Activity Detection Using Frequency Analysis and Off-the-shelf Devices

Fall Detection from Accelerometer Data

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Abstract— **Increasingly, applications of technology are being developed to provide care to elderly and vulnerable people living alone. This paper looks at using sensors to monitor a person's wellbeing. The paper attempts to recognise and distinguish falling, sitting and walking activities from accelerometer data. Fast Fourier Transformation (FFT) is used to extract information from collected data. The low-cost accelerometer is part of a Texas Instruments watch. Our experiments focus on lower sampling rates than those used elsewhere in the literature. We show that a sampling rate of 10Hz from a wrist-worn device does not reliably distinguish between a fall and merely sitting down.**

Keywords-Activity Detection, Fall Recognition, Accelerometer, Remote Healthcare Delivery

I. INTRODUCTION

The number of elderly people who could benefit from the remote delivery of healthcare is rapidly increasing [1], so developments in this area could have a major benefit on the standard of care. This paper looks at ways in which we can use accelerometer data to recognise certain activities that would be useful in delivering remote care for the elderly. By successfully recognising what activity a user is doing, such as distinguishing between walking and falling, it is then possible to monitor their wellbeing and give care in an emergency situation. Improving fall detection methods would be extremely beneficial to the elderly population.

Can we use accelerometer data successfully to recognise different activities? "An accelerometer is an electromechanical device that will measure acceleration forces. These forces may be static, like the constant force of gravity pulling at your feet, or they could be dynamic - caused by moving or vibrating the accelerometer"[2]. Accelerometers are able to measures forces and then transform these forces into data through X, Y and Z axes. Accelerometers are increasingly found in devices (e.g. mobile phones [3]), many of which are capable of supporting remote care delivery. The activities that will need to be recognised are falling, sitting down and walking.

The literature shows several studies by groups attempting to recognise falls from accelerometer data, however reliability and accuracy levels are still a problem [4]. This may be related to sampling rate.

Maurer et al. [5] used 15-20Hz and achieved recognition accuracy rates of up to 90%. A 90% recognition rate means that when a user is performing an activity (e.g. walk or run), then their method will successfully recognise the activity 90% of the time. Ravi et al. [4] and Pärkkä, Cluitmans and Ermes [6] use 50Hz for the sampling rate. Preece et al. [7] also use a high sampling rate of 64Hz, however there are certain issues using extremely high sampling frequencies which are that even the smallest movement can have a significant effect on the data. Preece et al. [7] say that at least 20Hz is needed for successful recognition of activities from the data; however Maurer et al. have already had success with lower rates than 20Hz.

Previous studies have all used sampling rates over 15Hz, but this paper investigates whether successful recognition can be achieved with cheap "off the shelf" components using a sampling rate of 10Hz. 10 samples per second should be fast enough to capture the necessary amount of data, yet slow enough not to capture unnecessary noise and anomalies.

We used two-minute sections of data to see if activity recognition can still be achieved by having larger amounts of data. Whilst performing the different experiments it was important for the accelerometer to start in the same orientation, and show consistency between the tests. The lack of consistency of the orientation could lead to possible recognition problems. Maurer et al. developed a method of reducing the influence of orientation by ensuring it is consistent throughout the tests. *"To reduce the dependency on the orientation, both X and Y values were combined calculating the squared length of the acceleration vector"* [5]. There is a possibility of using just one axis rather than three. This would have the benefit of reducing the complexity of the data and the correlation aspects. Pärkkä [6] used only the vertical direction of the 3-axis accelerometer and had successful recognition results.

We hypothesise that falling will show a clear peak in the frequency domain and it will be possible to differentiate the fall from the activity of sitting down. It is also expected that walking will show repeatable patterns due to the fact that an arm swing is a continuous repeatable action that will be represented in the frequency domain with a low frequency component.

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II. METHOD

A. Equipment and processing

The hardware requirement was to use inexpensive off-the-shelf components. We used a Texas Instruments eZ430-Chronos 868 MHz development watch with altered firmware (customised to achieve equal time spacing between the accelerometer samples). The watch samples the X, Y and Z axes each 1/10th of a second, and each transmitted packet is consecutively numbered. The watch was attached to the subject's wrist. To guarantee consistency between tests, the accelerometer was worn in exactly the same position, ensuring the axes were always pointing towards the same way. Two of the authors (SB and CC) were used as the experimental subjects.

Data was gathered using a software application (developed in C# using the C# Chronos.Net Library) that communicated with the Chronos USB RF receiver. The data was requested every 100 ms from the receiver, and then stored in an XML file and later processed and visualized.

Processing consisted of a Fast-Fourier transformation (FFT) of the whole data set. The transformation from the time domain into the frequency domain was expected to show features of the data set that were not otherwise visible before. Noise is present in the data and needs to be acknowledged in the data analysis.

B. Experiment procedure

We focused on three main activities: walking, sitting down and falling. Each activity test lasted for 2 minutes (chosen arbitrarily) and was repeated 10 times for each of the two test subjects. This means that 20 different data sets for each activity were available for the data processing. It was hypothesised that this will provide enough data to form a consistent pattern in the analysis stage. For the walking experiment, the test subjected walked in a circle, allowing their arms to swing freely. For the task of sitting down, a standard office chair was used with a height of 40 cm. The fall experiment had to be designed in such a way that the test person did not hurt himself. For that reason we had the person “trip” and fall facing the floor, so that it was possible to use their hands to soften the impact.

III. RESULTS

The experiments produced 60 different datasets. Each of the datasets were analysed, however only one from each activity is presented due to space constraints of the paper. This paper will not discuss the raw data, because each activity resulted in over 1000 single data points for each axis and is more meaningfully presented in a graph.

A. Walking

The first experiment conducted was walking. It was expected to be the simplest activity and show the most peaks in the time domain. In the time domain, the free swinging of the arms was likely to be projected as an oscillation, while the frequency domain should have a component in the lower area corresponding to the oscillation frequency.

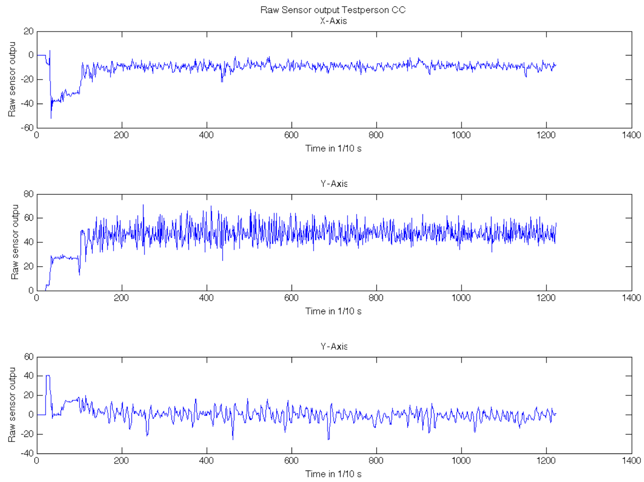

Figure 1. Walking Time Domain

Figure 1 shows the raw data of a walking experiment, presented in the time domain. The test started from time 150 onwards. The three graphs show the X, Y and Z axes that were monitored. During the experiment the oscillation is only marginal. Comparing the time domain with the other collected data sets from the walking experiments show similar behaviour. The expected arm movement was not visible. Using FFT the data was transformed from the time domain into the frequency domain (see Figure 2). For walking experiments no particular frequency component could be detected. The frequency components from 0–5 Hz are equally distributed with no high peaks. After reviewing further walking data, these peaks were evident throughout.

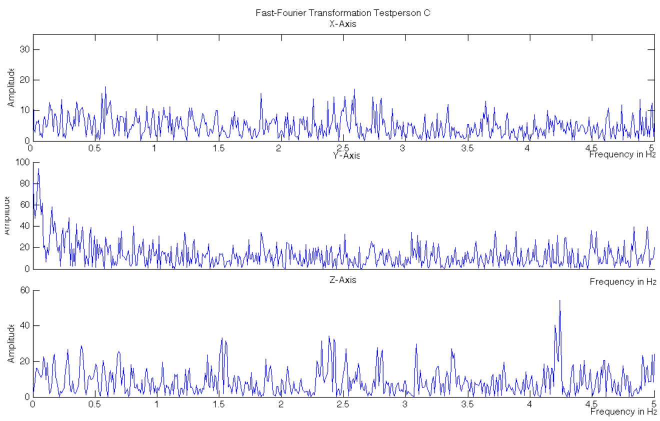

Figure 2. Walking Frequency Domain

B. Sitting

The next step was to perform the activity of sitting. The motion of sitting down and falling can look very similar in the time domain but each should be distinguishable from the other. Figure 3 shows the accelerometer data from a sitting down experiment in the frequency domain.

The movement evident at the beginning of the experiment is part of the movement to activate the RF link and is not relevant to the experiment. The activity of sitting down starts at the time 700. An increase in the acceleration can be seen for all three axes. The movements after this are the subject on the chair.

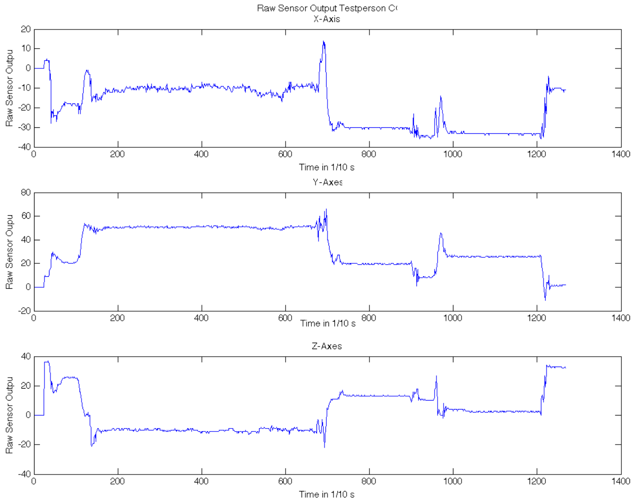

Figure 3. Sitting Time Domain

Figure 4 shows a high detail view of the activity in the time domain. A clear acceleration was detected in the X axis while the Y and Z axes only change slightly. The activity of sitting down occured in the time frame of 8-10s.

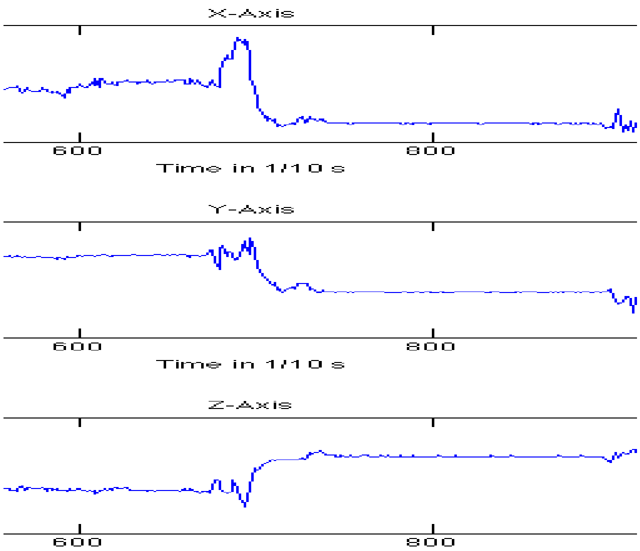

Figure 4. High Detail View of Sitting Time Domain

Transferring the data into the frequency domain is shown in Figure 5.

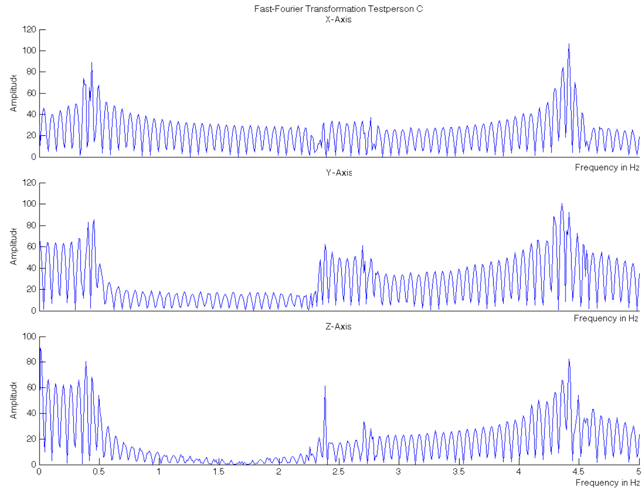

Figure 5. Sitting Frequency Domain

In the frequency domain, two main peaks can be detected in this data set. One peak is at 4.5Hz and another at 2.5Hz. The peak at 4.5Hz was also evident in the other data sets at slightly different frequencies (ranging from 4 – 4.5Hz).

C. Falling

The last activity was falling. While the motion is similar to sitting down, the hypothesis stated that it should look different, once transformed to the frequency domain.

In Figure 6 the time domain data is presented. The fall occurred at 800 on the timescale. The movements before this time point are random movements of the subject.

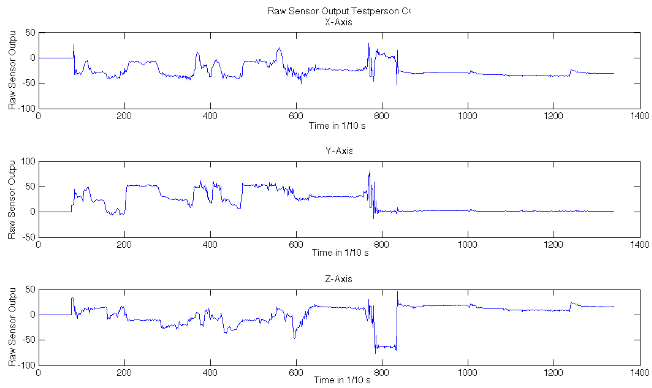

Figure 6. Falling Time Domain

While looking at the activity of falling in more detail (Figure 7), similarities to the sitting activity can be observed (compare Figure 4). Strong acceleration was evident in the X and Z axes while the Y axis only had weak changes.

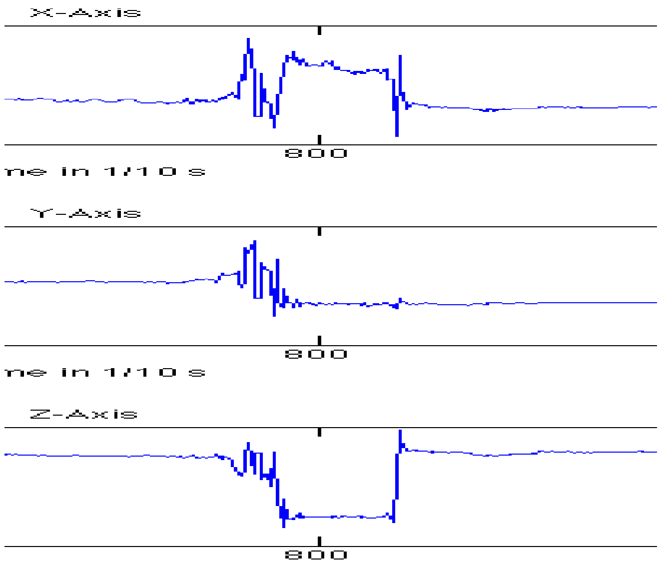

Figure 7. High Detail View of Sitting Time Domain

Figure 8 shows an FFT from the falling experiment. The same peak at 4.5Hz can be detected. This is the same as the sitting down experiment (compare Figure 5). Some of the other FFTs for this experiment also show a small peak at around 1.5Hz. So a clear distinction between the two activities of sitting down and falling cannot be guaranteed.

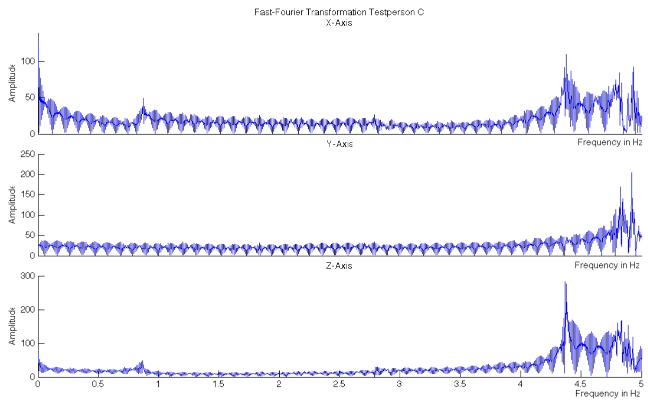

Figure 8. Falling Frequency Domain

IV. Discussion

Looking at the data samples of the test, it is not possible to accept the stated hypothesis. However, it is possible to distinguish between the activities of walking (on the one hand) and falling/sitting down (on the other). The problem lies in the differentiation between falling and sitting. While one activity is part of normal daily life, the other is not and therefore needs to be treated as an emergency situation.

The Fast-Fourier Transformations of the sitting down and falling datasets show peaks in the frequency domain. This confirms that sitting down and falling have a different spectrum from walking. This gives us encouragement to investigate variations in processing parameters and methods. From the recorded data it is only possible to view the acceleration - the orientation is not known. This aspect of an accelerometer was not foreseen but will be addressed in future work. The accelerometer is liable to be worn in slightly different orientations between tests and individuals; therefore the starting orientation of the axis will change during the experiments. This could be a possible reason for the lack of successful recognition whilst analysing the data. This issue is currently being investigated. Additionally, we have a second watch and are experimenting by wearing it at the waist. Future analysis will involve integrating the data from the two devices.

Another avenue which is being explored is the processing of the collected data using a moving window approach. In this, only the last few seconds will be used for the FFT. Huynh and Schiele recommend the optimum length of a window should be 1-2 seconds[8]. Future work will look at reducing the momentary window size and comparing the findings. We also envisage taking a heuristic approach, where classification of the different activities will be carried out using data mining methods such as neural networks or fuzzy logic algorithms. Further work will also include a solution to the missing acceleration orientation.

V. Conclusion

The work and results presented are encouraging and point to the possibility of using inexpensive sensors to categorise and recognise human activities successfully, including falling. In summary, it is not fully possible to use accelerometers on the wrist as reliable fall detectors at this time. Using one accelerometer, it is not possible to differentiate between a normal situation and a serious fall.

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