Fall Detection Using Wavelet Transform and Neural Network

Sang-Hong Lee

***Abstract*—**This paper proposes a method to detect falls using a Neural Network with Weighted Fuzzy Membership Functions(NEWFM) and wavelet-based feature extraction. Data extracted from study subjects were applied to the NEWFM after going through preprocessing and wavelet processes. From the created wavelet coefficients, 40 initial features were obtained using statistical methods, including frequency distributions and the amounts of variability in frequency distributions. In order to assess the fall detection performance of the NEWFM, the data were divided into training sets and test sets in ratio of 5:5 to conduct experiments with the respective ratios. Based on the results, the sensitivity, specificity and accuracy of the NEWFM were shown to be 98.02%, 98.99% and 98.5% respectively when the ratio of the training set and the test set was 5:5.

***Keywords*—**Fall Detection, Wavelet Transform, NEWFM, Signal Processing.

I. Introduction

RECENTLY, aged populations have been rapidly increasing because of the development of medical technology and emergency situations in daily life that can occur in elderly persons with reduced abilities for activities have been becoming serious problems. In addition, elderly persons' diseases and accidents are rising as social problems. Of elderly persons' health problems, weakened physical functions are the most common problems and these limitations on physical functions are becoming a factor to increase the risk of occurrence of falls in elderly persons. A fall refers to a sudden movement of a person's trunk, knee or hand from a standing posture to the floor or a low position and this is becoming a major cause of elderly persons' morbidity and mortality.

Previous studies conducted for detecting falls studied methods using thresholds [1][2][3] and methods using neural networks [4]. The methods using thresholds have a disadvantage that there are blind areas that cannot be detected in the case of unexpected falls. The methods using neural networks are structured more complicatedly compared to the threshold methods but they have an advantage that there is no blind area and thus they are effective in detecting falls.

This paper proposes a method to detect falls using a Neural Network with Weighted Fuzzy Membership Functions (NEWFM) [5][6][9]. Three-axis acceleration sensors constructed by vertically connecting two 2-axis acceleration sensors were used to collect data in this study. Eight hundred data sets were extracted from 10 test subjects and the extracted data sets were applied to the NEWFM after going through preprocessing and wavelet processes. From the created wavelet coefficients, 40 initial features were obtained using statistical methods, including frequency distributions and the amounts of variability in frequency distributions. In order to assess the fall detection performance of the NEWFM, the data were divided into training sets and test sets in ratio of 5:5 to conduct experiments with the respective ratios. Based on the results, the sensitivity, specificity and accuracy of the NEWFM were shown to be 98.02%, 98.99% and 98.5% respectively when the ratio of the training set and the test set was 5:5.

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II. Experimental Data and Preprocessing

Accelerations occurring in daily life are within a range of ±12g [7]. However, in cases where the sensor is attached to the waist, the range of acceleration is not over ±4g. In this respect, ADXL210Es that have a range of measurement of ±10g and a bandwidth of 60Hz shown in figure 1 were used to conduct experiments. The acceleration sensors were fixed to the waists of the subjects as shown in figure 2 when they were used.

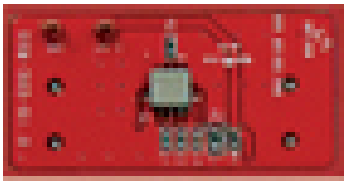

Fig. 1 Acceleration sensor

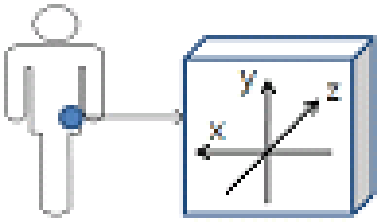

Fig. 2 Position where the acceleration sensor was worn

In this study, data were collected under eight scenarios as shown in Table I for experiments. To collect the data, ten males aged between the mid-20th to the mid-30th were selected as study subjects. To collect data under the eight scenarios as shown in Table I, experimental environments were constructed. In the experiments, diverse states of human body activities were classified into eight scenarios and 10 data were extracted under

each scenario per subject to extract and use a total of 800 data. A sampling rate of 60Hz was used to collect the data and as for window frames, the window size was applied for 3 seconds including 1.5seconds each before and after the maximum value. The 3-axis acceleration sensor used in this study is composed of two 2-axis acceleration sensors. Each of the acceleration sensors outputs the acceleration values of the X-Y axis (vector values) or those of the Y-Z axis (vector values).

$$XY_d(t) = |XY(t)-XY(t-1)|$$
$$YZ_d(t) = |YZ(t)-YZ(t-1)| \quad (1)$$
$$t = 1, 2, \ldots, 180 \ (1/60\text{sec})$$

$$S(t)=XYd(t)+YZd(t) \quad (2)$$

TABLE I
TYPES OF DATA COLLECTED

Classification	
Fall	Falls during walking
	Falls during running
	Falls from a chair
	Falls from a bed
Non-fall	Walking
	Running
	Sitting
	Lying

In this study, in order to apply two different values to wavelet transformations, the two values were transformed into one value by preprocessing them using the sum of the amount of changes in acceleration. For the preprocessing of the data collected as shown in Table I, when the acceleration signals of the XY and YZ axes outputted from the two 2-axis acceleration sensors are assumed to be XY (t) and YZ (t) respectively, XYd(t) and YZd(t) that are the amounts of changes in the acceleration of the XY and YZ axes were obtained through equation (1). Wavelet transformations compensate the disadvantage of Fourier analysis that gives information on global characteristics of frequencies by analyzing the characteristics of frequencies of certain local temporal points. Non-continuous wavelet transformations split time-frequency signals into non-continuous signals in diverse scales. In this study, a filter bank for implementing dichotomous non-continuous wavelet splitting was used [8]. The detail wavelet coefficients are High-pass Filter coefficients and the approximation wavelet coefficients are Low-pass Filter coefficients. Once the signals have been shortened in length to a half after passing the filter, the signals are repeatedly transformed at the next scale level. The wavelet coefficients extracted by the wavelet transformations are similarity to mother wavelets and they show frequency signals relative to the time given by scales.

The methods for extracting the features used in this paper from wavelet coefficients are explained in TABLE II. In this paper, feature 2 was newly added for the experiments. Features 1, 2, and 3, explained in TABLE II, represent the frequency distributions of the signals, and features 4 and 5 represent the amounts of variability in the frequency distributions [11].

TABLE II
FEATURE EXTRACTION DESCRIPTION

No	Feature Extraction Description
1	Mean of the absolute values of the coefficients in each sub-band
2	Median of the coefficients in each sub-band
3	Average power of the wavelet coefficients in each sub-band
4	Standard deviation of the coefficients in each sub-band
5	Ratio of the absolute mean values of adjacent sub-bands

III. NEURAL NETWORK WITH WEIGHTED FUZZY MEMBERSHIP FUNCTION (NEWFM)

A neural network with weighted fuzzy membership function (NEWFM) is a supervised classification neuro-fuzzy system using the bounded sum of weighted fuzzy membership functions (BSWFMs) [5][6][9]. The structure of the NEWFM, illustrated in Fig. 3, comprises three layers namely input, hyperbox, and the class layer. An *h*th input pattern can be recorded as $I_h=\{A_h=(a_1, a_2, \ldots, a_n), class\}$, where *class* is the result of classification and A_h is *n* features of an input pattern. 40 initial features were extracted from wavelet coefficients and these 40 initial features were used as inputs of the NEWFM as shown in Fig. 3.

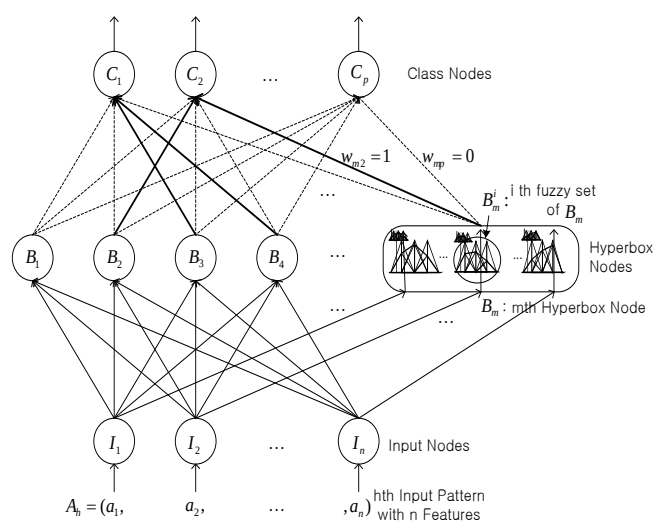

Fig. 3 Structure of NEWFM

IV. Experimental Results

In our previous study, WT was carried out to extract 32 features. The 32 features were used as the input data to distinguish fall from non-fall. However, in this study, from the created wavelet coefficients, 40 initial features were obtained using statistical methods, including frequency distributions and the amounts of variability in frequency distributions.

Fig. 4 shows the examples of fuzzy membership functions with respect to the 6 features among 40 initial features. These represent the BSWFM (bounded sum of weighted fuzzy membership functions) described in [5]. Through these, the difference in the non-fall and the fall with respect to the 6 features could be visualized and analyzed accordingly.

In Equation (1), TP (True Positive) indicates the cases where the fall was identified as that of the fall and TN indicates the cases where the non-fall is identified as non-fall. On the contrary, FP (False Positive) denotes the cases where the fall was identified as non-fall and FN (False Negative) denotes the cases where non-fall as fall. The performance of our previous study [10] and performance of NEWFM were compared in this study. Table III shows classification results of our previous study. Table IV shows the confusion matrix of classification results of NEWFM. Table V shows the sensitivity, accuracy, and specificity defined in Equation (1).

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$
$$Specificity = \frac{TN}{TN + FP} \times 100 \qquad (1)$$
$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \times 100$$

TABLE IIII
CLASSIFICATION RESULTS USING NEWFM (OUR PREVIOUS STUDY)

	Sensitivity	Accuracy	Specificity
Performance (%)	95	96.125	97.25

TABLE IV
CONFUSION MATRIX OF CLASSIFICATION RESULTS USING NEWFM

Fall	TP	FN
	198	2
Non-fall	FP	TN
	4	196

TABLE V
CLASSIFICATION RESULTS USING NEWFM (5 : 5)

	Sensitivity	Accuracy	Specificity
Performance (%)	98.02	98.5	98.99

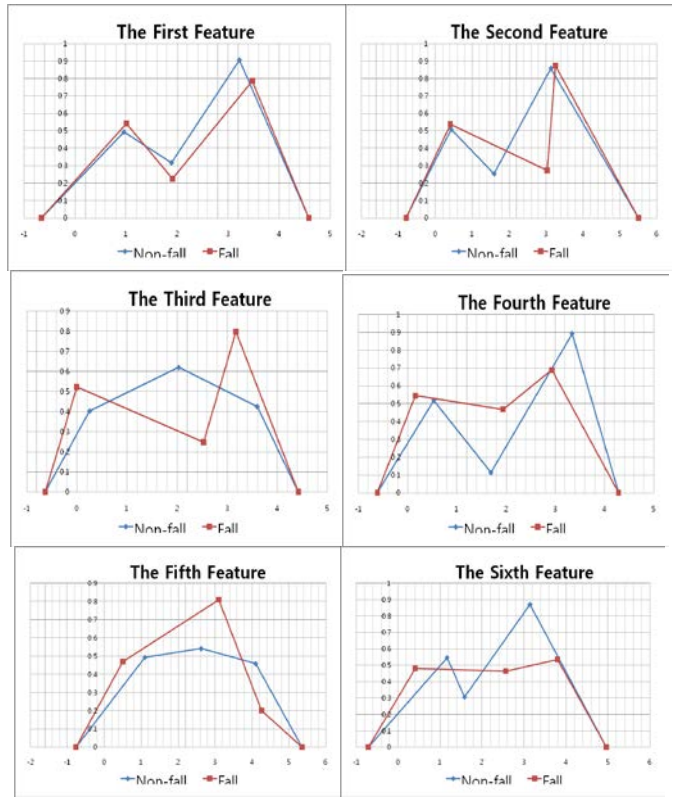

Fig. 4 Examples of the BSWFM of the 6 features among 40 features

V. Concluding Remarks

In this study, from the created wavelet coefficients, 40 initial features were obtained using statistical methods, including frequency distributions and the amounts of variability in frequency distributions. 40 initial features are used for distinguishing non-fall and fall. Through the method proposed in this article, the system to distinguish non-fall and fall can be realized in real-time. NEWFM shows the fuzzy membership functions of the 6 features by deriving their BSWFM. The fuzzy membership functions can be used in distinguishing non-fall from fall.

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