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The implementation of a smartphone-based fall detection system using a high-level fuzzy Petri net

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ABSTRACT

The falling down problem has become one of the very important issues of global public health in an aging society. The specific equipment was adopted as the detection device of falling-down in the early studies, but it is inconvenient for the elderly and difficult for future application. The smart phone more commonly used than the specific fall detection equipment is selected as a mobile device for human fall detection, and a fall detection algorithm is developed for this purpose. What the user has to do is to put the smart phone in his/her thigh pocket for falling down detection. The signals detected by the tri-axial G-sensor are converted into signal vector magnitudes as the basis of detecting a human body in a stalling condition. The *Z*-axis data sets are captured for identification of human body inclination and the occurrence frequencies at the peak of the area of use are used as the input parameters. A high-level fuzzy Petri net is used for the analysis and the development of identifying human actions, including normal action, exercising, and falling down. The results of this study can be used in the relevant equipments or in the field of home nursing.

1. Introduction

Thanks to the advances of medical technology and the decrease of birth date, Taiwan is making a steady pace into an aging society. The data of Directorate-General of Budget, Accounting and Statistics, Executive Yuan in 2012 showed that 11% of total population was 65 years or more, indicating the desperate needs for safety and caring of these senior citizens. The “2005 survey on citizen health and drug abuse” [1] suggested that the possibility was 28–35% for senior citizens aged 65 or more to fall down, and this number increased significantly to 32–42% for those aged 70 or more. Falling down not only leads to broken bones, pain, difficulty in mobility, and body deterioration of senior citizens; and in some extreme cases, death. Therefore, it is an issue requiring desperate attention to raise an alarm for the medical assistance when someone falls down and prevents further damage.

The fast growth of technology triggers the booming of smart phones. Most of market-available smart phones are equipped with G-sensor and proximity sensor [2,3]. Therefore, the smart phone, which is more commonly seen than human fall detection devices, is selected as a mobile device for human fall detection and a fall detection algorithm has been developed for this purpose. What the user has to do is to put the smart phone in his/her thigh pocket for fall detection.

Many factors lead to falling down, including environmental factors, deterioration of body functions, visual impairment, deterioration of muscle strength, and balancing disorder, which is commonly considered as the primary factor that results in falling down. A person falls down due to the loss of balance of human body for some reasons. The types of falling down include forward fall, backward fall, vertical fall, sideway fall, and fall on buttocks. Thus, for this study, falling down was defined as a falling behavior that is non-autonomous or uncontrollable. Falling down is a movement that a human body falls onto the floor due to inability to control the body. Therefore, falling down is a single incident that happens instantaneously, which separates it from walking or exercising which has the characteristics of frequent repetitiveness. In addition, the body is in a stalling condition when tilting at the instant of falling down, and thus the acceleration generated by human activities can be used as an important data set for identification of falling down.

A number of studies on human fall detection [4–6] have proposed the use of speed and tilting angles for the identification of falling down. Misidentification is easily possible when violent movements occur on a human body, for example, in exercising.

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Therefore, this factor or frequency was taken into account as part of identification basis for human fall detection. The signals collected by a tri-axial G-sensor are converted into signal vector magnitudes. Z-axis data sets are captured and occurrence frequencies are calculated as input parameters. The high-level fuzzy Petri net (HLFPN) was adopted for analysis, development and identification of normal action, exercising, and falling down. As such, an alarm can be raised when someone falls down, and medical assistance can be provided immediately to prevent injuries from aggravating and reduce the mortality due to falling down.

2. Literature review

In view of mobile and ubiquitous learning, a pervasive computing environment allows offering people with adaptive materials and services for learning anytime and anywhere [7]. On the other hand, the mobile management refers to the service or equipment unconstrained by time and place while the analysis and retrievals of manager's digital information records can facilitate users with acquisition of individual demand. Similar to the study on mobile learning conducted by Chang et al. [8], the mobile management includes three elements, namely, the mobile device, communication infrastructure, and management method. Under the supplement of mobile device, the managers can manage anytime and anywhere while such a device is capable of presenting information related to the managed, providing a bilateral wireless communication channel between the managers and the managed (or the managed objects) [3,9].

2.1. Signal vector magnitude

In general, the smart phones are equipped with sensors such as G-sensor or gyroscope. The G-sensor is selected for fall detection in this study. The data sets collected by the sensor in X, Y and Z axes are used in the calculation in a series of methods, one of which is the signal vector magnitude (SVM) proposed by Liu et al. [4] as shown in Eq. (1), where X, Y and Z are the acceleration of the respective axes measured by the G-sensor. SVM incorporates overall vibrations, thus making it easier to identify the difference in human motions [10,11].

$$\text{SVM} = \sqrt{X^2 + Y^2 + Z^2} \tag{1}$$

A possible falling down happens when it is detected that SVM is greater than a predefined value. However, human legs can generate higher SVMs in jogging, jumping or violent exercising than in falling down. The possibility of the error identification is expectedly high if this is only used for detection.

2.2. High-level fuzzy Petri net

Petri net theory was proposed by Dr. Carl Adam Petri in 1962. Petri nets are a graphical and mathematical modeling tool, which is concurrent, asynchronous, distributed, parallel, nondeterministic, and stochastic; and it can be used to model and analyze various systems [12]. However, along with the rapid advance of the information system, the descriptions of Petri net are more and more complex. Therefore, scholars one after another conduct their researches with extended Petri net theory, such as colored Petri net [13], timed Petri net [7], fuzzy Petri net [14], high-level fuzzy Petri net (HLFPN) [15–18], and so on. This paper adopted the HLFPN, focusing on the fall detection to make decisions. It provides with the characters of Petri net and fuzzy theories, which can be used to express fuzzy production rules and conduct fuzzy reasoning. The basic definitions and fuzzy reasoning approach are introduced as follows:

2.2.1. Definitions

Definition 1 *(HLFPN).* The HLFPN is defined as an 8-tuple.

$\text{HLFPN} = (P, T, F, C, V, \alpha, \beta, \delta)$

where

$P = \{p_1, p_2, p_3, \ldots, p_k\}$	A finite set of places.
$T = \{t_1, t_2, t_3, \ldots, t_l\}$	A finite set of transitions.
$P \cup T \neq \phi$	
$F \subseteq (P \times T) \cup (T \times P)$	Called the flow relation and is also a finite set of arcs, each representing the fuzzy set (i.e. fuzzy term) for an antecedent or a consequent; where the positive arcs (i.e. THEN parts) are denoted by $\rightarrow$.
$C = \{X, Y, Z\}$	A finite set of linguistic variables, e.g. X, Y, and Z, where $X = \{x_1, x_2, \ldots, x_n\}$, $Y = \{y_1, y_2, \ldots, y_m\}$, $Z = \{z_1, z_2, \ldots, z_q\}$.
$V = \{v_1, v_2, v_3, \ldots, v_l\}$	A finite set of fuzzy truth values known as the fuzzy relational matrix between the antecedent and the consequent of a rule.
$\alpha : P \rightarrow C$	An association function, mapping from places to linguistic variables. $\alpha(p_i) = c_i$, $i = 1, \ldots, I$, where $C = \{c_i\}$ is a set of linguistic variables in the knowledge base (KB) and is the number of linguistic variables in the KB.
$\beta : F \rightarrow [0, 1]$	Associations function, mapping from places to linguistic variables. $\alpha(p_i) = \{c_i\}$, $i = 1, \ldots, I$, where $C = \{c_i\}$ is a set of linguistic variables in the knowledge base (KB) and is the number of linguistic variables in the KB.
$\delta : T \rightarrow V$	An association function, mapping from transitions to fuzzy relational matrices.

Definition 2 *(Input and Output Functions).*

$I(t) = \{p \in P \mid (p, t) \in F\}$	A set of input places of transition t
$I(p) = \{t \in T \mid (t, p) \in F\}$	A set of input transitions of place p
$O(t) = \{p \in P \mid (t, p) \in F\}$	A set of output places of transition t
$O(p) = \{t \in T \mid (p, t) \in F\}$	A set of output transitions of place p

Definition 3 *(Negation).* In an IF-THEN-ELSE rule, the ELSE part is denoted by a negation arc $\bigcirc\!\!\rightarrow$ and the fuzzy set in the antecedent must be complemented and is denoted by $\urcorner$.

Definition 4 *(Membership Function).* The mapping function $Mem(p)$: $P \rightarrow [0, 1]$ assigns each place a real value, where $Mem(p) = \text{DOM}(\alpha(p))$, DOM represents the degree of membership in the associated proposition and data tokens are available in the set P of places.

Definition 5 *(Max–Min Compositional Rule).* In the HLFPN, $\forall$ transition t, $V(t) = \min(\text{fuzzy sets in } I(t))$; $\forall$ place p, $V(p) = \max(\text{fuzzy sets in } I(p))$. The *Max–Min* composition operator is denoted by $\bigcirc$.

Definition 6 *(Input Place, Hidden Place, and Output Place).* In the HLFPN, $\forall$ place $p_i \in P$, if $\forall t_j \in T$, $p_i \notin O(t_j) p_i$, then p_i is called an input place(IP) of t_j. If $\forall t_j \in T$, $p_i \notin I(t_j)$, then p_i is called an output place(OP) of t_j; otherwise, p_i is called a hidden place.

Definition 7 *(SISO, SIMO, MISO, MIMO).* There are four types of relationships in the HLFPN, shown as follows:

(1) SISO represents the single-input–single-output, i.e.,

$$\forall t_j \in T, |I(t_j)| = 1 \quad \text{and} \quad |O(t_j)| = 1.$$

(2) SIMO represents the single-input–multiple-output, i.e.,

$$\forall t_j \in T, |I(t_j)| = 1 \quad \text{and} \quad |O(t_j)| > 1.$$

(3) MISO represents the multiple-input–single-output, i.e.,

$$\forall t_j \in T, |I(t_j)| > 1 \quad \text{and} \quad |O(t_j)| = 1.$$

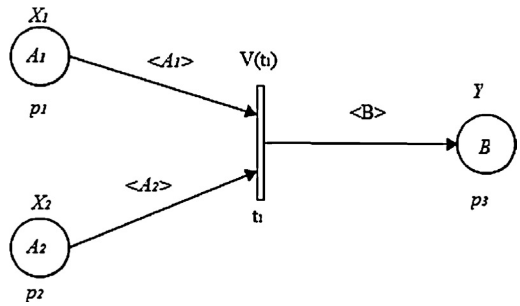

Fig. 1. HLFPN for Example 1.

(4) MIMO represents the multiple-input–multiple-output, i.e.,

$$\forall t_j \in T, |I(t_j)| > 1 \quad \text{and} \quad |O(t_j)| > 1.$$

Definition 8 *(Cyclic HLFPN).* In the HLFPN, either the subnet or the whole net, if an IP or OP is not empty and a path exists, and then we call it a cyclic HLFPN.

Definition 9 *(Heterogeneous Outputs).* In the HLFPN, if outputs possess different attributes, then we call them heterogeneous outputs.

2.2.2. Fuzzy reasoning

In the fuzzy reasoning method presented in [17], fuzzy production rules are used. In general, a fuzzy production rule describes fuzzy relationship between the antecedent and the consequent. Let R be a set of fuzzy production rules, where $R = \{R_1, R_2, \ldots, R_n\}$. The general form of the ith fuzzy production rule R_i is shown as follows:

$$R_i : \text{IF} \quad d_j(X \quad \text{is} \quad A), \quad \text{THEN} \quad d_k(Y \quad \text{is} \quad B); \quad \text{ELSE,}$$
$$d_w(Z \quad \text{is} \quad C)\ldots(V).$$

where d_j, d_k and d_w are propositions; X is called the input linguistic variable; Y and Z are called the output linguistic variables, respectively; A is called the input fuzzy set; B and C are called the output fuzzy sets, respectively; the fuzzy truth values of the propositions "X is A", "Y is B" and "Z is C" are restricted to $[0, 1]$; d_j is the antecedent of the fuzzy production rule R_i. d_k and d_w are the consequents of the fuzzy production rule R_i. Let V represent the fuzzy relational matrix between the antecedent and the consequent of a fuzzy production rule.

Example 1. Let us consider the fuzzy production rule R_1 shown as follows:

$$R_1 : \text{IF} \quad \text{it}(X_1) \quad \text{is} \quad \text{hot} \quad (A_1) \quad \text{AND} \quad \text{the sky} \quad (X_2) \quad \text{is cloudy} \quad (A_2),$$
$$\text{THEN the humidity}(Y) \text{ is high}(B).$$

Based on the transformation procedure presented in [15], we can transform the above fuzzy production rule R_1 into the following first-order logic form:

$$R'_1 : \text{IF} \quad X_1(A_1) \quad \text{AND} \quad X_2(A_2), \quad \text{THEN} \quad Y(B).$$

Then, the HLFPN model is shown in Fig. 1.

Assume that the fuzzy sets A_1, A_2 and B are shown as follows:

$$A_1 = \frac{0.20}{a_{11}} + \frac{0.54}{a_{12}} + \frac{0.24}{a_{13}}$$

$$A_2 = \frac{0.11}{a_{21}} + \frac{0.77}{a_{22}} + \frac{0.42}{a_{23}}$$

$$B = \frac{0.31}{b_1} + \frac{0.66}{b_2} + \frac{0.17}{b_3}$$

By the cylindrical extension operations [18], that is, a Cartesian product, we can obtain the antecedent fuzzy set A, shown as follows:

$$A = A_1 \times A_2 = \begin{pmatrix} 0.20 & 0.54 & 0.24 \end{pmatrix}^T \wedge \begin{pmatrix} 0.11 & 0.77 & 0.42 \end{pmatrix}$$
$$= \begin{vmatrix} 0.11 & 0.20 & 0.20 \\ 0.11 & 0.54 & 0.42 \\ 0.11 & 0.24 & 0.24 \end{vmatrix}$$

Then, the fuzzy relational matrices $V_1(t_1)$, $V_2(t_2)$ and $V_3(t_3)$ between antecedent and consequent of the fuzzy production rule R_1 can be obtained, shown as follows:

$$V_1(t_1) = \begin{vmatrix} 0.11 & 0.20 & 0.20 \\ 0.11 & 0.31 & 0.31 \\ 0.11 & 0.24 & 0.24 \end{vmatrix} \in A \times B \times b_1$$

$$V_2(t_2) = \begin{vmatrix} 0.11 & 0.20 & 0.20 \\ 0.11 & 0.54 & 0.42 \\ 0.11 & 0.24 & 0.24 \end{vmatrix} \in A \times B \times b_2$$

$$V_3(t_3) = \begin{vmatrix} 0.11 & 0.17 & 0.17 \\ 0.11 & 0.17 & 0.17 \\ 0.11 & 0.17 & 0.17 \end{vmatrix} \in A \times B \times b_3$$

The most widely used fuzzy reasoning method is the max–min composition inference [17]. Assume that the input fuzzy sets A'_1 and A'_2 are shown as follows:

$$A_1 = \frac{0.09}{a_{11}} + \frac{0.85}{a_{12}} + \frac{0.29}{a_{13}}$$

$$A_2 = \frac{0.29}{a_{21}} + \frac{0.89}{a_{22}} + \frac{0.45}{a_{23}}$$

Then, we can get

$$A_1 \circ V_1(t_1) = \begin{pmatrix} 0.09 & 0.85 & 0.29 \end{pmatrix} \circ V_1(t_1) = \begin{pmatrix} 0.11 & 0.31 & 0.31 \end{pmatrix}$$

$$A_1 \circ V_2(t_1) = \begin{pmatrix} 0.09 & 0.85 & 0.29 \end{pmatrix} \circ V_2(t_1) = \begin{pmatrix} 0.11 & 0.54 & 0.42 \end{pmatrix}$$

$$A_1 \circ V_3(t_1) = \begin{pmatrix} 0.09 & 0.85 & 0.29 \end{pmatrix} \circ V_3(t_1) = \begin{pmatrix} 0.11 & 0.17 & 0.17 \end{pmatrix}$$

Finally, we can obtain

$$B' = \begin{pmatrix} 0.29 & 0.89 & 0.45 \end{pmatrix} \circ \begin{vmatrix} 0.11 & 0.11 & 0.11 \\ 0.31 & 0.54 & 0.17 \\ 0.31 & 0.42 & 0.17 \end{vmatrix}$$
$$= \begin{pmatrix} 0.31 & 0.54 & 0.17 \end{pmatrix} = \frac{0.31}{b_1} + \frac{0.54}{b_2} + \frac{0.17}{b_3}$$

The above description is the fuzzy reasoning process of HLFPN.

2.2.3. Fuzzy reasoning algorithm

In this section, we briefly review a fuzzy reasoning algorithm (FRA) from [14] to determine whether there exists a fuzzy relational matrix between the antecedent and the consequent of a fuzzy production rule or not.

INPUT: $Mem(p_i)\ \forall\, p_i \in \mathrm{IP}$, where IP denotes a set of input places.
OUTPUT: $Mem(p_i)\ \forall\ p_i \in \mathrm{OP}$, where OP denotes a set of output places.
PROCEDURE

Step 1. Initially, assume that only the degree of memberships (DOMs) in the propositions operating on input variables are available. Consequently, the initial marking function is shown as follows:

$$M(p_i) = 0, \quad \text{if} \quad p_i \notin \mathrm{IP}$$

$$M(p_i) = \text{the number of data tokens}, \quad \text{if} \quad p_i \in \mathrm{IP}$$

Step 2. $\forall t_j \in T$, compute $V(t_j) = W_a \times W_c = (w_{a1}, w_{a2}, \ldots, w_{am})^T \wedge (w_{c1}, w_{c2}, \ldots, w_{cn})$, where T denotes a set of transitions; $V(t_j)$ is a fuzzy relational matrix between the antecedent and the consequent of rule t_j; $W_a = \{w_{a1}, w_{a2}, \ldots, w_{am}\}$ is a fuzzy set of weights for the antecedent; $W_c = \{w_{c1}, w_{c2}, \ldots, w_{cn}\}$ is a fuzzy set of weights for the consequent; and each element of a fuzzy set is denoted by a fuzzy weight interval.

Step 3. Input a data pattern to $W_{a\text{-}input}$.

Step 4. Fire the enabled transitions. Let t_j be any enabled transition. Then, compute

$$t_j \in T / \forall p_k, \quad M(p_k) = \text{the number of data tokens}$$

$$W'_a = W_{a\text{-}input}$$

$$W'_c = W'_a * \circ V(t_j) \ \text{ or } \ \neg\ W'_a \circ V(t_j)$$

if an ELSE part is available.

Step 5. For every output variable O, its associated membership distribution is $W'_c = \{w'_{ci}\} = \vee\ w'_{ci}$, $i = 1, 2, \ldots, I$, where I is the in degree of output variable O. Then, W'_c becomes an actual output.

Step 6. Go back to Step 4, while

$$\exists t_j \in T / M(p_i) = 1 \quad \forall p_i \in I(t_j)$$

(That is, while the enabled transitions still exist, go to Step 4).

Step 7. The Maxima defuzzification method is applied, and the real operating value is computed.

3. HLFPN-based fall detection model

Falls are inevitable incidents among the elderly people and particularly dangerous for the elderly were living alone. Hence, the fall detection becomes one urgent issue that requires reasonable solutions. A vast number of methods that detect falls through portable devices are determined by single incidents incorporated with threshold values and the angle of inclination. Such a method comprises many limitations such as misjudgment related to high threshold values resulted from the user's engagement in intense sports. Due to the difference in height, weight, and gender among people, body motions tend to vary accordingly, and so the falls. Sometimes, noises such as the wearing angle of electronic devices and postural differences could lead to some variations in values measured. Consequently, the application of sole threshold value as the determination for fall detection is highly subjective.

Due to some difference of motions between people, the study suggests to apply this fuzzy method. We first capture the value from user's 3-axis accelerator sensor through the electronic devices and then convert the value into SVM and measure the frequency of occurrences, followed by substituting the numbers into the membership function formulated by the experiment to generate the fuzzy degree. Then, the HLFPN is used to infer the results. Additionally, many studies adopt customized wearing devices that require fixed-wearing on specific area, such as the chest, back, hand, foot and waist. Over the long run, such a customized device could cause some inconveniences for users. Hence, the study adopts relatively accessible smart phones as mobile carriers for fall detection that can be stored on any thigh pocket of the users, thereby facilitating the effect of promotion.

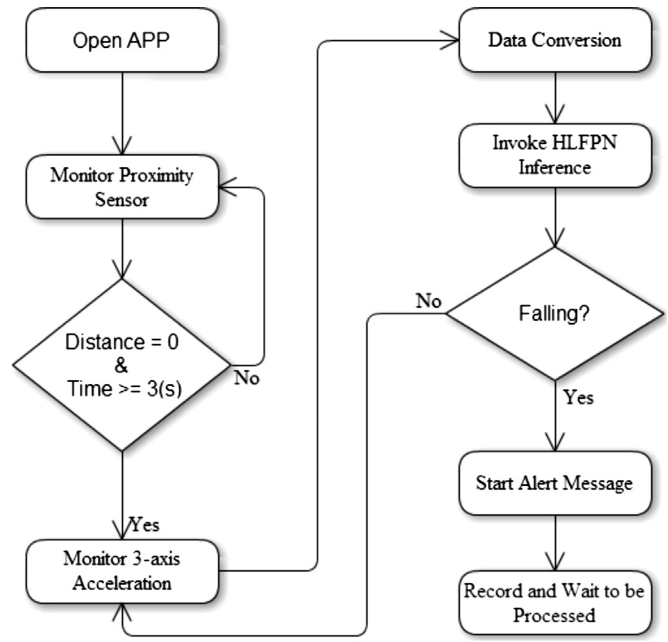

Fig. 2. Process of detection system.

3.1. System process

We adopted JAVA as the main programming language of this application, which was installed in Android-based smart phones to detect falls. Users can put the device into any one of the thigh pocket to start detection. This App is used to monitor user's behavior in real-time and continues to collect data of the 3-axis accelerator sensor in order to convert the data needed for inference. Such data sets are used as the input parameters of the inference in order to yield a result. If the result is falling, the App will issue an alarm signal to broadcast through voice and transmits data to the server for relevant personnel to handle afterwards. The system process is shown in Fig. 2.

3.1.1. Frequency parameter

Falling down is a single incident that happens instantaneously, which separates it from general exercising that has the characteristics of repetitiveness. Therefore, the factor of frequency is included to separate the difference of violent vibrations caused in these two conditions. For this study, the frequency parameter was defined as follows: the frequency parameter is the sum of the frequency of point p and all the frequency at point pf captured at the peak of other areas within range e between top and bottom amplitudes at time t when it starts at point p. The frequency parameter is shown in Fig. 3.

To avoid misjudgment due to single intense shaking after t period of intense sports, if the status is determined as a sport after taking the frequency parameters, time t will be added to continue calculation of frequency parameters in addition to accumulating the values from the last frequency parameters.

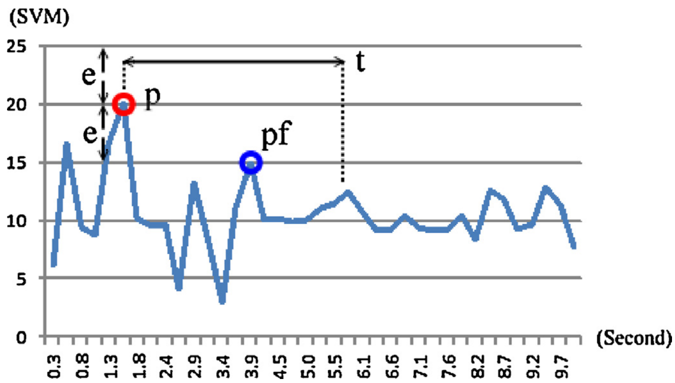

Fig. 3. The frequency parameter definitions.

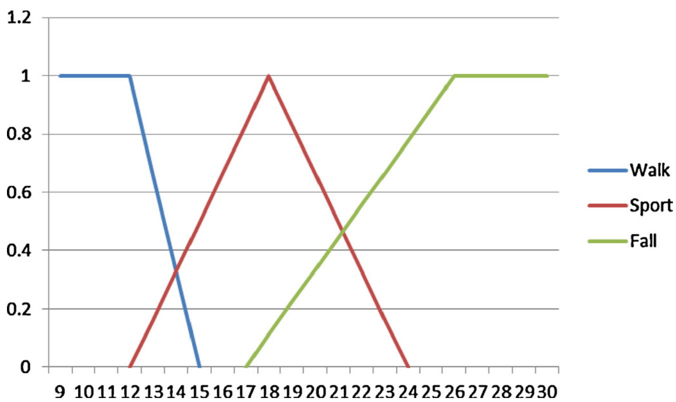

Fig. 4. The types of membership function for signal vector magnitude.

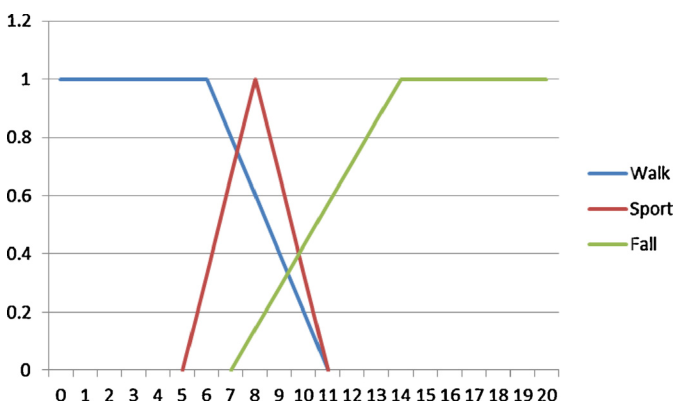

Fig. 5. The types of membership function for *Z*-axis.

3.2. Definition of membership function

SVM can be used to determine whether the user engages in intense motions, while *Z*-axis acceleration value identifies whether the user is engaged in inclination. User's frequency parameters do not repeat in almost all of the time due to the single-incident nature of falling. Hence, the paper adopts SVM, *Z*-axis acceleration value, and frequency parameters to define the membership function. The study divides the functions into three statuses: high, medium, and low, which are developed according to the experiments, as shown in Figs. 4–6.

The study applies three input parameters, namely, the signal vector magnitude, *Z*-axis, and frequency parameter. We divide the membership functions into "high," "medium," and "low". To meet practical requirements, the study also assigns the "high," "medium" and "low" levels to each membership function, as shown in Table 1.

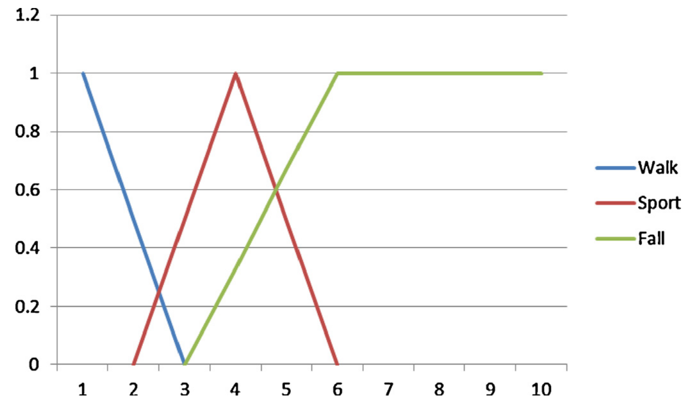

Fig. 6. The types of membership function for frequency parameter.

Table 1
Membership functions of technical indices.

Input parameter	Low		Middle			High	
SVM	12	15	12	18	24	17	26
Z	6	11	7	10	13	9	16
F	1	3	2	4	6	3	6

The experimental analysis shows that the SVM value usually falls between 9.8 and 27 while *Z*-axis acceleration value falls between 0 and 17 and the frequency falls between 1 and 10. For the general walking, the SVM value usually falls between 10 and 15 while the *Z*-axis acceleration value falls between 0 and 11 and the frequency falls between 2 and 6. During falls, the SVM value usually falls between 17 and 27 while the *Z*-axis acceleration value falls between 9 and 17 and the frequency falls between 1 and 3. Because the membership is required to fall between 0 and 1, we convert the three input parameters between 0 and 1 by substituting the basic algorithm to complete this task.

α, β and γ each represents SVM, *Z*-axis acceleration value, and the frequency parameter, respectively; whereas *H*, *M*, and *L* each denotes the "High," Medium" and "Low" membership function. The fuzzifier conversion process is defined as follows:

$$\alpha_H = \begin{cases} 1 & \chi \geq 26 \\ \dfrac{1}{6}(\chi - 17) & 17 < \chi < 26 \\ 0 & \chi \leq 17 \end{cases}$$

$$\alpha_M = \begin{cases} 0 & \chi \geq 24 \\ \dfrac{-1}{6}(\chi - 24) & 18 \leq \chi < 24 \\ \dfrac{1}{6}(\chi - 12) & 12 < \chi < 18 \\ 0 & \chi \leq 12 \end{cases}$$

$$\alpha_L = \begin{cases} 0 & \chi \geq 15 \\ \dfrac{-1}{3}(\chi - 15) & 12 \leq \chi < 15 \\ 1 & \chi \leq 12 \end{cases}$$

$$\beta_H = \begin{cases} 1 & \chi \geq 16 \\ \dfrac{1}{7}(\chi - 9) & 9 < \chi < 16 \\ 0 & \chi \leq 9 \end{cases}$$

$$\beta_M = \begin{cases} 0 & \chi \geq 13 \\ \frac{-1}{3}(\chi - 13) & 10 \leq \chi < 13 \\ \frac{1}{3}(\chi - 7) & 7 < \chi < 10 \\ 0 & \chi \leq 7 \end{cases}$$

$$\beta_L = \begin{cases} 0 & \chi \geq 11 \\ \frac{-1}{5}(\chi - 11) & 6 < \chi < 11 \\ 1 & \chi \leq 6 \end{cases}$$

$$\gamma_H = \begin{cases} 1 & \chi \geq 6 \\ \frac{-1}{3}(\chi - 15) & 12 < \chi < 15 \\ 0 & \chi \leq 15 \end{cases}$$

$$\gamma_M = \begin{cases} 0 & \chi \geq 6 \\ \frac{-1}{2}(\chi - 6) & 4 \leq \chi < 6 \\ \frac{1}{2}(\chi - 2) & 2 < \chi < 4 \\ 0 & \chi \leq 2 \end{cases}$$

$$\gamma_L = \begin{cases} 0 & \chi \geq 3 \\ \frac{-1}{2}(\chi - 3) & 1 < \chi < 3 \\ 1 & \chi \leq 1 \end{cases}$$

3.3. Fuzzy reasoning and building HLFPN

We set up the various parameters according to the previously defined fuzzy sets and their corresponding membership functions. The parameters are converted into various memberships through the fuzzifier. To establish the fuzzy production rules, we convert the memberships into "If. . .then. . ." syntax according to the size of parameters. Consequently, we can also infer the results according to the corresponding status resulted from the inputs after generating the fuzzy production rules. For example, if SVM is high, Z-axis value is high and the frequency is low, then it is determined as a fall. If SVM is low, Z-axis value is low and the frequency is low, then it is determined as a normal action. We will produce three results through these three rules, namely, normal action, sports, and fall.

We configure input linguistic variables as signal vector magnitude (SVM), Z-axis data (Z), and frequency parameter (F), whereas different linguistic variables are defined as "High," "Medium," and "Low" with the following fuzzy production rules generated:

R_1: IF SVM is L AND Z is L AND F is H THEN D is NA.
R_2: IF SVM is M AND Z is M AND F is M THEN D is S.
R_3: IF SVM is H AND Z is H AND F is L THEN D is F.

Based on the conversion procedures, the above production rules are converted to the HLFPN as shown in Fig. 7.

The parameters in Fig. 7 are described in Table 2.

Upon drafting the HLFPN model, the inference method is applied with the fuzzy rules of various input parameters as a basis. The study applies standard operators for computation in the inference process and eventually adopts Maxima's defuzzification method to yield the output results, as shown in the following formulas:

Table 2
Description of parameters.

Name of parameter	Description of parameter
S	Represents signal vector magnitude value, i.e. input place p_1.
Z	Represents Z-axis's value, i.e. input place p_2.
F	Represents frequency of occurrence value, i.e. input place p_3.
D	Represents detection status, i.e. output place p_4.
H, M, L	Represent high, middle, and low fuzzy vector, respectively.
Normal action, Sport, Fall	Represent normal action, sport, and fall fuzzy vector, respectively.
$V(t_i)$, i = 1,2,3	Represents the fuzzy relational matrix of SVM, Z, F, and detection status decision.
H', M', L'	Represent high, middle, and low fuzzy vector of input values, respectively.

Fuzzy union:

$$(A \cup B)(x) = \max(A(x), B(x)) \tag{2}$$

Fuzzy intersection:

$$(A \cap B)(x) = \min(A(x), B(x)) \tag{3}$$

Fuzzy complement:

$$\bar{A}(x) = 1 - A(x) \tag{4}$$

3.4. Example of HLFPN for fuzzy reasoning

An example is presented in this section to demonstrate the feasibility of fuzzy hypothesis and find the fuzzy reasoning results.

Step 1. Initially, assume that only the DOMs in the propositions operating on input variables are available. Assume that ten fuzzy sets are shown as follows:

$$SVM_L = \frac{0.4}{svm_{ll}} + \frac{0}{svm_{lm}} + \frac{0}{svm_{lh}}$$

$$Z_L = \frac{0.3}{z_{ll}} + \frac{0}{z_{lm}} + \frac{0}{z_{lh}}$$

$$F_M = \frac{0.4}{f_{ml}} + \frac{0}{f_{mm}} + \frac{0}{f_{mh}}$$

$$SVM_M = \frac{0}{svm_{ml}} + \frac{0.6}{svm_{mm}} + \frac{0}{svm_{mh}}$$

$$Z_M = \frac{0}{z_{ml}} + \frac{0.45}{z_{mm}} + \frac{0}{z_{mh}}$$

$$F_H = \frac{0}{f_{hl}} + \frac{0.6}{f_{hm}} + \frac{0}{f_{hh}}$$

$$SVM_H = \frac{0}{svm_{hl}} + \frac{0}{svm_{hm}} + \frac{0.7}{svm_{hh}}$$

$$Z_H = \frac{0}{z_{hl}} + \frac{0}{z_{hm}} + \frac{0.6}{z_{hh}}$$

$$F_L = \frac{0}{f_{lh}} + \frac{0}{f_{lm}} + \frac{0.73}{f_{ll}}$$

$$Status = \frac{0.4}{s_l} + \frac{0.5}{s_m} + \frac{0.7}{s_h}$$

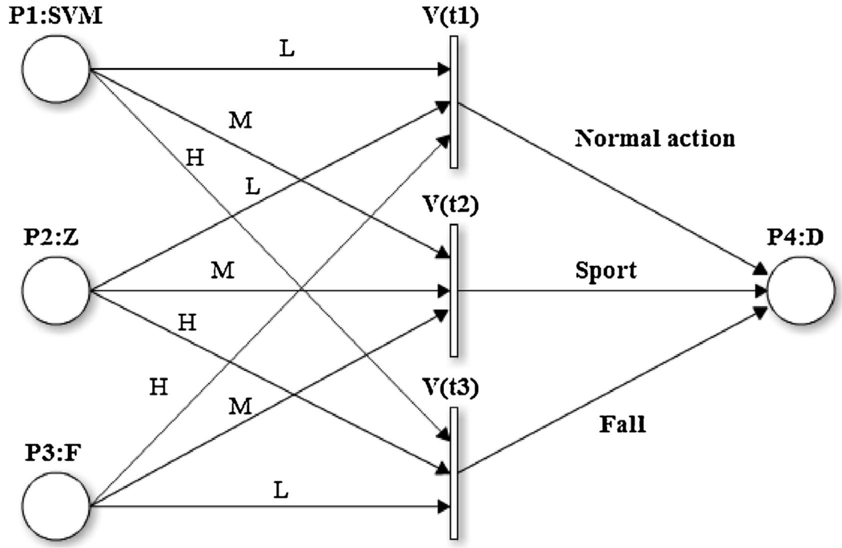

Fig. 7. The HLFPN model representing the three fuzzy production rules.

Step 2. By cylindrical extension, that is, computing the Cartesian product, we obtain the antecedent fuzzy relational matrices shown as follows:

$$P_1 = SVM_L \times Z_L \times F_M$$
$$= \left(\begin{pmatrix}0.4 & 0 & 0\end{pmatrix}^T \wedge \begin{pmatrix}0.3 & 0 & 0\end{pmatrix}\right)^T \wedge \begin{pmatrix}0.4 & 0 & 0\end{pmatrix}$$
$$= \begin{bmatrix}0.3 & 0 & 0\\ 0 & 0 & 0\\ 0 & 0 & 0\end{bmatrix}^T \wedge \begin{pmatrix}0.4 & 0 & 0\end{pmatrix} = \begin{bmatrix}0.3 & 0 & 0\\ 0 & 0 & 0\\ 0 & 0 & 0\end{bmatrix}$$

$$P_2 = SVM_M \times Z_M \times F_H$$
$$= \left(\begin{pmatrix}0 & 0.6 & 0\end{pmatrix}^T \wedge \begin{pmatrix}0 & 0.45 & 0\end{pmatrix}\right)^T \wedge \begin{pmatrix}0 & 0.6 & 0\end{pmatrix}$$
$$= \begin{bmatrix}0 & 0 & 0\\ 0 & 0.45 & 0\\ 0 & 0 & 0\end{bmatrix}^T \wedge \begin{pmatrix}0 & 0.6 & 0\end{pmatrix} = \begin{bmatrix}0 & 0 & 0\\ 0 & 0.45 & 0\\ 0 & 0 & 0\end{bmatrix}$$

$$P_3 = SVM_H \times Z_H \times F_L$$
$$= \left(\begin{pmatrix}0 & 0 & 0.7\end{pmatrix}^T \wedge \begin{pmatrix}0 & 0 & 0.6\end{pmatrix}\right)^T \wedge \begin{pmatrix}0 & 0 & 0.73\end{pmatrix}$$
$$= \begin{bmatrix}0 & 0 & 0\\ 0 & 0 & 0\\ 0 & 0 & 0.6\end{bmatrix}^T \wedge \begin{pmatrix}0 & 0 & 0.73\end{pmatrix} = \begin{bmatrix}0 & 0 & 0\\ 0 & 0 & 0\\ 0 & 0 & 0.6\end{bmatrix}$$

$\forall t_j \in T$, compute the fuzzy relational matrices $V(t_j)$, where T denotes a set of transitions. $V(t_j)$ is a fuzzy relational matrix between the antecedent and the consequent of rule t_j. Compute the fuzzy relational matrices, shown as follows:

$$V(t_1) = \begin{bmatrix}0.3 & 0 & 0\\ 0 & 0 & 0\\ 0 & 0 & 0\end{bmatrix} \in P_1 \times Status \times s_l$$

$$V(t_2) = \begin{bmatrix}0 & 0 & 0\\ 0 & 0.45 & 0\\ 0 & 0 & 0\end{bmatrix} \in P_2 \times Status \times s_m$$

$$V(t_3) = \begin{bmatrix}0 & 0 & 0\\ 0 & 0 & 0\\ 0 & 0 & 0.6\end{bmatrix} \in P_3 \times Status \times s_h$$

Step 3. Input a data pattern. Consider the input data patterns shown as follows:

$$SVM' = \frac{0}{svm_l} + \frac{0.79}{svm_m} + \frac{0.66}{svm_h}$$

$$Z' = \frac{0.42}{z_l} + \frac{0.43}{z_m} + \frac{0.74}{z_h}$$

$$F' = \frac{0}{f_m} + \frac{0.33}{f_h} + \frac{1}{f_l}$$

Step 4. Fire the enabled transitions:

$$S'_1 = SVM' \circ V(t_1) \circ Z' \circ F'$$
$$= \begin{bmatrix}0 & 0.79 & 0.66\end{bmatrix} \circ \begin{bmatrix}0.3 & 0 & 0\\ 0 & 0 & 0\\ 0 & 0 & 0\end{bmatrix} \circ \begin{bmatrix}0.42 & 0.43 & 0.74\end{bmatrix} \circ \begin{bmatrix}0 & 0.33 & 1\end{bmatrix}$$
$$= \begin{bmatrix}0 & 0 & 0\end{bmatrix}$$

$$S'_2 = SVM' \circ V(t_2) \circ Z' \circ F'$$
$$= \begin{bmatrix}0 & 0.79 & 0.66\end{bmatrix} \circ \begin{bmatrix}0 & 0 & 0\\ 0 & 0.45 & 0\\ 0 & 0 & 0\end{bmatrix} \circ \begin{bmatrix}0.42 & 0.43 & 0.74\end{bmatrix} \circ \begin{bmatrix}0 & 0.33 & 1\end{bmatrix}$$
$$= \begin{bmatrix}0 & 0.33 & 0\end{bmatrix}$$

$$S'_3 = SVM' \circ V(t_3) \circ Z' \circ F'$$
$$= \begin{bmatrix}0 & 0.79 & 0.66\end{bmatrix} \circ \begin{bmatrix}0 & 0 & 0\\ 0 & 0 & 0\\ 0 & 0 & 0.6\end{bmatrix} \circ \begin{bmatrix}0.42 & 0.43 & 0.74\end{bmatrix} \circ \begin{bmatrix}0 & 0.33 & 1\end{bmatrix}$$
$$= \begin{bmatrix}0 & 0 & 0.6\end{bmatrix}$$

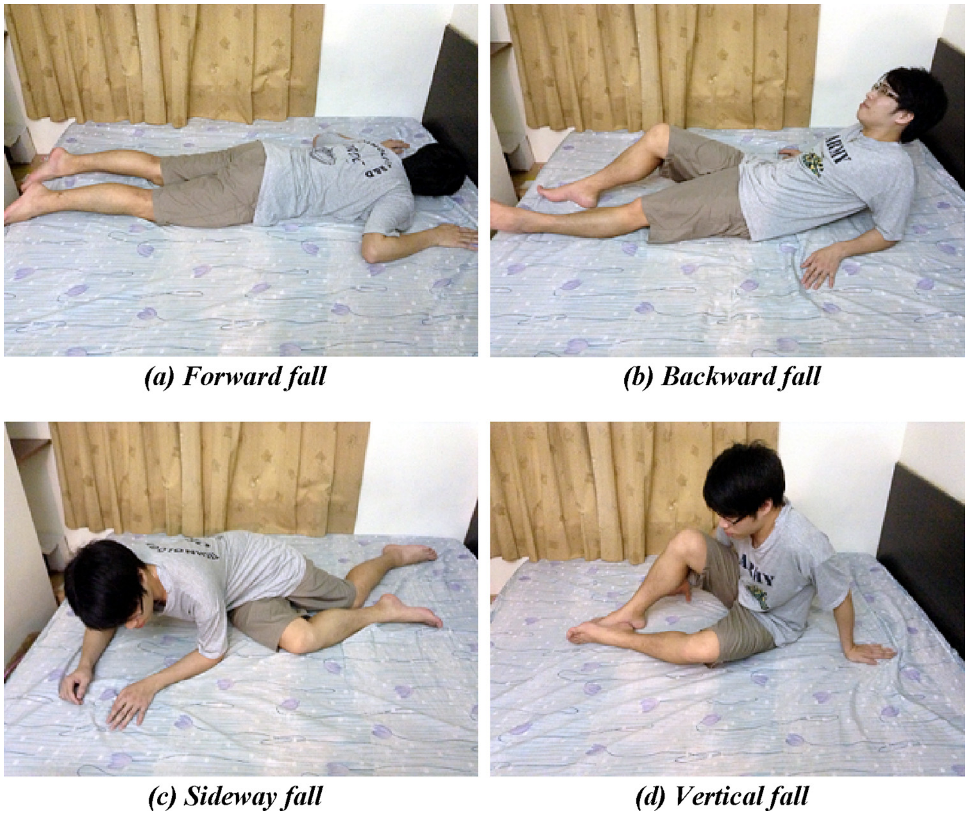

Fig. 8. Kinds of falling.

Steps 5 and 6. Finally, the fuzzy reasoning result is:

$$D = S_1' \cup S_2' \cup S_3' = \frac{0}{d_1} + \frac{0.33}{d_2} + \frac{0.6}{d_3}$$

Steps 7 and 8. If the Maxima Defuzzification method is applied, then the real operation value “Decision” can be made as follows:

Because d_3 has the maximal membership grade, this situation is determined as “fall”.

4. Experimental results

To prove the feasibility of HLFPN in the fall detection system, this section conducts verification on this system. The study first explains the scope and limitation of the research, followed by exhibiting the experimental data of various motions. Finally, the system conducts testing on the motions in daily routines in addition to exhibiting the inference results.

4.1. Research scope

The study is designed for seniors aged 65 years or older and the research scope of fall detection emphasizes the common fall conditions in daily routines for analysis, including falling forward, falling back, falling left, falling right, and vertical falls, in addition to the discussion on several motions frequently appearing in daily routines. The study samples comprise 12 volunteers whose ages fall between 20 and 56 years old, height between 155 cm and 183 cm, and weight between 44 kg and 72 kg. More information is shown in Table 3.

The fall detection system uses smart phone HTC Desire S with Android 2.3 based operating system, adopting Qualcomm Snapdragon MSM8255 1 GHz processor, 768MB RAM, 1.1GB ROM, and equipped with S-sensor and proximity sensor. For Apps, Eclipse is used as programming development tool with major computer programming language in JAVA. The operating system of the server is Microsoft Windows 7, Web Server as Apache 2.2.28, Database as MySQL 5.0.51b, and major programming language in PHP. The respondents are asked to be in falling and non-falling motions, with the falling motions imitating four common falling motions to a soft cushion. The illustration of various fallings is shown in Fig. 8.

Table 3
Volunteer information.

No.	Gender	Age	Height	Weight
1	Male	24	172	71
2	Male	23	160	50
3	Female	23	173	58
4	Male	23	183	70
5	Female	24	158	47
6	Female	23	160	60
7	Male	22	170	58
8	Female	20	155	45
9	Female	20	156	45
10	Female	56	161	58
11	Male	53	169	72
12	Female	23	154	44

4.2. Experimental data

Figs. 9 and 10 show the changes in SVM and Z-axis value for jogging. Due to $e = 4$ and $t = 5$, the following five peak values are adopted: SVM values of 18.32, 15.29, 14.82, 18.13, and 16.38 generated at 2.06 s, 2.78 s, 3.46 s, 3.53 s, and 4.97 s. In particular, the maximum SVM value (18.32) is used as input. The maximum value within 5 s is adopted for Z-axis accelerator value and hence the −6 generated at 2.78 s will be included as input and converted into 6 during data conversion. Then, we substitute SVM = 18.32, $Z = 6$ and $F = 5$ into the equation, yielding $S_1 = 0$, $S_2 = 0.45$ and $S_3 = 0$ after

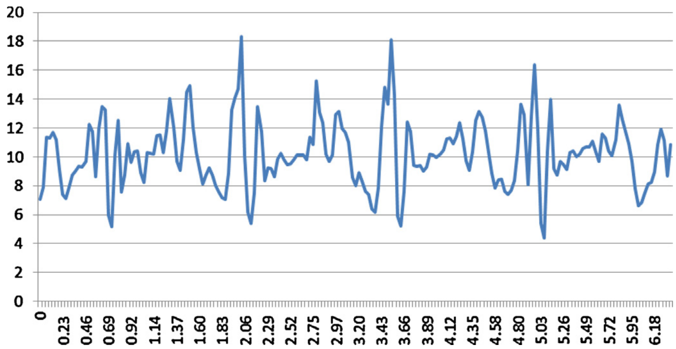

Fig. 9. SVM of jogging.

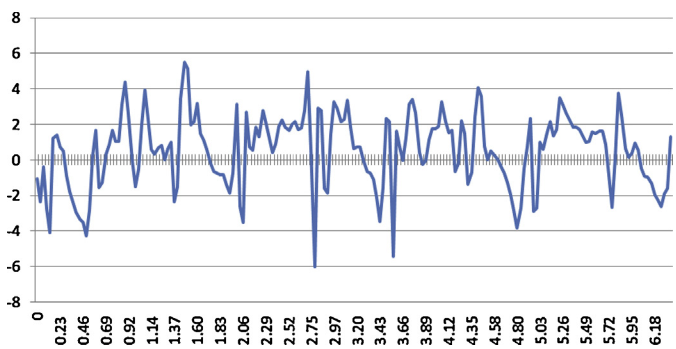

Fig. 10. *Z* of jogging.

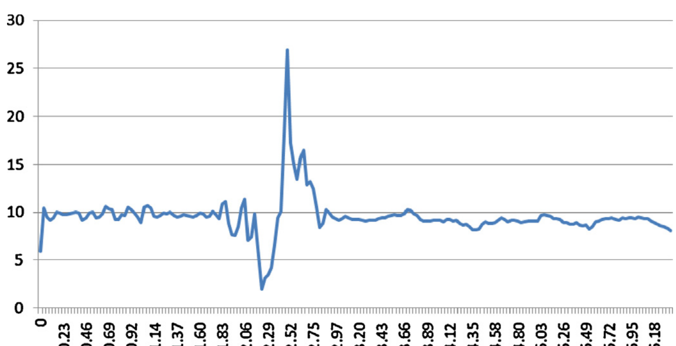

Fig. 11. SVM of forward fall.

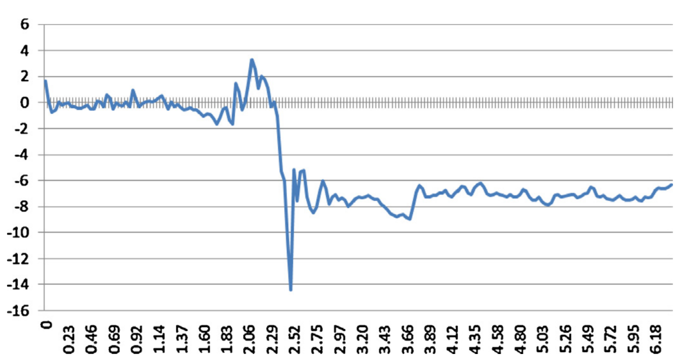

Fig. 12. *Z* of forward fall.

inference. Consequently, the result is determined as "Sport" according to Maxima defuzzification.

Figs. 11 and 12 show the changes in SVM and *Z*-axis value for forward fall. Due to $e = 4$ and $t = 5$, SVM value of 26.91 at 2.48 s is used as input. The maximum value within 5 s is adopted for *Z*-axis

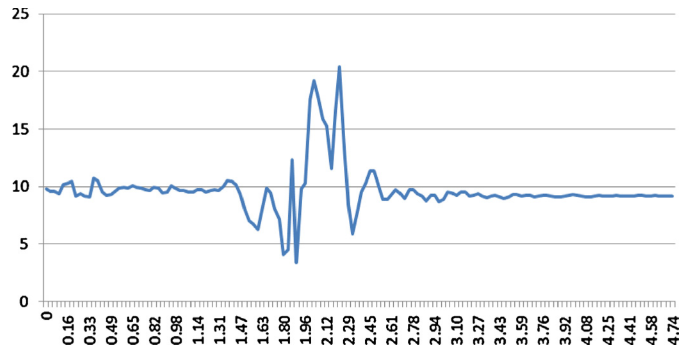

Fig. 13. SVM of vertical fall.

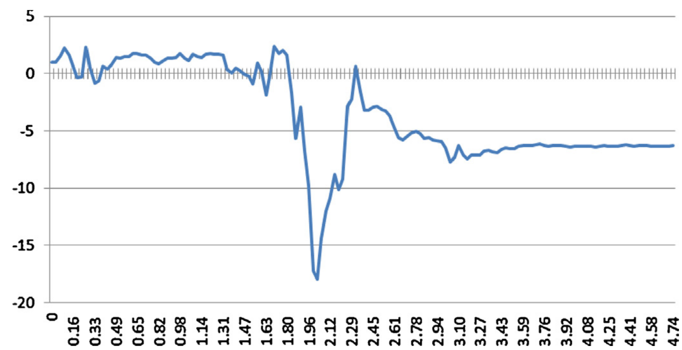

Fig. 14. *Z* of vertical fall.

accelerator value and hence the −14.44 generated at 2.48 s will be included as input and converted into 14.44 during data conversion. Then, we substitute SVM = 26.91, $Z = 14.44$ and $F = 1$ into the equation, yielding $S_1 = 0$, $S_2 = 0$ and $S_3 = 0.6$ after inference. Consequently, the result is determined as "Fall" according to Maxima defuzzification.

Figs. 13 and 14 show the changes in SVM and *Z*-axis value for vertical fall. Due to $e = 4$ and $t = 5$, the following two peak values are adopted: SVM values of 19.23 and 20.41 generated at 2.03 s and 2.2 s. In particular, the maximum SVM value (20.41) is used as input. The maximum value within 5 s is adopted for *Z*-axis accelerator value and hence the −17.97 generated at 2.03 s will be included as input and converted to 17.97 during data conversion. Next, we substitute SVM = 20.41, $Z = 17.97$ and $F = 2$ into the equation, yielding $S_1 = 0$, $S_2 = 0.2$ and $S_3 = 0.43$ after inference. Consequently, the result is determined as "Fall" according to Maxima defuzzification.

4.3. Experimental data analysis

The model stated above is implemented to an Android-based smart phone for experiments. Taking the falls and daily routines of general users into consideration, the fall test was conducted on the soft padding. The falls are categorized into forward falls, backward falls, vertical falls, and sideway falls, and the daily routines selected are walking, jogging, jumping, sitting down, and squatting down. The test subjects consist of 12 males and females ranging from 20 to 56 years of age, 1.55 to 1.83 m in height, and weighing 44 to 72 kg. For safety, the falls were performed by volunteers under 30 years old. The results are shown in Table 4.

The study assigns sit-down, squat, walking to "Normal Action", and running and jumping to "Sports". The four common falling situations, namely, forward fall, backward fall, sideway fall, and vertical fall are assigned to "Fall."

Eq. (5) was used for accuracy calculation, where FDA denotes the accuracy of fall detection, DF denotes the number of falls

Table 4
The experimental results of the fall detection.

Events	Action times		Detected falling		Detected non-falling		Accuracy rate	
	HLFPN	SVM	HLFPN	SVM	HLFPN	SVM	HLFPN	SVM
Forward falling	30		30	30	0	0	100%	100%
Backward falling	30		30	30	0	0	100%	100%
Sideway falling	30		23	28	7	2	76.6%	93.3%
Vertical falling	30		25	29	5	1	83.3%	96.7%
Walking	30		0	0	10	0	100%	100%
Running	30		0	30	30	0	100%	0%
Jumping	30		0	24	30	6	100%	20%
Sit-down	30		4	4	26	26	75%	75%
Squat	30		0	0	30	30	100%	100%

Table 5
A comparison of fall detection systems.

	dSVM and mdSM [4]	Fuzzy logic and neural network [5]	SVM and monoaxial acceleration [6]	HLFPN reasoning
Position	Chest and wrists	Waist	Waist	Thigh pocket
Fixed on the body	Yes	Yes	Yes	No
Device	Proprietary wearable hardware	Proprietary wearable hardware	Proprietary wearable hardware	Smartphone
Forward fall	Support	Support	Support	Support
Backward fall	Support	Support	Support	Support
Sideway fall	Support	Support	Support	Support
Vertical fall	Unsupported	Support	Unsupported	Support
Accuracy rate	90.66%	94%	95.83%	90%
Misidentification of daily routines	0.89%	Unknown	Unknown	2.7%

detected, and FDNF denotes the number of falls not detected. Taking all events into consideration, Eq. (6) is the misidentification of daily routines, where NFDA denotes the misidentification percentage of daily routines, NFDF denotes the number of daily routines misidentified as a fall, and NFDNF denotes the number of correct identifications of daily routines. The conducted experiments are summarized in Table 4. In our experiments we set two parameters, $t=5$ and $e=4$ in the frequency parameters. Because DF = 36, FDNF = 4, NFDF = 3 and NFDNF = 52, the accuracy percentage of fall detection of HLFPN is up to 90%, and the misidentification percentage of daily routines is 2.7%. From Table 4, the HLFPN performs better than SVM.

$$\mathrm{FDA} = \frac{\mathrm{DF}}{\mathrm{DF} + \mathrm{FDNF}} \tag{5}$$

$$\mathrm{NFDA} = \frac{\mathrm{NFDF}}{\mathrm{NFDF} + \mathrm{NFDNF}} \tag{6}$$

The experimental findings show that sit-down is commonly misjudged compared to general routines because sit-down has low frequency of occurrence while some respondents tend to sit down in faster speed, which could lead to misjudgment. Additionally, the majority of fall misjudgment is more likely to occur with sideway fall due to the relatively lower SVM generated at sideway fall, and therefore more easily to lead to misjudgment.

4.4. Performance of fall detection system

To prove the comfort, economy, reliance, and promotion of the study, we have compared the three methods proposed by the study. As shown in Table 5, dSVM and mdSM methods both require fixture on chest and wrists while the use of fuzzy logic and neural network as well as SVM and monoaxial acceleration also require fixture on waist. These three methods all require proprietary wearable hardware. The study only proposes placing smart phones on thigh pocket which is relatively convenient and comfortable. Moreover, this study has applied common smartphones in the market as mobile carriers for fall detection, which therefore possesses advantages in promotion. As for fall posture, only fuzzy logic and neural network methods and the study take the vertical fall into consideration. The accuracy rates for the four methods applied are 90.66%, 94%, 95.83%, and 90%, respectively. Although the accuracy rate of the study is slightly lower than other methods, its comfort, economy and promotion are significantly better than those of other methods.

5. Conclusion

A user-friendly human fall detection algorithm and the accompanying application were developed based on the widespread use of smart phones equipped with multiple sensors. The purchase of expensive sensing equipments is no longer required, and the smartphone does not have to be secured on the waist or chest. The pocket has enough space to carry it. The normal action and exercising were excluded through the development of multiple parameters and the HLFPN for minimization of misidentification.

The contributions of the paper include: (1) Using smartphone as a portable device for fall detection and users do not need to purchase additional electronic devices to increase the feasibility of promotion. (2) Detection can be invoked by placing the smartphone on either side of the thigh pocket without specific figure on certain area, adding considerably more comfort. (3) Distinguishing the situations of most walking, sports, and falling-down to avoid misjudgment. (4) Using the frequency parameters as alternative reference data for fall detection.

Although the detection system developed in the study possesses the aforementioned advantages, some complex situations and movements cannot be detected accurately, such as falling down from the stairs, multiple collisions, or temporal unbalance motions. As a result, the system in this study is expected to enhance its detecting accuracy when diagnosing some complex situations and multiple movements in the future. In addition, the calibration mechanism is in need for automatic tuning parameters when applying the Apps to different smart phones or mobile devices.

The future goal is to apply this technology to a bigger variety of health conditions, such as liver function, diabetes, cholesterol, and carcinogens, or to join medical database during different time periods and to make the system more complete by integrating it with cloud computing.

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