and descending stairs. The goal is to point out aspects that apply to the majority of world's population and their most common everyday activities. Furthermore gesture detection involves processing power which is limited on mobile devices and also battery draining. Methods like configuring sampling rate in this way help saving power and optimizing the activity recognition task. *CRITICAL: Do Not Use Symbols, Special Characters, Footnotes, or Math in Paper Title or Abstract.

***Index Terms*—Human Activity Recognition, accelerometer, movement pattern detection**

I. Introduction – Simon

Epic intro

II. Related Work – Paul

As activity recognition - especially HAR - is a popular topic, there already many studies and papers recording detection of gestures in both natural and laboratory settings as well as using regular mobile accelerometers and multiple high-performant accelerometers attached to different parts of the body.

Although the use of multiple separate acceleration sensor devices can improve results drastically up to 80% and more [1], cell phones are the easiest solution to spread the capability of measuring and classifying movement patterns. The use of smartphone sensors is not only practicable but also allows developing applications at low-cost [2].

Cell phones however are disadvantageous to the effect that the device tilt is uncertain oftentimes [2]. So sensor data for a particular movement patterns may differ from each other significantly. Under that circumstance algorithms therefore are far more complex and their results more inaccurate. In one approach for instance the orientation of the tri-axial sensor is used to distinguish between standing and sitting [3], which is not a real-world scenario for everybody as every individual user might carry the phone in a different way. As the performance of algorithms and devices have increased, the problems of phone orientation can be dealt with by now. Also wearing the sensor at different body parts is worsening the situation. Therefore a training phase combined with an Artificial Intelligence (AI) learning algorithm can help to improve detection results [1], [3]. Most studies discussing activity recognition with mobile devices usually introduce training phases for collecting sensor data. For example each individual user has a preferred way to hold the phone, like

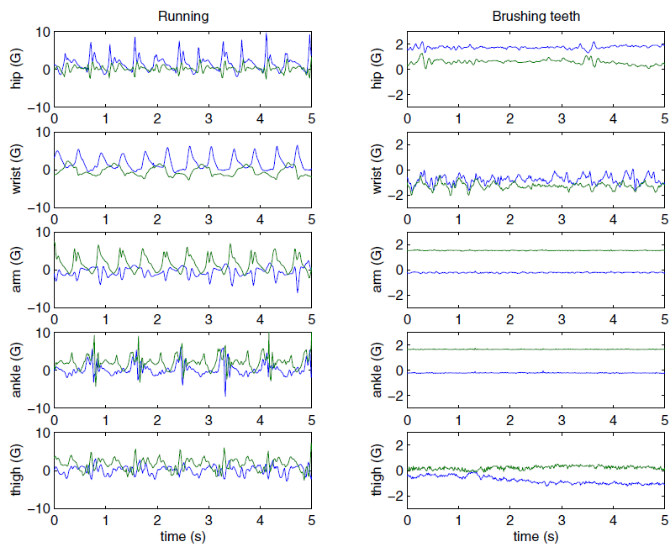

Fig. 1. As noted by Bao and Intille [1] this picture shows the use of five accelerometers placed on the described body parts. Multiple accelerometers allow more accurate detection but is also complex and only suitable in laboratory conditions when compared to mobile device accelerometers.

a chest pocket, front trousers pocket, a rear trousers pocket, an inner jacket pocket, ... [2]. This is essential as different sensor placement on the body produce different acceleration data. The experimental results show that when the sensor is placed on different rigid body, different models are required for certain activities [4].

While multi-sensor approaches focus on detecting a large set of activities [1], many studies that make use of just one triaxial smartphone accelerometer are concentrating on a smaller subset like walking, jogging, ascending stairs, descending stairs, sitting and standing which is sufficient for detecting standard activities of most people's everyday lives.

A critical point is real-time detection of gestures. Analyzing data beforehand is necessary in order to recognize certain movement patterns. Real-time capability of systems can be essential for detecting running in a sports and health application or even monitoring aged people or anyone under medical control [2]. Today's mobile devices have enough computing power to collect and detect for example a fall which as a emergency requires fast reaction. The solution of handling calculations on the mobile device is also highly scalable as no additional server is necessary for data processing [3].

Concerning feature extraction different configurations chosen in the particular studies. Ravi et al. [5] for instance collected data for a window size of about 5.12 seconds using a sampling frequency of 50Hz while Kwapisz et al. [3] divided the data into segments of 10 seconds at sampling frequency of just 20Hz. Although the settings vary from each other the extracted features almost always are similar [5]. Typical features are

- mean
- standard deviation
- energy
- correlation.

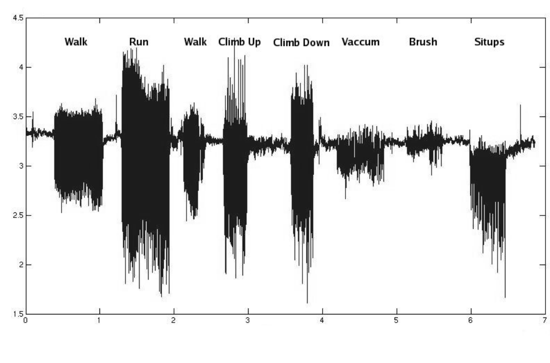

Fig. 2. A graph by Ravi et al. [5] showing the X-axis readings for different activities

Like figure 2 is suggesting activities all have a certain pattern. Of course these patterns can be distinguished from each other as this is a basic requirement for detecting different activities. Therefore activities are mapped to classes, which requires classification techniques. A common toolkit for classification is the Weka toolkit that was called into action in many existing studies. Also different algorithms of this toolkit are compared as their performance as well as accuracy differs. Common algorithms are [5]

- decision tables
- decision trees
- k-nearest neighbors
- Support Vector Machines (SVM)
- naive bayes.

Activity	Smart choice
Stand	16Hz
Walk	16Hz
Sit	16Hz
Downstairs	16Hz
Elevator up	5Hz
Elevator down	5Hz

TABLE I
SMART CHOICE OF SAMPLING FREQUENCIES ACCORDING TO YAN ET AL. [6].

As mobile devices nowadays are highly connective and come with additional sensors such as Global Positioning System (GPS) sensors, vision sensors, audio sensors, light sensors, temperature sensors or direction sensors [3], activity recognition offers even more possibilities. The availability of these technologies creates new data mining opportunities [3].

Similar to GPS sensors executing gesture detection algorithms and reading accelerometer data is also battery draining for mobile devices. Therefore energy saving on mobile devices is an essential task. An human's lifestyle consists of a sequence moderately-long lasting activities. Saving energy can for example be achieved by using different sampling frequencies. The choice of both accelerometer sampling frequency and the classification features are essential [6]. There are is a set of recommended frequencies for basic activities as shown in the following table:

As stated in table I sampling frequencies for many basic activities like standing, walking or sitting are equal. This simplifies things as the sampling frequencies have to be adapted in real-time to always keep the situation optimal. The algorithm developed by Yan et al. [6] shows that for users running the A3R application on their Android phones savings of 50% under ideal conditions and overall energy savings of 20-25% can be achieved.

A. *Subsection blabla*

subsection

III. Evaluation – Simon

A. Results

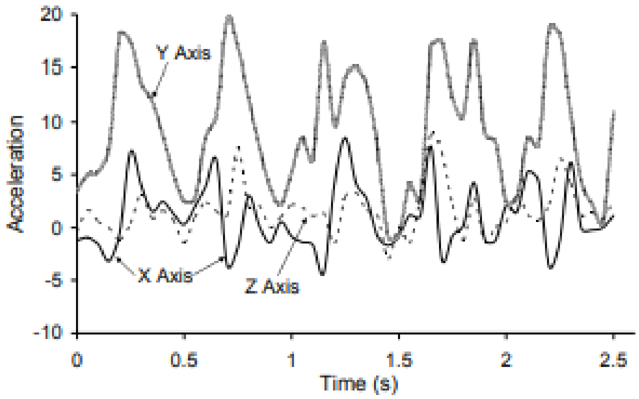

Fig. 3. Walking

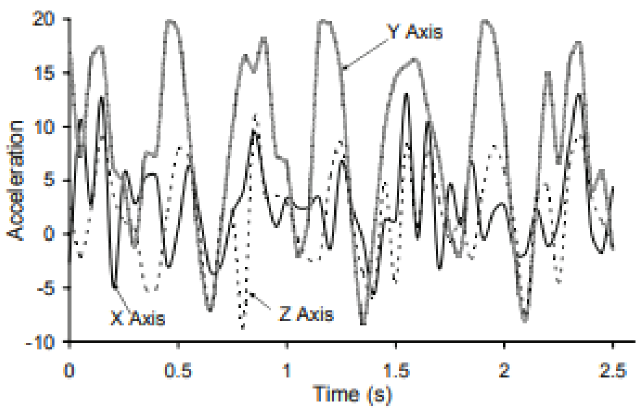

Fig. 4. Jogging

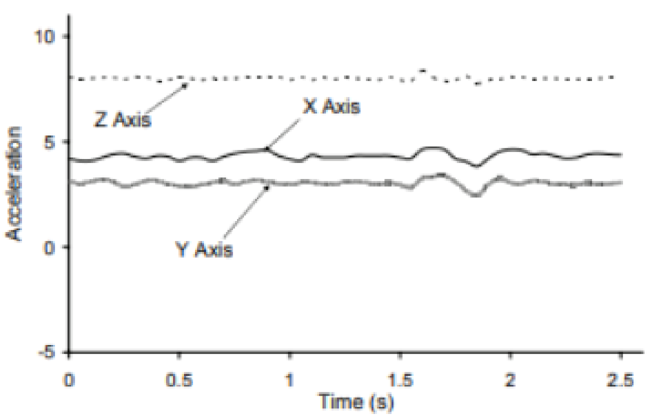

Fig. 5. Sitting

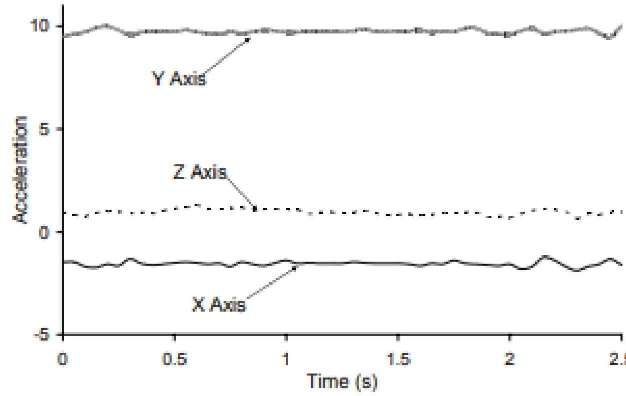

Fig. 6. Standing

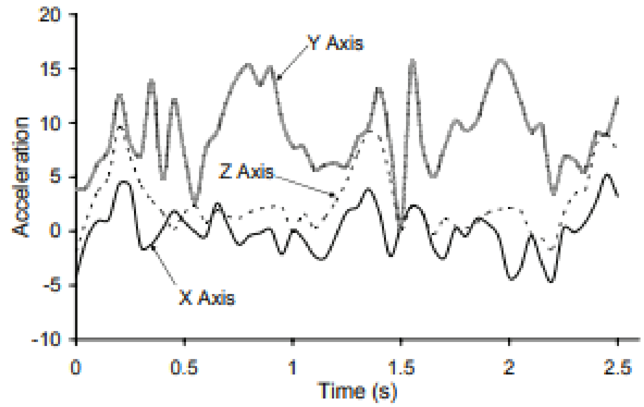

Fig. 7. Ascending Stairs

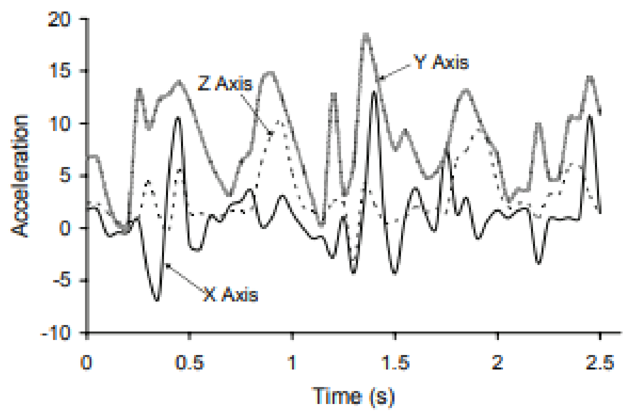

Fig. 8. Descending Stairs

B. Analysis

TODO some analysis shit

IV. Conclusion – Paul

The use of smartphones for activity recognition is appropriate to achieve a high number of users, however it not the most accurate approach. Smart wearable devices are getting more popular, which could allow the use of multiple sensors increasing accuracy of gesture detection. As there is a large variety of such wearables and the majority still owns one single cell smartphone, attaching multiple accelerometers on different parts of the body generally is not a natural use-case. We think that focusing on a high number of users by concentrating on evaluating just smartphone sensor data is significant, as the goal is to give as many people as possible access to the technology of activity recognition. Cell phone accelerometer data still can be enhanced by developing more sophisticated software processing sensor data and learning user behaviors, so that a basic set of gestures like walking, standing or climbing stairs can be detected maintaining a low error rate while keeping the number of users at an upper level. Although activity data is sensitive information for each individual user, it is valuable for statistical researches. By obtaining movement patterns of a high number of users many different insights of the world's population can be won. This would also contribute in improving a persons lifestyle, for example by helping him find an appropriate amount of exercise. As smartphones are highly connected to the internet this process can be automatized and reported to the user in real-time. Also comparing activity data between users might increase the willingness of people doing sports and prevent medical risks.

Could be important for the health, aging, monitoring people under medical control

List of Abbreviations

AI	Artificial Intelligence
GPS	Global Positioning System
HAR	Human Activity Recognition
SVM	Support Vector Machines

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