Exploiting IMU Sensors for IOT Enabled Health Monitoring

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ABSTRACT

Inertial Measurement Units (IMUs) embedded in commercial mobile devices are a good choice for continuous monitoring in healthcare domain due to their attractive form factor and low power consumption. We present improved and accurate sensing algorithms using a single IMU to sense basic events like step count, stride length, fall, immobility etc. Our algorithms have been shown to perform better than the state of the art algorithms, and are implemented in such a way that IMU is not bound to any specific position or orientation with respect to the user. We propose a 3-layer based framework for a complete end-to-end system architecture for IoT enabled health monitoring, useful for application in areas like individual fitness monitoring and elderly care.

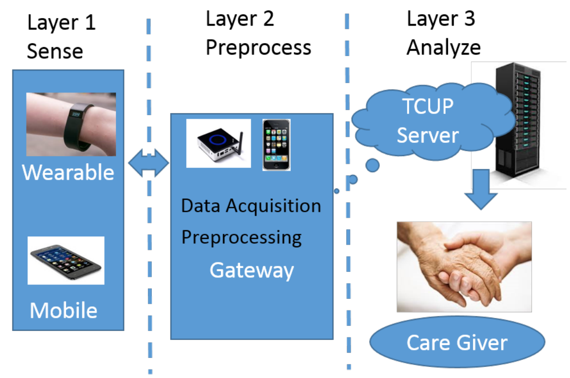

Figure 1: System Architecture

1. SYSTEM ARCHITECTURE

Figure 1 depicts the proposed system architecture. Layer 1 serves as a sensory system comprising of an IMU sensor, either embedded in wearables or found in smartphones. The sensed signals are preprocessed and forwarded by a gateway system (layer 2) to a cloud based repository (layer 3). The smartphone itself may act as a gateway, or a separate hardware can be used for this purpose. Layer 3, the cloud environment, can be built on TCUP [2] or similar platform which has provisions for data security, multi-patient, multi-sensor time-series data analysis. The system can be used in elderly monitoring or for individual fitness purpose. However, in this work we mainly concentrate on layer 1.

2. EVENT DETECTION ALGORITHMS

In this paper we investigate four basic events namely *fall*, *immobility*, *step count*, and *stride length*. Fall detection plays an important role in elderly monitoring scenario. Higher level events like *calories burnt* can be deduced from step count and stride length data, as discussed in section 2.5, which plays a crucial role in tracking individual fitness.

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2.1 Fall Detection

The algorithm is outlined in Figure 2. Our method shows a substantial improvement on mobifall dataset [10] with an average sensitivity of 0.855 when compared to the method by Sposaro and Tyson [9] standing at 0.51, Dai et. al. [6] at 0.44, and He et. al. [7] at 0.64, for falls including forward lying, side lying, and front knees lying from the dataset.

2.2 Immobility Detection

Immobility or inactivity after a fall is an alarming condition especially for ageing subjects or for chronic patients. Using standard deviation of acceleration with 50% overlapping windows as feature for a Support Vector Machine (SVM) classifier, we achieved an F-Score of 0.99 after testing the algorithm on 5 subjects ($2min$ normal activity + $1min$ inactivity).

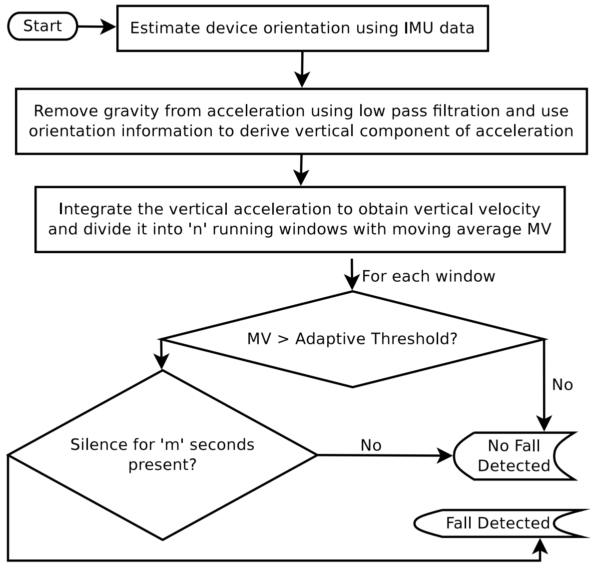

Figure 2: Fall Detection Flowchart

2.3 Step Count

For an accurate step count, we adopt our previously published work, AcTrak [5] for mobile devices, which provides an accuracy of 95% for step count, and has been tested on random orientations and placements (shirt pocket, trouser's front/back pockets) of the device.

2.4 Stride Length and Distance Estimation

Distance traversed can be estimated by summing up stride lengths of individual steps. We improve the existing stride length method of Li et. al. [8] by devising Equation 1, which eliminates the need of per-user training (as done in [8]) for an accurate stride length by including the height factor of the user.

$$StrideLength = (a_{A_i} \times SF) + \left(\frac{d}{c} \times H\right) + (b_{A_i} - d) \quad (1)$$

where $A_i \in \{Walking, Brisk\ Walking, Running\}$, SF is the step frequency, and H is the subject's height in cm. The three activities in A_i are categorised using AcTrak system [5]. 20 subjects (15 for training, 5 for testing) in age group of $20 - 40$ years and height between $160 - 180$ cm, performed these three activities for a distance of $40m$ while carrying the phone in pockets/hand in random orientations. The parameters a_{A_i}, b_{A_i}, c and d were estimated using linear regression over data collected from 15 users. The peak error yielded by our method while walking ($3.5cm$ per step) is less than that by Alzantot et. al. [4] ($5.9cm$ per step), assuming first $100s$ from the published data results by Alzantot et. al. [4], and a normal walking speed. For all the three activities, our method showed an average error of mere $3.7cm$ per step tested on 5 users (different from the training set) of varied demographics.

2.5 Calorie Estimation

We first estimate the user's walking speed using the total distance traversed (section 2.4). We then use Metabolic Equivalent intensity levels (MET)[3] to map this speed to the corresponding MET value, M. Then the calories expended, C, for user with weight W kg during the window of I seconds is given as:

$$C = M \times 1000 \times W \times \frac{I}{3600} \quad (2)$$

Our method yielded and average accuracy of 99% when benchmarked against the Nike+ [1] app installed in an iPod, which the 5 test subjects carried along.

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