Activity Recognition with mobile devices

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Abstract—**This document is a model and instructions for LaTeX. This and the IEEEtran.cls file define the components of your paper [title, text, heads, etc.]. *CRITICAL: Do Not Use Symbols, Special Characters, Footnotes, or Math in Paper Title or Abstract.**

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

I. INTRODUCTION – SIMON

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intro

II. Related Work – Paul

As activity recognition 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 3 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 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 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]. As mobile devices nowadays are highly connective and come with additional sensors such as 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].

A. Subsection blabla
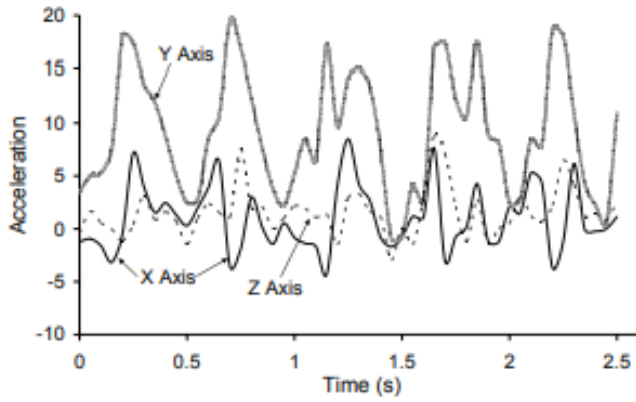
subsection

III. Evaluation – Simon

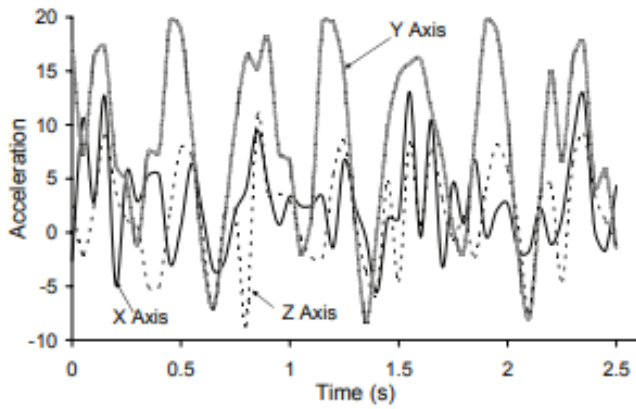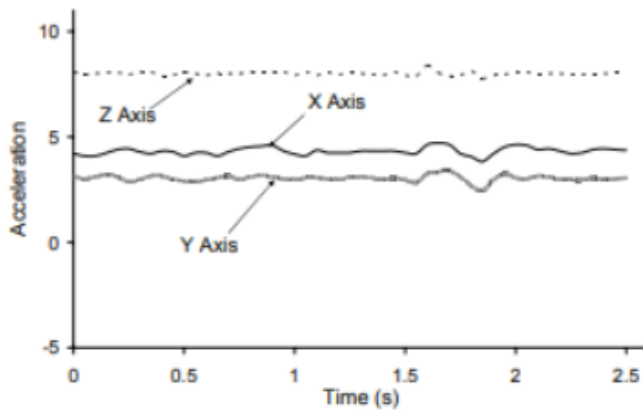### A. Results

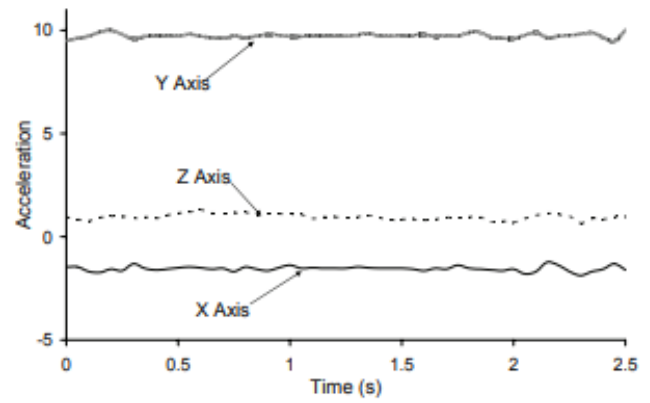Fig. 1. Walking

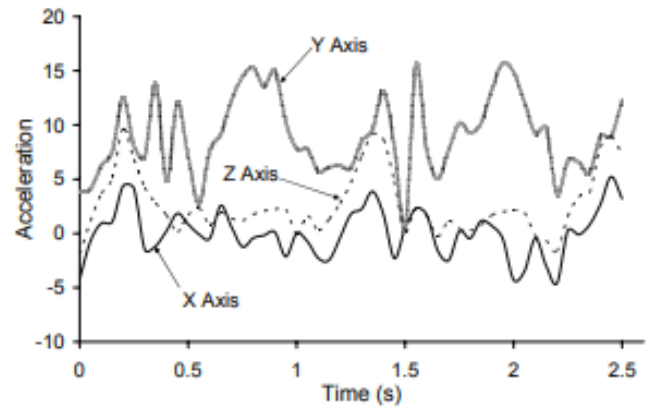Fig. 2. Jogging

Fig. 3. Sitting
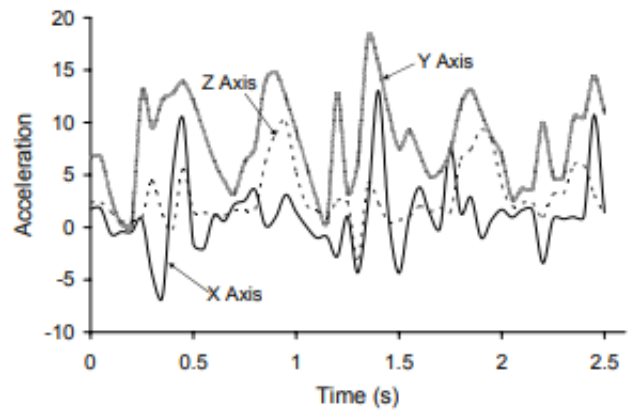

Fig. 4. Standing

Fig. 5. Ascending Stairs

Fig. 6. 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

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TODO Abbreviations

REFERENCES

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[2] Tomas Brezmes, Juan-Luis Gorricho, and Josep Cotrina. Activity recognition from accelerometer data on a mobile phone. In *International Work-Conference on Artificial Neural Networks*, pages 796–799. Springer, 2009.

[3] Jennifer R Kwapisz, Gary M Weiss, and Samuel A Moore. Activity recognition using cell phone accelerometers. *ACM SigKDD Explorations Newsletter*, 12(2):74–82, 2011.

[4] Apiwat Henpraserttae, Surapa Thiemjarus, and Sanparith Marukatat. Accurate activity recognition using a mobile phone regardless of device orientation and location. In *Body Sensor Networks (BSN), 2011 International Conference on*, pages 41–46. IEEE, 2011.

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