International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-12, October 2019

Fall Detection for Elderly Person using Neuro-fuzzy System and Wavelet Transformation

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Abstract*: This study proposes a new methodology to detect falls and non-falls using a Neural Network with Weighted Fuzzy Membership Functions (NEWFM). Dataset acquired from subjects was applied to NEWFM after carrying out wavelet transforms. In order to test the performance evaluation of the fall detection by the NEWFM, the dataset was separated test set and training set at 2 to 8 and 5 to 5 ratios to carry out experiments. Based on the performance evaluation of the NEWFM, the sensitivity, accuracy, and specificity were shown to be 94.67%, 91.86% and 89.41%, respectively when the test set to the training set at the ratio was 2 to 8 and 91%, 91% and 91%, respectively, when the test set to the training set at the ratio was 5 to 5. This study also compares the performance evaluation of backpropagation (BP) and that of NEWFM.

Keywords: **Fall Detection, NEWFM, Acceleration, Wavelet Transform.**

I. INTRODUCTION

The elderly people population has been growing very fast with the recent development of medical technology. With the large number of the elderly people who want to live independently without receiving care from the family, emergencies in daily living that can happen to the elderly people with low ability of activity are becoming a serious issue and danger. In particular, falls, which mean sudden unintentional failing that injures bones and muscles are one of the most fearful problems for the elderly people. Furthermore, the importance of a system that can classify falls in real time and provide a linking service to hospitals for patients who need rapid treatment for heart disease, stroke, concussion, or other diseases in the event of a fall is increasing.

Existing studies to detect falls include a threshold method [1][2][3] and a method using the neural network [4]. Wearable-sensors and smart-phone are used for fall detection [5][6][7]. Many studies are under way to improve the accuracy [8][9]. However, the threshold method has the disadvantage of a blind area in which unexpected falls cannot be determined.

Revised Manuscript Received on October 30, 2019.
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Furthermore, using the neural network is more complex than the threshold method, but is effective for fall detection because it has no blind area.

This study proposes a new methodology to detect falls and non-falls using the NEWFM [10][11][12]. This study used triaxis acceleration sensors by orthogonally combining two biaxial acceleration sensors for collecting experimental dataset. 10 test subjects participated in our experiment, and then 800 datasets were acquired from our experiment. The acquired datasets were used to be trained for the NEWFM after carrying out wavelet transforms. In order to test the performance evaluation of the fall detection by the NEWFM, the data was separated training set and test set at 8 to 2 and 5 to 5 ratios to carry out experiments. Based on the performance evaluation of the NEWFM, the sensitivity, accuracy, and specificity were shown to be 94.67%, 91.86% and 89.41%, respectively when the test set to the training set at the ratio was 2 to 8 and 91%, 91% and 91%, respectively, when the test set to the training set at the ratio was 5 to 5. This study also compares the performance evaluation of backpropagation (BP) and that of NEWFM.

II. EXPERIMENTAL DATA AND PREPROCESSING

The acceleration sensor outputs the vibration, acceleration, and other states of objects by using the application principles of inertial force, gyro, and electric deformation. The acceleration sensor can continuously detect the motions of objects, and is widely applied to various transportations such as automobiles, vessels, and aircrafts, and to control systems such as factory automation and robots. 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. ADXL210E is a micro acceleration sensor of 5mm×5mm×2mm that operates with a low power of 0.6mA. This study used the acceleration sensors on the waists of the subjects shown in Fig. 2.

This study made 8 scenarios in Table I for collecting experimental dataset. In this experiment, various human physical activities were separated 8 scenarios, and then 10 datasets were achieved under each scenario per subject to make 800 dataset with a sampling rate of 60Hz for 3 seconds.

Fig. 1. Acceleration sensor ADXL210E

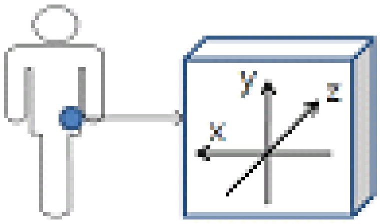

Fig. 2. Position of acceleration sensor

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 used wavelet transform (WT) as the feature extraction method. WT can make features from original signals and shows excellent performance evaluation in removing the noises of signals. WT can perform simultaneous analysis in the time-frequency domain for signal processing and is being widely applied to signal and image processing now. The WT applies windows of different sizes to the time and frequency domains. Moreover, in addition to sine and cosine functions, WT can also use the mother wavelet, which is more complex. Therefore, it allows more detailed analysis by selecting a mother wavelet that is appropriate to the characteristics of specific signals [13].

WT uses the concepts of scale and shifting for more accurate analysis in the time-frequency domain. Briefly, scale enables various approaches by increasing or decreasing functions. The movement of functions facilitates detailed analysis on the time axis by applying various scaled functions along the time axis.

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

NEWFM is a kind of supervised classification fuzzy neural network with the bounded sum of weighted fuzzy membership functions (BSWFMs) [10][11][12]. The structure of the NEWFM is comprised of three layers that are input, hyperbox, and the class layer in Fig. 3. This study used 32 features generated by the WT as input.

The Adjust(B_l) operation method adjusted the weights and the center of membership functions in Fig. 4. 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. 3 includes three *weighted fuzzy membership functions* (*WFMs*). In Fig. 5, the WFM means grey membership functions. 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:

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

The BSWFM means bold line in Fig. 5. The two BSWFMs graphically show the difference between fall and non-fall for each input feature.

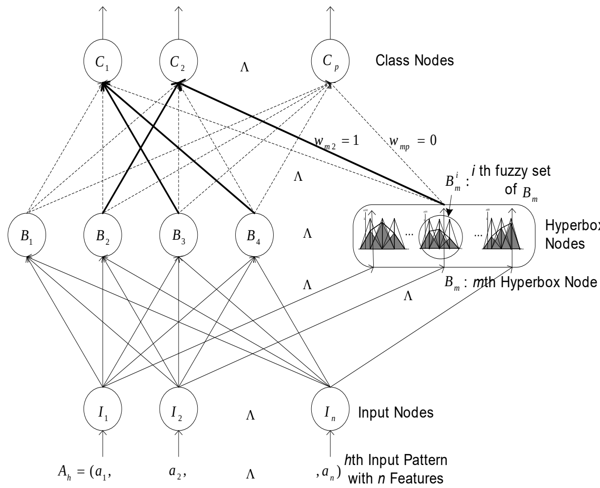

Fig. 3 Structure of NEWFM

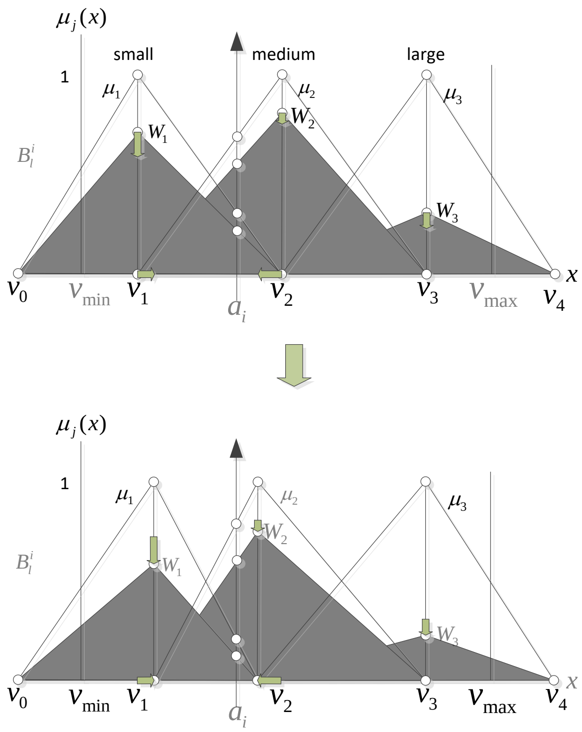

Fig. 4 Example of *Adjust*(B_l) operation

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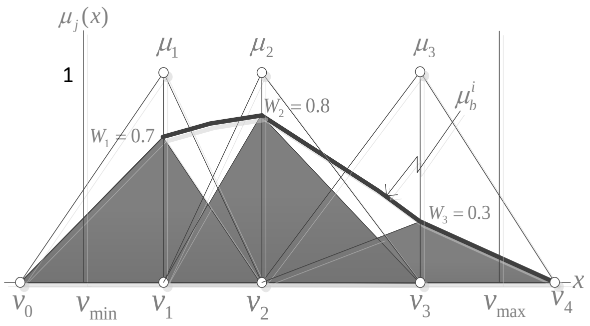

Fig. 5 Example of the 3 BSWFMs

IV. EXPERIMENTAL RESULTS

The WT was accomplished to make 32 features in this study. This study used the 32 features as the input to detect fall. Fig. 6 shows the examples of the BSWFMs with reference to the 6 features from 32 features made by the WT. The NEWFM shows the difference in the fall and the non-fall through the BSWFMs. The BSWFMs can be visualized and analyzed to show the difference in the fall and the non-fall. The NEWFM has the advantage of applicability to mobile and embedded environments because it can understand the meanings of the inputs and make judgment on the input by using only BSWFMs of the extracted fuzzy rules.

$$Sensitivity = \frac{TP}{TP+FN} \times 100$$
$$Specificity = \frac{TN}{TN+FP} \times 100 \qquad (2)$$
$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \times 100$$

TABLE II
Confusion Matrix of Performances by NEWFM (8 to 2)

Fall	TP	FN
	71	9
Non-fall	FP	TN
	4	76

TABLE III
CONFUSION MATRIX OF PERFORMANCES BY BP (8 TO 2)

Fall	TP	FN
	74	6
Non-fall	FP	TN
	6	74

TABLE IV
CONFUSION MATRIX OF PERFORMANCES BY NEWFM (5 TO 5)

Fall	TP	FN
	182	18
Non-fall	FP	TN
	18	182

TABLE V
CONFUSION MATRIX OF PERFORMANCES BY BP (5 TO 5)

Fall	TP	FN
	191	9
Non-fall	FP	TN
	33	167

TABLE VI PERFORMANCES BY BP (8 TO 2)

Epochs	Number of Hidden Nodes	Sensitivity	Accuracy	Specificity
5000	4	88.1	90	92.11
	6	89.16	90.63	92.21
	8	88.24	90.63	93.33
	10	**92.5**	**92.5**	**92.5**
10000	4	88.37	91.25	94.59
	6	87.36	90.63	94.52
	8	89.29	91.25	93.42
	10	89.16	90.63	92.21
15000	4	88.24	90.63	93.33
	6	90.48	92.5	94.74
	8	89.16	90.63	92.21
	10	90.36	91.88	93.51

(Learning rate: 0.01, momentum: 0.7)

TABLE VII PERFORMANCES BY BP (5 TO 5)

Epochs	Number of Hidden Nodes	Sensitivity	Accuracy	Specificity
5000	4	86.64	89.75	93.44
	6	87.16	90.5	94.51
	8	86.43	90.25	94.97
	10	85.27	89.5	94.89
10000	4	87.21	90.75	95.03
	6	87.67	91.25	95.58
	8	85.4	90	95.98
	10	88.89	92	95.65
15000	4	86.76	90.25	94.48
	6	**90.09**	**92.5**	**95.21**
	8	87.27	91	95.56
	10	88.26	90.75	93.58

(Learning rate: 0.01, momentum: 0.7)

In Equation (2), 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 evaluation of backpropagation (BP) [15] and that of NEWFM.

Table II and Table IV show the confusion matrix of performance evaluation of NEWFM. Table III and Table V show the confusion matrix of performance evaluation of BP. Table VI, Table VII, Table VIII, and Table IX show the sensitivity, specificity, and accuracy defined in Equation (2).

TABLE VIII
Performances by NEWFM (8 to 2)

	Sensitivity	Accuracy	Specificity
Performance (%)	94.67	91.86	89.41

TABLE IX
PERFORMANCES BY NEWFM (5 TO 5)

	Sensitivity	Accuracy	Specificity
Performance (%)	91	91	91

Fig. 6. Examples of BSWFMs

V. CONCLUDING REMARKS

This study accomplished the WT to make 32 features. This study used the 32 features as the input to detect fall. The NEWFM shows the difference in the fall and the non-fall with the BSWFMs. The BSWFMs can be visualized and analyzed to show the difference in the fall and the non-fall.

ACKNOWLEDGMENT

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. NRF-2019R1F1A1055423).

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Sang-Hong Lee received the B.S., M.S., and Ph.D. degrees in computer science from Gachon University, Korea in 1999, 2001, and 2012, respectively. He is currently an assistant professor in the department of computer engineering at Anyang University, Korea. His research focuses on deep learning systems, neuro-fuzzy systems, and biomedical prediction systems.