A Neural Network Based Fall Detector

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Abstract

In this project we present an intelligent fall detector system based on a 3-axis accelerometer and a neural network model that allows recognizing several possible motion situations and performing an emergency call only when a fall situation occurs, with low false negatives rate and low false positives rate. The system is based on a two module platform. The first one is a Mobile Station (MS) and should be carried always by the person. An accelerometer is implemented in this module and its information is transferred via a radio-frequency channel (RF) to the Base Station (BS). The BS is fixed and is connected to a GSM (Global System for Mobile communication) module. A neural network model was built into the BS and is able to identify falls from other possible motion situations, based on the received information. According to the neural network response the system sends a SMS (Short Message Service) to a destination number requesting for assistance.

1. Introduction

Statistics prove that falls or emergency situations that lead to a fall in elderly people or critical groups are frequent. In some cases these groups live alone so there is no one to do the emergency call to assist them. Sometimes the lack of assistance can be fatal or lead to dramatic physical consequences. The faster medical assistance could be provided, the better are the chances of recovery or survival. In this context an automatic intelligent fall detector that executes an emergency call to a phone number or sends an SMS to someone that can perform the emergency call is very useful.

There are already some devices that realize similar functions [1]. However, its implementation is almost every time based on direct sensor information (like tilt sensors or infra-red detectors) that could lead the system to confound other situations to falls and perform false emergency calls.

2. System Architecture

The system is based in two modules: the BS and the MS. The Mobile Station integrates a three axis accelerometer as motion sensor, a microcontroller unit (Parallax Propeller with 8 processing cores) and a transceiver device to perform the communications with the BS (Figure 1).

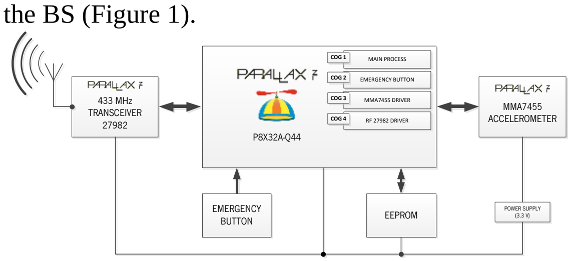

Figure 1 – Architecture of the Mobile Station.

The BS has the same microcontroller as the MS unit, a transceiver to receive data sent by the MS and a GSM module to perform the emergency call (Figure 2). The neural classifier was implemented in this microcontroller using C language.

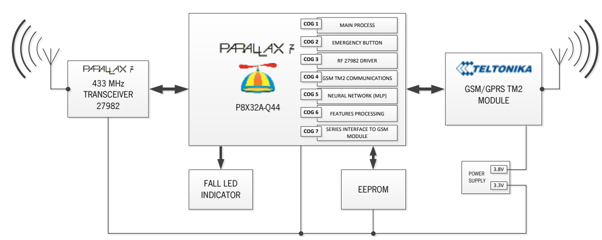

Figure 2 – Architecture of the Base Station.

3. Features Extraction and Neural Classifier

To accomplish the objective of this work, the system has to be able to distinguish several motion patterns. Basically, the system needs to learn the patterns that are associated to a fall situation and the patterns associated to other activities. To do so, it must go through a training phase during which several different situations are presented to the system (including fall and non-fall situations). During the training, the system must learn the main features present in each situation in such way that, after this phase, it will be able to classify a new motion as a fall or non-fall situation. Samples of several different motion cases were acquired, namely walking, fall situation, sit down, walk on all fours, etc. A fall signal example is represented in Figure 3. The graph evidences the acceleration (G) values for three axes, which were acquired using the system developed in this work for a period, started by a trigger G value, of 4s with a total of 240 samples.

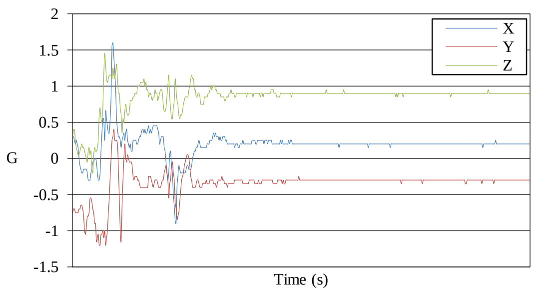

Figure 3 – Fall signal samples for a period of 4 seconds.

The feature-processing module is responsible for reading the acceleration samples that are received in the Base Station unit. Moreover, the feature-processing module has to extract features from those samples, namely the average acceleration of each axis and the acceleration average variance of the three axes. Those features allow minimizing the neural network dimension and the size of the examples set. Consequently, they improve the neural generalization capacity and speed up the whole process.

The feature module splits the frame, containing the 240 samples, in two windows: the first window is smaller and corresponds to the first sampling second (60 samples); the remaining samples are embedded in the next larger second window. With this scheme the initial moments of a motion are better perceived which is very important as those moments are most significant in a fall event at that period. The average acceleration in each axis and the average variance of the three axes are calculated independently for each sampling window. Therefore, from each window four features are extracted, resulting in eight features by example (motion). The average is referred to a length of 60 samples in the sampling window1 and to a length of 180 samples in the sampling window2.

These features are used to train a Feed-Forward neural network. The training algorithm used was the Backpropagation based in the gradient descent [2]. After the training phase, the features are also acquired on-line using the RF modules, and the neural classifier will set its output to a value informing about the class pattern (motion) (1: fall or 0: not fall) of that features.

Several runs were performed using different structures for the neural network model and the best classification results were obtained using the following architecture (Figure 4) of the neural classifier (multilayer perceptron): input layer: 8 nodes, a unique hidden layer: 4 nodes, output layer: 1 node, activation function: hyperbolic tangent, training algorithm: Delta-Bar-Delta [3].

The number of examples that were produced to form the motion patterns set was 763. The first half part of this set is formed by acceleration patterns concerning the fall class and the other part is concerning the non-fall class. These patterns were acquired asking to seven persons to perform different motion situations.

The training process was stopped when the validation set, regarding a cross validation strategy, starts revealing an increase in its Mean Square Error (MSE) value.

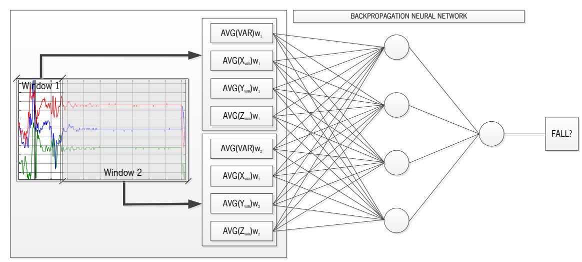

Figure 4 – Classifier architecture.

4. Conclusions

The best training run reached a 0.0036223 MSE value. The trial performed using the test set shown a generalization performance that allows using the system in a real scenario. For the total performed tests the system was able to identify all the falling situations correctly. However, it is necessary to refine the classifier in order to reduce the false positives cases (15% FP @ 0% FN), where the system is recognizing non-fall motions as falls.

5. References

[1] Qiang Li, *et al.*, *Accurate, Fast Fall Detection Using Gyroscopes and Accelerometer-Derived Posture Information*, Proceedings of the 2009 Sixth International Workshop on Wearable and Implantable Body Sensor Networks, pp. 138-143, 2009.

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[3] Robert A. Jacobs, *Increased Rates of Convergence Through Learning Rate Adaptation*, Neural Networks, Vol. 1, pp. 295-307, 1988.