ABSTRACT

Elderly people are prone to fall due to the high rate of risk factors associated with ageing. Existing fall detection systems are mostly designed for a constrained environment, where various assumptions are applied. To overcome these drawbacks, we opt to use mobile phones with standard built-in sensors. Fall detection is performed on motion data collected by sensors in the phone alone. We use Genetic Programming (GP) to learn a classifier directly from raw sensor data. We compare the performance of GP with the popular approach of using threshold-based algorithm. The result shows that GP-evolved classifiers perform consistently well across different fall types and overall more reliable than the threshold-based.

Keywords

Fall detection, genetic programming, mobile sensing

1. INTRODUCTION

Automatic fall detection could enable timely rescue and follow-up to minimize possible negative impacts of the fall. Literature on fall detection research can be broadly divided into three categories, namely wearable device based, ambience sensor based and vision based. Almost all techniques require manually designing a feature set.

With the ubiquitous uptake of smart phones, there has been increasing interest in exploiting their sensing capabilities. Most mainstream consumer phones now come with built-in sensors, originally for user interface enhancement. Various human activities can be inferred from the phone sensor data.

We propose a learning based approach for fall detection. Our technique does not require manually setting thresholds or strenuously composing feature sets. The learning process is expected to find the discrimination rule to separate falls from non-falls (normal activities). The method is based on Genetic Programming (GP), a powerful evolutionary learning method. We enable GP to work directly on raw sensor data of the accelerometer, gyroscope and magnetometer. Three fall types, specifically fall while standing, fall while walking and fall while sitting, are investigated. We perform experiments with two phone placement options, those are tight pants pocket and loose pants pocket.

2. RESEARCH ON FALL DETECTION

Most of the studies on fall detection are based on thresholding data collected from one or more inertial sensors. The most common type of sensor used is accelerometer. Threshold-based approaches are prone to high false alarms, especially when fall-like events are present.

More sophisticated systems employ context-based reasoning methods to eliminate false positives. For example, location sensor data can be used to work out where the event happens [3]. This helps to differentiate a dramatic fall on the floor with a normal quick lay down on the sofa.

Machine learning has been used for fall detection in place of manual thresholding [1] or in conjunction with thresholding to increase accuracy [4]. To the best of our knowledge, GP has not been used for detecting falls before.

3. GP METHODOLOGY

GP is a global search technique inspired by biological evolution. The basic process of GP training involves generating an initial population of computer programs to solve the problem at hand. A fitness function is used to evaluate each program individual, and the better-performed programs are chosen to undergo genetic operation to create the next generation. This iterative process ceases when a terminating condition is met, in this case, a solution with 100% accuracy is found or the maximum number of generation is reached. Details of the GP representation used in this study can be found in our early work [6].

4. EXPERIMENTS AND RESULTS

For each fall type, we collected 20 falls for training and 20 falls for testing. All falls are simulated by a male in his 20s with floor contact on a mattress. Between the falls, the subject performs other activities of daily life such as walking and running. Table 1 provides some statistics of the data collection. We sample the data at 10Hz and use sliding windows of size 12, overlapping by 1. These values are decided empirically.

For comparison, we implemented the popular threshold-based method similar to the one described in [2] and [5]. The threshold setting is based on the assumptions that the phone
has undergone a large acceleration and rotational change during a fall.

Table 1: Data collection summary

<table>
<thead>
<tr>
<th>Number of subject</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensing medium</td>
<td>Samsung Galaxy S4 GT-I9505 HTC One</td>
</tr>
<tr>
<td>Sensor type</td>
<td>Accelerometer Gyroscope Magnetometer</td>
</tr>
<tr>
<td>Sensor placement</td>
<td>Loose front pant pocket Tight front pant pocket</td>
</tr>
<tr>
<td>Fall type</td>
<td>Stand-fall: Fall while standing Walk-fall: Fall while walking Sit-fall: Fall from the chair</td>
</tr>
</tbody>
</table>

Table 2 displays the test result for the GP approach and threshold method. In terms of performance metrics, we report accuracy (Acc.), True Positive rate (TP) and True Negative rate (TN). We found the performance of the threshold technique deteriorates in the presence of sudden stop events. When the phone is placed in the loose pant pocket setting, which introduces noise as the phone can enjoy some degrees of movement, GP outperforms threshold method.

5. CONCLUSION AND FUTURE WORK

We have shown that reliable fall detection can be achieved with GP. GP work directly on raw sensor input and does not rely on manually selected features. This means the requirement for human expert intervention can be minimised. For future works, we would like to investigate the reliability of our method on more fall scenarios and with more participating subjects.

6. REFERENCES