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Falling Cognitive improving System Method Utilizing a Fuzzy Logic

Daepyo Lee*, Jong-Yong Lee and Kye-Dong Jung ****

** Department of Information System, Kwangwoon University Graduate School of Information Contents, 20 Kwangwoon-ro, Nowon-gu, Seoul 01897, Korea.*

*** Ingenium College of liberal arts, KwangWoon University, 20 Kwangwoon-ro, Nowon-gu, Seoul 01897, Korea.*

**Corresponding author: Kye-Dong Jung*

Abstract

Falling to industrial workers now causes serious injuries. Therefore, many researchers are actively studying the fall by using acceleration sensor, gyro sensor, pressure sensor and image information. As these studies increase, the recognition rate increases, but there is no specificity and sensitivity. Also, in the present falling APP, when shaken, it is perceived as falling and lowers the recognition rate. Therefore, in this paper, we propose a falling algorithm using fuzzy logic instead of a binary logic algorithm which falling to 0 and 1 by using the acceleration sensor of a smartphone, and correct the falling APP when it is shaken, , And the reliability of the algorithm is improved through the analysis of singularity and sensitivity.

Key Words: Smartphone, Acceleration Sensor, Falling Detection, SVM, Fuzzy Logic

1. Introduction

People are classified as one of the causes of major injuries, such as fractures, from small wounds due to fallings in a variety of situations, thereby requiring social overhead and time. To cope with these problems, we have studied how to recognize falls and coping strategies that can be quickly resolved if we recognize fallings [1].

In general, the simplest way to determine the state is to propose a method of analyzing the acceleration data measured by the acceleration sensor. The Acceleration sensors, depending on the movement of objects or people, The values of the axes are used to determine dynamic or static conditions, SVM values were determined to determine fallings. [2,3]

Previously, a device using multiple sensors was attached to the body, and sensor data from the device was analyzed to recognize the falling condition [4]. As the number of studies on falling awareness increased, the number of fall determination applications increased accordingly.

As the number of these studies increased, the limitations of the studies were also revealed. First, since the data on the simple fallings were collected and presented, the reliability of the data was not high because the comparison with the non-falling data was not performed properly, There is a limitation of the system such as movement and inconvenience in order to recognize fallings in the case of judging by the attachment sensor. In addition, falling recognition rate decreased due to simplification of algorithms and reduction of computational throughput for rapid falling detection. In addition, falling recognition rate of current falling determination application is low, and some of applications have not been able to judge moving (shaking, shift) as a falling.

Table 1 below is a survey of studies on past falling judgment. Sensors used to judge falling in each study, usage factors of algorithms, presence of falling applications, and shake correction are described.

Table 1. Summary of existing research

Category	RK. Jennifer [5]	DP Lee [6]	H. Medjahed [7]	Suggestion
Using sensor	Accelerometer	Accelerometer	Accelerometer /Infrared sensor /microphone	Accelerometer
Using logic	Binary logic	Binary logic	Fuzzy logic	Fuzzy logic
Falling App	X	O	X	O
Calibration	X	X	X	O

The proposed method is as follows :

First, we use fuzzy logic to increase the probability of falling detection by making it possible to determine the falling of an ambiguous number that was not identifiable with binary logic. Second, the reliability of falling judgment is enhanced through the specificity / sensitivity analysis, which does not show falling determination probability using only falling data. Third, it has a form similar to a fall in the falling application, and corrects the misjudged moving (shaking, shift) data to make a proper fall judgment. Finally, the data is measured using only a three-axis acceleration sensor inside the smartphone[8].

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FUZZY FALLING DETECTION SYSTEM

Fuzzy Logic

Fuzzy logic is a logic concept that expresses ambiguous states and ambiguous states as a multidimensional deviation from true or false binary logic. Fuzzy logic is a rule-based technique that can express inaccuracies by generating rules that use approximate or subjective values.

The concept of a fuzzy set is a set that expresses the extent to which each object belongs to a group, departing from the binary logic that each object belongs to or does not belong to any group, and displays the membership function together with the corresponding object.

In general, the fuzzy logic control system proceeds with the four main elements shown in Fig. 1. fuzzy interface, fuzzy inference engine, fuzzy rule, and finally defuzzification interface.

Analysis

Currently, in order to distinguish between falling data (non-falling data) and moving (shaking, shift) data that are not distinguished in some falling applications, two data should be compared and analyzed and a specific point based on difference should be made.

Figure 1 below shows a graph of basic falling and moving(shaking, shift) data.

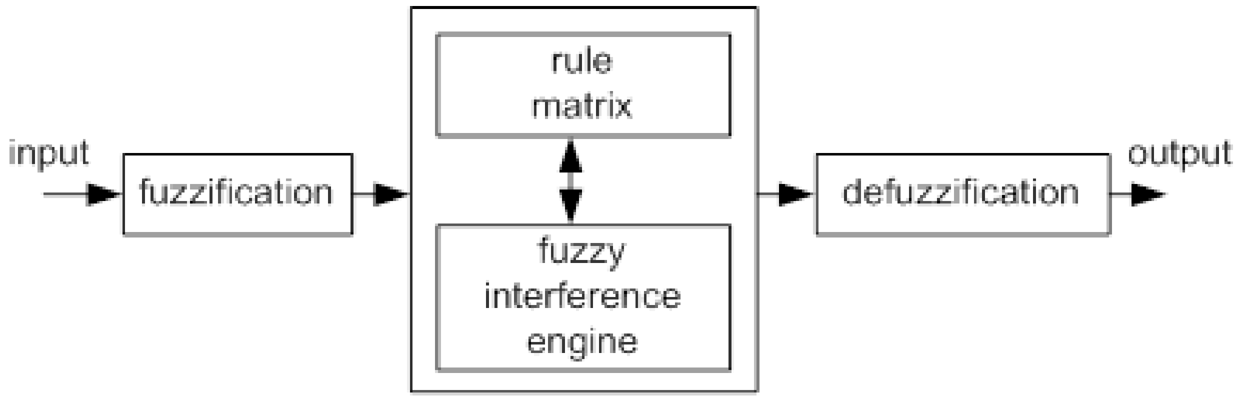

Figure 1. Fuzzy logic controller

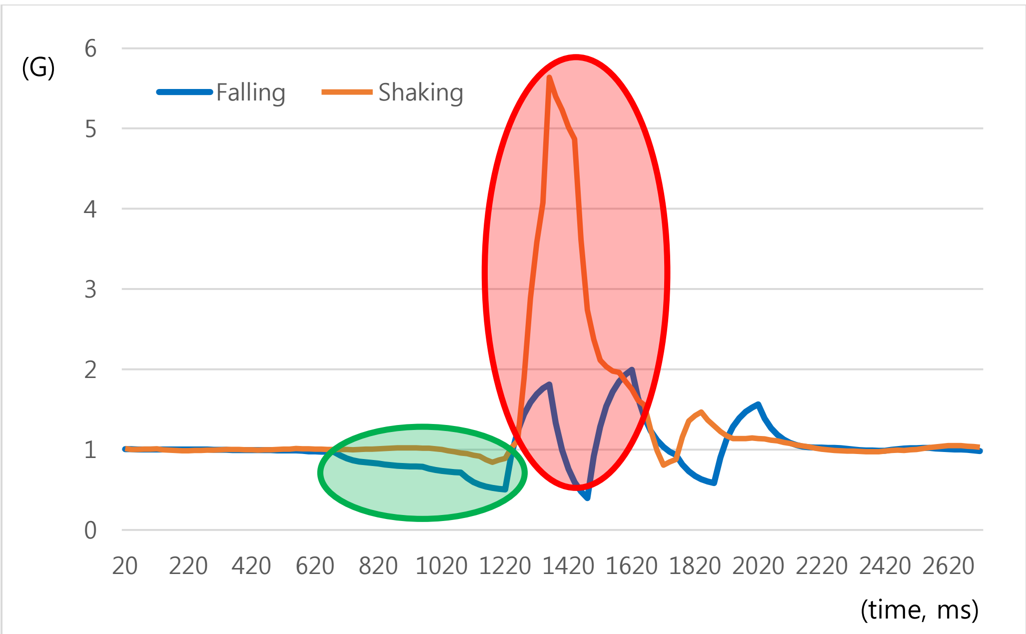

Figure 1. SVM data comparison of falling and moving(shaking, shift)

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In Figure 1, there are two main differences between falling and shaking data. One is divided by the difference between the leading downward peak value and the area before the upward peak indicated by the green circle occurs, and the other is the difference between the peak value and the peak number indicated by the red circle.

The difference between the two above can be further subdivided as follows.

- Before the first upward peak appears (green circle)

  - The area between 1G line and measured data

    - Downward peak value

- During Upward peak(s) (red circle)

  - Upward peak value

    - The number of Upward peak

The specific points are subdivided into individual fuzzy input variables.

Fuzzy Input / Output

Figure 2, Figure 3. shows the conversion of the four specific points into each fuzzy input variable.

Figures 2 and 3 show the difference between four falling and non-falling (shaking) data into fuzzy variables. Each input variable has a weight and a standard deviation on the ratio of the collected falling and non - falling data values, and the interval is adjusted to the fuzzy variable.

Figure 4 shows the fuzzy output .

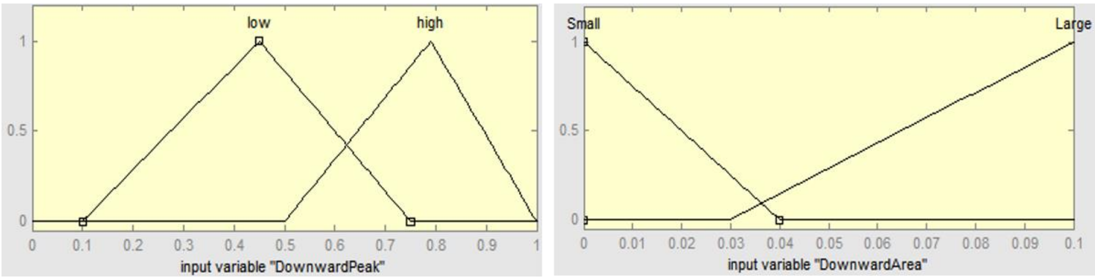

Figure 2. Fuzzy Input Variables of Downward

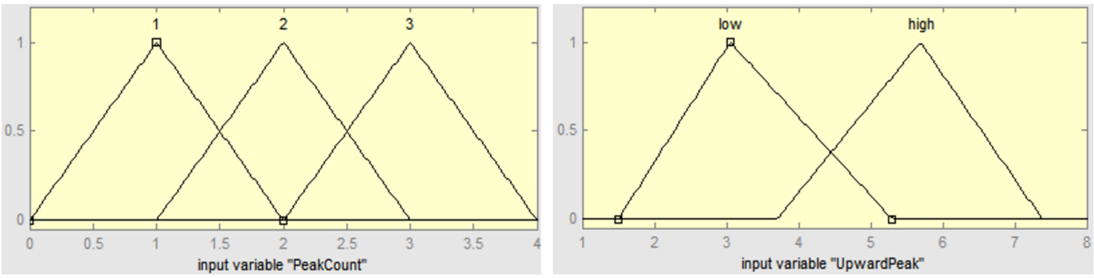

Figure 3. Fuzzy Input Variables of Upward

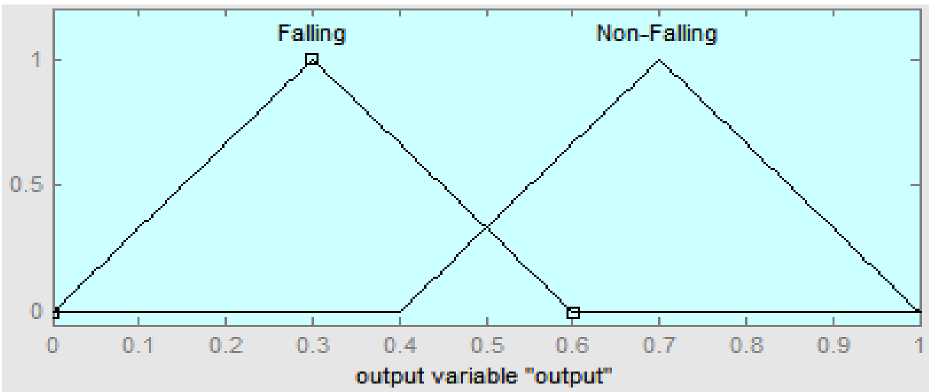

Figure 4. Fuzzy Output Variables

Fuzzy rules and Defuzzification

We constructed 24 fuzzy rules with the fuzzy input variables. Table 2 below is a table showing Fuzzy Rule.

Table 2. Fuzzy Rule table

Rule	PeakCount	UpwardPeak	DownwardPeak	DownwardArea	Output
1	1	Low	Low	Small	Non-Falling
2	1	Low	Low	Large	Falling
3	1	Low	High	Small	Non-Falling
4	1	Low	High	Large	Falling
…	if			then	
21	3	High	Low	Small	Non-Falling
22	3	High	Low	Large	Falling
23	3	High	High	Small	Non-Falling
24	3	High	High	Large	Falling

The final process of fuzzy logic, inverse fuzzy operations, is to find one definite value that summarizes the fuzzy set. It can be represented using several mathematical techniques such as centroid, bisector, mean, maximum, maximum and weighted average.

In this paper, the most accurate and commonly used method among the above techniques, Centroid of Area (CoA), is used to represent the value. The formula can be expressed by the following equation (1).

$$Z_{CoA} = \frac{\int \mu_i(x)xdx}{\int \mu_i(x)dx} \qquad - (1)$$

COMPARISON PERFORMANCE

Sensitivity / Specificity

Considering the case of a falling, you can judge the situation by dividing it into two cases when you have fallen greatly or when you have not fallen. Results can be expressed as positive (classified as falling) or negative (classified as non-falling). The test results for each item may or may not match the actual state of the subject.

The table for the values of the binary classification test can be represented as a 2x2 table as follows:

Table 3. Falling / Non-falling Considering Table

	Standrad (+)	Standrad (-)
Finding(+)	TP (true positive)	FP (false positive)
Finding(-)	FN (false negative)	TN (true negative)

Each of the items shown in Table 3 is described below:

- Tp(True positive) : Those who are falling are correctly recognized as those who have fallen.
- FP(False positive) : People who are not fall are mistakenly perceived as falling.
- TN(True negative) : People who are not fall are correctly perceived as not falling
- FN(False negative) : Those who are fall are perceived as not being fall.

The above items can be combined in various ways to represent different probabilities. Among them, sensitivity and specificity are statistical measures of the performance of binary classification tests, also known as statistical classification functions.

Sensitivity measures the percentage of correctly identified positive reactions. For example, when a person falls, he or she judges the person to falling accurately. The sensitivity equation is shown in the following equation (2).

$$\frac{TP}{TP+FN} X100 \qquad - (2)$$

Uniqueness measures the proportion of correctly identified voices. For example, a non-falling case is a non-falling case. The formula for the specificity is shown in the following equation (3).

$$\frac{TN}{FP+TN} X100 \qquad - (3)$$

Comparison Performance

Experimental data of this study shows that the amount of change in the acceleration sensor is measured and 85 data are collected while the smartphone is put in the right pants pocket. Table 4 shows the experimental data.

Table 4. Experimental data

Data	Count
Falling	65
Non-Falling	20

Of the total 85 experimental data, 65 were tested for falling and 20 for non – falling data. Table 5 shows the results of comparison with the method of each paper based on the above experimental data.

Table 5. Comparison Performance

	DP Lee[6]	C Dinh[9]	Suggestion
Sensitivity	64.615%	94%	96.923%
Specificity	10%	99.65%	100%

Sensitivity and specificity were checked by the method of judgment of each article through the experimental data of Table 4. In [6], a simple binary algorithm without fuzzy logic was used to judge falling only when the upper peak value was two. Previous data has a high falling recognition rate, but it is seen that the sensitivity is low due to the accumulation of data resulting in a large number of data that are not two peaks. In addition, it can be seen that the specificity is low because almost non-falling is detected. In [9], fuzzy logic is used and the sensitivity and specificity are shown as 94% and 99.65%, respectively, by using the data of the acceleration sensor. The proposed method has higher sensitivity and specificity than the previous two methods.

CONCLUSION

In this paper, firstly, the shaking data was introduced for comparison with falling data, and specific points were presented to compensate for the falling shaking data which was judged to falling. Second, the recognition rate is improved by correcting the non-falling (shaking) data recognized as a fall in the falling recognition application. Third, the fuzzy theory is used to improve the recognition rate. Finally, we use the probability of specificity and sensitivity to improve the reliability of falling recognition rates.

In the future, I plan to make a falling determination application and compare it with other applications.

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