

A NEURAL NETWORK-BASED SENSOR FOR ELDER FALLING DETECTION

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Abstract: Falling down is going to be a crucial problem to an elder today. In many countries, unintentional injury was being one of the leading causes of death in persons over age 65 years. As the society now, there are more and more solitary elders of life alone and because of the isolation, it is necessary to design an intelligent and sensitive falling detector for the elderly people. In this paper, we present an intelligent and portable fall detection device based on artificial neural network technology. This fall detector consists of two main components: accelerometer and microprocessor. The tri-axis accelerometer is used to continuously measure the variation of elder's 3 ways acceleration. The microprocessor reads the signals from the accelerometer and performs the fall activity recognition through a back-propagation neural network model. This device is integrated in a small box which can be holding on the belt for elder.

1 INTRODUCTION

Approximately 20% to 30% of elderly persons over age 65 years fall each year, and this rate of falling increases with age (Tinette, 1994). Therefore, the falling has become a crucial problem of public health and clinical problem among elderly persons. As reported by (Doughty, 2000; Blake, 1992), falls may lead to injury, fear of falling again, or traumatic death. In many countries, unintentional injury was being one of the leading causes of death in persons over age 65 years (Haga, 1986; Tinette, 1994). In general, a typical homecare emergency service model for elder fall consists of four basic phases: (1) discovering the fall event; (2) communicating the call centre or hospital for requesting an emergency service; (3) the call centre dispatch an ambulance to the elder's house; and (4) rescuing the elder. It is obviously that all the activities of emergency service are derived by discovering the elder falling down. Therefore, as soon as possible to discover the fall accident can effectively reduce the risk of death for elder.

However, as the society now, there are more

and more elders choose solitary life or have only oneself at home alone in the daytime. It makes the discovery of fall accident more difficult. Therefore, the objective of this paper is to develop an automatic and intelligent fall detector. This fall detector consists of two main components. First, the tri-axis accelerometer is used to continuously measure the variation of elder's 3 ways acceleration. Second, the microprocessor reads the signals from the accelerometer and performs the fall activity recognition through a back-propagation neural network model. The incident that if fall, the microprocessor unit will immediately alarm the nearby persons to help quickly.

2 RELATED WORK

The simplest detection approach is that passive to find the fall event. That is, when the elder falling down, it needs the elder oneself to push a button on the device to alarm the nearby person. The main drawback of such devices is that need a human to initiate the alarm. It will be useless when the elder is

unconsciousness.

Another type of detection approaches is that active to detect the fall event. The active detection approaches can be further classified as portable (personal worn device) and positioned (environmental build-in):

1. Positioned fall detector: Equipments such as video cameras or sensors are positioned on particular places to detect the fall event. For examples, Williams et al (Williams, et al, 1998) put the vibration detector and posture sensor on the floor to detect the fall event. Yamaguchi (Yamaguchi, 1998) has place the infrared sensors on the door of bathroom to detect the time spent in bathroom. However, due to the sensors are fixed on the environment, it will unworkable when the elder is out of the detectable area.

2. Portable fall detector: The sensors integrated with the microprocessor which having the fall decision algorithms embedded into a small box or on a cloth. For examples, Noury (Noury, 2002) measures the vertical acceleration, posture, and physiological vibrations by different sensors. After a level triggering, a Boolean data is generated for the position, fall, and vibration which is further interpreted by an algorithm for the decision of the fall. Degen et al (Degen and Jaekel, 2003) designed a fall detector in the form of a wrist watch. Their approach is to integrate the norm of the three axes acceleration vector and the two integrals. In these approaches, the decision of fall event is based on the predefined thresholds.

The main advantage of positioned detector is that the device will not uncomfortable to the elder, but there is restriction of activity area. The design relative to positioned type, the portable device makes the activity area not limit. According to the considerations of privacy and portability, we focus on developing a portable fall detector. Compared our approach with the others portable detectors, the main different is that the use of neural network classifier to instead of a predefined falling thresholds.

3 MATERIAL

3.1 Principle of Fall Detection

The first step of our approach is to measure the three axes acceleration vector via an accelerometer. As shown in Figure 1, a free falling down will result the accelerations of body's three axes have changes in various degree. For example, the y axis and z axis will have more huge acceleration variation during a

forward fall.

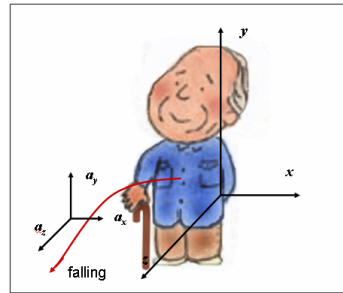


Figure 1: During fall the accelerations of three directions have changes in various degrees.

Artificial neural network technique was used to perform the second step, i.e. the fall confidence pattern recognition. There are two phases in neural network: learning phase and recalling phase (see Figure 2).

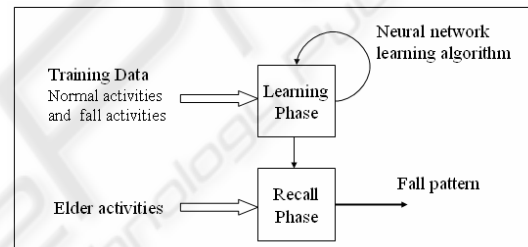


Figure 2: A neural network based approach to classifying fall activities.

In the learning phase, a supervised learning algorithm is adapted to train the neural network from positive examples and negative examples. The learning rule to adjust the weights and biases of the network is based on the back-propagation training algorithm. By the iterative training process, the connective weights and bias in the neural network can be refined to fit the generation of expect output. Thus, in the recalling phase (also called predicate phase) the input elder activities can be classified or predicted by the trained neural network.

3.2 Architecture of the Intelligent Fall Detector

The intelligent fall detector that proposed in this paper comprised two key components: an accelerometer module and a processing unit. Figure 3 shows the functional block diagram for the intelligent fall detector.

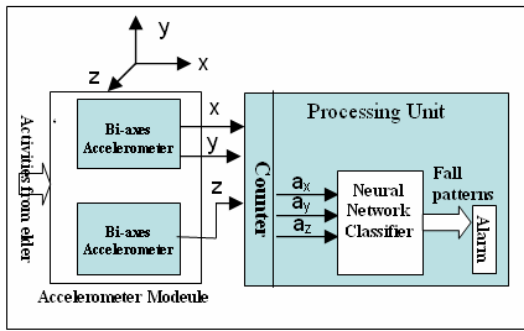


Figure 3: The block diagram for intelligent fall detector.

The accelerometer module (implemented by two bi-axes accelerometers, ADXL 202JE, Analog Device Inc.) senses the elder activities continuously. The output signal from accelerometer is modulated by pulse width modulation (PWM). The processing unit (implemented by MSP430, TI) handles three activities: reads the incoming data from the accelerometer module (the PWM signals that output from accelerometers are calculated by a counter in order to get the numerical value of acceleration); performs neural network-based classification to determine the fall activities; and produces an alarm to indicate a fall event in happening.

3.3 The Structure of Neural Network Classifier

An artificial neural network (ANN) based on back-propagation algorithm is trained for classifying falling activities. The structure of the back-propagation network model comprises four layers: one input layer, two hidden layer, and one output layer. The input layer which consists of three neurons reads data from the three axes accelerations. The hidden layer consists of two layers which arranged as 10 neurons and 7 neurons respectively. The output layer represents the fall patterns, i.e. fall, and not fall. This structure is gained after numerous explorations of different hidden layers and neurons. This network is a fully-connected architecture. The structure of ANN is shown in Figure 4.

The activity output from this detector can be classified into two possible patterns: fall and not fall. If the “fall” pattern is recognized, it will trigger an alarm to indicate the accident to nearby persons. The “not fall” pattern means nothing of accident.

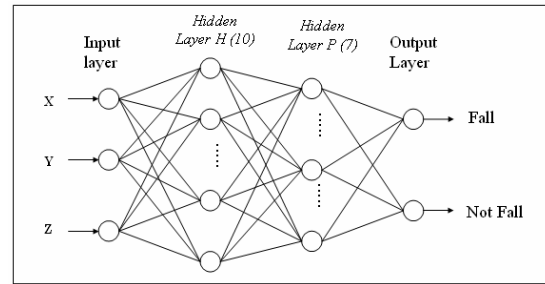


Figure 4: The structure of the back-propagation neural network classifier.

4 RESULTS

A prototype of the intelligent fall detector has been prepared, which implements the methodology explained above. According to the safety consideration, the experimentation is took place in the laboratory and only young people chosen as the subject in the experimentation. It involved six subjects whose aged between 21 and 23.

The initial setup for back-propagation neural network model is summarized in Table 1.

Table1: The setup for Back-propagation neural network.

Numbers of neurons in each layer	Input / Output layers: 3 / 2 Hidden layers H / P: 10 / 7
Learning cycle	20000 times
Learning rate	0.5
Momentum	0.01
Activation function	Hyperbolic tangent function $f(x) = \frac{1 - e^{-ax}}{1 + e^{-ax}}$

In the experimentation, each subject simulates different possible activities which included 12 normal and 6 fall activities. Here, the basic normal activities of daily living, where extended from (Wu, 2000), included walking, slow running, sitting down and rising from a chair or sofa, climbing and descending the stairs, picking up an object from the floor, transferring in and out of a tub, and getting up and lying down to a bed. The fall activities can be simply classified according to the posture of elder’s normal activities and ways of falling. We defined six possible ways of falling activities:

- The body vertical (stand, walking, or running) and falling forward,
- The body vertical and falling backward,
- The body vertical and falling right side or left side,
- The body crooked (sit, squat, or stoop) and

- falling forward,
- The body crooked and falling backward, and
- The body crooked and falling right side or left side.

These activities are simulated by the MatLab7 neural network tool in the learning phase. Through 20,000 times iterative learning, the back propagation network is converged. In the recall phase, we evaluate 90 activities which are the same activity types as in the learning phase. In the evaluation, two types of failure are adapted in our testing (Yamaguchi, 1998). The first type of failure is that the device indicating a fall event, but the real situation is nothing. The next type of failure is the fall accident is real in happened, but not detected by the detector. The evaluation results are shown in Table 2.

Table 2: The evaluation result for detecting normal and fall activities.

Activities	Num. of evaluation	Success detection	Error detection	Correct rate
Normal activities	60	No alarmed 57	Alarmed 3	95%
Fall activities	30	Alarmed 28	No Alarmed 2	93.3%

The similar experiment is repeated several times. We have found that detection errors in testing normal activities are almost distributed in “sit down” activity. The errors in testing fall activities are distributed in the “body crooked and falling right side”. Next, the factors of subject’s agility, the distance from detector to ground, and the numbers of learning cycle in back-propagation neural network are also infected the correct rate in the experiment.

5 CONCLUSIONS

An intelligent fall detector that based on artificial neural network technology is introduced in this paper. Comparing with other approaches, the correct rate of recognition of fall activity by neural network learning approach is better than the predefined threshold value approach. In the future research, we will explore the others learning approaches, such as Hidden Markov Model classifier, to compare with the neural network approach.

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