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Wavelet Transforms Based Fall Detection with Neuro-Fuzzy Systems Based Feature Selection

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***Abstract:** This study proposes a method to detect fall with minimum features selected by a non-overlap area distribution measurement (NADM) method. In preprocessing step, wavelet transforms were carried out to extract wavelet coefficients from dataset acquired by subjects. The NADM was used to select the minimum number of features from wavelet coefficients, and then 19 features were finally selected from the 33 features. The performance result of the fall detection was tested with 19 features, and then the sensitivity, accuracy, and specificity were shown to be 95%, 96.13%, and 97.25%, respectively.*

***Keywords** : Fall Detection, Feature Selection, Wavelet Transform, NEWFM.*

I. INTRODUCTION

Recently, due to the development of medical technology, the elderly population is rapidly increasing, and the emergency in everyday life that can occur to the elderly who are less active is a serious problem. In particular, fall is one of the most feared problems of the elderly, and it is an accident in which the bones and muscles, or the musculoskeletal system, are suddenly fallen down regardless of their will. In addition, the importance of a system that can classify falls in real time and provide linkage services with hospitals for patients in need of prompt treatment in case of a fall, such as heart disease, stroke, concussion, etc.

Previous studies to detect falls with a threshold method [1][2][3] and a method by the neural network [4]. Smart-phone and wearable-sensors are used for fall detection [5][6][7]. Dean proposed a fall classification method using threshold and Support Vector Machine (SVM), but the proposed method only classifies a fall when the subject's body tilts more than 45°. Hence, it cannot detect falls on a hill or stairs, and the fall accuracy rate was low at 95.6% [8]. Tong Zhang classified falls by using 1-Class SVM (Support Vector Machine), KFD (Kernel Fisher Discriminant), SVM (Signal Vector Magnitude), and k-NN. However, the fall accuracy rate was low at 93.3% and the method has the disadvantage of a highly complex classification algorithm [9]. Tong Zhang extracted 6 features from data obtained through SVM and low-pass filtering, and then the accuracy rate was 96.7%, but it has the disadvantage of a highly complex method for extracting 6 features [10].

Many studies had the disadvantage of high complexity when the performance result was high, and the threshold method has the disadvantage of a blind area where falls cannot be determined. Therefore, this study proposes a fall detection model that has a low complexity and no blind area, and shows a high performance result.

This study proposes a fall detection model that can classify falls through the signals of three-axis acceleration sensor. For the input of the detection model, a coefficient extracted by applying the wavelet transform. Thirty-three wavelet coefficients extracted through wavelet transforms (WTs) to 4 levels were used as the input for a neural network with weighted fuzzy membership functions (NEWFM) [11][12][13]. To select the minimum number of feature, 19 features were selected by the non-overlap area distribution measurement (NADM) method supported by the NEWFM from the 33 initial features. To evaluate the performance of the NADM, the Principal Component Analysis (PCA), which is a multivariate statistical analysis method, was used. The fuzzy rules are formed with the minimum feature by the NADM. The extracted fuzzy rules are implemented as an embedded module, which determines fall and non-fall when a fall actually occurs.

The performance result of the fall detection of the NADM is that the sensitivity, accuracy, and specificity were shown to be 95%, 96.13%, and 97.25%, respectively, with 19 minimum features.

II. EXPERIMENTAL DATA AND PREPROCESSING

For experimentation, dataset was collected in 8 scenarios as shown in TABLE I. For dataset collection, 10 men in their 20s and 30s were selected as the experimental group. To acquire the signals of three-axis acceleration sensor, a sensor module was attached to the waist of each subject. The states of various physical activities were classified into 10 scenarios and 10 dataset were extracted for each scenario. A total of 800 dataset were used for this experiment.

The two-axis acceleration sensor by Analog Device, ADXL210E, was used for this experiment, which has a measurement range of ±10g and a bandwidth of 60 Hz as shown in Fig. 1. The subject fixed the acceleration sensors on the waists in Fig. 2.

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Fig. 1 Acceleration sensor

Fig. 2 Position of acceleration sensor

This study used the three-axis acceleration sensor that is comprised of two 2-axis acceleration sensors. Each acceleration sensor outputs the acceleration value (vector value) of X-axis and Y-axis and the acceleration value (vector value) of the Y-axis and Z-axis. In this section, to apply these two different values to WT, they were converted to one value by preprocessing using the sum of acceleration changes.

Fig. 3 shows a filter bank for implementing binary discontinuous wavelet separation. g(n) is the detail coefficient of the finite impulse response (FIR) high-pass filter. h(n) is the approximation coefficient of the FIR low-pass filter. When a h(n) signal passes through each filter, its length is reduced by half, and the signal is repeatedly transformed in the next scale level. The wavelet coefficient extracted by WT is similarity to the mother wavelet, which represents the frequency signal over time given by the scale [14]. In Fig. 3, di and ai denote the detail and approximation coefficients of each scale level i.

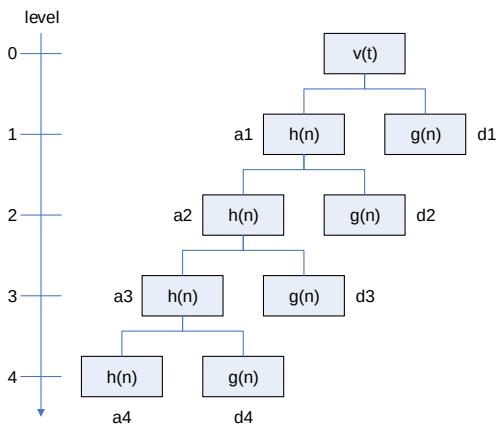

Fig. 3 4-level Wavelet Transform

A total of 33 features including 22 d3 coefficients and 11 d4 coefficients were extracted by WT, which can be easily ported to an embedded system due to simple structure and implementation and has good performance in noise removal and feature extraction.

TABLE I TYPES OF COLLECTED DATASET

Classification	
Fall	Falls while walking
	Falls while running
	Falls on a chair
	Falls on a bed
Non-fall	Walking
	Running
	Sitting
	Lying

This study describes the Principal Component Analysis (PCA) used to compare and evaluate the objective performance of NADM. The PCA has been applied in many fields as a multivariate statistical analysis method used to understand the basic data structure from several features or to extract a small number of features that well describe the properties of the entire dataset. The results of the analysis are used as a means for further analysis rather than conclusions about the problem. In this study, we use the reduced dimension feature that best describes the fall from the 33 features obtained through wavelet.

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

A neural network with weighted fuzzy membership function (NEWFM) is a kind of supervised fuzzy neural network systems using the bounded sum of weighted fuzzy membership functions (BSWFMs) [5][6][9]. The structure of the NEWFM in Fig. 4, is comprised of three layers that are input, hyperbox, and the class layer. This study used 33 features generated by the WT as input.

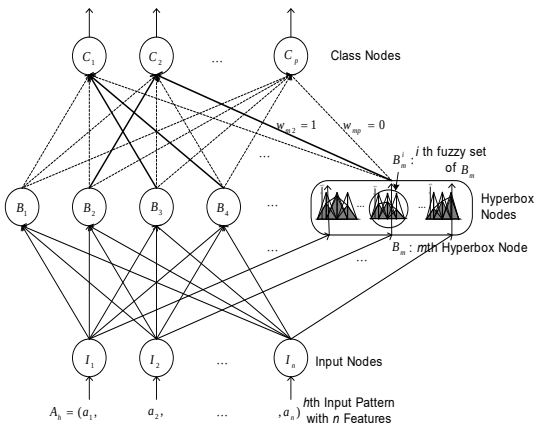

Fig. 4 Structure of NEWFM

The Adjust(B_l) operation method adjusted the weights and the center of membership functions in Fig. 5. W_1, W_2, and W_3 are moved down or up, v_1 and v_2 are moved up to a_i, and v_3 stays in the same position. After accomplishing Adjust(B_l), each of all fuzzy sets in hyperbox node B_l in Fig. 4 contains three *weighted fuzzy membership functions* (*WFMs*). The WFM means grey membership functions in Fig. 6. The *bounded sum* of WFMs (BSWFM) in the *i*th fuzzy set of $B_l^i(x)$ denoted as $\mu_b^i(x)$ defined by:

$$\mu_b^i(x) = \sum_{j=1}^{3} B_l^i(\mu_j(x)). \qquad (1)$$

The BSWFM means bold line in Fig. 6. The two BSWFMs graphically show the difference between fall and non-fall for each input feature.

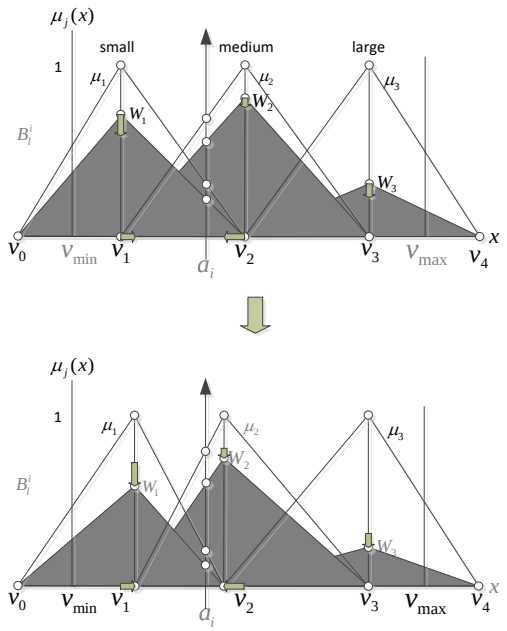

Fig. 5 Example of *Adjust*(B_i) operation

Fig. 7 overlaps two BSWFMs in Fig. 6 for the 30th wavelet coefficient of fall and non-fall. The fall area (A_E^i) in part A of Fig. 7 is the area where the fuzzy value of fall is high, and the non-fall area (A_N^i) in part B of Fig. 7 is non-fall. If the area is large and the areas of and are evenly distributed, it can be said that the two classes have more features to classify. The non-overlap area function for the *i*th feature is defined in Equation (2).

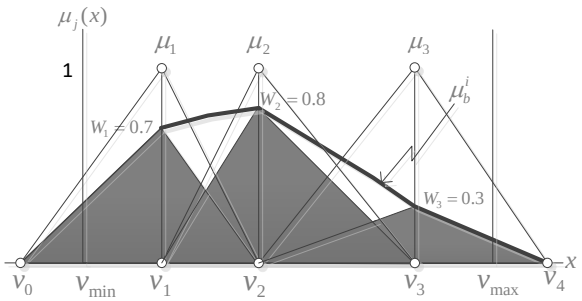

Fig. 6 Example of the three BSWFMs

$$f(i) = (Area_E^i + Area_N^i)^2 \Big/ \left(\frac{1}{1+e^{-|Area_E^i - Area_N^i|}}\right) \quad (2)$$

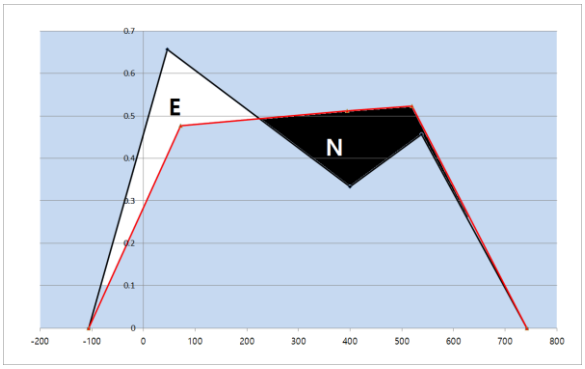

Fig. 7 Example of the NADM

TABLE II

Selected 19 minimum features from 33 wavelet coefficients

No	wavelet coefficients		selected	No	wavelet coefficients		selected
1	D4	1st		18	D3	7th	
2		2nd	Yes	19		8th	Yes
3		3rd		20		9th	
4		4th	Yes	21		10th	Yes
5		5th	Yes	22		11th	Yes
6		6th	Yes	23		12th	Yes
7		7th	Yes	24		13th	Yes
8		8th	Yes	25		14th	Yes
9		9th	Yes	26		15th	Yes
10		10th		27		16th	Yes
11		11th		28		17th	Yes
12	D3	1st		29		18th	
13		2nd		30		19th	
14		3rd	Yes	31		20th	
15		4th	Yes	32		21st	
16		5th		33		22nd	
17		6th	Yes				

In order to select the minimum features, the NADM was used to automatically remove one of the 33 initial features, one of the least important ones, and select the 19 minimum features with the highest performance result. TABLE II shows the 33 wavelet coefficients used as initial features and the highest selected 19 minimum features.

IV. EXPERIMENTAL RESULTS

In this study, the NEWFM is a new model proven for its excellent performance by the NADM. It enables analysis of the hidden layer by the convergence of neural network theory and fuzzy theory and can improve the classification accuracy by using the BSWFM. Furthermore, the NEWFM has the good advantage of easy application to embedded systems because simpler fuzzy rules can be created by removing features of low importance by the NADM.

In this study, falls were detected from the signals of a three-axis acceleration sensor using the NEWFM. To select minimum features, analyses were conducted using 33 features. As shown in TABLE III, in the case of the PCA, the maximum average classification rate was 90.3% when the number of features was 23. When the NADM was used, a higher classification rate of 91.21% than that of the PCA was achieved with 19 features, fewer than those of the PCA. The minimum 19 features selected by the NADM were used as input of the NEWFM. The experiment showed stable results with a high performance rate of 96.13%, sensitivity of 95%, and specificity of 97.25% in TABLE IV.

In Equation (3), True Positive (TP) means the cases where the fall was recognized as that of the fall and True Negative (TN) means the cases where the non-fall is recognized as non-fall. On the contrary, False Positive (FP) indicates the cases where the fall was recognized as non-fall and False Negative (FN) indicates the cases where non-fall as fall. This study compared the performance of backpropagation (BP) [15][16][17] and that of NEWFM in TABLE IV and TABLE V.

TABLE III
Comparisons of performance result of PCA and NADM

No of feature	PCA	NADM	No of feature	PCA	NADM
6	87.72	89.51	20	87.8	90.87
7	88.78	89.81	21	88.58	90.27
8	88.23	89.86	22	88.9	89.99
9	88.06	89.62	23	90.3	89.36
10	88.06	89.73	24	89.04	90.41
11	88.14	89.55	25	89.06	89.39
12	87.87	89.78	26	89.19	89.24
13	87.54	89.86	27	89.17	88.6
14	87.52	89.84	28	88.75	88.82
15	87.61	90.19	29	88.87	88.5
16	87.42	90.53	30	89.05	88.31
17	87.57	90.97	31	88.77	88.28
18	87.64	99.99	32	89	88.11
19	87.76	91.21	33		

Fig. 8. Examples of the BSWFMs

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

$$Specificity = \frac{TN}{TN + FP} \times 100 \qquad (3)$$

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \times 100$$

TABLE IV
Classification Results by NEWFM

	Sensitivity	Accuracy	Specificity
Performance (%)	95	96.125	97.25

TABLE V
Classification Results by BP

	Sensitivity	Accuracy	Specificity
Performance (%)	89.125	89.5	85.25

TABLE VI
Classification Results by Fall Scenario

Classification		Total	Correct	Error	Accuracy
Fall	Falls during walking	100	94	6	94
	Falls during running	100	94	6	94
	Falls from a chair	100	94	6	94
	Falls from a bed	100	98	2	98
Sub total		400	380	20	95
Non-fall	Walking	100	100	0	100
	Running	100	98	2	98
	Sitting	100	94	6	94
	Lying	100	97	3	97
Sub total		400	389	11	97.25
Total		800	769	31	96.13

TABLE VI lists the performance of the fall diagnosis model for each fall scenario. Out of the 400 fall dataset, 20 dataset were classified as non-falls, sowing 95% classification rate. Out of the 400 non-fall dataset, 11 dataset were classified as falls, showing 97.25% classification rate. Falling from the chair showed the highest classification rate of 98%, whereas floor, bed, and running showed relatively low classification rates. In particular, running showed the lowest classification rates for both falls and non-falls.

The conventional neural network methods are impossible to understand the meaning of the inputs of the neural network due to the complexity of the hidden layer after learning and the difficulty of optimization. The NEWFM has the good advantage of applicability to embedded environments and mobile because it can understand the meanings of the inputs by using the x and y coordinates of the extracted fuzzy rules.

Fig. 8 shows the examples of fuzzy membership functions on the 6 features. The examples represent the BSWFM described in [13]. This study can visualize and analyze the difference in the non-fall and the fall with reference to the 6 features.

V. CONCLUDING REMARKS

In this study, the fall is classified from the 3-axis acceleration sensor signal using the NEWFM. For dataset collection, three-axis acceleration dataset composed of two two-axis accelerators connected vertically were used. 800 samples were generated from 10 subjects, and making it easy to be embedded, and applying wavelet transform, which shows good performance in noise removal and feature extraction, 22 d3 coefficients, 11 d4 coefficients, and total 33 features were extracted.

In order to select the minimum features, 33 features were applied to the PCA and the NADM, and performance evaluation was performed. The NADM showed better performance than principal component method. 19 minimum features selected by the NADM were used as inputs for NEWFM. Experimental results showed a high classification rate of 96.125%, stable results of 95% sensitivity, and 97.25% specificity. Existing neural network methods are difficult to understand the meaning of neural network input because the complexity and optimization of hidden layer after learning is difficult. In the case of NEWFM, it is possible to grasp the meaning according to the input used, and it can be applied to mobile and embedded environments because the input can be judged using only the coordinate values of the extracted fuzzy rules.

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