Using Type-2 Fuzzy Models to Detect Fall Incidents and Abnormal Gaits Among Elderly

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***Abstract*— June 2012, 11% of the overall population in Taiwan was over the age of 65. This ratio is higher than the average figure for the United Nations (8%). Critical issues concerning elderly in healthcare include fall detection, loneliness prevention and retard of obliviousness. In this study we design type-2 fuzzy models that utilize smart phone tri-axial accelerometer signals to detect fall incidents and identify abnormal gaits among elderly. Once a fall incident is detected an alarm is sent to notify the medical staff for taking any necessary treatment. When the proposed system is used as a pedometer, all the tri-axial accelerometer signals are used to identify the gaits during walking. Based on the proposed type-2 fuzzy models, the walking gaits can be identified as normal, left-tilted, and right-tilted. Experimental results from type-2 fuzzy models reveal that the accuracy rates in identifying normal walking and fall over are 92.3% and 100%, respectively, exceeding what are obtained using type-1 fuzzy models.**

Keywords- type-2 fuzzy models; gait; fall detection; accelerometer; healthcare.

I. INTRODUCTION

Parkinson's disease, stroke and dementia are three geriatric diseases that have tremendous effect on peoples' health. The common symptoms for these diseases include trembling, stiffness, moving with slow pace, and standing unstable. Apart from those symptoms, others consist of expressionless faces, excess saliva, tilted to forward body, decreasing arm concordant vibration during walking, and mini-step walking. Among those symptoms, arm trembling is a visible symptom. Tilted walking and decreasing arm concordant vibration require long-term observation to identify the symptoms. Thus, it is necessary to regularly observe the gait that in turn can help discover the geriatric diseases early as well as provide valuable information for elderly rehabilitation.

This study bases on the tri-axial accelerometers embedded in smart phones to detect geriatric fall incidents. We use the variations of accelerometer signals to establish fuzzy detection models. The changes of Y-axis and Z-axis signals are compared to decide which fuzzy model will be fired and which directions of the fall incidents are.

This study also integrates both pedometer and abnormal gaits into a novel judging model. After finishing the pedometer function, all the gaits during the walking are recorded in the system. The gait information contains the average tilted angle and the change of tilted angles, that is, the body main-axis and amplitude of vibration during walking. Those two representative features are used to judge whether the gait is abnormal. To design a universal system that fits individuals and different gaits among diverse age levels, type-2 fuzzy sets [[10], [13], [16], [17]] are used.

This paper is organized as follows. Section II reviews the related work of type-2 fuzzy sets. Section III introduces the proposed systems. Experimental results and discussions are given in section IV. Conclusions and future work are made in the final section.

II. RELATED WORK

Type-2 fuzzy models have various applications in the realm of health care. Lee et al. [1] used gender, age, height, weight, and regularly prepared menu to design a type-2 fuzzy model that recommended personalized menu good for diabetics. The personalized courses can help patients have a balanced diet and control their blood sugar levels. Khosravi et al. [2] proposed a type-2 fuzzy model for short-term prediction of power load and the results were compared to a type-1 fuzzy model and a neural network. Since the type-2 fuzzy model is better than the type-1 fuzzy model in handling uncertain situations it has higher prediction accuracy. However, their present study did not take the power bill into consideration.

Lai et al. [3] applied SVM (Sum Vector Magnitude) and SMA (Signal Magnitude Area) to estimate the amount of user's activity that is used to judge their activity status. A user was asked to wear 6 accelerometers on the left arm, right arm, body, left leg, right leg and neck so that the estimation of user's activity can be more accurate. The problems in their design were the high cost and difficulty of wearing the six accelerometers. Khan et al. [4] exploited the characteristic vector formed by self regression coefficients, area of signal strength and tilted angles of body to judge daily activities of users.

Bianchi et al. [5] combined both tri-axial accelerometers and barometers and proposed an algorithm that was based on sum of signal vector strength and area of signal strength to improve the detection rate of fall incidents. Curone et al. [6] combined both tri-axial accelerometers and heartbeat rates to identify user activity and to further infer whether there was an accident event. Roy et al. [7] integrated the accelerometers to sEMG (Surface Electromyography) and applied multi-layer neural network and adaptive neural fuzzy inference system to remote monitor user activities. Six accelerometers and sEMG were placed at upper left and right arms, left and right front arm, thigh, and chest to identify the user activities. Their proposed systems also had a high cost and were cumbersome to wear. Kurihara et al. [8] used the measured tri-axial accelerometer signals to calculate the amount of body activity. They also defined various walking exercise intensities from different walking patterns by MET (Metabolic Equivalent) to identify what kind of exercise a user was doing.

III. Proposed Methods

A. Fall Detection System

In this study we use the acceleration variations measured by the tri-axial accelerators in the smart phones to design the type-2 fuzzy systems [11], [12], [15] that are focused on detecting whether an elderly fell at home [18]. The proposed system flowchart for fall detection is shown in Fig. 1. At the beginning, the proposed system smoothes on the measured tri-axial acceleration signals. Then, the system compares the larger acceleration variations between the Z-axis and the Y-axis to initiate either forward-backward or left-right fuzzy model for fall detection. If the inferred result from the fuzzy model is assured to be fall incident, an alarm signal is sent to notify preset receivers such as medical staff and family member for emergent treatment.

To design the feasible type-2 fuzzy membership functions, we conducted a multitude of simulations to record the acceleration variations during normal walking and fall incident patterns. In our simulations, the user is asked to wear the smart phone, which is put in a wallet, near the waist. To find the distribution of acceleration variations, the user is also asked to walk quickly, normally, or slowly. Based on the acceleration variations, the type-1 fuzzy membership functions for X-axis, Y-axis, and Z-axis are constructed. Note that the cores of the membership functions are calculated from the means of each axis acceleration variations. The leftmost boundary and rightmost boundary for each membership function correspond to the minimum and maximum variations, respectively.

According to the method proposed by Mendel et al. [9], a type-2 membership function can be constructed from type-1 membership functions. The core of type-2 upper membership function (UMF) extends from the original leftmost to rightmost cores of type-1 membership functions while the leftmost and rightmost boundaries of type-2 upper membership function correspond to the original leftmost and rightmost boundaries of type-1 membership functions, respectively. The type-2 lower membership function (LMF) is formed by the intersection of the original type-1 membership functions that has the minimum intersected area.

Based on our experimental data, the type-2 membership functions are shown in Fig. 2. Since the current design focuses on detecting whether a fall incident occurs, only two cases, i.e., normal (N) and fall (F), are considered for the consequent parts in the fuzzy rules. The designed fuzzy rule base for identifying left-right fall incidents is given below:

Rule1: If ΔgZ is Low and ΔgX is Low, then output is N.
Rule2: If ΔgZ is Low and ΔgX is High, then output is N.
Rule3: If ΔgZ is High and ΔgX is Low, then output is F.
Rule4: If ΔgZ is High and ΔgX is High, then output is F.

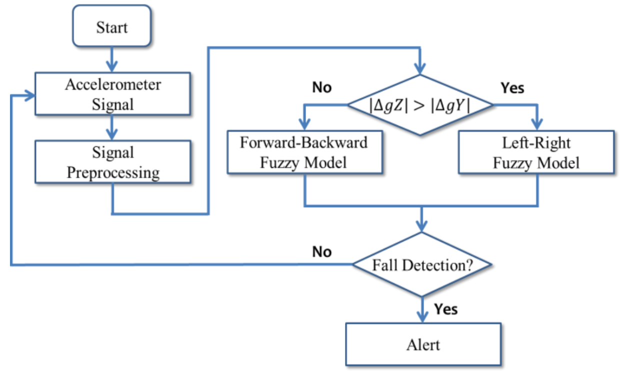

Fig. 1. The proposed system flowchart for fall detection.

While the designed fuzzy rule base for detecting forward-backward fall incidents is given below:

Rule1: If ΔgY is Low and ΔgX is Low, then output is N.
Rule2: If ΔgY is Low and ΔgX is High, then output is N.
Rule3: If ΔgY is High and ΔgX is Low, then output is F.
Rule4: If ΔgY is High and ΔgX is High, then output is F.

Based on both the upper and lower firing strength, the output interval of each rule can be determined. The upper and lower membership functions are determined as follows:

$$\text{LMF}(O) = \min\left(\underline{f}(x), LMF(I)\right), \tag{1}$$

$$\text{UMF}(O) = min\left(\overline{f}(x), UMF(I)\right), \tag{2}$$

where $\overline{f}(x)$ and $\underline{f}(x)$ correspond to upper and lower firing strength of each rule, respectively. *LMF(I)* and *UMF(I)* represent the lower and upper boundaries of consequent membership function, respectively. The union of all fired rule intervals is then taken for defuzzification to infer the desired output.

Due to the complexity and computational cost when type-2 fuzzy rules are used in inference and defuzzification, this study applies the method proposed by Mendel et al. that simplified the original membership functions into interval type-2 membership functions. The fuzzy intervals resulted from fuzzy inference must be order-reduced to infer a crisp output. This process is completed through KM algorithm to obtain an approximate output value. The KM algorithm is summarized as follows: first, rearranging the fired rules in ascending order according to the values of consequent parts. In the initialization of KM algorithm, the initial firing strength of a rule is the average of upper and lower firing strength. Then, using the initial firing strength and the corresponding consequent values to determine the center of area and find the output at the 0^{th} generation as follows:

$$y_{ini} = \frac{\sum_{i=1}^{n} f_{ini}[i] * output[i]}{\sum_{i=1}^{n} f_{ini}[i]}, \tag{3}$$

where n is the number of sampling points at the consequent interval, $f_{ini}[i]$ is the initial firing strength at the sampled point, and output[i] is the consequent value at the sampled point.

Then, by identifying which two fuzzy rules where the output value is located to find both left switch point and right switch point. And a new output is generated through the KM algorithm. Finally, the newly generated output is compared with the previous generated value to decide whether the process continues. If no noticeable difference exists between both new and old values, this implies that the output is the defuzzified result.

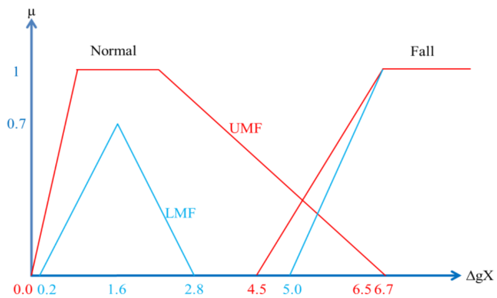

Fig. 2(a). Type-2 fuzzy membership functions for the X-axis.

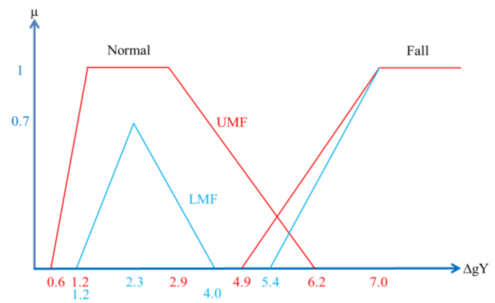

Fig. 2(b). Type-2 fuzzy membership functions for the Y-axis.

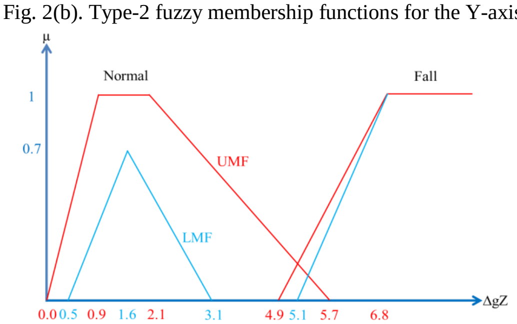

Fig. 2(c). Type-2 fuzzy membership functions for the Z-axis.

B. Abnormal Gait Judgment

The procedure for judging abnormal gait is shown in Fig. 3. When the user pressed the start button to initiate the pedometer the system continues to receive the acceleration signals that were used to judge the tilt angles and the changes of tilt angles. When the user pressed the stop button, the system calculated the average tilt angle and the average of changes of tilt angles during the walking experiment. Those two variables were used to be the inputs of type-2 fuzzy system to infer the user gait pattern. The inferred output was recorded in the database for further analysis.

B.1 Calculation of Tilt Angles

When a handset is placed on a table the acceleration is only exerted on the Z-axis and the gravity is 1g. When a smart phone is rotated, the gravity is decomposed into tri-axis components. For example, when a handset is rotated around X-axis by θ_x angles, the Y-axis acceleration is the measured component on Y-axis. Similarly, when a handset is rotated around Y-axis by θ_y angles, the X-axis acceleration is the measured component on X-axis.

When a smart phone is tilted by 30° the measured acceleration is 0.5g. If there is no tilt and the smart phone is placed perpendicular to the earth surface, the measured acceleration is 1g. Based on the earth gravity exerted on the smart phones, we obtain the tilt angles as follows:

$$\theta_z = \sin^{-1}\left[\frac{gY}{g}\right],$$
$$\theta_y = \sin^{-1}\left[\frac{gZ}{g}\right], \qquad (4)$$

where θ_z (θ_y) is the angle when the smart phone is rotated around the Z-axis (Y-axis) when it is fixed. gY (gZ) is the measured Y-axis (Z-axis) component. g is the measured acceleration of smart phone when the gravity is 1g.

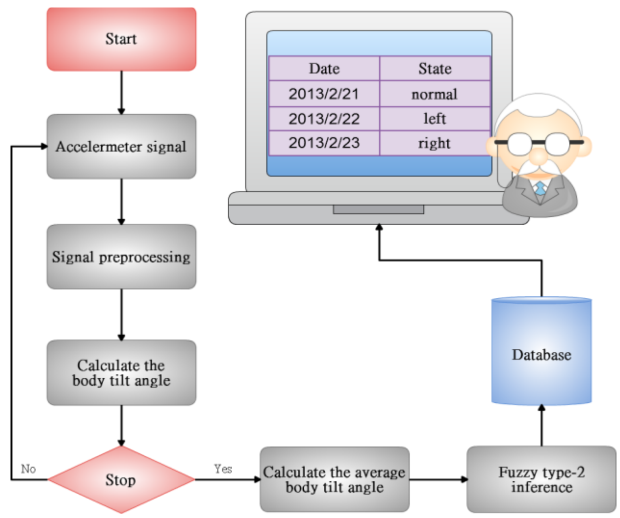

Fig. 3. The flowchart for judging abnormal gait.

B.2 Peak Detection ofTilt Angles

We did several experiments on the body tilt angles during normal walking and observed their variations [14]. The measured accelerometer signals are plotted as curves. When calculating both the average tilt angle and change of tilt angles, only the turning points on the curve are considered. Note that those dots are the peaks that indicate the changing points of tilt directions. The flowchart for the proposed peak detection method that is combined with the derived tilt angles is given in Fig. 4.

Initially, the first datum is saved. When the second datum is larger than the first one it is judged as tilting to the right. On the contrary, it is judged as tilting to the left. After deciding the initial direction, the system continues to receive data until it finds the peak angles on the detected side. Then, the system keeps on finding the peak on the other side until the stop button is pressed by the user to terminate the experiment.

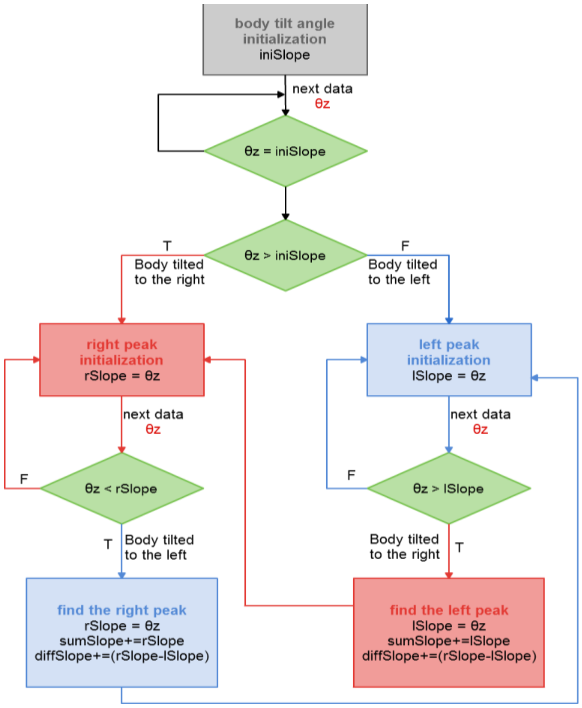

Fig. 4. Detecting peak tilt angles.

B.3 Type-2 Fuzzy Inference Model

In this study we propose a type-2 fuzzy model to infer whether a fall incident has occurred. We did multitudes of experiments on normal, left tilted, and right tilted walking. The membership functions constructed from the experimental data are shown in Fig. 5 and Fig. 6, where N stands for normal patterns and A is abnormal. Note that both Fig. 5(a) and Fig. 6(a) are type-1 fuzzy membership functions. To transform type-1 into type-2 functions, it is necessary to clarify the uncertain areas. In this study, we use the standard deviation of the simulated data to the uncertain areas of type-2 fuzzy membership functions as shown in Fig. 5(b) and Fig. 6(b). Fig. 7 is the type-1 membership functions of consequent part where NP represents normal output while AP is for abnormal output.

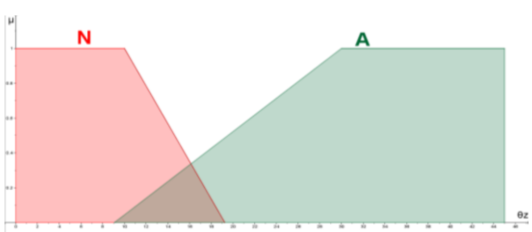

Fig. 5(a). The average tilt angle (θz) for type-1 membership functions.

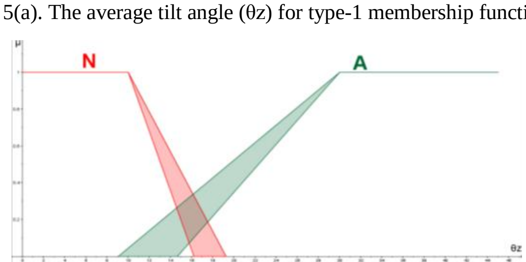

Fig. 5(b). The average tilt angle (θz) for type-2 membership functions.

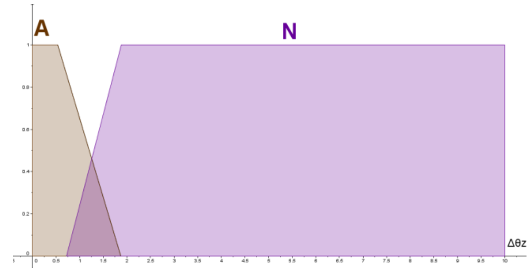

Fig. 6(a). The change of average tilt angle (Δθz) for type-1 membership functions.

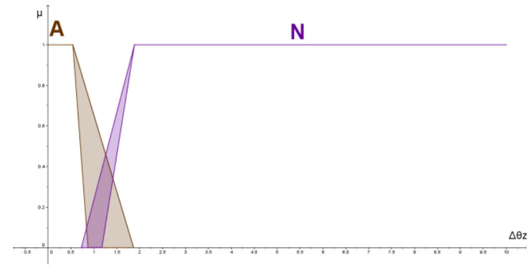

Fig. 6(b). The change of average tilt angle (Δθz) for type-2 membership functions.

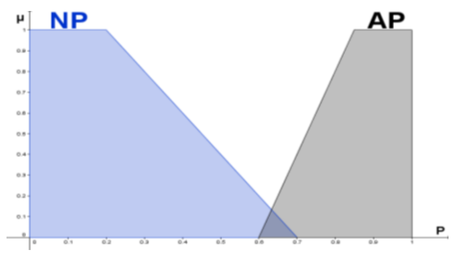

Fig. 7. The type-1 membership functions for consequent part.

Since each variable (θz and Δθz) has only two labels (A and N), the fuzzy rule base contains 4 rules from the combinations:

Rule1: If θz is N and Δθz is N, then state is NP.
Rule2: If θz is N and Δθz is A, then state is NP.
Rule3: If θz is A and Δθz is N, then state is NP.
Rule4: If θz is A and Δθz is A, then state is AP.

IV. Experimental Results and Discussion

A. Fall Detection

Data measured from tri-axial accelerometers that simulated users' normal and abnormal gaits are used to verify the inference effectiveness of the proposed type-2 fuzzy models. Seven subjects, including 5 males and 2 females with an average height of 171.8±6.7cm, participated our experiments. Taking the forward-backward fall detection model for example, part of 78 of the experimental data is listed in Table 1. For those normal walking gaits, our model can identify the patterns with 92.3% accuracy. Six normal gaits in Table 1 are misidentified as fall incidents due to the fact that they have higher changes in the Y-axis accelerometer signals as compared to other normal patterns. This implies that a fine adjustment of the type-2 membership functions is indispensable to reach a perfect accuracy of identification. Once a fall incident is detected the proposed model can identify the fall incident with 100% accuracy as shown in

Table 2. The detection rates from normal walking and fall over by type-2 and type-1 fuzzy models are compared in Table 3 and Table 4, respectively. When the measured ΔgX signal is a little bit large as the third data pair shown in Table 1 during the normal walking the type-1 fuzzy model had a false alarm while this situation is overcome by the type-2 fuzzy model.

Table 1. Inference results from normal walking gaits.

No.	normal (ΔgX, ΔgY)	inf.	status
1	(2.1,4.6)	0.24	Normal
2	(3.4,5.9)	0.69	Fall
3	(6.8,2.6)	0.22	Normal
4	(2.3,5.2)	0.41	Normal
⋮	⋮		
77	(4.5,2.7)	0.23	Normal
78	(1.6,5.3)	0.46	Normal
Correct data	72		
Incorrect data	6		
Accuracy rate	92.3%		

Table 2. Inference results from fall incidents.

No.	fall (ΔgX, ΔgY)	inf.	status
1	(1.0,6.3)	0.77	Fall
2	(9.8,5.9)	0.71	Fall
3	(2.0,8.3)	0.79	Fall
4	(1.1,8.2)	0.79	Fall
⋮	⋮		
47	(4.4,5.6)	0.58	Fall
48	(4.3,6.7)	0.78	Fall
Correct data	48		
Incorrect data	0		
Accuracy rate	100%		

Table 3. Comparison of accuracy rates from type-2 and type-1 fuzzy models during normal walking.

Normal	Type-2	Type-1
Correct data	72	67
Incorrect data	6	11
Accuracy rate	92.3%	85.8%

Table 4. Comparison of accuracy rates from type-2 and type-1 fuzzy models during fall over.

Fall	Type-2	Type-1
Correct data	48	48
Incorrect data	0	0
Accuracy rate	100%	100%

B. Abnormal Gait Judgment

To judge whether a user has abnormal gait during walking, six different combinations of experiments were performed. The six experiments include the cases when the smart phone is carried around the user's left waist under normal walking, around the right waist under normal walking, around the left waist under left-tilted walking, around the right waist under left-tilted walking, around the left waist under right-tilted walking, and around the right waist under right-tilted walking.

Table 5 compares the inference results under normal walking from our type-2 fuzzy models. When the threshold is set to 0.6 the average judging rate is about 92.5%. For the left-tilted and right-tilted experiments the inference results are shown in Table 6 and Table 7, respectively. When the threshold is set to 0.6, the accuracy is approximately 82.5%. The comparison results from normal and abnormal tilt gaits are given in Table 8. By analyzing the results shown in both Table 6 and Table 7, it is interesting to find when the smart phone is carried around the user's right waist it gives better identification accuracy than carried around the left waist if the user had a left-tilted tendency during walking. Similarly, for a right-tilted gait it would be better that the smart phone is carried around the left waist to achieve better identification accuracy. Of course, the results are individually dependent. However, through multitudes of experiments the better position to carry the smart phone can be located to improve the average identification accuracy.

Table 5. Inference results under normal walking.

smart phone at left waist				smart phone at right waist			
θz	Δθz	inf.	status	θz	Δθz	inf.	status
16.67	-2.48	0.4	Normal	-11.95	-1.64	0.57	Normal
16.62	-1.49	0.57	Normal	-10.96	-1.5	0.57	Normal
19.28	-2.69	0.4	Normal	-13.62	-3.82	0.4	Normal
8.06	-3.31	0.28	Normal	-8.42	-3.14	0.28	Normal
14.33	-1.37	0.65	Abnormal	-15.56	-1.33	0.65	Abnormal
18.65	-2.13	0.4	Normal	-13.05	-2.73	0.38	Normal
14.12	-1.98	0.4	Normal	-12	-1.27	0.57	Normal
10.89	-1.16	0.57	Normal	-12.93	-1.44	0.57	Normal
11.86	-0.72	0.55	Normal	-17.37	-1.26	0.65	Abnormal
11.75	-0.75	0.55	Normal	-12.69	-1.48	0.53	Normal
6.18	-2.54	0.28	Normal	6.36	-2.88	0.28	Normal
0.89	-3.6	0.28	Normal	-11.73	-1.97	0.4	Normal
12.91	-3.97	0.38	Normal	-9.92	-3.08	0.28	Normal
2.75	-3.37	0.28	Normal	-17.26	-4.38	0.4	Normal
16.29	-3.52	0.4	Normal	-5.97	-2.44	0.38	Normal
16.99	-6.87	0.4	Normal	-8.1	-2.64	0.28	Normal
2.66	-1.36	0.4	Normal	-10.86	-1.89	0.4	Normal
3.76	-3.9	0.28	Normal	-3.58	-3.03	0.28	Normal
14.72	-2.53	0.4	Normal	-8.3	-1.12	0.4	Normal
7.84	-3.9	0.28	Normal	-7.59	-5.15	0.28	Normal

Table 6. Inference results under left-tilted walking.

smart phone at left waist				smart phone at right waist			
θz	Δθz	inf.	status	θz	Δθz	inf.	status
17.33	0.34	0.6	Normal	-26.2	0.16	0.85	Normal
19.82	1.01	0.53	Abnormal	-14.58	0.33	0.53	Abnormal
29.12	0.3	0.85	Normal	-17.3	0.79	0.6	Normal
30.4	0.11	0.85	Normal	-22.93	0.05	0.85	Normal
22.71	1.27	0.65	Normal	-19.5	1.05	0.6	Normal
26.9	1.05	0.6	Normal	-22.07	0.53	0.85	Normal
23.12	0.11	0.85	Normal	-20.84	0.07	0.85	Normal
32.3	1.87	0.4	Abnormal	-18.58	0.43	0.6	Normal
24.79	0.66	0.85	Normal	-26.91	0.19	0.85	Normal
27.18	1.68	0.57	Abnormal	-19.62	0.85	0.6	Normal

Table 7. Inference results under right-tilted walking.

smart phone at left waist				smart phone at right waist			
θz	Δθz	inf.	status	θz	Δθz	inf.	status
21.13	-0.21	0.85	Normal	-19.69	0.5	0.85	Normal
29.28	0.7	0.85	Normal	-28.05	0.99	0.53	Abnormal

19.08	-0.56	0.6	Normal	-19.95	-0.24	0.85	Normal
23.77	-0.13	0.85	Normal	-14.99	-0.04	0.53	Abnormal
38.54	0.27	0.85	Normal	-19.07	-0.18	0.6	Normal
25.62	-0.69	0.85	Normal	-15.19	-0.48	0.53	Abnormal
19.6	0.16	0.85	Normal	-27.29	-0.81	0.6	Normal
24.02	-0.08	0.85	Normal	-18.63	-0.7	0.65	Normal
27.97	-0.11	0.85	Normal	-21.25	0.14	0.85	Normal
16.66	0.86	0.65	Normal	21.64	0.71	0.85	Normal

Table 8. Comparison of accuracy rate.

	normal tilt gait	abnormal tilt gait
Correct data	37	33
Incorrect data	3	7
Accuracy rate	92.5%	82.5%

V. Conclusions

In this study we proposed type-2 fuzzy models from smart phones tri-axial accelerometer signals to identify whether an elderly has fallen at home. The elderly body tilted angles and the change of tilted angles during walking are used to construct a type-2 fuzzy model to infer whether the elderly gait is normal or not. The long-term recorded gait patterns can provide useful information to monitor the health conditions of elderly.

All the models created to identify elderly fall incidents are based on type-2 fuzzy sets. Different to the type-1 fuzzy sets, the uncertain areas in type-2 fuzzy sets can represent the variations of tri-axial accelerometer signals from normal walking and fall over of different elderly. Consequently, the type-2 fuzzy models can resolve the problems remained in type-1 fuzzy models.

The current experimental results indicate that there remains false alarm in identifying walking patterns. When an elderly has unusual body vibration during walking there is a chance that the pattern may be misidentified as fall incidents. The future work will focus on automatically adjusting the parameters defined the type-2 membership functions to reach an almost perfect detection rate. Moreover, more elderly will be invited to install our system so that various walking and fall patterns can be used to train the proposed type-2 fuzzy models and in the hope to design a feasible system to identify fall incidents.

Acknowledgments

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