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A DYNAMIC EVIDENTIAL FRAME WORK USING WEIBULL DISTRIBUTION - DEMPSTER SHAFER THEORY (WD-DST) FOR FALL DETECTION

Veeramuthu Venkatesh*[1], D Jagadeeswara Rao[1], P Krishna Dheeraj[1], R. Seethalakshmi[2]
[1]School of Computing, SASTRA University India- 613401
[2]School of Humanities & Sciences, SASTRA University India- 613401.
Email: thambivv@gmail.com

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Abstract

Multi-sensor data fusion is an emerging technology in which data from various sensor inputs are fused in order to produce more reliable, accurate and complete detail description of the environment. However the present-day sensor network experience some uncertainty, inaccuracy and conflict. Especially the current models are not fully suited for the context-based cognitive functions. The problem was addressed in detail in the circumstance of belief theory in order to deal with uncertainty and different forms of conflict information. Among several fusion techniques Dempster Shafer Theory (DST) is considered as most predominant method for signifying and processing the uncertainty. But DST is not capable of differentiating the improper information.

In order to overcome the weakness information to be fused the Weibull Distribution is used to give reliable information that is given as input to DST. The proposed WD-DST used to find the defective information and also to perform data fusion in evidential networks. In our work, we have considered the heterogeneous and multi-sensor data fusion for a Remote medical monitoring (RMM) platform. Based on this frame work it automatically increase the performance of RMM. The efficiency and performance of this frame work is evaluated in RMM context.

Keywords: Decision-making problem, Contextual information, Dempster Shafer theory, Remote-medical monitoring, Multi-sensor data fusion

1. Introduction

Elderly people population has increased considerably during the past few decades .This increased population with independent living are more prostrate to domestic accidents. Among several accidents, falls are considered as major public health issue that affects millions of elderly people over the past few decade worldwide, affording physical and psychological consequences.

Generally, it is not possible for the elderly people to bring themselves up on their own after fall, so someone needs to be intimated about it and therefore it necessary to detect this event as earlier as possible. This fall detection [1-2] problem is one among the important research topic in the field of Remote Medical Monitoring [3-4]

In the heterogeneous sensor network data fusion [5-7] techniques are mandatory in order to combining sensor information from the various sources to obtain exact and quality information. There are several techniques that were proposed in the literature survey such as Bayesian, fuzzy systems, rough set and Dempster –Shafer theory (DST) [8-10]. These models are also considered as more suitable for representing the uncertainty and imperfect information, it is necessary to model the information in a more accurate way. DST can be considered as more precise model to deal with imperfect, impure and faulty data. Comparable with Bayesian networks the DST trust on a graphically represented evidential network. DST model has a very strong theoretical foundation that not only deals with the problem related to uncertainty caused by arbitrariness factors but also deals with vagueness initiated by uncertainty in environment. The sensor information fusion process includes two factors one is time domain and another one is frequency domain. By integrating both the domain we can significantly increase the recognition rate of fall detection.

2. Weibull Distribution

Weibull distribution is a probability distribution that is widely used for reliability analysis.

The 2-parameter Weibull:

The 2-parameter Weibull probability density function for a variable t is

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad (1)$$

where: $f(t) \geq 0, t \geq 0$ or γ

$\beta > 0; \eta > 0$

β = shape parameter (or slope)

η = scale parameter (or characteristic life)

2.1. Weibull Distribution (WD) Functions

Weibull Cumulative Density Function (CDF):

The equation for 2-parameter Weibull CDF is given by:

$$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad (2)$$

Weibull Reliability Function:

The reliability function of a given distribution is one minus the CDF, the reliability function for 2-parameter Weibull distribution is given by:

$$R(t) = e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad (3)$$

The scale and shape values can be calculated by plotting a linear graph for CDF.

$$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}}$$

$$\underbrace{\ln(\ln(\frac{1}{1 - F(t)})}_{y} = \underbrace{\beta.\ln(t)}_{mx} - \underbrace{\beta.\ln(\eta)}_{c} \quad (4)$$

A linear graph is plotted between $\ln(\ln(\frac{1}{1-F(t)})$ and$\ln(t)$. The slope of the linear plot is shape parameterβ, y intercept gives the value of the scale parameterη.

2.2. Dempster Shafer theory of Evidential Networks

In sensor network the pressing issue is dealing with uncertainty. To overcome this Dempster Shafer theory [8-10] is used which is based on the belief and plausibility functions which are obtained from the mass functions. The frame of discernment in Dempster Shafer theory (DST) is a set of mutually exhaustive values. In DST, the frame of discernment is represented by U. For a binary sensor, the frame of discernment is U = {active, inactive}. Then the power set of U is P (U) = { $\emptyset$, {active},{inactive},U} which consists of 2^U elements. The element U = {active, inactive} is the uncertainty of the sensor being active or inactive and it is used to represent the errors associated with sensors. The term 'evidence' in DST is the degree of belief in the range [0, 1] that is assigned to a sensor. The function m:$2^\theta \rightarrow [0,1]$ is called mass function that determines the belief distribution. The mass function follows the following properties

$$m(\emptyset) = 0, \text{ and} \quad (5)$$

$$\sum_{A \in 2^U} m(A) = 1 \quad (6)$$

The main advantage of DST is that it assigns an interval of possibilities instead of a single value. The lower bound and the upper bound of the probabilities are belief and plausibility respectively. The belief and plausibility can be found out as follows

$$Bel(A) = \sum_{B|B \subseteq A} m(B) \quad (7) \qquad Pl(A) = \sum_{B|B \cap A \neq \phi} m(B) \quad (8)$$

Bel (A) gives the probability that A is definitely true whereas Pl (A) gives the probability that A is definitely not false. So it can be considered that belief is the pessimistic attitude and plausibility is the optimistic attitude. Some sensors are prone to malfunctioning or misreading because of their category and the position where they are connected. So the mass functions of the sensors are decreased to reflect the impact in positions of discounting rate r ($0 \leq r \leq 1$). The discounted mass function is

$$m^r(A) = \begin{cases} (1-r)m(A) & A \in U \\ r + (1-r)m(A) & A = U \end{cases} \quad (9)$$

Where the sensor is completely reliable for r = 0, completely unreliable for r = 1 and reliable with a reduction rate of r for $0 < r < 1$.

By using the multivalued mapping, there would be several belief distributions on a single space of discernment by different sources. Thus to obtain the cumulative belief distribution, Dempster combination rule is used. Let n different sources produce$m_1 \ldots m_n$ mass functions on U. B… C are focal elements of$m_1 \ldots m_n$ respectively. Then the new mass function $m_1 \ldots m_n$ which is the combination of $m_1 \ldots m_n$ is obtained by using Dempster combination rule.

$$m_{1,2}(A) = \frac{1}{1-K} \sum_{B \cap C = A} m_1(B).m_2(C), \quad (10)$$

Where $K = \sum_{B \cap C = \emptyset} m_1(B).m_2(C)$.

3. Weibull Distribution - Dempster Shafer Theory(WD-DST) for Fall Detection

The fall-detection [1-2] system we are proposing in this paper is an alarm-based system that triggers the alarm instantly when a fall is detected. This system is primarily composed of two subsystems in order to detect the fall with less uncertainty and without any ambiguity. Those two subsystems are: Environmental Monitoring System (EMS) and Personified Position Detector System (PPDS).

The EMS involves a network of infrared sensors installed in the RMM. These sensors are innately capable of responding to the movements of any person within the environment. Thus the presence of any person is captured and inferred by these sensors.

The position of any one can also be estimated by combining the values of two sensors, one for the horizontal motion detection and another for vertical detection. The PPDS consists of a portable device that can be worn by the person. This device can automatically identify person's activity, fall, etc. The actual need of this system is to remotely monitor the person's condition.

4.1. Reliability calculation using Weibull Distribution [16]

Table 1: Failure Data

Environmental Monitoring System		**Personified Position Detector System**	
Samples	No. of detections	Samples	No. of detections
1	3,84,558	1	2,58,006
2	4,83,331	2	3,43,280
3	5,08,077	3	4,45,834
4	5,15,201	4	5,29,082
5	6,15,432	5	6,50,570
6	6,66,686	6	7,29,957
7	7,26,044	7	7,30,049
8	7,55,223	8	7,30,640
9	8,07,863	9	9,59,903
10	8,48,953	10	9,73,224

There are many methods of calculating the cumulative distribution function. We here use median ranks method to calculate the CDF. To calculate median ranks first arrange the data in increasing order of their number of detections before failure and rank them in serial order. Using these data median ranks can be calculated as follows.

$$F(t) = MR \sim \frac{i - 0.3}{N + 0.4} \quad (11)$$

where i = rank, N = total sample size.

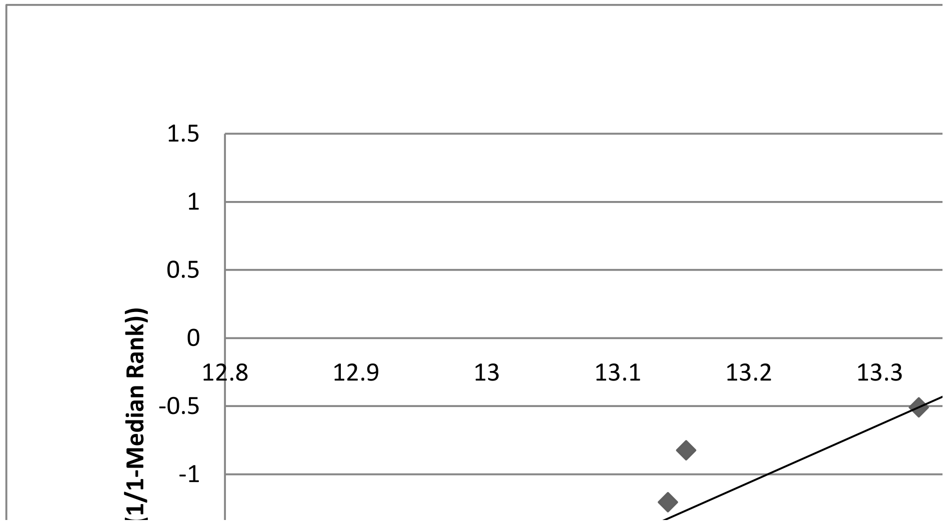

Figure 1: Line Fit Plot for EMS System.

Table 2 gives the reliabilities of both the systems on basis of the number of detections.

Table 2: Weibull Reliability Calculator.

No. of detections	EMS Reliability	PPDS Reliability
1,00,000	0.999795	0.994186
2,00,000	0.995694	0.965075
3,00,000	0.974704	0.902712
4,00,000	0.913313	0.805137
5,00,000	0.785304	0.678497
6,00,000	0.583675	0.535784
7,00,000	0.346519	0.393438
8,00,000	0.148750	0.266749
9,00,000	0.040887	0.165856

4.2. Decision Making using WD-DST

We use DST [8-10] to combine the mass functions generated by EMS and PPDS. The mass function is then used to obtain the degree of belief and plausibility hereby able to detect the fall. The EMS consists of infrared sensors that are activated by the presence of the person. There are two types of infrared sensors in this system, one vertical infrared sensor for vertical motion detection and a horizontal infrared sensor for horizontal motion detection.

The PPDS is a wearable terminal that is worn by the person that is used to detect distress situations like soft fall, cardiac arrest etc. The PPDS consists of a decision making system which is able to decide the posture of the person such as standing/lying. These positions are further used for the detection of fall detection.

The objective here is to calculate the mass function of fall $m(\{Fall\})$. There frame of discernment consists of U= {Fall,−Fall}. The belief of fall is $m(\{Fall\})$, belief of not a fall is $m(\{-Fall\})$ and the uncertainty is denoted by $m(\{Fall, -Fall\})$. In the Environmental Monitoring System, each IR sensor can have one of the two states {excited, non-excited}. The excited state is represented by {IR} and non-excited state is represented by {−IR}. Also in Personified Position Detector System there are two cases one is lying down or standing/sitting represented by $\{R_l\}$ and falling or not falling represented by $\{R_{Fall}\}$. $\{R_l\}$ represents lying down and $\{-R_l\}$ represents sitting/standing. Similarly $\{R_{Fall}\}$ represents falling and $\{-R_{Fall}\}$ represents not falling conditions. Here after in this work we use the abbreviations as follows: $Movement_h$=M_h, $Movememt_v = M_v$, $Lying_p = L_p$, $\overline{Fall}_p = \overline{F}_p$, $Lying_E = L_E$, $Fall_E = F_E$. Initially we consider the sensors to be 100% reliable. Thereby the mass functions of each node is as follows,

$m(\{-IR_v\}) = 1;$ $m(\{-IR_h\}) = 1;$ $m(\{P_l\}) = 1;$ $m(\{P_{Fall}\}) = 1;$

4.3 Discounting the mass functions:

In general, no sensor is 100% reliable so we should be aware of the reliability of each sensor provided by the manufacturer. We assume that for the EMS, the sensitivity and specificity as r_1 and for PPDS, sensitivity and specificity asr_2. Thus the discounted mass functions are calculated as follows,

$m^r(\{-IR_v\}) = 1 - r_1;$ $m^r(\{IR_v, -IR_v\}) = r_1;$

$m^r(\{-IR_h\}) = 1 - r_1;$ $m^r(\{IR_v, -IR_v\}) = r_1;$

$m^r(\{P_l\}) = 1 - r_2;$ $m^r(\{P_l, -P_l\}) = r_2;$

$m^r(\{P_{Fall}\}) = 1 - r_2;$ $m^r(\{P_{Fall}, -P_{Fall}\}) = r_2$

4.4 Transferring sensor nodes to activity nodes:

The mass functions of sensor nodes obtained are transferred to activity nodes. Activity nodes are Movement, Lying and Fall. After transferring mass functions the mass functions of activity nodes are as follows:

$m(\{-M_v\}) = m^r(\{-IR_v\}) = 1 - r_1;$ $m(\{M_v, -M_v\}) = m^r(\{IR_v, -IR_v\}) = r_1$

$m(\{-M_h\}) = m^r(\{-IR_h\}) = 1 - r_1;$ $m(\{M_h, -M_h\}) = m^r(\{IR_h, -IR_h\}) = r_1$

$m(\{L_p\}) = m^r(\{P_l\}) = 1 - r_2;$ $m(\{L_p, -L_p\}) = m^r(\{P_l, -P_l\}) = r_2$

$m(\{\overline{F}_p\}) = m^r(\{P_{Fall}\}) = 1 - r_2;$ $\qquad m(\{\overline{F}_p, -\overline{F}_p\}) = m^r(\{P_{Fall}, -P_{Fall}\}) = r_2$

4.5 Transferring activity nodes to composite nodes using weighted sum:

Multivalued mapping is done on the activity nodes. The multivalued mass functions are as follows:

$m(\{-(M_v, M_h)\})_v = m(\{-M_v\}) = 1 - r_1;$ $\quad m(\{(M_v, M_h), -(M_v, M_h)\})_v = m(\{M_v, -M_v\}) = r_1;$

$m(\{-(M_v, M_h)\})_h = m(\{-M_h\}) = 1 - r_1;$ $\quad m(\{(M_v, M_h), -(M_v, M_h)\})_h = m(\{M_h, -M_h\}) = r_1;$

$m(\{-(L_p, \overline{F}_p)\})_L = m(\{L_p\}) = 1 - r_2;$ $\quad m(\{(L_p, \overline{F}_p), -(L_p, \overline{F}_p)\})_L = m(\{L_p, -L_p\}) = r_2;$

$m(\{-(L_p, \overline{F}_p)\})_F = m(\{\overline{F}_p\}) = 1 - r_2;$ $\quad m(\{(L_p, \overline{F}_p), -(L_p, \overline{F}_p)\})_F = m(\{\overline{F}_p, -\overline{F}_p\}) = r_2;$

Weighted sum is the fraction that represents the weight that need to be given to each parameter. The range of weighted sum is [0, 1]. The chosen weighted sums are:

$$m(\{-(M_v, M_h)\}) = w_v m(\{-(M_v, M_h)\})_v + w_h m(\{-(M_v, M_h)\})_h$$

$$= 0.3 \times (1 - r_1) + 0.7 \times (1 - r_1) = 1 - r_1;$$

$$m(\{(M_v, M_h), -(M_v, M_h)\}) = w_v m(\{(M_v, M_h), -(M_v, M_h)\})_v +$$

$$w_h m(\{(M_v, M_h), -(M_v, M_h)\})_h$$

$$= 0.3 \times r_1 + 0.7 \times r_1 = r_1;$$

$$m(\{(L_p, \overline{F}_p)\}) = w_L m(\{(L_p, \overline{F}_p)\})_L + w_F m(\{(L_p, \overline{F}_p)\})_F$$

$$= 0.1 \times (1 - r_2) + 0.09 \times (1 - r_2) = 0.93;$$

$$m(\{(L_p, \overline{F}_p), -(L_p, \overline{F}_p)\}) = w_L m(\{(L_p, \overline{F}_p), -(L_p, \overline{F}_p)\})_L + w_F m(\{(L_p, \overline{F}_p), -(L_p, \overline{F}_p)\})_F$$

$$= 0.1 \times r_2 + 0.9 \times r_2 = r_2;$$

4.6Transferring mass functions of composite activity nodes to higher level activity nodes:

The node (M_v, M_h) represents the position of the person. The node $-(M_v, M_h)$ means the person is lying because if the infrared sensors are not excited it means that the person is lying. So we can assign it to L_E node.

$$m(\{L_E\}) = m(\{-(M_v, M_h)\}) = 1 - r_1; \qquad m(\{L_E, -L_E\}) = m(\{(M_v, M_h), -(M_v, M_h)\}) = r_1;$$

Multivalued mapping is done on L_E and L_P. After mapping we have,

$$m(\{(L_E, L_P)\})_E = m(\{L_E\}) = 1 - r_1 \qquad m(\{(L_E, L_P), -(L_E, L_P)\})_E = m(\{L_E, -L_E\}) = r_1$$

$$m(\{(L_E,L_p)\})_p = m(\{L_p\}) = 1 - r_2 \qquad m(\{(L_E,L_p),-(L_E,L_p)\})_p = m(\{L_p,-L_p\}) = r_2$$

4.7 Transferring activity nodes to higher level composite nodes using weighted sum:

The experimentally chosen weight sums are $W_{Le} = 0.3$ and $W_{Lp} = 0.7$. The weighted sum:

$$m(\{L_E,L_p\}) = W_{Le}m(\{L_E,L_p\})_E + W_{Lp}m(\{L_E,L_p\})_p$$

$$= 0.3 \times (1 - r_1) + 0.7 \times (1 - r_2) = 1 - 0.3r_1 - 0.7r_2$$

$$m(\{(L_E,L_p),-(L_E,L_p)\}) = W_{Le}m(\{(L_E,L_p),-(L_E,L_p)\})_E + W_{Lp}m(\{(L_E,L_p),-(L_E,L_p)\})_p$$

$$= 0.3 \times r_1 + 0.7 \times r_2 = 0.3r_1 + 0.7r_2;$$

4.8 Deducing from activity node to deduced activity node:

Here we obtain pre-fused data from the Environmental Monitoring System. For this deduction the person is in hall so we have the following mapping:

$$m(\{L_E,L_p\} \xrightarrow{\text{Hall}} \{F_E\}) = 0.8$$

$$m(\{L_E,L_p\} \xrightarrow{\text{Hall}} \{F_E,-F_E\}) = 0.2$$

$$m(\{-(L_E,L_p)\} \xrightarrow{\text{Hall}} \{-F_E\}) = 1$$

$$m(\{L_E,-L_p\} \xrightarrow{\text{Hall}} \{F_E,-F_E\}) = 1$$

Using this deduction we can obtain the Fall activity node result.

$$m(\{F_E\}) = m(\{L_E,L_p).m(\{L_E,L_p\} \longrightarrow \{F_E\})$$

$$= (1 - 0.3r_1 - 0.7r_2) \times 0.8 = 0.8 - 0.24r_1 - 0.56r_2$$

$$m(\{F_E,-F_E\} = m(\{L_E,L_p).m(\{L_E,L_p\} \xrightarrow{\text{Hall}} \{F_E,-F_E\}) +$$

$$m(\{(L_E,L_p),-(L_E,L_p)\}.m(\{(L_E,L_p),-(L_E,L_p)\} \xrightarrow{\text{Hall}} \{F_E,-F_E\})$$

$$= (1 - 0.3r_1 - 0.7r_2) \times 0.2 + (0.3r_1 + 0.7r_2) \times 1$$

$$= 0.2 + 0.24r_1 + 0.56r_2$$

Thus the mass functions of the fall activity node for EMS is obtained

4.9 Translating composite node to activity node:

The mass function of the composite activity node $(L_p,\overline{F}_p)$ is transferred to F_p activity node.

$m(\{Fp\}) = m(\{(L_p, \overline{F}_p)\}) = 1 - r_2$

$m(\{Fp, -Fp\}) = m(\{(L_p, \overline{F}_p), -(L_p, \overline{F}_p)\}) = r_2$

4.10 Combining mass functions from both the systems:

The mass functions of fall activity node obtained by two systems EMS and PPDS is combined using Dempster combination rule.

$$m_{E,P}(\text{Fall}) = \frac{(0.8 - 0.24r_1 - 0.56r_2) \times (1 - r_2) + (0.8 - 0.24r_1 - 0.56r_2) \times r_2 + (1 - (0.2 + 0.24r_1 + 0.56r_2)}{1 - 0}$$

$$= 1 - 0.2r_2 - 0.24r_1r_2 - 0.56{r_2}^2$$

$$m_{E,P}(\text{Fall}, -\text{Fall}) = \frac{(0.2 + 0.24r_1 + 0.56r_2) \times r_2}{1 - 0}$$

$$= 0.2r_2 + 0.24r_1r_2 + 0.56{r_2}^2$$

Thus the result is by substituting the values of reliabilities in the above equations. k=0 because there is no null intersection.

4.11 Determining the Cause of the Fall

As soon as the fall is detected, it is intimated to the nearby care taker through an alarm. But it would be better if the intimation includes the cause for the fall so that respective first aid measures can be carried out in an informed fashion. The major causes for fall include cardiac arrest, low blood pressure and low glucose level. So to determine the cause of fall, we keep on monitoring the pulse rate, blood pressure and glucose level of the patient every second through a device that is worn by the patient. Once a fall is detected, immediately the previous thirty values of pulse rate, blood pressure and glucose level are taken into account and their basic probability assignment (BPA) is calculated to find out the exact cause of fall. The functions of pulse rate and blood pressure sensors are defined as follows: Pulse rate sensor is P(t), blood pressure sensor is B(t) and glucose level is G(t).

The variation rate of heart rate sensor is calculated as follows:

$$\Delta P(t_n) = \frac{P(t_n) - P(t_{n-1})}{t_n - t_{n-1}} \qquad (10)$$

To have the BPA α of the pulse rate measurement, the variation rate is used. BPA is determined for pulse rate sensor as follows:

$$\alpha = \frac{\sum_{j=0}^{n} \arctan\left(\Delta P(t_j)\right)}{\sum_{j=0}^{n} \arctan\left(\left|\Delta P(t_j)\right|\right)} \cdot \left(\frac{t_n}{T}\right)^2, \text{ where T=total time.} \quad (11)$$

The α value is taken as $|\alpha|$ if $\alpha < 0$ and 0 if ≥ 0. It is because positive α value means heart rate is increasing and the person is getting better. So we are considering only the decreasing value of heart rate.

The variation rate of blood pressure sensor is calculated as follows:

$$\Delta B(t_n) = \frac{B(t_n) - B(t_{n-1})}{t_n - t_{n-1}} \quad (12)$$

To have the BPA α of the blood pressure measurement, the variation rate is used. BPA is determined for blood pressure sensor as follows:

$$\alpha = \frac{\sum_{j=0}^{n} \arctan\left(\Delta B(t_j)\right)}{\sum_{j=0}^{n} \arctan\left(\left|\Delta B(t_j)\right|\right)} \cdot \left(\frac{t_n}{T}\right)^2, \text{ where T=total time.} \quad (13)$$

The α value is taken as $|\alpha|$ if $\alpha < 0$ and 0 if ≥ 0. It is because positive α value means blood pressure increasing and the person doesn't faint due to high pressure. So we are considering only the decreasing value of blood pressure.

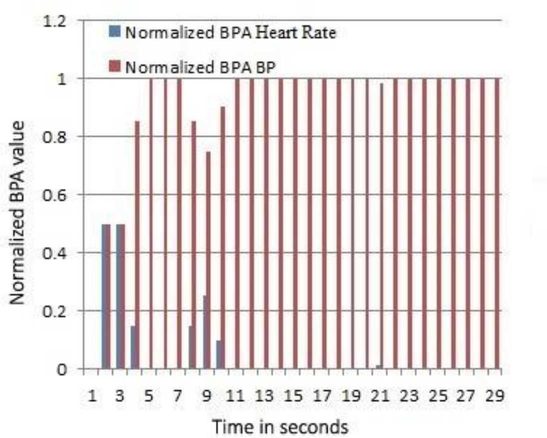

Figure 2: Results of calculation for CASE-1

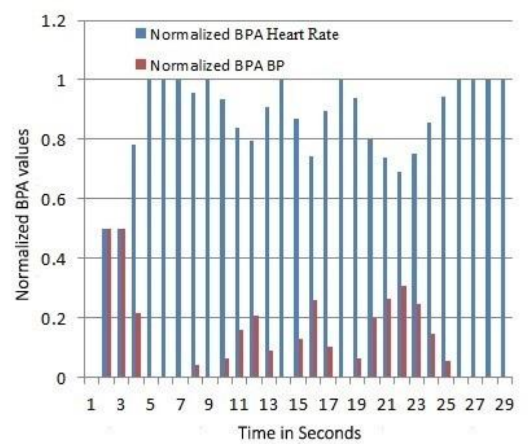

Figure 3: Results of calculation for CASE-2

Figure 3, it is clear that blood pressure values occupy more weightage in the normalized BPA. Thus it can be inferred that the cause for the fall is due to the decrease in blood pressure. Similarly from the graph in Figure 4, it is clear that the heart rate values occupy more weightage in the normalized BPA. Thus it can be inferred that the cause for the fall is due to the decrease in heart rate.

Conclusion and future enhancements.

Sensors and actuators are the most important factors for the forthcoming era that is touted for producing knowledge-filled situation-aware, mission-critical and people-centric services (IT as well as business) in plenty. With the availability of highly advanced algorithms, like evidential network for remote medical monitoring seems to be a highly promising method for application like fall detection. The improved WD-DST method can successfully solve the issues like data conflict, reliability by integrating various sensor used for fall detection .So the proposed WD-DST can effectively avoid false detection over RMM .The calculation and comparison table shows that the proposed WD-DST improves sensor fusion result effectively. In future some network extension and additivity for dynamic algorithm can be included.

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Corresponding Author:

Veeramuthu Venkatesh*,

Email: *thambivv@gmail.com*