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Majority-consensus fusion approach for elderly IoT-based healthcare applications

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Abstract Nowadays, tremendous growth of Internet of Things (IoT) applications is seen in smart environments such as medical remote care applications which are crucial due to the general aging of the population. With the recent advancements in IoT-based healthcare technologies, activity recognition can be used as the key part of the intelligent healthcare systems to monitor elderly people to live independently at homes and promote a better care. Recently, the evidence theory and its derivates approaches began to take place in the fields of activity recognition in these smart systems. However, these approaches are generally inconsistent with the probability calculus due to the lower and upper probability bounds considering the combined evidences. To overcome these challenges and to get more precisely the reconcilement between the evidence theory with the frequentist approach of probability calculus, this work proposes a new methodology for combining beliefs, addressing some of the disadvantages exhibited by the evidence theory and its derivatives. This methodology merges the non-normalized conjunctive and the majority rules. The proposed rule is evaluated in numerical simulation case studies involving the activity recognition in a smart home environment. The results show that this strategy produces intuitive results in favor of the more committed hypothesis.

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1 Introduction

The rapid increase in the number of elderly people brings major issues to elderly health care including a rise in care cost, high demand in long-term care, decrease caregiver burden, and insufficient and ineffective care. With the recent advancements in Internet of Things (IoT)-based healthcare technologies, accelerometer, pressure, ECG, smartphone, and assisted living technologies, activity recognition can be used as the key part of the intelligent pervasive systems to monitor elderly people for sustaining independent living at homes and promote a better care [1, 17]. These intelligent IoT-based healthcare systems are becoming more prevalent in every-day life by enabling the systems to adapt according to the elderly health and positioning context-awareness information. However, the contextual information cannot be identifying precisely because of the limitations and the imperfection nature of sensing technologies due to the wearable sensors' inaccuracy. This imperfection of contextual information will be translated to high-level contexts resulting in building inaccurate activity recognition. A good contextual information modeling formalism reduces the imperfection of contextual information and enhances the accuracy of activity recognition. So, one of the main challenges in IoT-based healthcare applications is managing these forms of uncertainty due to sensor's measurements which are prone to uncertainty. An extensive literature review in wearable sensor-based activity recognition and its applications in health care have been carried out over the past few decades.

These applications are conducted on context representation and reasoning in order to infer activity from accurate as well as inaccurate context in IoT-based healthcare solutions [40]. Among the existing inference approaches, the evidence theory [45] is a major constituent and commonly used to handle uncertainty and incompleteness of context in pervasive computing environments [12, 15, 19, 28, 39, 43, 67]. This theory offers a good alternative to some activity recognition methods where domain knowledge is applied [29] instead of training data that are not easily available in ubiquitous environments. However, most of the approaches based on the evidence theory produce incompatible results compared to the frequentist approach of probability calculus. The main aim of this paper is to develop a novel method for multi-sensor-based activity recognition of activity of daily living (ADL) of elderly people for an intelligent assisted living system in order to reach the reconcilement of the evidence theory with the frequentist appoach of probability calculus. Our approach is based on the merging of two combination rules. This mixture allows to favor the evidence with a big consensus because it is accordant to the objective of uncertainty reasoning over evidence accumulation. The proposed combination alternative rule for activity recognition of elderly healthcare applications, called Majority-Consensus combination Rule (MCR), is evaluated and compared on Shafer's model with the evidence theory and its most famous derivates. The results show that the present rule produces the intuitive results in favor of the more committed activity and gives generally a high consistency with the frequentist approach of probability calculus.

The outline for this paper is organized as follows: Section 2 presents the approaches used to carry out the research and the inference systems of the multi-sensor activity recognition for elderly healthcare systems. Section 3 introduces the background of evidence theory and decision making in this theory. Section 4 describes the mathematical foundations of a new combination rule for uncertainty management strategy. The proposed context-aware system architecture of the multi-sensor activity recognition and the simulated results are reported and discussed in Section 5. Finally, Section 6 concludes the paper with future directions.

2 Review of sensor-based activity recognition approaches

In the past decade, a variety of sensors have been used to allow the elderly patients with diseases to achieve continuous monitoring of their health condition [1, 2, 6, 31]. Current research in activity recognition from wearable sensors covers a wide range of topics, with research groups focusing on topics such as the recognition of ADLs in the context of health care and elderly care which represent an important class of applications [35]. A major goal of current research in activity recognition in general is to enable healthcare applications for the elderly population to live more independent lives and reduce the burden of caregivers. For this way, IoT-based healthcare technologies and the fusion approaches help to increase the quality and efficiency of care of elderly people and thus activity recognition accuracy may be improved [22]. Villalba et al. [55] have designed a system for vital elderly body signs which indicate imminent health threats in order to complement the traditional emergency in potentially dangerous situations. Si et al. [46] aim to support persons suffering from dementia through the use of context-aware reminders and similar assistance. Wu et al. [61] have developed a smart approach that classifies cane usage and walking patterns, and informs the elderly in case of high risk of falling. Barnachon et al. [5] present a novel framework for recognizing streamed actions using motion capture data. The proposed framework aims at achieving early recognition of ongoing activities. Bravata et al. [51] proposed a system which is able to infer elders' health by monitoring the level of physical activity performed. Based on assistive technologies for elders and caregivers Ambient Assisted Living (AAL) systems, other authors are focused on improving care processes by providing electronic health records [21], remote medical attention and suggestions [14], and intelligent vital signs monitors [30]. Monitoring and assessing the performance of daily activities is relevant for the continuous assessment of elders' health and independence [34]. The work proposed in [20] used the temperature sensor as part of their activity recognition systems, e.g., the difference of temperature of 15 min is used to determine the use of a shower. The proposed approach can provide a detailed activity detection; however, it suffers limitations in terms of feasibility. The approach proposed in [11] allows to identify any changes in activities such as changes walking speed and sleep rhythm. Some researchers have also introduced to older adults fall detection area using wearable device based, ambience sensor based, and camera based [32]. Based on body acceleration sensors to measure the patients' movements, the authors [3] provide a rhythmic auditory signal that stimulates the patient to resume walking. Hossain [16] introduced the concept of virtual caregivers to assist the caregiver in making some basic decisions for health-related applications to monitor elderly people to live more independent daily lives. The proposed system uses context information to promote more active and thus healthy lifestyle, or to actively support elderly or disabled people in performing everyday activities. Analyzing more heterogeneous sensor sources, the system make elders' health inferences. Chernbumroong et al. [8] proposed a novel multi-sensor-based activity recognition system. The approach uses multiple low-cost, non-intrusive, non-visual wearable sensors on the wrist. The sensor fusion is performed at two levels (feature and classifier level). Other works are focused on a predictive schedule system that blends caregiver using sensor measurements instead of trying to substitute the caregiver with an automatic caring system [52]. To infer situations and activities in the context of elderly health care, the preceding applications use Bayesian networks [12, 39, 64], dynamic Bayesian network (DBN) [38], conditional random field (CRF) [19, 54], and hidden Markov models [9, 19, 36, 59]. These methods are usually based on training data to recognize activities inferred from lower-level sensor information. Van Kasteren et al. [19] use hidden Markov models to infer high-level activities of a person's in the home. In the proposed model, activity patterns over time are learned from training data. In [13], the authors propose the use of hidden Markov models to classify six different activities. Bayesian networks were used to determine the activities from lower-level sensor data. Wang et al. [58] investigate the problem of recognizing multi-user activities using wearable sensors in a home setting. The authors develop a multi-modal, wearable sensor platform to collect sensor data for multiple users using two temporal probabilistic models, the coupled hidden Markov model (CHMM) and the factorial conditional random field (FCRF). In [25], the authors use the hierarchical conditional random fields to derive high-level activities and to identify places from GPS data. Recently, the evidence theory began to take place in the fields of activity recognition in smart environments and ubiquitous computing [15, 28, 60, 67]. Wu [60] uses the DS theory to fuse the sensor evidence in his sensor fusion model. Wu uses a static weighting on sensor mass functions to indicate evidence reliability. To model the activity structure, a situation directed acyclic graphs (DAGs) is proposed in [28] and two types of evidential networks: activities-activity and sensors-contexts-activity are proposed in [15, 43].

3 The evidence theory and its derivates

The evidence theory [45] has attractive properties which provide significantly richer information in the fusion field. Based on Shafer's model, the frame of discernment is a set of mutually exclusive and exhaustive hypotheses about the problem domains. From a frame of discernment Θ correspondingly, $2^{\Theta}$is the power set of Θ, then a basic belief assignment (bba) or proper mass is defined as a mapping $m(\cdot)$:

$$m(\emptyset) = 0 \text{ and } \sum_{X \in 2^{\Theta}} m(X) = 1 \tag{1}$$

The Dempster's combination rule is the normalized conjunctive operation which aims to aggregate evidence from multiple independent sources defined within the same frame of discernment. Based on Shafer's model of the frame Θ, Dempster's rule is defined by the following equations for two sources:

$$m_{\mathrm{DS}}(X) = \frac{m_{12}^{c}(X)}{1 - m_{12}^{c}(\emptyset)} \tag{2}$$

$$m_{12}^{c}(X) = \sum_{\substack{X_1, X_2 \in 2^{\Theta} \\ X_1 \cap X_2 = X}} m_1(X_1) m_2(X_2) \tag{3}$$

$$m_{12}^{c}(\emptyset) = \sum_{\substack{X_1, X_2 \in 2^{\Theta} \\ X_1 \cap X_2 = \emptyset}} m_1(X_1) m_2(X_2) \tag{4}$$

where $m_{12}^{c}(X)$ and $m_{12}^{c}(\emptyset)$ represent the conventional conjunctive consensus operator and conflict of the combination between the two sources, respectively.

From a given bba m, the decision functions are defined as follows:

- The belief function $\mathrm{Bel}(X)$ measures the belief that hypothesis X is true and it is given by :

$$\mathrm{Bel}(X) = \sum_{Y \subseteq X} m(Y) \tag{5}$$

- The plausibility function $\mathrm{Pl}(X)$ can be interpreted as a measure of the total belief that hypothesis X can be true and it is given by the following formula:

$$\mathrm{Pl}(X) = \sum_{X \cap Y \neq \emptyset} m(Y) \tag{6}$$

- The pignistic probability transformation [48, 50] is generally considered as a good criteria for a decision rule. It is defined for all $X \in 2^{\Theta}$, with $X \neq \emptyset$; by:

$$\mathrm{Bet}P(X) = \sum_{\substack{Y \in 2^{\Theta} \\ Y \neq \emptyset}} \frac{|X \cap Y|}{|Y|} \frac{m(Y)}{1 - m(\emptyset)} \tag{7}$$

However, some researchers argue that this combination rule has an abnormal behavior when the conflict between sources becomes high [41, 42, 47, 56, 66]. So, several attempts have been proposed to avoid this abnormal behavior. These attempts to modify Dempster's rule can be divided into two main categories : corrective-evidence approaches [7, 18, 23, 24, 33, 62, 65] and the conflict redistribution approaches [10, 26, 47, 50, 63]. The first approaches consist of corrective strategies of the initial basic belief assignments while using thereafter Dempsters rule for combining these corrective evidences. The idea behind the second approaches is to transfer conflicting masses proportionally to empty or non-empty sets according to some combination results. However, the problem with these approaches can be relieved to some extent by replacing the evidences with inappropriately small-weights evidence values. Moreover, all these approaches are inconsistent with the probability calculus where the information combination results are sometimes counterintuitive and very far compared to those obtained by the probability calculus. This abnormal behavior and the inconsistency of these derivate rules will be illustrated through some examples studied in the following sections.

Table 1 reports the combination results and comparison of existing combination rules using some well-known examples discussed in the literatures where Dempster's rule and some alternative combination rules give counter-intuitive results. The underline combination results in the table show that the results are judged to be counter-intuitive. As it can be seen from Table 1, when the conflicting mass is computed, the Dempster's rule for combining evidences produces counter-intuitive results that do not reflect the actual distribution of beliefs in some cases. This later does not reflect the actual distribution of beliefs in some cases such as loss of majority opinion, total certainty to minority opinion, and unearned certainty. However, using original evidence sources and the results of the conjunctive consensus, PCR6 rule redistributes an evidential conflict in proportion to the focal set elements, which is a compromise strategy and gives more intuitive results.

For the disappearing ignorance, Pearl criticized the disappearing ignorance [37] caused by the operation of intersection in Dempster's rule, and Murphy proposed a combination which does not have the effect [33]. For the certainty convergence case, Yager, Smets, and Dubois rules fail to converge toward the focal element supported by both pieces of evidence. The problem of total certainty to minority opinion caused by the operation of intersection in the Dempster rule [66] is solved in many alternatives.

The operation of intersection in the Dempster rule causes also the exclusion of elements which are not contained in focal elements of one or more bodies of evidence. Known

Table 1 Comparative results for well-known

	Rules					
Cases	Dempster	Murphy	PCR6	Yager	Smets	Dubois
Disappearing ignorance						
$m_1(\{a\}) = 0.5$	m{a}=0.5	m{a}=0.3571	m{a}=0.5	m{a}=0.5	m{a}=0.5	m{a,b,c}=1
$m_1(\{b\}) = 0.5$	m{b}=0.5	m{b}=0.3571	m{b}=0.5	m{b}=0.5	m{b}=0.5	
$m_2(\{a, b\}) = 1$		m{a,b}=0.2857				
Certainty convergence						
$m_1(\{a\}) = 0.5$	m{a}=0.6667	m{a}=0.6667	m{a}=0.625	m{a}=0.5	m{a}=0.5	m{a}=0.25
$m_1(\{b\}) = 0.5$	m{b}=0.3333	m{b}=0.25	m{b}=0.375	m{b}=0.25	m{b}=0.25	m{a,b,c}=0.75
$m_2(\{a\}) = 0.5$		m{a,b}=0.0833		m{a,b}=0.25	m{ Ø }=0.25	
$m_2(\{a, b\}) = 0.5$						
Total certainty to minority opinion						
$m_1(\{a\}) = 0.9$	m{b}=1	m{a}=0.488	m{a}=0.486	m{b}=0.01	m{a}=0.01	m{b}=0.01
$m_1(\{b\}) = 0.1$		m{b}=0.024	m{b}=0.028	m{a,b,c}=0.99	m{ Ø }=0.99	m{a,b}=0.09
$m_2(\{b\}) = 0.1$		m{c}=0.488	m{c}=0.486			m{a,c}=0.81
$m_2(\{c\}) = 0.9$						m{b,c}=0.09
Loss of majority opinion						
$m_1(\{a\}) = 0.9$	m{c}=1	m{a}=0.7336	m{a}=0.3958	m{c}=0.01	m{a}=0.98	m{a,b}=0.36
$m_1(\{a, c\}) = 0.1$		m{b}=0.1657	m{b}=0.1305	m{a,b,c}=0.99	m{a,c}=0.02	m{c}=0.01
$m_2(\{a, b\}) = 0.8$		m{c}=0.0477	m{c}=0.1342			m{a,b,c}=0.54
$m_2(\{a, c\}) = 0.2$		m{a,b}=0.0503	m{a,b}=0.307			
$m_3(\{b\}) = 0.5$		m{a,c}=0.0027	m{a,c}=0.032			
$m_3(\{c\}) = 0.5$						
Unearned certainty						
$m_1(\{a\}) = 0.5$	m{a}=1/3	m{a}=0.3	m{a}=0.375	m{a}=0.25	m{a}=0.25	m{a,b}=0.25
$m_1(\{b, c\}) = 0.5$	m{b}=1/3	m{b}=0.2	m{b}=0.25	m{b}=0.25	m{b}=0.25	m{a,c}=0.25
$m_2(\{c\}) = 0.5$	m{c}=1/3	m{c}=0.3	m{c}=0.375	m{c}=0.25	m{c}=0.25	m{b,c}=0.25
$m_2(\{a, b\}) = 0.5$		m{a,b}=0.1		m{a,b,c}=0.25	m{ Ø}=0.25	m{a,b,c}=0.25
		m{b,c}=0.1				

as the loss of majority opinion, this case is solved by a few alternative combination rules [27, 33, 63].

The problem of unearned certainty known as unwarranted mass is also caused by the operation of intersection in the rule. It is solved by most of the alternatives.

4 Proposed uncertainty management strategy

The evidential reasoning is an important technique of uncertainty context modeling in multi-sensor-based activity recognition in elderly healthcare applications. The present section introduces our combination merging rule technique to manage the uncertainty for activity recognition in health care applications. The starting point of our combination rule investigations is to describe the strategy for combining the belief functions. Thereafter, we introduce a new notion to verify the consistency of the combination rule of evidence with the probability calculus. In this work, we made a strong assumption that security is guaranteed by using an appropriate mechanism such as the use of a cryptographic system ensuring an end-to-end security.

4.1 The proposed rule principle

The evidence theory and its derivates have given birth to a large family of rules to combine multiple evidences. To overcome the drawbacks of the previously presented rules, we propose an alternative combination rule which mixes the non-normalized conjunctive rule, given by Smets [49] (the conventional conjunctive consensus operator in the evidence theory) and the simple fusion rule based on the majority rule. The idea behind our combination rule is that it redistributes the global conflict into already implicated focal element sets entering in the majority and the consensus results. This rule allows to bring about a reconciliation between the belief functions theory and the probability calculus.

The formulation of our rule is based on the normalization of the sum of masses fused with the result of masses obtained by the majority rule and those obtained by the conjunctive consensus operator. So, our rule transfers the total conflicting mass and total masses to non-empty sets proportionally to their resulting masses obtained by these two operators.

The proposed combination rule for multiple sources ($s \geq 2$) is formulated as follows:

$(\forall X \neq \emptyset) \in 2^{\Theta}$

$$m_{1,2\cdots,s|\mathrm{MCR}}(X) = \frac{1}{s+1-k}\left(m_{\mathrm{Maj}}(X) + m_{\mathrm{Conj}}(X)\right) \quad (8)$$

where $m_{\mathrm{Maj}}(X)$ and $m_{\mathrm{Conj}}(X)$ denote the majority and the non-normalized conjunctive rules of the focal element X, respectively.

The non-normalized conjunctive rule, given by Smets [49] is defined as follows:

$$m_{\mathrm{Conj}}(X) = \sum_{\substack{X_1, X_2\cdots, X_j \in 2^{\Theta} \\ X_1 \cap X_2 \cap \cdots X_j = X}} \prod_{i=1}^{s} m_i\left(X_j\right) \quad (9)$$

The majority rule is defined by:

$$m_{\mathrm{Maj}}(X) = \sum_{i=1}^{s} m_i(X) \quad (10)$$

A general measure of the global conflict in evidence is defined by the following formula:

$$k = \sum_{\substack{X_1, X_2\cdots, X_j \in 2^{\Theta} \\ X_1 \cap X_2 \cap \cdots X_j = \emptyset}} \prod_{i=1}^{s} m_i\left(X_j\right) \quad (11)$$

where $X_j \in 2^{\Theta}$ denotes a response of the information source i, and $m_i(X_j)$ denotes the associated belief function.

This formulation of the combined mass yields the next result.

Theorem 1 *The mass $m_{1,2,\cdots,s|MCR}(\cdot)$ is a proper mass.*

Proof A proper mass means that a mass $m_{1,2,\cdots,s|MCR}(\cdot)$ must satisfy all requirement given by Eq. 1. When X is an empty set, the value of $m(X)$ is equal to 0. By definition, the mass $m_{1,2,\cdots,s|\mathrm{MCR}}(X) = \frac{1}{s+1-k}\left(m_{\mathrm{Maj}}(X) + m_{\mathrm{Conj}}(X)\right)$.

Hence,

$$\begin{aligned}\sum_{X \in 2^{\Theta}} m_{1,2,\cdots,s|\mathrm{MCR}}(X) &= \sum_{X \in 2^{\Theta}} \left[\frac{1}{s+1-k}\left(m_{\mathrm{Maj}}(X)\right.\right. \\ &\qquad \left.\left. + m_{\mathrm{Conj}}(X)\right)\right] \\ &= \frac{1}{s+1-k}\left[\sum_{X \in 2^{\Theta}} m_{\mathrm{Maj}}(X)\right. \\ &\qquad \left. + \sum_{X \in 2^{\Theta}} m_{\mathrm{Conj}}(X)\right]\end{aligned}$$

By definition of the majority and conjunctive rules, it is easy to see that:

$$\sum_{X \in 2^{\Theta}} m_{\mathrm{Maj}}(X) = s$$

and

$$\sum_{X\in 2^{\Theta}} m_{\mathrm{Conj}}(X) = 1 - k.$$

Then, we get $\frac{s+1-k}{s+1-k} = 1$. Therefore, $m_{1,2,\cdots,s|\mathrm{MCR}}(\cdot)$ is a proper mass. □

As an example, consider a simple monitoring for an emergency detection system. For illustration, we treat a scenario (see Fig. 1) of health monitoring example for an elderly people activities of daily living. In order to shift the care to a personalized level, we consider two kinds of Internet of Things sensors: those that use external wearable sensors that are attached to different parts of the elderly body and those that use embedded inertial sensors of the smartphone where it is not mandatory to mount or fix position of the sensor. Our scenario consider four activities: exercising, watching TV, sleeping, and fall detection which is another important area of emergency detection, and can be especially useful for the elderly. Figure 1 visualizes a scenario in which an elderly patient's health profile and vitals are captured using portable medical devices (wireless accelerometer and heart monitor rate) attached to his or her body and smartphone for communication. Captured data from these medical devices are then communicated to the smartphone and thereafter, stored data become useful for activity recognition, aggregation, and inference. Based on aggregation and evidential inference, doctors or caregivers can monitor an elderly patient from any location and respond accordingly in risk situation such as elderly fall detection.

Supposing that a dataset contains data from these sensors: wireless acceleration sensor, smartphone, and wireless heart rate monitor. Assume that the resulting training data induces the following masses bba's for activity recognition.

$$m_1(\text{Falling}) = 0.8 \quad m_1(\{\text{Falling,Watching TV}\}) = 0.2$$
$$m_2(\text{Falling}) = 0.1 \quad m_2(\text{Sleeping}) = 0.9$$
$$m_3(\text{Falling}) = 0.25 \quad m_3(\{\text{Exercising,Watching TV}\}) = 0.75$$

According to these masses, the classes' distribution for each activity are : the accelerometer indicates that the elderly people is falled down with 80% and the remaining 20% are imprecise recognition rate for two activities $\{falling\}$ or $\{WatchingTV\}$. The smartphone indicates that the elderly people sleeping with 90% while 10% reflects that he/she is falling. However, the heart rate monitor indicates that imprecise recognition of 75% of the elderly people exercises on an abdominal bench or watching TV and 25% for elderly fall detection.

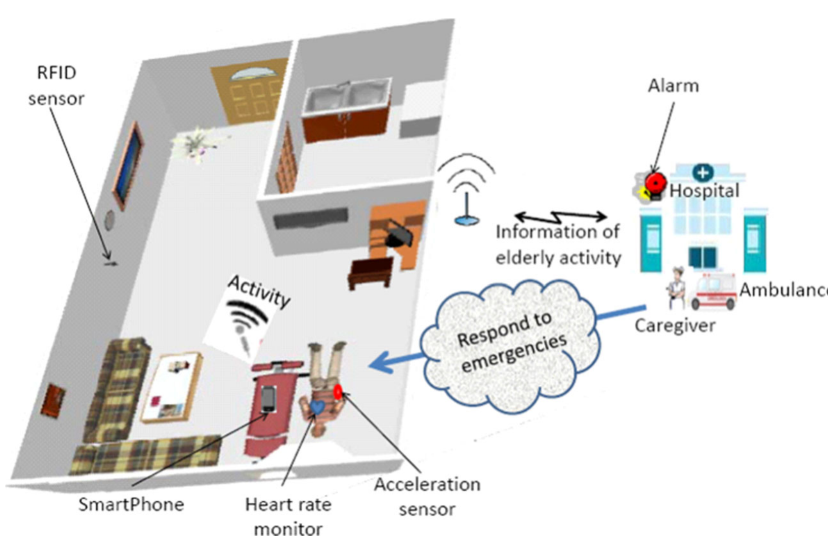
We assume that each sensor provides its activity selection independently. The non-normalized conjunctive consensus of the basic belief assignments yields the following results for this example:

$$m_{\mathrm{Conj}}(\text{Falling}) = 0.025 \quad m_{\mathrm{Conj}}(\{\text{Falling,Watching TV}\}) = 0$$
$$m_{\mathrm{Conj}}(\text{Sleeping}) = 0 \quad m_{\mathrm{Conj}}(\{\text{Exercising,Watching TV}\}) = 0$$

The global conflicting mass k_{123} is 0.975 and the masses fused with the majority rule are:

$$m_{\mathrm{Maj}}(\text{Falling}) = 1.15 \quad m_{\mathrm{Maj}}(\{\text{Falling,Watching TV}\}) = 0.2$$
$$m_{\mathrm{Maj}}(\text{Sleeping}) = 0.9 \quad m_{\mathrm{Maj}}(\{\text{Exercising,Watching TV}\}) = 0.75$$

Fig. 1 Scenario illustration for elderly medical care



By applying Eq. 8, the final combined masses are:

$m_{123|\mathrm{MCR}}(\text{Falling}) = 0.388$ $m_{123|\mathrm{MCR}}(\{\text{Falling,Watching TV}\}) = 0.066$
$m_{123|\mathrm{MCR}}(\text{Sleeping}) = 0.298$ $m_{123|\mathrm{MCR}}(\{\text{Exercising,Watching TV}\}) = 0.248$

Using the maximum of the plausibility or the pignistic probability to provide a decision from the remaining combined masses, we select the falling situation that occur ($Pl(Falling) = 0.455$ and $BetP(Falling) = 0.421$) as a plausible activity that the elderly people is doing. Thus, the smartphone send an alert signal alarm to the hospital and notified and provided an available caregiver with inventory information of elderly activity. In this case, it is necessary to provide an alert signal for available caregiver and ambulance driver within seconds of a risky situation to prevent a compromise to an elder's health. This result involves a continuous supervision which is due to the fact that most of basic belief assignments are in favor to this situation in respect with the sensors data collection. As a result, our rule provides a good evidence combination for data fusion in the way that it preserves the majority and the consensus of each sensor.

The present rule is commutative since the conjunctive and the sum operators have this property. However, it is not associative as the most evidence theory derivates but can become quasi-associative if we save the result of the conjunctive and majority rules at each step before the normalization process. Unfortunately, our rule does not preserve the vacuous belief assignment when some sources become totally ignorant. The disappearing ignorance propriety is an advantage in combination process because only the evidences without ignorance are combined. However, some authors [33, 37, 56, 57] have criticized this propriety caused by the conjunctive operation and specified that the counterintuitive results of Dempster's rule are caused by this ignorance. Hence, in our approach, we cannot suppress or neglect the weaker belief committed to the area's activity of elderly people which can be supported by the vacuous belief assignment because we presume that the disappearing ignorance is not justified in all situations.

4.2 Combination rule reconcilement consistency

The notion of the combination consistency represents the interval of reconcilement (approximation) of the combination of evidence result computed by the frequentist approach of probability calculus and the evidence theory and its derivates.

According to belief and plausibility functions and the frequentist approach of probability calculus, the real lower and upper bounds of an unknown probability measure is defined on Θ and compatible with the basic belief assignment $m(\cdot)$ by the following definitions.

Definition 1 (Real lower bound) Let Θ be a frame of discernment and let $m_i(\cdot)$ be the basic belief assignments associated to a given focal set $X_i \in 2^{\Theta}$. We define the real lower bound of the singleton focal element $X \in \Theta$ (denoted $\mathrm{Bel}^L(X)$) as follows:

$$\mathrm{Bel}^L(X) = \frac{1}{s}\sum_{i=1}^{s} m_i(X) \tag{12}$$

Definition 2 (Real upper bound) Let Θ be a frame of discernment and let $m_i(\cdot)$ be the basic belief assignments associated to a given focal sets $X_i \in 2^{\Theta}$. We define the real upper bound of the singleton focal element $X \in \Theta$ (denoted $\mathrm{Pl}^U(X)$) as follows:

$$\mathrm{Pl}^U(X) = \frac{1}{s}\sum_{X_i \cap X \neq \emptyset} m_i(X_i) \tag{13}$$

The real lower bound definition corresponds to the average of evidence for each hypothesis X. In other words, it represents the fusion using the arithmetic mean operator. However, the real upper bound measures the average mass of the total mass which can visit somewhere within X but may move outside as well (each mass of the ignorance containing X is added to the mass of the focal element $\{X\}$). Obviously, we have $\mathrm{Bel}^L(X) \leq \mathrm{Pl}^U(X)$ for all $X \in \Theta$. Note that these real bounds are different from the belief and plausibility functions defined in the Dempster-Shafer theory (see Section 3).

These two definitions represent the reconcilement interval of a combination rule of evidences with the frequentist approach of probability calculus.

Let us reconsider our elderly people example. To show the inconsistency of some well-known rules with the probability calculus, let us examine the activity selections in the reality. Hence, we compute the real interval (the real lower and upper bounds) of each activity selection when every

Table 2 The real lower and upper bounds

Elderly people activity	Lower bound	Upper bound
Falling	0.383	0.450
Sleeping	0.3	0.3
Exercising	0	0.250
Watching TV	0	0.317

sensor has finally selected only one activity at the same time. For this example, the real lower and upper bounds can be defined supposing the three sensors are gathered into a single sensor. Hence, applying equations 12 and 13, we have obtained the results reported in Table 2. In the first row, the real lower bound means that only the precise selections of the falling situation (activity) are considered by the three sensors. However, the real upper bound of this activity assumes in addition to the precise selection that the accelerometer sensor had finally selected the falling situation. Clearly from these real bounds, the final selection by the three sensors corresponds to that the elderly people must be an emergency since the real lower bound of the falling situation is greater than each real upper bound of the other activities.

The results reported in Table 3 show the inconsistency of the evidence theory and its derivates to compute the lower and upper bounds compared to the results reported in Table 2. Clearly based on Dempster-Shafer rule, the lower and upper bounds specify that sleeping, watching TV and exercising activities ([0; 0]) could never have been selected according to the real probability of the selection which are given by the three sensors. The PCR6 rule selects the abnormal activity detection, sleeping with the pignistic probability equals to 0.377 which is outside the real lower and upper bounds interval ([0.3; 0.3]). This abnormal behavior of this rule is due to the absorption of the conflict by the focal element sleeping activity which has a bigger mass (m_2(Sleeping) $= 0.9$) in the conflict redistribution step. Murphy's rule favors the falling situation by the averaging technique of its masses and gives the lower and upper bounds of the falling situation equal to [0.607; 0.609]. This result is outside the real bounds ([0.383; 0.450]). However, the result obtained by our rule are reasonable for this example since the belief, the plausibility, and the pignistic probability of each activity's selection is inside the interval of the real bounds except for the sleeping activity which approximates the real probability (Bet$P$(Sleeping) $=$ 0.298).

Table 3 The lower and upper bounds according to the preceding rule classes

Elderly people activity	Rule	[Bel(X); $Pl(X)$]	BetP(X)
Falling	Dempster's	[1; 1]	1
	Murphy's	[0.607; 0.609]	0.608
	PCR6	[0.3407; 0.365]	0.353
	Our rule	[0.388; 0.455]	0.421
Sleeping	Dempster's	[0; 0]	0
	Murphy's	[0.181; 0.181]	0.181
	PCR6	[0.377; 0.377]	0.377
	Our rule	[0.298; 0.298]	0.298
Exercising	Dempster's	[0; 0]	0
	Murphy's	[0; 0.104]	0.052
	PCR6	[0; 0.258]	0.129
	Our rule	[0; 0.248]	0.124
Watching TV	Dempster's	[0; 0]	0
	Murphy's	[0.106; 0.212]	0.159
	PCR6	[0; 0.282]	0.141
	Our rule	[0; 0.314]	0.157

5 Simulation studies

The foregoing sections have provided background on the proposed combination rule. Now, we return to evaluate our rule with simulation studies based on the elderly healthcare scenario cases. The first part of this section describes our uncertain context information modeling in IoT-based healthcare systems. The second part describes experimental simulations according to elderly healthcare scenario cases.

5.1 Uncertain context modeling

IoT-based healthcare systems for elderly people need to represent many different types of uncertain context information, such as sensor information, spatial information, medical history, and activities profiles. As introduced in [44], the context can be divided into three layers or levels: sensors, abstracted context, and situation (or activity). The sensor layer refers to the physical layer where sensors or any other IoT devices are used to provide contextual information such as temperature, acceleration and motions, etc. In the second layer, raw data provided by the first layer are translated into more human understandable representation by using abstraction. For example, accelerometer reading are translated to sates of "in motion," "falling," or "immobile." This human understandable representation of context will follow a formal representation in order to be used in pervasive systems such as the ontology model. This model is particularly interesting to provide an explicit commonly agreed upon representation of concepts in a hierarchal manner. The last layer is the high-level context abstraction defined by fusing multiple information contexts to infer activity or situation. Then, this infrastructure can employ the IoT health care to enable communication between elderly individuals, caregivers, and doctors. In the next, we explain our uncertain context representation and reasoning mechanisms.

Our ubiquitous computing framework proposed in [44] aims to build new applications to provide assistive services for people in autonomously simulation way. These framework must adapt their behaviors to provide services that match current user needs. The proposed approach presents a context-aware ubiquitous framework based on lightweight coupling between multi-agent system and the OSGi (Open Service Gateway initiative) framework [53]. Figure 2 illustrates the architecture of our ubiquitous framework system. In the smart home healthcare scenario, various elderly body and home environmental sensors are deployed to gather as much information about and around the elderly as possible. The lower layer represents a set of context sensors and actuators which encapsulate the hardware devices of IoT-based healthcare technologies. The second layer is called the OSGi layer. The goal of this layer is to acquire context information from the ubiquitous environment and to control devices and equipments. The third layer represents the multi-agent layer. This layer aims to interpret, infer, and share uncertain contextual information data. Thus, we use the ontology markup language OWL for our ontology context-based representation to share information acquired from the environment or aggregated by the agents. In our ubiquitous framework, we have extended USARSim simulator [4] as simulation infrastructure for the proposed

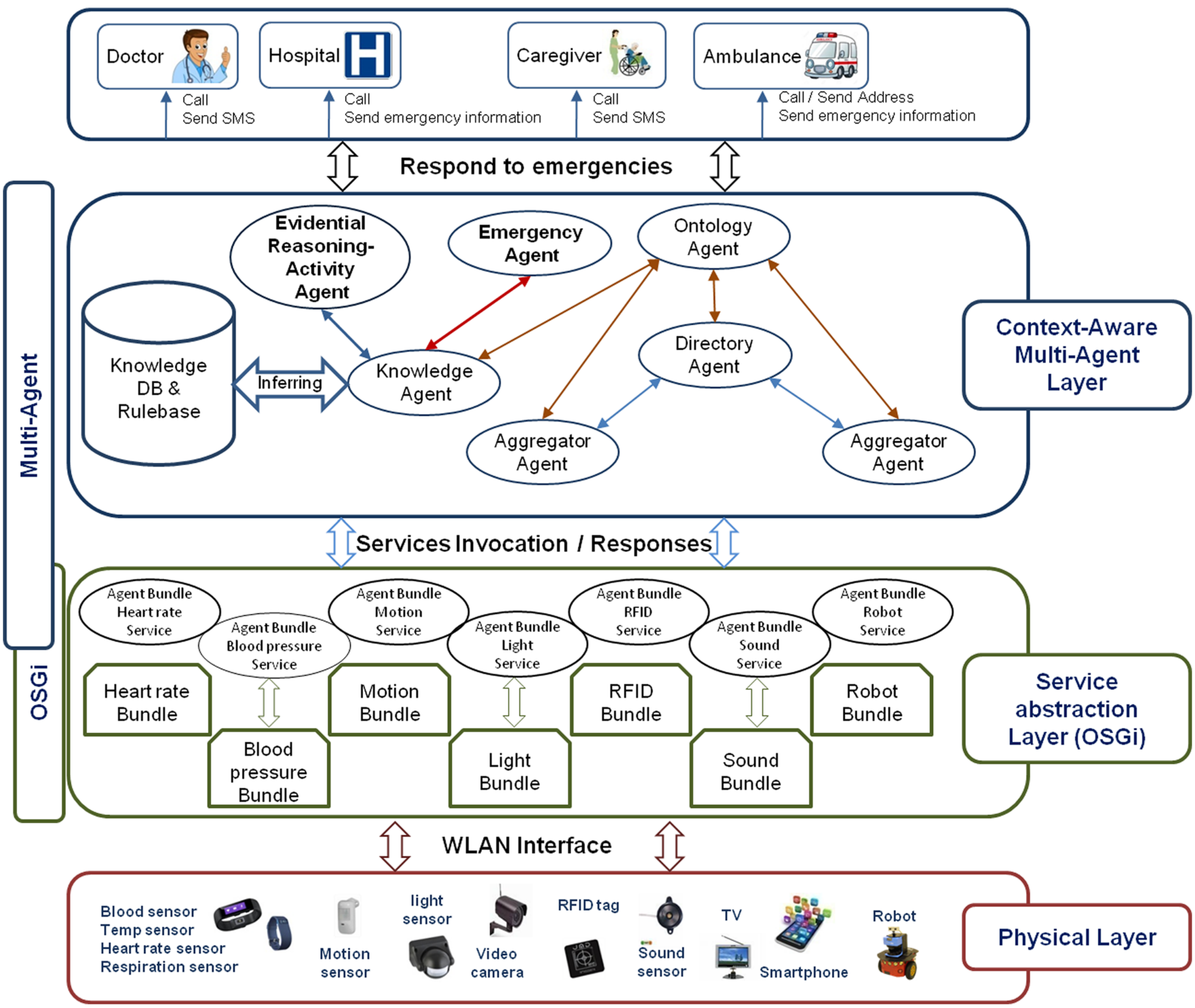


Fig. 2 Overview of the multi-agent–OSGI context-aware framework

elderly's IoT-based healthcare system. Some simulation images from simulated configurable sensors and environments are showed in Fig. 3.

In our ubiquitous framework system, the evidential reasoning agent is capable of performing the following reasoning tasks: (i) continuous information contextualization of the physical state of an elderly person (motion, localization, medical monitors,...), (ii) recognition of possibly activities and risky situations (exercising, sleeping, fall detection,...), and (iii) notification of emergency situations indicating a health risk by sending signal alarm to notify hospital staff (doctor, caregiver, ambulance driver,...). For example, when smart home monitor agent localized current elderly people localization and evidential agent infers fall detection situation, it sends to the emergency agent the following request medical associated rule:

Rule :

IF

(Elderly Has Fallen Down) AND (HeartRate is Very High) AND

(Respiration Rate is Low) AND (Elderly Do Not Responded To Sign (phone call))

Then

(Send Emergency Signal to Hospital) AND (Provide Elderly Inventory

Information to an Available Caregiver) AND (Call Ambulance Driver)

This request rule describes that if the elderly person has fallen down and after he/she has been notified but he/she has not responded yet, then the system send an emergency signal alert to the hospital and an available caregiver receive an elderly person inventory information and the ambulance driver is called too.

5.2 Experimental simulation cases

5.2.1 The Bayesian bbas selections

The experimental simulations are designed and implemented based on a modified USARSim simulator [4] and extended multi-agent OSGi inference mechanism introduced in [44]. In this section, we are going to present the behavior of our rule to combine bodies of evidence in Shafer's model using the Bayesian bbas. Suppose that the sensors mentioned in our simplest elderly monitoring for emergency detection where each sensor infers one preferred activity or situation as follow:

Accelerometer sensor: Falling < Sleeping < Watching TV

$$m_1(\text{Falling}) = a_1 \quad m_1(\text{Sleeping}) = b_1$$
$$m_1(\text{Watching TV}) = 1 - a_1 - b_1$$

Smartphone: Sleeping < Watching TV < Falling

$$m_2(\text{Falling}) = a_2 \quad m_2(\text{Sleeping}) = b_2$$
$$m_2(\text{Watching TV}) = 1 - a_2 - b_2$$

Heart monitor sensor: Watching TV < Falling < Sleeping

$$m_3(\text{Falling}) = a_3 \quad m_3(\text{Sleeping}) = b_3$$
$$m_3(\text{Watching TV}) = 1 - a_3 - b_3$$

Using these masses, one gets the following lower and upper bounds

$$\text{Bel}^L(\text{Falling}) = \text{PL}^U(\text{Falling}) = \frac{1}{3}\sum_{i=1}^{3} a_i$$

$$\text{Bel}^L(\text{Sleeping}) = \text{PL}^U(\text{Sleeping}) = \frac{1}{3}\sum_{i=1}^{3} b_i$$

$$\text{Bel}^L(\text{Watching TV}) = \text{PL}^U(\text{Watching TV}) = \frac{1}{3}\sum_{i=1}^{3}(1 - a_i - b_i)$$

To illustrate the consistence of the combination rules, we have implemented a Monte-Carlo simulation where the masses were distributed randomly according to a uniform distribution. Thus, we have generated randomly 1000 samples for the three sensor selections. Figure 4 illustrates the consistency results of our rule compared to the evidence theory and its derivates for the elderly fall detection. For a reason of clarity of the presented comparison results, we show only the results for 100 samples. The frequentist approach of probability calculus was initially used to calculate the lower and upper bounds with respect to activity selections used here. We report the relative comparison of the selection result for our rule and the evidence theory and its derivates (Murphy's and PCR6 rules) based on the maximum pignistic of probabilities criterion. It is clear from this figure that, in the Bayesian case, our rule has a high approximation of the real probabilities where the majority of the pignistic probability values are near the real probability values computed from the frequentist

Fig. 3 Some simulated activities

(a) Falling (b) Sleeping

(c) WatchingTV

approach of probability calculus. However, the PCR6 gives a good result compared to Murphy's and Dempster-Shafer's rules. Note that if the majority rule yields the same combined masses, Murphy's rule fails to distinguish between the bodies of evidence combination. It can be seen in this figure that our rule has a good consistency which implies that the reconcilement of our rule and the frequentist approach of probability is almost perfect.

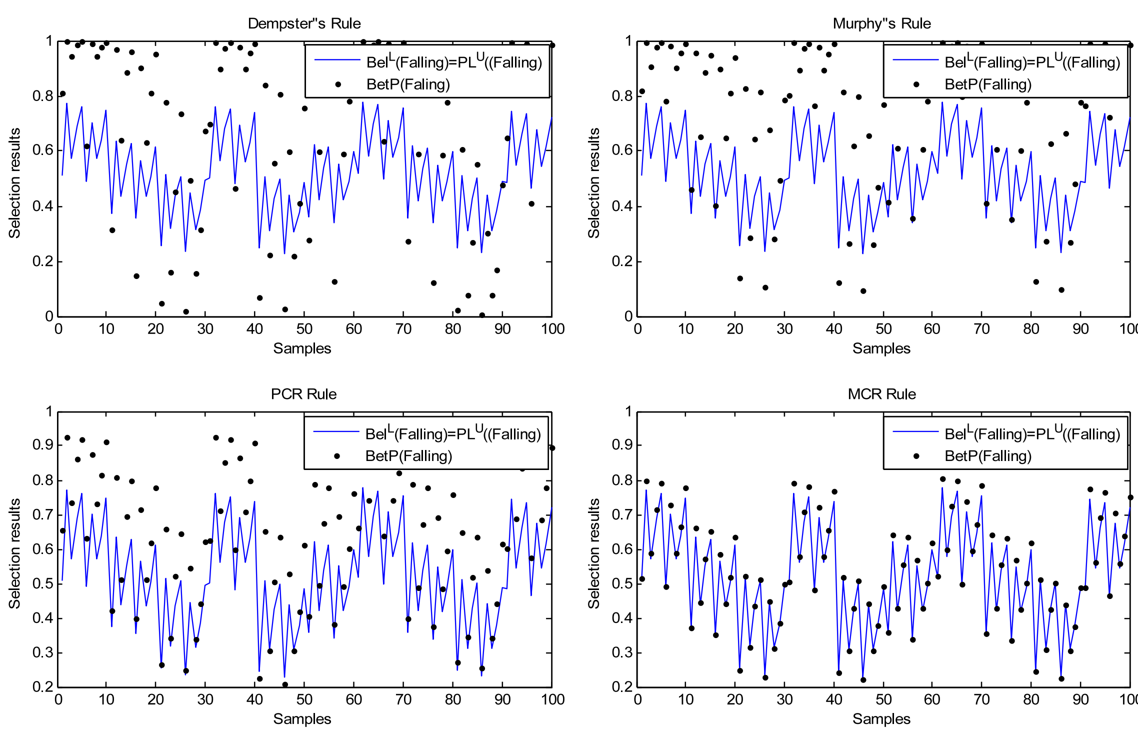


Fig. 4 The consistency for Bayesian selections of elderly fall detection: MCR, PCR6, Dempster's, and Murphy's rules

5.2.2 Non-Bayesian bbas selections

Now, assume that the three sensors provide imprecise bodies of evidence with the following preferences:
Accelerometer sensor

$$m_1(\{\text{Falling, Sleeping}\}) = a_1$$
$$m_1(\{\text{Falling, Watching TV}\}) = b_1$$
$$m_1(\{\text{Sleeping, Watching TV}\}) = 1 - a_1 - b_1$$

Smartphone

$$m_2(\{\text{Falling, Sleeping}\}) = a_2$$
$$m_2(\{\text{Falling, Watching TV}\}) = b_2$$
$$m_2(\{\text{Sleeping, Watching TV}\}) = 1 - a_2 - b_2$$

Heart rate monitor sensor

$$m_3(\{\text{Falling, Sleeping}\}) = a_3$$
$$m_3(\{\text{Falling, Watching TV}\}) = b_3$$
$$m_3(\{\text{Sleeping, Watching TV}\}) = 1 - a_3 - b_3$$

Assuming that for these imprecise bodies of evidence, the three sensors have finally selected one activity with the combined masses at the same time. This yields the non-Bayesian activity inferences for the lower and upper bounds computation. Thus, we obtain

$$\text{Bel}^L(\text{Falling}) = \text{Bel}^L(\text{Sleeping}) = \text{Bel}^L(\text{Watching TV}) = 0$$
$$\text{PL}^U(\text{Falling}) = \frac{1}{3}\sum_{i=1}^{3}(a_i + b_i)$$
$$\text{PL}^U(\text{Sleeping}) = \frac{1}{3}\sum_{i=1}^{3}(1 - b_i)$$
$$\text{PL}^U(\text{Watching TV}) = \frac{1}{3}\sum_{i=1}^{3}(1 - a_i)$$

We remark that the results obtained from the pignistic probability values of elderly fall detection in all rules are compatible. This is due to the inclusion of the pignistic probability value by the corresponding lower and upper bounds for each sample (see Fig. 5). So that, the consistency measure of "fall detection" is higher in this case.

5.2.3 The hybrid bbas selections

Finally, assume that the three sensors have precise and imprecise selections with the following masses:
Accelerometer sensor

$$m_1(\text{Falling}) = a$$
$$m_1(\{\text{Falling, Sleeping, Watching TV}\}) = 1 - a$$

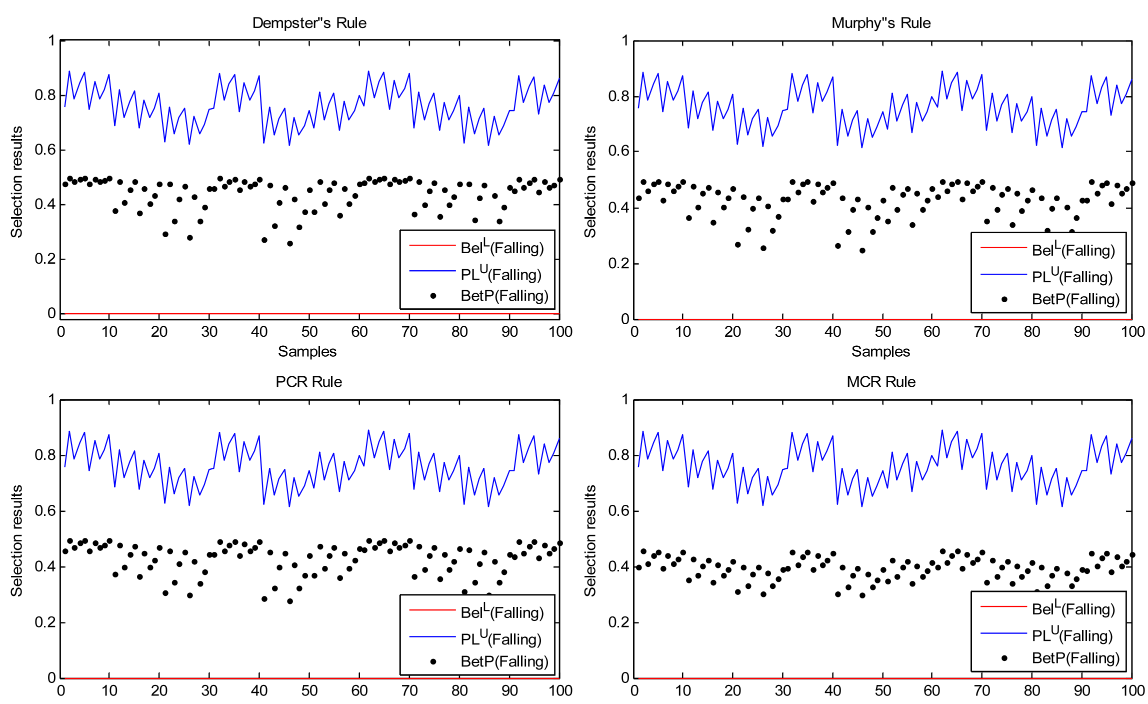


Fig. 5 The consistency for non-Bayesian selections of elderly fall detection: MCR, PCR6, Dempster's, and Murphy's rules

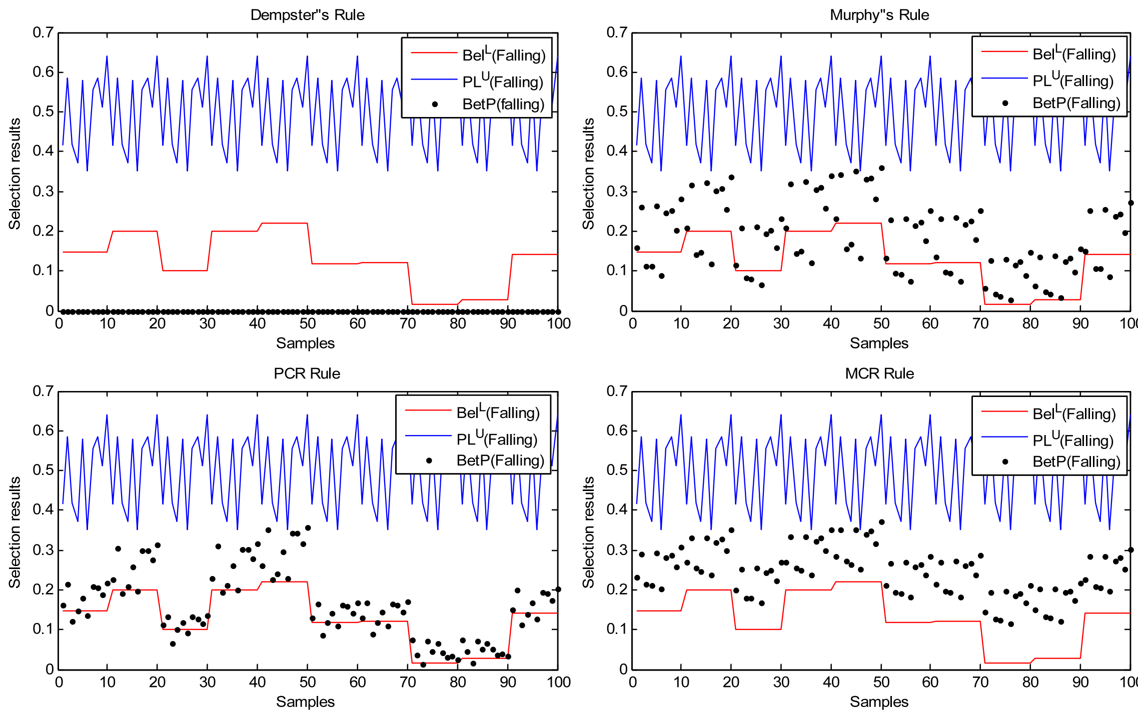


Fig. 6 The consistency for hybrid bbas selections of elderly fall detection: MCR, PCR6, Dempster's, and Murphy's rules

Smartphone

$m_2(\{\text{Falling, Watching TV}\}) = b \quad m_2(\text{Sleeping}) = 1 - b$

Heart monitor sensor

$m_3(\{\text{Watching TV}\}) = c$

$m_3(\{\text{Sleeping, Watching TV}\}) = 1 - c$

As illustrated in Fig. 6 for these three hybrid pieces of evidence, our rule gives also the consistent result where the total pignistic probability values for elderly fall detection are included in the corresponding lower and upper bounds. The reason for this success is that the MCR rule merges the majority and the conjunctive rules. The effect of this latter can be observed from the Bayesian case of Fig. 4, where the pignistic probabilities calculated from the evidence theory and its derivates give a low consistency measure. Therefore, it can be concluded that the majority criterion merged with the consensus one gives a highest consistency for our combination rule with the frequentist approach of probability calculus compared to the evidence theory and its derivates.

6 Conclusion

The IoT has a variety of application domains, including elderly healthcare applications. In order to reach the reconcilement of evidence theory with the frequentist appoach of probability calculus for activity recognition in this domain, we have proposed in this work a new framework for combining evidences. The key point of our belief-based fusion approach is twofold. First, we have proposed an alternative combination rule which merges the majority and the conjunctive rules. Second, we have introduced a new notion of the consistency measure of combination rule as an evaluation criterion of this reconcilement. The proposed rule has interesting properties compared to the evidence theory and its derivates when our rule produces intuitive results in several situations. We note that the present results pertain in the highly conflicting situation or not. Moreover, the simulation results which have been carried out in order to evaluate the effectiveness of the proposed merging rules indicate that, first of all, the merging strategies that take into account the majority rule and the conjunctive ones are more effective than the rule that uses only the conjunctive consensus. Furthermore, the simulation studies show that the majority criterion merged with the consensus ones gives almost a perfect reconcilement in accordance with probability calculus while other rules are far from being close in Bayesian and hybrid cases. For future work, we plan to implement our simulation system for an elderly healthcare monitoring system in real applications in respect with the security aspect.

References

1. Acampora G, Cook DJ, Rashidi P, Vasilakos AV (2013) A survey on ambient intelligence in healthcare. Proc IEEE 101(12):2470–2494
2. Armstrong N, Nugent C, Moore G, Finlay D (2010) Using smartphones to address the needs of persons with Alzheimer's disease. Ann Telecommun 65(9-10):485–495
3. Bächlin M, Plotnik M, Roggen D, Maidan I, Hausdorff JM, Giladi N, Tröster G (2010) Wearable assistant for Parkinsons disease patients with the freezing of gait symptom. IEEE Trans Inf Technol Biomed 14(2):436–446
4. Balaguer B, Balakirsky S, Carpin S, Lewis M, Scrapper C (2008) Usarsim: a validated simulator for research in robotics and automation. In: Workshop on" robot simulators: Available software, scientific applications, and future trends" at IEEE/RSJ
5. Barnachon M, Bouakaz S, Boufama B, Guillou E (2014) Ongoing human action recognition with motion capture. Pattern Recogn 47(1):238–247
6. Biswas J, Tolstikov A, Jayachandran M, Foo V, Wai AAP, Phua C, Huang W, Shue L, Gopalakrishnan K, Lee JE, et al. (2010) Health and wellness monitoring through wearable and ambient sensors: exemplars from home-based care of elderly with mild dementia. Ann Telecommun 65(9-10):505–521
7. Chena Y, Wub J, Congc J, Jied W, Denga Y (2011) A more effective definition of evidential conflict combined with evidential distance. International Journal of Web Information Systems 8(9):1729–1734
8. Chernbumroong S, Cang S, Yu H (2015) Genetic algorithm-based classifiers fusion for multisensor activity recognition of elderly people. IEEE Journal of Biomedical and Health Informatics 19(1):282–289
9. Clarkson B, Mase K, Pentland A (2000) Recognizing user context via wearable sensors. In: The 4th International Symposium on Wearable Computers. IEEE, pp 69–75
10. Dubois D, Prade H (1988) Representation and combination of uncertainty with belief functions and possibility measures. Comput Intell 4(3):244–264
11. Franco C, Demongeot J, Villemazet C, Vuillerme N (2010) Behavioral telemonitoring of the elderly at home: detection of nycthemeral rhythms drifts from location data. In: 2010 IEEE 24th International Conference on Advanced information Networking and Applications Workshops (WAINA). IEEE, pp 759–766
12. Gu T, Pung HK, Zhang DQ, Pung HK, Zhang DQ (2004) A Bayesian approach for dealing with uncertain contexts. In: AustriaN computer society. Citeseer
13. Han CW, Kang SJ, Kim NS (2010) Implementation of hmm-based human activity recognition using single triaxial accelerometer. IEICE Trans Fundam Electron Commun Comput Sci 93(7):1379–1383
14. Havasi F, Kiss Á (2008) Ambient assisted living in rural areas: vision and pilot application. In: Constructing ambient intelligence. Springer, pp 246–252
15. Hong X, Nugent CD, Mulvenna MD, McClean SI, Scotney BW, Devlin S (2009) Evidential fusion of sensor data for activity recognition in smart homes. Pervasive and Mobile Computing 5(3):236–252
16. Hossain MA (2014) Perspectives of human factors in designing elderly monitoring system. Comput Hum Behav 33:63–68
17. J E (2013) An introduction to the paper by Acampora, Cook, Rashidi, and Vasilakos: a survey on ambient intelligence in healthcare. Proc IEEE 101(12):2467–2469
18. Jousselme AL, Grenier D, Bossé É (2001) A new distance between two bodies of evidence. Information fusion 2(2):91–101
19. Kasteren TV, Noulas AK, Englebienne G, Kröse BJA (2008) Accurate activity recognition in a home setting. In: 10Th International Conference, UbiComp 2008, ACM International Conference Proceeding Series, vol 344. ACM, pp 1–9
20. Khan ZA, Sohn W (2010) Feature extraction and dimensions reduction using r transform and principal component analysis for abnormal human activity recognition. In: 2010 6th International Conference on Advanced Information Management and Service (IMS). IEEE, pp 253–258
21. Kim EH, Kim Y (2010) Digital divide: use of electronic personal health record by different population groups. In: 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, pp 1759–1762
22. Lexis M (2013) Activity monitoring technology to support homecare delivery to frail and psychogeriatric elderly persons living at home alone. Technol Disabil 25(3):189–197
23. Li B, Wang B, Wei J, Huang Y, Guo Z (2001) Efficient combination rule of evidence theory. In: Multispectral image processing and pattern recognition, pp. 237–240. International society for optics and photonics
24. Liang XR, Yao PY, Liang DL (2008) Improved combination rule of evidence theory and its application in fused target recognition. Electron Opt Control 12:010
25. Liao L, Fox D, Kautz H (2007) Extracting places and activities from gps traces using hierarchical conditional random fields. Int J Robot Res 26(1):119–134
26. Martin A, Jousselme AL, Osswald C (2008) Conflict measure for the discounting operation on belief functions. In: 2008 11th International Conference on Information Fusion. IEEE, pp 1–8
27. Martin A, Osswald C (2006) A new generalization of the proportional conflict redistribution rule stable in terms of decision. Advances and Applications of DSmT for Information Fusion: Collected Works 2:69–88
28. McKeever S, Ye J, Coyle L, Bleakley CJ, Dobson S (2010) Activity recognition using temporal evidence theory. JAISE 2(3):253–269
29. McKeever S, Ye J, Coyle L, Dobson SA (2009) Using dempster-shafer theory of evidence for situation inference. In: Barnaghi PM, Moessner K, Presser M, Meissner S (eds) 4th European Conference on Smart Sensing and Context, EuroSSC, Lecture Notes in Computer Science, vol 5741. Springer, pp 149–162
30. Megalingam RK, Pocklassery G, Mourya G, Jayakrishnan V (2012) 747–752. In: 2012 annual IEEE India Conference (INDICON). IEEE
31. Mokhtari M, Ali Feki M, Nugent CD (2010) Ambient intelligence for ubiquitous health and wellbeing. Ann Telecommun 65(9):477–478
32. Mubashir M, Shao L, Seed L (2013) A survey on fall detection: principles and approaches. Neurocomputing 100:144–152
33. Murphy CK (2000) Combining belief functions when evidence conflicts. Decis Support Syst 29(1):1–9
34. Onyimadu O, Harding F, Briggs J (2011) Designing a telecare product for the elderly. In: 2011 5th International conference on Pervasive computing technologies for healthcare (pervasivehealth). IEEE, pp 336–339
35. Ouchi K, Doi M (2012) Living activity recognition using off-the-shelf sensors on mobile phones. Ann Telecommun 67(7-8):387–395
36. Patterson DJ, Fox D, Kautz H, Philipose M (2005) Fine-grained activity recognition by aggregating abstract object usage. In: Proceedings of the 9th IEEE international symposium on Wearable computers, 2005. IEEE, pp 44–51
37. Pearl J (1990) Reasoning with belief functions: an analysis of compatibility. Int J Approx Reason 4(5):363–389

38. Philipose M, Fishkin KP, Perkowitz M, Patterson DJ, Fox D, Kautz H, Hahnel D (2004) Inferring activities from interactions with objects. IEEE Pervasive Computing 3(4):50–57
39. Ranganathan A, Al-Muhtadi J, Campbell RH (2004) Reasoning about uncertain contexts in pervasive computing environments. IEEE Pervasive Computing 3(2):62–70
40. Riazul Islam S, Kwak D, Humaun Kabir M, Hossain M, Kwak K. S (2015) The internet of things for health care: a comprehensive survey. Access, IEEE 3:678–708. doi:10.1109/ACCESS.2015.2437951
41. Sebbak F, Benhammadi F, Bouznad S, Amirat Y et al (2014) An alternative combination rule for evidential reasoning. In: 17Th International Conference on Information Fusion (FUSION) 2014. IEEE, pp 1–8
42. Sebbak F, Benhammadi F, Bouznad S, Chibani A, Amirat Y (2014) An evidential fusion rule for ambient intelligence for activity recognition belief functions: theory and applications. Springer, pp 356–364
43. Sebbak F, Benhammadi F, Chibani A, Amirat Y, Mokhtari A (2014) Dempster–Shafer theory-based human activity recognition in smart home environments. Ann Telecommun 69(3–4):171–184
44. Sebbak F, Mokhtari A, Chibani A, Amirat Y (2010) Context-aware ubiquitous framework services using jade-osgi integration framework. In: 2010 international conference on Machine and web intelligence (ICMWI). IEEE, pp 48–53
45. Shafer G (1976) A mathematical theory of evidence, vol 1. Princeton University Press, Princeton
46. Si H, Kim SJ, Kawanishi N, Morikawa H (2007) A context-aware reminding system for daily activities of dementia patients. In: 27th international conference on Distributed computing systems workshops, 2007. ICDCSW'07. IEEE, pp 50–50
47. Smarandache FE, Dezert JE (2009) Advances and applications of DSmt for information fusion. Collected works. Vol. 3., vol 3. American Research Press (ARP), Rehoboth, USA
48. Smets P (1989) Constructing the pignistic probability function in a context of uncertainty. In: UAI, pp 29–40
49. Smets P (1990) The combination of evidence in the transferable belief model. IEEE Transactions on Pattern Analysis and Machine Intelligence 12(5):447–458
50. Smets P, Kennes R (1994) The transferable belief model. Artificial intelligence 66(2):191–234
51. Smith-Spangler C, Gienger A, Lin N, Lewis R, Stave C, Olkin I (2007) Using pedometers to increase physical activity: a systematic review. JAMA 298:2296–2304
52. Soto-Mendoza V, García-macías JA, Chá vez E, Martínez-García AI, Favela J, Serrano-Alvarado P, Rojas MRZ (2015) Design of a predictive scheduling system to improve assisted living services for elders. ACM Transactions on Intelligent Systems and Technology (TIST) 6(4):53
53. Std OA (2011) Osgi service platform release 4.3. OSGi Alliance
54. Vail DL, Veloso MM, Lafferty JD (2007) Conditional random fields for activity recognition. In: Proceedings of the 6th International Joint Conference on Autonomous Agents and Multiagent Systems. ACM, p 235
55. Villalba E, Ottaviano M, Arredondo MT, Martinez A, Guillen S (2006) Wearable monitoring system for heart failure assessment in a mobile environment. In: Computers in Cardiology, 2006. IEEE, pp 237–240
56. Voorbraak F (1991) On the justification of Dempster's rule of combination. Artif Intell 48(2):171–197
57. Walley P (1987) Belief function representations of statistical evidence. Ann Stat:1439–1465
58. Wang L, Gu T, Tao X, Chen H, Lu J (2011) Recognizing multi-user activities using wearable sensors in a smart home. Pervasive and Mobile Computing 7(3):287–298
59. Ward JA, Lukowicz P, Troster G, Starner TE (2006) Activity recognition of assembly tasks using body-worn microphones and accelerometers. IEEE Transactions on Pattern Analysis and Machine Intelligence 28(10):1553–1567
60. Wu H, Siegel M, Stiefelhagen R, Yang J (2002) Sensor fusion using Dempster-Shafer theory [for context-aware hci]. In: Proceedings of the 19th IEEE instrumentation and measurement technology conference, 2002. IMTC/2002, vol 1. IEEE, pp 7–12
61. Wu W, Au L, Jordan B, Stathopoulos T, Batalin M, Kaiser W, Vahdatpour A, Sarrafzadeh M, Fang M, Chodosh J (2008) The smartcane system: an assistive device for geriatrics. ICST (Institute for Computer Sciences Social-Informatics and Telecommunications Engineering, p 2
62. Xu G, Tian W, Qian L, Zhang X (2007) A novel conflict reassignment method based on grey relational analysis (gra). Pattern Recogn Lett 28(15):2080–2087
63. Yager RR (1987) On the Dempster-Shafer framework and new combination rules. Inf Sci 41(2):93–137
64. Ye J, Dobson S (2010) Exploring semantics in activity recognition using context lattices. Journal of Ambient Intelligence and Smart Environments 2(4):389–407
65. Yong D, WenKang S, ZhenFu Z, Qi L (2004) Combining belief functions based on distance of evidence. Decis Support Syst 38(3):489–493
66. Zadeh LA (1984) Review of a mathematical theory of evidence. AI Mag 5(3):81–83
67. Zhang D, Guo M, Zhou J, Kang D, Cao J (2010) Context reasoning using extended evidence theory in pervasive computing environments. Future Generation Comp Syst 26(2):207–216