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A New Service-Aware Computing Approach for Mobile Application with Uncertainty

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Abstract: It is known to all that service-aware computing is an important part of pervasive computing for Web-based mobile application with uncertainty. Because multi-source service-aware evidence information with uncertainty is dynamic and changing randomly, in order to ensure the QoS of different mobile application fields based on it, we modified the fusion method of evidence information after considering context's reliability, time-efficiency, and relativity, which has improved the classical fusion rule of D-S (Dempster-Shafer) Evidence Theory when being used in the pervasive computing paradigm. We call it EDS. After extending the process, we overcome the drawbacks of classical D-S Evidence Theory. All the suggested technologies have been successfully used in our service-aware computing projects. We compare EDS with relative methods, such as Random Set Theory (RST), Bayesian Theory (BT). By comparisons, the more validity of new service-aware computing approach based on EDS has been tested successfully. The efficiency of our researches has been shown by our many application practices.

Keywords: pervasive computing, Dempster-Shafer, Random Set, evidence reasoning

1. Introduction

As we know, service-aware computing is an important part of pervasive computing for Web-based mobile application with uncertainty [1]. The model of this service is disparate from traditional human-computer interaction paradigm. In the pervasive mobile application environment, the computer remembers information of past, recognizes information of the present, and predicate the future [2]. It reasons human's intention through analysis of all the information collected based on its accumulated data of database or knowledge base. Then it serves Web-based mobile application [3, 4].

The content of service-aware information is changed with user's task and activity in pervasive computing mode, which means the presence of uncertainty [5, 6]. Owing to the dynamic change of service context stands out, the complexity of uncertainty is obvious. As we know, the service-aware information is very important because for the same input, different information may be different annotation. Service-aware computing method is helpful to realize Web-based pervasive mobile application, especially, the evaluation of service, reasoning and making decision in time.

The requirement to service-aware computing runs through each layer from lower system to upper application [7, 8]. In our opinion, the main target of service-aware computing approach should include as follows.

1) Awaring and fusing of service context information with uncertainty. In order to exchange the service context information among different modules, system, environment, the model of service-aware computing must be set up, including the expression of service context, fusing method of service context information with uncertainty, and reasoning of uncertainty [9, 10]. The method of expression and fusing for service context information must be general, such as probability, D-S Evidence Theory, which can permit the same service context information to be understood by different process module or agent. Owing to the noise of sensing data, the probability and statistic character of service context information with uncertainty, the reasoning capability should be used frequently. If the service context information is for reasoning, we call it evidence according to what Dempster-Shafer said. Paul Cas-

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tro studied reasoning of context's parameters and relative state based on Bayesian network and classical Dempster-Shafer Evidence Theory [11, 12]. But Bayesian network is too slow and classical Dempster-Shafer Evidence Theory has ignored the reliability, time-efficiency, relativity of service context information with uncertainty.

2) Using of service context information with uncertainty. Many problems about using of service context information with uncertainty are very important. It is how to query and store the service-aware information, how to schedule the service context information and actively supply the service in the presence of uncertainty for Web-based pervasive mobile applications, and so on.

Among the two aspects mentioned above, we focus on the first aspect to be studied, namely, mainly study computing approach of dynamic multi-source evidence with uncertainty based on service-aware computing theory for pervasive mobile application.

We believe that the advantage of the Dempster-Shafer Evidence Theory over previous approaches (such as Random Sets Theory, Bayesian Probability Theory, and so on) is its ability to model the narrowing of the hypothesis set with the accumulation of evidence, a process that characterizes diagnostic reasoning in medicine and expert reasoning in general [13,14]. An expert uses evidence that, instead of bearing on a single hypothesis in the original hypothesis set, often bears on a larger subset of this set. The functions and combining rule of the Dempster-Shafer theory are well suited to represent this type of evidence and its aggregation. But when it is used in the service-aware computing for pervasive mobile application, the drawbacks of Dempster-Shafer theory are existed, because the classical Dempster-Shafer theory was not considered the reliability, time-efficiency and relativity of service contexts. Therefore we propose a kind of new service-aware computing approach in this paper, which is based on classical Dempster–Shafer Evidence Theory [illegible] 16]. In other words, we will extend the classical Dempster-Shafer Evidence Theory.

The rest of this paper will be organized as follows. Firstly, we discuss related work and basic Dempster–Shafer Evidence Theory. Then we propose service-aware computing approach of considering reliability, time-efficiency, and relativity of service context. At the same time, we propose an integrated service-aware computing approach. Later we discuss validation test of the approach and comparisons with other relative methods by our mobile application project, which [illegible]ed in fusion of dynamic multi-source evidences with uncertainty based on service-aware computing. Finally, we give conclusions and future works.

2. RELATED WORKS

Random Sets Theory (R[illegible]) [17] is one theory of applied mathematicians, which can be used to induce distributed decision making dynamically and do service-aware computing with uncertainty for Web-based pervasive mobile application. Using the notion of the Janossy density [18], we can define the joint probability density of two random finite sets X and Y, and the conditional probability density such as $P(X|Y)$ and $P(Y|X)$. Suppose X is a finite random set modeling the unknown number of objects to be estimated and Y is an observation with respect to X given as another finite random set. If the Janossy density is jointly defined for the two random sets, X and Y, then we can apply Bayes' rule

$$P(X|Y) = P(Y|X)P(X)/P(Y) \tag{1}$$

Which gives us a formal "answer" to the multi-object estimation problem that is defined by the object model $P(X)$ and the observation model $P(Y|X)$. Assuming that, for the most part, "objects" are all static, a typical model X for objects is a Poisson point process with an intensity measure G on the state space E. In order to define a multi-sensor problem, let us consider N observations that are given as the random sets, $Y_1, Y_2, .., Y_N$, in measure[illegible] spaces, $E_1, \ldots, E_N$, each having σ-finite measure [illegible] assume conditional independence of observations as

$$P((Y_k)_{k=1}^N|X) = \prod_{i=1}^{N} P(Y_k|X) \tag{2}$$

Then the problem can be defined completely when we specify each measurement model $P(Y_k|X)$. A typical model, assuming (i) object-wise independent detection, (ii) object-wise measurement mechanism, (iii) independent Poisson point process modeling false alarms, can be written as

$$P(Y_k|X) = e^{-v_k} \sum_{a\in A(X,Y_k)} \Big(\prod_{x\in Dom(a)} p_m((a(x)|x) \; p_D(x)) \bullet \Big(\prod_{x\notin X\setminus Dom(a)} (1-p_D(x))\Big) \bullet\Big(\prod_{y\notin Im(a)} r_k(y)\Big) \tag{3}$$

as a conditional Janossy density, where $p_m(y|x)$is the density of the object-state-to-measurement transition probability, $p_{D(x)}$ is the probability of an object at state x. Being detected (included) in the observation Y_k, R_k is the density of the intensity measure of the Poisson point process modeling false alarms in Y_k with $v_k = \int_{E_k} r_k(y)\mu_k(dy)$, and $A(X, Y_k)$ is the set of all the one-to-one functions a defined on a subset $Dom(a)$ of X taking values in Y_k. Then, for any integer k', there is a collection E, which is called data-to-data association hypotheses, of tracks, each of which is a subset of the tagged cumulative data sets, $\bigcup_{k=1}^{k'} Y_k \times \{k\}$, such that we have

$$P(X|(Y_k)_{k=1}^{k'}) = \sum_{\lambda\in\Lambda_{k'}} (p'(\lambda)) \bullet \sum_{a\in A'(\lambda,X)} \Big(\prod_{\tau\in Dom(a)}$$

$$p'(a(\tau)|\tau)) \bullet (e^{-v'_{k'}} \prod_{x\in X\backslash Im(X)} r'_{k'}(x)) \quad (4)$$

Where $p'(\lambda)$ is the probability of each hypothesis λ such that $\sum_{\lambda\in\Lambda}(\lambda) = p'(x|\tau)$ is the density of the probability distribution of an object at x, E conditioned by all the measurements specified by track τ, $r'_{k'}$ is the density of the intensity measure of the objects that are not detected in any of Y_k such that k, k', with $v'_{k'} = \int_E r_{k'}(x)\mu(dx)$, and $A'(\lambda, X)$ is the collection of all the one-to-one function a defined on λ taking values in X.

Without any approximation (truncation), the cardinality of the collection I of all the finite sets in E, i.e., the system state space, can be expressed as (By $n = w(A)$, we mean that the cardinality of set A is n)

$$w(I) = \sum_{n=0}^{\infty} \frac{(w(E)^n)}{n!} = exp(w(E)) \quad (5)$$

When repeated elements are not ignored but the orders in sequences are ignored, thereby considering quotient spaces of the direct-product space E^n induced by permutations of elements. On the other hand, when the object state space E is finite, then we have $I = 2^E$ that is the power set of E, and hence, we have $w(I) = 2^{w(E)}$. In any case, when we use a large enough upper bound n' on the number of objects, the cardinality of the state space becomes close to either $e^{w(E)}$ or $2^{w(E)}$, depending on how the repeated elements are interpreted.

In many cases less than 600 for $w(E)$ may not enough number to realistically represent any practical problem. With $w(E) > 600$, either $e^{w(E)}$ or $2^{w(E)}$ becomes a very big number. We do not think any computer can handl[illegible] such a large state space in the foreseeable future. In sens[illegible] the direct numerical calculation approach in effect replac[illegible] the curse of hypotheses explosion in formula (2.4) by the curse of dimensional explosion. A solution to this p[illegible]em of dimensional explosion was proposed in [19], in which, for each (hypothesized) number n of objects, the [illegible]ity functions $p'_{n1}, p'_{n2}, , p'_{nn}$ of n a posteri[illegible] probability [illegible]tributions on the object state space E, to[illegible] with the a posteriori probability on the number of obj[illegible], q'_n, approximate the a posteriori Jonassy density funct[illegible]mula (2.4) as

$$P(X|(Y_k)_{k=1}^{k'}) = q'_{w(x)} \bullet \sum_{a\in A(X)} \prod_{x\in X} p'_{w(x)\text{[illegible]}}(x) \quad (6)$$

Where A(X) is the set of all the [illegible]-one fun[illegible]ons defined on set X in E ta[illegible]alues in t[illegible]$(X)\}$ of integers. For each [illegible]zed) number n of objects, the joint probabili[illegible] of the st[illegible] of n objects is approximated by n ind[illegible]ndent pro[illegible]ons in formula (2.6). In [illegible]er words, [illegible] all the associated hypotheses a[illegible]mbined [illegible]nd cross-correlation among n objects are igno[illegible]or a given n, a non-Gaussian extension of the algori[illegible]nown as Joint Probabilistic Data Association (JPDA) is [illegible]. The cross-correlation among objects is, however, a dire[illegible] reflection of data association uncertainty. Hence, the reduction of complexity is obtained by ignoring one of essential consequences of data association uncertainty, which may make this generalized JPDA approximation formula (2.6) share the same set of drawbacks of the JPDA.

Nonetheless, this direct numerical calculation approach appears very attractive since it is very easy to generalize observation models. Formula (2.4) is an application model assuming no merged measurement and no split measurement, as reflected [illegible]ne-to-one function a in formula (2.4). For example, we c[illegible]odify formula (2.4) to accommodate merged measure[illegible]

$$P\{Y|\{x_1, x_2, ..., x_n\}\} = \text{[illegible]}(x_1, x_2) \bullet \sum_{y\in Y} \text{[illegible]}$$
$$(Y|(x_1, x_2))p_{CD}(x_1, x_2)p_{FA}\text{[illegible]}\})$$
$$+(1 - p_C(x_1, x_2))\text{[illegible]}\sum_{a\in A(\text{[illegible]}\},Y)} (\prod_{i\in Im(a)} p_m(y|x)$$
$$p_D(x)) \bullet (\prod_{i\notin Im(a)} \text{[illegible]}1 - \text{[illegible]}(x)) \bullet \text{[illegible]}_A(Y\backslash Im(a))) \quad (7)$$

Wh[illegible](x_1, x_2) an[illegible](x_1, x_2) are the probability of two [illegible] at x_1 and x_2 being merged and that of the merged me[illegible]being included in the data set Y, [illegible]$_{CM}(\bullet|\bullet)$ is [illegible] density of joint-where-state-to-m[illegible]urement tra[illegible]sition probability, and $p_{FA}(\bullet)$ is the Jan[illegible]y density of [illegible] random set of false alarms. The obje[illegible]wise detectio[illegible] probability p_D and the density of the st[illegible]-measur[illegible]ent transition probability p_m are the same as [illegible] previous section.

[illegible]nother interesting variation of the sensor model (2.3) ma[illegible]re-detection tracking model, such as

$$\text{[illegible]}(Y|X) = P((y(j)_{j\in J})|X) = \prod_{j\in J} \frac{1}{\sqrt{2\pi}\sigma(j)}$$
$$\times \exp(-\frac{1}{2}(\frac{y(j) - \sum_{x\in X} S(j|X)}{\sigma(j)})^2) \quad (8)$$

[illegible]hich is a conditional probability density of an obser[illegible]ation $Y = (y(j))_{j\in J}$ as a collection of intensity values integrated within each quantized two or three dimensional cells, conditioned by the collection of objects modeled by a random finite set X. In formula (2.8), $S(j|x) = s(x)\int_j O(\eta - h(x))d\eta$ is the integrated contribution of an object at x within a cell, where $s(x)$ is the signal strength part of the object state x, $h(x)$ is the projection of the object state onto a focal plane or measurement space,$\phi(\bullet)$ is an appropriate point- spread function, and $\sigma(j)$ is the standard deviation of the integrated noise in cell J , assuming cell-wise independent noises. To the best of our knowledge, however, there is not yet any clear single effective method for solving the problem expressed by formula (2.8).

By this approach, we are generating aggregate statistics for a group of objects in service-aware computing. Such objects may remain in a single statistical cluster for an extended period of time, because they behave as a group. This naturally leads to another important class of problems, i.e., tracking groups of objects [20], rather than individual objects. In the past thirty years, numerous algorithms have been proposed but, to our knowledge, there has not been any model that is mathematically rigorously defined.

In addition, the Bayesian evidential reasoning technique is strongly founded upon the framework of Bayesian (probability) Theory (BT) [21]. It also can be used to induce distributed decision making dynamically and do service-aware computing with uncertainty for Web-based pervasive mobile application. Bayesian reasoning assumes that the pieces of evidence E_i to be aggregated are statistically independent. This assumption may not be true in cases where causal or contextual relationships exist, however for the purposes of fusing multiple neural forecasters, we will assume that the evidence sources are "independent" with respect to the errors they make.

Bayesian theory uses an "Odds-Likelihood Ratio" formulation of Bayes' rule to aggregate the evidence from multiple sources. The a priori odds $O(H)$ of a given class Hypothesis H (e.g., upward trend, downward trend) is related to it's a priori probability $P(H)$ by the following relations: O(H)=P(H)$\frac{\quad}{P(\bar{H})}$ $P(H)=\frac{O(H)}{1+O(H)}$

The likelihood of the evidence E_i, given that the hypothesis H is true, is: L(E$_i|H) = \frac{P(E_i|H)}{P(E_i|\bar{H})}$

The class probabilities for each hypothesis may be estimated from training data, and the outputs divided by these probabilities to produce scaled likelihood, where the scaling factor is the reciprocal of the unconditional input probability. The formula for updating the a posteriori odds of a hypothesis H, given the evidence E_i observed, is: O(H—E$_1, E_2, ..., E_n) = O(H)\prod_{i=1}^{n} L(E_i|H)$

And, the "belief" or a posterior probability for a hypothesis is simply: P(H—E$_1, E_2, ..., E_n)$ = $\frac{O(H|E_1,E_2,...,E_n)}{1+O(H|E_1,E_2,...,E_n)}$

The final prediction is chosen to be the hypothesis H having the greatest probability given the accumulated evidence.

3. BASIC DEMPSTER-SHAFER EVIDENCE THEORY

The drawbacks of pure probabilistic methods and of the certainty factor model have led us in recent years to consider alternative approaches. Particularly appealing is the mathematical theory of evidence developed by Arthur Dempster. We are convinced it merits careful study and interpretation in the context of expert systems. This theory was first set forth by Dempster in the 1960s and subsequently extended by Glenn Sharer [10].

It is known to all that Glenn Shafer gives a talk expositing Dempster's work on upper and lower probabilities. Basic Dempster-Shafer Evidence Theory is one of the results of the ensuing effort. It offers a reinterpretation of Dempster's work, a reinterpretation that identifies his "lower probabilities" as epistemic probabilities or degrees of belief, takes the rule for combining such degrees of belief as fundamental, and abandons the idea that they arise as lower bounds over classes of Bayesian probabilities. During the past several years, the Dempster-Shafer Evidence Theory has attracted considerable attention within the AI community and other research domains as a promising method of dealing with uncertainty.

The Dempster-Shafer theory uses a number in the range [0, 1] to indicate belief in a hypothesis given a piece of evidence. This number is the degree to which the evidence supports the hypothesis. Recall that evidence against a hypothesis is regarded as evidence for the negation of the hypothesis.

The impact of each distinct piece of evidence on the subsets of Θ is represented by a function called a basic probability assignment (bpa). A bpa is a generalization of the traditional probability density function; the latter assigns a number in the range $[0, 1]$ to every singleton of Θ such that the numbers sum to 1. Using 2^{Θ}, the enlarged domain of all subsets of Θ , a bpa denoted m assigns a number in $[0, 1]$ to every subset of Θ such that the numbers sum to 1.

The quantity m(A) is a measure of that portion of the total belief committed exactly to A, where A is an element of 2^{Θ} and the total belief is 1.

This portion of belief cannot be further subdivided among the subsets of A and does not include portions of belief committed to subsets of A. Since belief in a subset certainly entails belief in subsets containing that subset it would be useful define a function that computes a total amount of belief in A. This quantity would include not only belief committed exactly to A but belief committed to all subsets of A. Such a function, called a belief function.

The quantity $m(\Theta)$ is a measure of that portion of the total belief that remains unassigned after commitment of belief to various proper subsets of Θ. For example, evidence favoring a single subset A need not say anything about belief in the other subsets. If $m(A) = s$ and m assigns no belief to other subsets of Θ , then $m(\Theta) = 1 - s$. Thus the remaining belief assigned to Θ and not to the negation of the hypothesis (equivalent to c, the set-theoretic complement of A), as would be required in the Bayesian model.

4. SERVICE-AWARE COMPUTING APPROACH CONSIDERING RELIABILITY

There is a belief degree function mass to process the combination computing according to the classical Dempster -Shafer Evidence Theory [22], which is more free than traditional Probability Theory, that is $m(\Theta)$ may not be 1, if $X \subseteq Y$, $m(X)$ may not be less than $m(Y)$, meanwhile , $m(X)$ and $m(X')$ may not have a certain amount relationship. Because the sensed multi-source data as dynamic evidence service-aware information is with noise and uncertainty, the application in fact requires high reliability, we must consider context reliability factor during fusion of them, which means if the classic Dempster-Shafer Evidence Theory is used as fusion method and reasoning theory, we must modify it, which we call it extended Dempster-Shafer Evidence Theory (EDS).

Lemma 1 Suppose Θ is frame of recognition, U is a set of individual object space of given information system S,ϕ is a empty set, a random function Bel: $2^U \rightarrow [0,1]$ is belief function if only if:

(i) $Bel(\phi) = 0$

(ii) $Bel(\Theta) = 1$

(iii) If $\forall X_1, X_2, ..., X_n \subset \Theta$(n is a certain integer) then

$$Bel(\bigcup_{i=1}^{n} X_i) \geq \sum_{i=1}^{n} Bel(X_i)$$
$$-\sum_{i<j} Bel(X_i \cap X_j) + ...$$
$$+(-1)^{n+1} Bel(\bigcap_{i=1}^{n} X_i) = \sum_{I \subset \{1,2,...,n\}} (-1)^{|I|+1}$$
$$Bel(\bigcap_{i<I} X_i) \qquad (9)$$

The proof of this lemma can be found in the reference [22]. According to this lemma, we can decide whether or not a certain function is belief function which was defined by Dempster-Shafer and can compute the belief degree Bel.

Definition 1: Suppose the function mass is $m(\bullet)$ of a ce[illegible]tain evidence, we can define the exchange form $\hat{E}$ of thi[illegible] evidence E , where Θ is defined above, A_i is foc[illegible] ele-ment ($m(A_i) > 0$, i is the number of focus numbe[illegible] which meets the condition)

$$\hat{m}(A_i) = \delta m(A_i), A_i \neq \Theta \qquad \text{[illegible]}$$

$$\hat{m}(\Theta) = \delta m(\Theta) + (1 - \delta) \qquad (11)$$

where $\delta \in [0,1]$ is context reliability factor after as[illegible]ment according to specified case,$\sum \hat{m}$[illegible] $\hat{m}$ is basic probability assignment , then E is c[illegible]ed the [illegible]gin[illegible]l evidence, and ,$\hat{E}$ is mapped evidence [illegible] E.

If $\delta = 1$, E and $\hat{E}$ is approxim[illegible] a[illegible]s regar[illegible]d as full efficient evidence, then $m = \hat{m}$. [illegible]0, it is r[illegible]rded invalid evidence, the[illegible]1, it is n[illegible]ally.

Lemma 2 Suppose [illegible]$_1(\bullet)$, m[illegible]) are two basic probability assignment fu[illegible]tions in th[illegible] Space U.s, t is the focus element set , re[illegible]ctively. Su[illegible]$(s)m_2(t) <$ 1,then the follo[illegible] defin[illegible] function m:$2^U \rightarrow [0,1]$ also is basic probability [illegible]

$$m(X) = \{ 0 \ , X = \Phi \frac{\sum_{s \cap t = X} [illegible]_1(s) m_2(t)}{(1 - \sum_{s \cap t = \Phi} m_1(s) m_2(t))}, X \neq \Phi \qquad (12)$$

The proof of this lemma also can be found in the above reference. According this lemma, we can deduce a new fusion method considering reliability of service-aware information with uncertainty.

When not considering the time-efficiency, if the mass m_1, m_2 of two evidences (service-aware information) are mapped to $\hat{m}_1$, $\hat{m}_2$, and their reliability factor is δ_1,δ_2, respectively, then the computing approach $\hat{m}$:

$$\hat{m}_1 \hat{\oplus} \hat{m}_2(A) = c^{-1} \sum_{A = A_i \cap A_j} [illegible](A_i) * \hat{m}_2(A_j)$$
$$= c^{-1} \sum_{A = A_i \cap A_j; A_i, A_j \neq \Theta} \delta[illegible]_1(A_i) * \delta_2 [illegible]$$
$$+ c^{-1} \sum_{A = A_i \neq \Theta; A_j = \Theta} \delta_1 m_1 ([illegible] m_2(\theta) [illegible] 1 - \delta_2)]$$
$$+ c^{-1} \sum_{A_i = \Theta; A = A[illegible]\Theta} \delta_2 m_2 ([illegible]_j)[\delta[illegible] m_1(\theta) + (1 - \delta_1)],$$
$$A \neq \theta \qquad (13)$$

$$\hat{m}_1 \hat{\oplus} \hat{m}_2 [illegible] [\delta_1 m_1 ([illegible]_1)][\delta_2 m_2(\theta) + (1 - \delta_2)] \qquad (14)$$

where normalize[illegible]r is

$$c = 1 [illegible] \sum_{A_i \cap A_j = \Phi} \hat{m}_1(A_i) [illegible]_2(A_j)$$

$$= [illegible] \hat{m}_1(A_i) [illegible](A_j)$$

[illegible]ulas (4.5) and (4.6), if $\delta_1 \delta_2 \neq 1$, then $\hat{m}_1$, $\hat{m}_2$ is no co[illegible]

The f[illegible] computing approach of n evidences consid-e[illegible]g cont[illegible]t reliability is as follows.

In [illegible]e same condition, if the mass m[illegible]$_2(\bullet), ..., m_n(\bullet)$ of n evidences (service-aware information) is mapped to $\hat{m}_1, \hat{m}_2, ..., \hat{m}_n$, and their reliability factor is$\delta_1, \delta_2, ..., \delta_n$, then the computing approach $\hat{m}$ is

$$\hat{m}(A) = \quad c^{-1} \sum_{\cap A_i = A} \prod_{1 \leq i \leq n} \hat{m}_i(A_i)$$
$$= c^{-1} \sum_{\cap A_i = A} \prod_{1 \leq i+j \leq n; i \neq j, 1 \leq i \leq n; 0 \leq j \leq n}$$
$$\{\delta_i m_i(A_i)[\delta_j m_j(\theta) + (1 - \delta_j)]\}, A \neq \theta \qquad (15)$$

$$\hat{m}(\Theta) = c^{-1} \prod_{1 \leq i \leq n} \{\delta_i m_i(\Theta) + (1 - \delta_i)\} \qquad (16)$$

where $c = 1 - \sum_{\cap A_i = \Phi} \prod_{1 \leq i \leq n} \hat{m}_i(A_i) = \sum_{\cap A_i \neq \Phi} \prod_{1 \leq i \leq n} \hat{m}_i(A_i)$

In formulas (4.7) and (4.8), if $c \neq 0$, then the sum result m is also a probability assignment function, if $c = 0$, then no the sum result m, we call $m_1, m_2, ..., m_n$ is conflicted each other. According to the formulas (4.1) and (4.2), if only one i can lead to $\delta_i = 1$, then $\hat{m}_1, \hat{m}_2, ..., \hat{m}_n$ is not conflicted absolutely.

5. SERVICE-AWARE COMPUTING APPROACH CONSIDERING TIME-EFFICIENCY

Fusion computing approach considering time-efficiency of evidence is the continuous improvement of computing approach considering reliability of evidence.

When the multi-source evidence information with uncertainty is dynamic, although it is reliable, the continuous changes in many aspects of the interested object often lead to the change of its time-efficiency. If the classic combination rule of D-S Evidence Theory directly is used, we often get the conflicted result /conclusion which are not consistent with the intuition. After the analysis, we believe that time-efficiency of service context is necessary to be considered. Although some researchers [23,24] have found this case and solved it using some technologies to special interested objects, such as adding a certain assistant rule, intelligent technology, timely weight, other relative theories. But the process methods are mainly based on the time-interval or special time point of service context information and the time difference of multi-source evidence information when multiple sensors which supply their sensed data and give the decision are independent, that is to say, the time coordinate of dynamic object needs to be tuned consistence, because of different time stamp, the belief degree of the service context information is possibly different. In many cases, the change of the time-difference of multi-source evidence information is arbitrary. Currently, there is no better method [illegible] this problem [25, 26]. In our opinion, if the ch[illegible]ge di[illegible]cipline is expressed with a time-function, then [illegible] chan[illegible] case of belief degree can be grasped, and in the[illegible]eory, [illegible] can modify the computing approach as followin[illegible] whi[illegible] is general.

Definition 2: Suppose the function mass [illegible] $m(\bullet)$ of a ce[illegible]tain evidence E at the time-point t_0, [illegible]e can define the exchange form of the fu[illegible]ction mass as [illegible]$(A_i,t) = \xi(t-t_0)m(A_i), A_i \neq \Theta$

$$\hat{m}(\Theta,t) = \xi(t-t_0)m(\Theta) + [1 - \xi(t \text{[illegible]})] \quad (17)$$

Where $(t-t_0) = \delta f(t-t_0)$ [illegible] reliability [illegible], $f(t-t_0)$ is function of time-effic[illegible] [illegible] is supplied by the expert of the special field [illegible] the in[illegible]este[illegible] object and can be tuned after being asse[illegible]ed. T[illegible] form [illegible] this function of time-efficiency is vario[illegible] [illegible] changea[illegible]e, in different field, the desc[illegible] may be [illegible]rent [illegible] as subsection function, t[illegible] function, [illegible] on. An example of trigon[illegible]etric fun[illegible]n is: f(t-t_0) $= |Sin(t-t_0)|$

An[illegible] example [illegible] function is: f(t-t_0) $=$
$\{ (t-$[illegible]$)/(t_1-t$[illegible]
$1, t_1$[illegible]$< t_2$
$(t_3-t)/$[illegible]$, t_2 \leq t \leq t_3$

Where t_0 [illegible] t_3 is time point each, and the value of them ma[illegible] determined by a certain condition or restriction rule. [illegible]e time-efficiency factor $\xi \in [0,1]$,$\sum \hat{m}(A_i,t) = 1$,$\hat{m}$ is basic probability assignment funsion, C is time-efficiency belief function of m. If $t = t_0$, when $\xi = 1$, the evidence of focus is the whole efficiency evidence, and $m = \hat{m}$ is right. When $\xi = 0$, the evidence of focus is invalid evidence, we can get $\hat{m}(\Theta,t) = 1$, which means the case is unknown totally, in another word, the belief degree is uncertain absolutely.

Suppose the function mass $m_1(\bullet), m_2(\bullet)$ are basic probability function of two evidences in the Space U, the function mass [illegible] are basic probability function of two evidences at the [illegible] point t_1, t_2, then after considering the time-efficien[illegible]dence, the computing approach is in the foll[illegible]ing at the [illegible]nt time point t:

$$\hat{m}_1 \hat{\oplus} \hat{m}_2(A,t) = \text{[illegible]}^{-1} \sum_{\text{[illegible]}=A_i \cap A_j} \hat{m}\text{[illegible]}A_i,t) * \hat{m}_2(A_j,t)$$

$$= c^{-1}(t) \sum_{\text{[illegible]}=A_i \cap A\text{[illegible]}_i, A\text{[illegible]} \neq \Theta} \text{[illegible]}(t-t_1)m_1(A_i)$$

$$*\zeta(t - \text{[illegible]})m_2(\text{[illegible]}) + c\text{[illegible]}) \sum_{A=A_i \neq \Theta, A_j = \Theta} \xi(t-t_1)$$

$$m\text{[illegible]}A_i)\{\xi(\text{[illegible]}) + [1 - \xi(t-t_2)]\}$$

$$\text{[illegible]}(t) \sum_{\Theta, A\text{[illegible]}_j \neq \Theta}$$

$$\text{[illegible]}(t-t_2)m_2(\text{[illegible]})\{\xi(t-t_1)m_1(\Theta) + [1 - \xi(t-t_1)]\},$$

$$A \neq \Theta \quad (18)$$

$$\hat{m}_1 \hat{\oplus} \hat{m}_2(\text{[illegible]}) = c^{-1}(t)\{\zeta(t-t_1)m_1(\theta)$$
$$\text{[illegible]} - t_1)]\} * \{\zeta(t-t_2)m_2(\theta) + [1 - \zeta(t-t_2)]\}$$

where

$$\text{[illegible]} = 1 - \sum_{A_i \cap A_j = \Phi} \hat{m}_1(A_i,t) * \hat{m}_2(A_j,t)$$

$$= \sum_{A_i \cap A_j \neq \Phi} \hat{m}_1(A_i,t) * \hat{m}_2(A_j,t)$$

Meanwhile, if $c(t) \neq 0$, then the sum result function m is also a basic probability function. If $c(t) = 0$, then there is no sum result m, then m_1 is conflicted with m_2.

Similarly, in the formula mentioned above, if there is at most one t between t_1, t_2, then $\hat{m}_1, \hat{m}_2$ is not conflicted absolutely, that is compatible partly.

The fusion computing approach of n evidences considering context's reliability is like this.

Suppose the function mass $m_1(\bullet), m_2(\bullet), ..., m_n(\bullet)$ are basic probability function of n evidences in the Space U at the time point $t_1, t_2, ..., t_n$, and the mapped time-efficiency function is $\hat{m}_1, \hat{m}_2, ..., \hat{m}_n$, respectively, then the fusion method $\hat{m}$ at the time point t is as follows:

$$\hat{m}(A,t) = c^{-1}(t) \sum_{\cap A_i = A} \prod_{1 \leq i \leq n} \hat{m}_i(A_i,t),$$

$$A \neq \theta = c^{-1}(t) \sum_{\cap A_i = A} \prod_{1 \leq i+j \leq n; i \neq j, 1 \leq i \leq n; 0 \leq j \leq n}$$

$$\{\zeta(t-t_i)m_i(A_i) * \{\zeta(t-t_j)m_j(\theta)$$
$$+[1 - \zeta(t-t_j)]\}\} \quad (19)$$

$$\hat{m}(\theta,t) = c^{-1}(t) \prod_{1\le i\le n} \{\zeta(t-t_i)m_i(\theta)+[1-\zeta(t-t_i)]\} \quad (20)$$

where

c(t)=1-$\sum_{\cap A_i=\Phi}\prod_{1\le i\le n}\hat{m}_i(A_i,t) = \sum_{\cap A_i\ne\Phi}\prod_{1\le i\le n}\hat{m}_i(A_i,t)$

Similarly, if $c(t) \neq 0$, then the sum result m is also a probability function , if $c(t) = 0$, then there is no sum result function m, we call that $m_1, m_2, ..., m_n$ is conflicted each other., namely, the each evidence is conflicted each other.

6. SERVICE-AWARE COMPUTING APPROACH CONSIDERING RELATIVITY

Fusion computing approach considering relativity of evidence is also the continuous improvement of fusion computing approach considering time-efficiency of evidence. Because there is a restriction condition that the evidence must be independent when the classical D-S Evidence Theory is used. But in many cases of applications, the relativity between evidences is existed absolutely [27, 28]. From the relativity degree, we can classify it into two cases: relativity partly, relativity totally. If we have not processed this relativity, whether it is partly or absolutely, before using this evidence, the result of fusion is not true or reasonable, which reduce the QoS. In order to solve this problem, we use the energy function to measure the relativity degree between evidence information, and by getting rid of relativity, we can translate relativity evidence into i[illegible]dependent evidence and then fuse them. In order to ma[illegible] the step of getting rid of relativity stand out, we exchang[illegible] the time-stamp that is used for tuning the time-effici[illegible]cy.

Because the influence of evidence informatio[illegible] decided by the focus elements, the relativity of evi[illegible] information is measured according to the focus el[illegible] from the same information source. We [illegible] the en[illegible]ergy of evidence information as follows:

Definition 3: The energy function $\psi(E)$ o[illegible]ce E can be defined

$$\psi(E) = \sum_{i=1}^{n(E)} m(A_i)/|A_i|, A_i \neq \Theta \quad [illegible] (21)$$

where A_i is the set of focus elem[illegible]$|A_i|$ is the [illegible]adix of A_i, $n(E)$ is the nu[illegible] of eleme[illegible] th[illegible]set of power, $m(A_i) = \hat{m}$[illegible]$- t_0), A_i$ [illegible] $m(\Theta) = (\hat{m}(\Theta,t) - [1 -$ [illegible]$t - t_0)]$[illegible]$(t-t_0), \xi(t-t_0) \neq 0, \hat{m}(A_i,t), \hat{m}(\Theta$[illegible]$), \xi(t-t_0$[illegible] defined above.

If the func[illegible]n mass m[illegible]$m_2(\bullet)$ are basic probability functio[illegible]wo evi[illegible]ces E_1, E_2, Their focus element is A_i, B_j, [illegible]ly, obviously, some focus elements of E_1 and E_2 [illegible]be relative, and the relativity degree is decided partly [illegible]e number of focus element and its basic probability [illegible]signment. For example, $E_1 = \{A,B,AB\}, |A_i| = 2, n(E_1) = 3. E_2 = \{B,C,D,BC\}, |A_i| = 3, n(E_1) = 4. E_1 \cap E_2 = \{B\}, E_1 \cup E_2 = \{A,B,C,D,AB,BC\}, |A_i| = 4$. So we define the relative degree as follows:

Definition 4: The coefficient of relativity μ_{12} which is E_1 to E_2 and The coefficient of relativity μ_{21} which is E_2 to E_1 is defined $\mu_{12} = 1/2\varphi(E_1,E_2)\psi(E_2)/\psi(E_1)$ $\mu_{21} = 1/2\varphi(E_1,E_2)\psi(E_1)/\psi(E_2)$ where $\varphi(E_1,E_2)$ is the relativity degree of evidence E_1 and E_2 which can be computed as $\varphi(E_1,E_2) =$[illegible]$(E_1,E_2)/(\psi(E_2)+\psi(E_1))$

Suppose the function mas[illegible]$(\bullet)$, $m_2(\bullet)$ are basic probability functions of two evi[illegible] E_2 in the Space U, $\{A_i\}$ and $\{B_j\}$ are the se[illegible]f focus ele[illegible]ts ,then the computing approach consid[illegible]ng Context R[illegible]vity is as follows

$$\hat{m}(A) = \sum_{A_i\cap B_i=A} m_1'(A_i)m_2'(\text{[illegible]}$$

$$\Theta\hat{m}(\Phi) = 0$$

$$\hat{m}(\Theta) = (\sum_{A_i\cap B_j=\text{[illegible]}} m_1'(\text{[illegible]})m_2'(\text{[illegible]})) + \eta \quad (22)$$

where

$$\text{[illegible]}_i) = \{m_1\text{[illegible]}(1-\mu_{12}), \quad A_i \neq \Theta$$

$$\sum_{A_i\subset\Theta} m_1'(A_i)\text{[illegible]}$$

$$A_i = \text{[illegible]}$$

$$\text{[illegible]}) = \{m_2(B_j)(1-\mu_{21}), \quad B_j \neq \Theta$$

$$1 - \sum_{B_j\subset\text{[illegible]}} \text{[illegible]}'(B_j),$$

$$\text{[illegible]} = \Theta\eta \quad \sum_{A_i\cap B_j=\Phi} m_1'(A_i)m_2'(B_j)$$

The [illegible]sion computing approach of n evidences consid[illegible]ering [illegible]ontext reliability is in the following.

Similarly, Suppose the function mass $m_1(\bullet), m_2(\bullet), ..., m_n(\bullet)$ are basic probability func[illegible]on of n evidences in the Space U , the mapped function [illegible]s $\hat{m}_1, \hat{m}_2, ..., \hat{m}_n$, respectively, then the fusion method $\hat{m}$ is

$$\hat{m}(\Phi) = 0$$

$$\hat{m}(A) = c^{-1} \sum_{\cap A_i=A} \prod_{1\le i\le n} m_i'(A_i), A \neq \Phi$$

$$\hat{m}(\Theta) = (\sum_{\cap A_i=\Phi} \prod_{1\le i\le n} m_i'(A_i)) + \eta \quad (23)$$

where

$$m_i'(A_i) = \{m_i(A_i)(1-\mu_{i(n-i)}), \quad A_i \neq \Theta,$$

$$1 - \sum_{A_i\subset\Theta} m_i(A_i), \quad A_i = \Theta$$

$$\eta = \sum_{\cap A_i=\Phi} \prod_{1\le i\le n} m_i'(A_i)$$

$$c = 1 - \sum_{\cap A_i = \Phi} \prod_{1 \le i \le n} m'_i(A_i) = \sum_{\cap A_i \ne \Phi} \prod_{1 \le i \le n} m'_i(A_i)$$

From the mentioned above or analyzing the essence of fusion method, we can summarize the difference between fusion method of evidence information considering context relativity and classic combination rule based on the D-S Evidence Theory.

In fact, formulas (6.2) and (6.3) firstly convert the relative evidences into independent evidences. Then fuse the converted evidences. But the fusion rule based on the classical D-S Evidence Theory does not consider the relativity of these evidences, or exclude the evidences with relativity. Our method improves the quality of fusion of evidence information. At the same time, it extends the adapted range of the classical D-S method.

In our method, we put the part of conflict of evidence information into the set Θ, because we can not the conflict detail of evidence information, we let it distribute all elements not in several focus elements, which means that the uncertainty is smoothed. This kind of improvement can make the fusion be done effectively both in the case of evidence information with reliability and in the case of evidence information with conflict highly in the dynamic complexity case, but the correctness rate is higher.

7. INTEGRATED SERVICE-AWARE COMPUTING APPROACH

As we know, in the most general situation, a given body of evidence supports many of the subsets of Θ, each to varying degrees. The simplest situation is that in which the evidence supports only one subset to a certain degree and the remaining belief is assigned to Θ.

During the application, firstly, the relativity degree $\varphi(\cdot)$ among evidences should be checked, if it is greater than the special relativity threshold ε, the formula (6.2) should be adopted. Then the time-efficiency ξ among evidences should be checked, if $\xi(t_1 - t_0) \ne \xi(t_2 - t_0)$ is correct, the formulas (5.2) and (5.3) should be adopted. And then the reliability among evidences should be checked, if $\delta_i \ne 1$ is right, the formulas (4.5) and (4.6) should be adopted. Otherwise, the classical D-S method will be used.

Now, we propose an implementation of integrated service-aware computing approach based on considering evidence's reliability, time efficiency, and relativity mentioned by section 5, section 6, and section 4 as follows:

(1) If relativity degree $\varphi(\cdot) >$ relativity threshold ε then Call formula (6.2)

(2)Else if $\xi(t_1 - t_0) \ne \xi(t_2 - t_0)$ then Call formula (5.2) and formula (5.3)

(3)Else if $\delta_i \ne 1$ then Call formula (4.5) and formula (4.6)

(4) Else classical D-S method as follows:

$$\hat{m}_1 \hat{\oplus} \hat{m}_2(A) = c^{-1} \sum_{A = A_i \cap A_j} \hat{m}_1(A_i) * \hat{m}_2(A_j)$$

$$c = 1 - \sum_{A_i \cap A_j = \Phi} \hat{m}_1(A_i)\hat{m}_2(A_j)$$

$$= \sum_{A_i \cap A_j \ne \Phi} \hat{m}_1(A_i)\hat{m}_2(A_j)$$

From now on, we call the integrated service-aware computing approach as Extended D-S method, in brief, EDS.

8. TEST AND COMPARISON

Because our improved computing approach is based on the combination rule of classical D-S Evidence Theory that its correctness has been proved [29, 30], it is unnecessary to give their proofs from the mathematic analysis, but we give the evaluation and experimental results.

In order to test Web-based mobile application, such as mobile learning, mobile meeting, and so on, smart space are selected as test bed. It is a work environment with embedded computers, information appliances, and multi-modal sensors allowing people to perform tasks efficiently by offering unprecedented levels of access to information and assistance from computers [31]. Smart Meeting Room [32] is just such a Smart Space deployed in a meeting room. We augment an ordinary meeting room with wall-sized displays, sensors, cameras and the associated computing and perception modules so as to allow the user to complete Web-based mobile application.

As software part of Smart Meeting Room, Agents [illegible]4], such as facilitator agent, facial-voice identification agent, motion-tracking agent, speech recognition agent, virtual mouse agent, etc, have been used in order to support the function of Web-based pervasive mobile application. When external service or information is required by a given agent, the agent submits a high-level expression describing the needs and attributes of the request to a specialized facilitator agent. The facilitator agent will fuse relative information and make decisions in the presence of uncertainty about which agents are available and capable of handling sub-parts of the request, and will manage all agent interactions required to handle the complex query. Such distributed agent architecture [35] allows the construction of systems that are more flexible and adaptable than distributed object frameworks. Individual agents can be dynamically added to the community, extending the functionality that the agent community can provide as a whole. The agent system is also able to adapt to available resources in a way that hard-coded distributed objects systems can't.

The computing approach of dynamic multi-source evidence information with uncertainty based on service-aware computing approach mentioned above has been used in the development of Smart Meeting Room and all these developed technologies have been successfully integrated [36,37]. In the Smart Meeting Room, we have designed and developed multiple computing agents mentioned above: the face recognition agent which can recognize the person's identity to login the system, such as teachers, the virtual mouse agent which can track person's movement, especially, the hand's movement (There are two cameras to do these work, one is loaded on the top of media board, another is loaded above the platform. When the person look forwards the media board, the hand's movement in the space can be detected and recognized, this result can drive the cursor on the media board, which can help the person complete all functions of traditional mouse without any assistant additive device, so we call it virtual mouse), the voice recognition agent which can recognize the person's voice and send the communication message to target agent, so adding or modifying the voice command conveniently, the media agent which encapsulates the software system [38,39]. Now we select three scenes of these to demonstrate in the prototype system.

8.1. Scenario I: Test for reliability

Suppose determining a person's identity by fusing the service-aware from two information sources, face recognition agent and voice recognition agent, and then track the activities of the person. If reliability factor of the voice recognition agent $\delta_1 = 0.8$, reliability factor of the face recognition agent$\delta_2 = 1$. According to the gathered the voice, the decision result of identity made by the voice recognition agent is as $m_1(\{S, Z\}) = 0.85$, which means the belief degree of S or Z of the person's identity determined by voice recognition agent is 85%. But according to the collected image information by camera, the decision result of the person's identity by the face recognition agent is $m_2(\{S\}) = 0.95$, which means the belief degree of S of the person's identity is 90%. Based on the hypothesis, the fusion agent of evidence information computes the belief degree about the person's identity based on the formula (4.5) and (4.6), and the process of computing and the results are as follows:

$$\hat{m}_1(\{S, Z\}) = \delta_1 m_1(\{S, Z\}) = 0.8 * 0.85 = 0.68,$$
$$\hat{m}_1(\Theta) = 1 - \hat{m}_1(\{S, Z\}) = 1 - 0.68 = 0.32$$
$$\hat{m}_2(\{S\}) = \delta_2 m_2(\{S\}) = 1 * 0.95 = 0.95$$
$$\hat{m}_2(\Theta) = 1 - \hat{m}_2(\{S\}) = 1 - 0.95 = 0.05.$$

Table 1 computing of belief degree of evidence information

	$\hat{m}_2(\{S\}) = 0.95$	$\hat{m}_2(\Theta) = 0.05$
$\hat{m}_1(\{S, Z\}) = 0.68$	$\{S\}0.646$	$\{S, Z\}0.034$
$\hat{m}_1(\Theta) = 0.32$	$\{S\}0.304$	$\Theta 0.016$

In table 8.1, the mass for decision of the person's identity and the multiplication of intersection set have been given, each item is from multiplying by the intersection item. When the mass is known, according to the formula (4.5) and (4.6), we can get them together as follows:
$\hat{m}_3(\{S\}) = \hat{m}_1 \hat{\oplus} \hat{m}_2(\{S\}) = 0.646 + 0.304 = 0.95$ belief degree of the person is S
$\hat{m}_3(\{S, Z\}) = \hat{m}_1 \hat{\oplus} \hat{m}_2(\{S, Z\}) = 0.034$ belief degree of the person is S or Z
$m_3(\Theta) = \hat{m}_1 \hat{\oplus} \hat{m}_2(\Theta) = 0.016$ belief degree of the person is uncertain

Where $\hat{m}_3(\{S\})$ expresses the belief degree of the person's identity is S. Because there is addition belief degree in the $\hat{m}_3(\{S, Z\})$ and $m_3(\Theta)$ which means the addition information about S or Z, both of S or Z, the addition belief degree is 0.034 + 0.016=0.05, so we can determine that belief degree of S is 0.95, and the belief degree region of S is $[0.95, 1]$, that is to say, the belief of S about the person's identity is more than 95%. Based on this computing result and a decision rule of threshold, we can decide the person's identity is S.

The computing result is consistent of our experiences and no conflict, so we can believe the efficiency of improvement considering reliability of service-aware information.

8.2. Scenario II: Test for time-efficiency

Based on Scenario I, we consider the continuously dynamic changing scene. For example, we want to determine a person's identity and his activities or action in the changing Scene by fusing the service-aware from the face identification agent and voice recognition agent. In this scene, maybe there are many persons and the face character and voice of some of them may be similar, at the same time, the speed cases of voice are different in the different time: some speak fast, but some speak slowly to different persons, and speak fast some time, but speak slowly some time to the same person. That is to say, time-difference is existed always, so we must consider the time-efficiency when fusing the evidence information/service-aware information.

Suppose the time-efficiency function $f(t - t_0)$ in the formula is $|Cos(t - t_0)|$, then the belief degree of the person's identity computed by formula (5.2) for evidence information done by the fusion agent is

When $t = t_0, \hat{m}_1 \hat{\oplus} \hat{m}_2(S, t) = 0.95$. When $t = t_0 + \pi/6, \hat{m}_1 \hat{\oplus} \hat{m}_2(S, t) = 0.792$,When $t = t_0 + \pi/4, \hat{m}_1 \hat{\oplus} \hat{m}_2(S, t) = 0.687$. When $t = t_0 + \pi/3, \hat{m}_1 \hat{\oplus} \hat{m}_2(S, t) = 0.473$.

According to the belief region computed by the fusion agent, after tuning the time-efficiency function, the belief degree of S for the person's identity is reflected truly, which can overcome the error decision to the person's identity form the time-difference. By modifying, the conclusion is consistent with our experiences of the Smart Meeting Room, so the process is correct.

8.3. Scenario III:Test for relativity

In the Smart Meeting Room, besides the service-aware information of face and voice, there are many kinds of service-aware information, such as emotion, gesture, position, direction, state, we collect these context-aware information mainly from the camera fixed in the corner of Meeting Room, In order to process in time, we design and develop a additional detection agent which can gather the relative information dynamically, such as face's emotion, gesture, direction, position, and so on. Now, we reason the person's activity state according to supposed service-aware information with uncertainty.

Suppose A mentioned above of evidence E_1 expresses informal talk of the person, B of evidence E_1 expresses formal speech of the person. B of evidence E_2 expresses formal speech of the person, C expresses that the person is using the virtual mouse, and D expresses the body language of the person. Obviously, there is certain relativity between the two service-aware, so the computed result according to the formula (6.2) by the fusion agent is as follows.

If the context decision form dynamic timely detection & recognition agent is that $m_1(A) = 0.25, m_1(B) = 0.55, m_2(B) = 0.55, m_2(C) = 0.45, m_2(D) = 0.1. E_1 \cap E_2 = \{B\}$. Then according to formula (6.3), the fusion agent can compute the result of μ_{12} and μ_{21}.

$\psi(E_1) = (0.25 + 0.55)/2 = 0.40$,
$\psi(E_2) = (0.55 + 0.45 + 0.1)/3 = 0.37$,
$\psi(E_1, E_2) = 0.55/4 = 0.1375$,
$\varphi(E_1, E_2) = 2 * 0.1375/(0.4 + 0.37) = 0.357$,
$\mu_{12} = 0.357 * 0.37/0.40/2 = 0.165$,
$\mu_{21} = 0.357 * 0.40/0.37/2 = 0.193$.

And the fusion result is $m(A) = 0.073, m(B) = 0.487, m(C) = 0.428, m(D) = 0.006, m(\Theta) = 0.006$.

According the decision rule of threshold, the agent can give a conclusion that the person is making speech by using the virtual mouse.

8.4. Comparison with other relative methods

Here we give the comparisons with other relative methods [16, 17] in the same experimental examples. Firstly, we compare our Extended D-S method with classical D-S method. Then we compare it with RST and BT.

With the increase of evidences, the mean error ratio of Extended D-S method with classical D-S method will decrease. EDS is from 0.245% to 0.086%. Classical D-S method is from 0.2... to 0.122%. But under the same number of evidences, the mean error ratio is much lower than that of classical D-S method. The comparison result can be shown in Figure.8.1.

From the comparison curve in Figure8.1, we can see that the change trends and error ratio between Extended D-S method and classical D-S method. Why? Because when

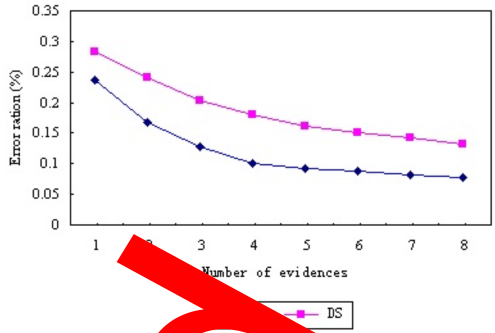

Figure 1 Comparison result of EDS and DS

Extended D-S method is adopted, it has considered the reliability, time-efficiency and relativity of service context of mobile applications. But classical D-S method is ignored these parameters.

With the increase of checked objects, the mean error ratio of EDS, RST and BT will decrease. EDS is from 0.156% to 0.048%. RST is from 0.201% to 0.063%. BT is from 0.252% to 0.109%. Our result is shown their change trends and error ratio. Based on comparison, the advantage of EDS is apparent.

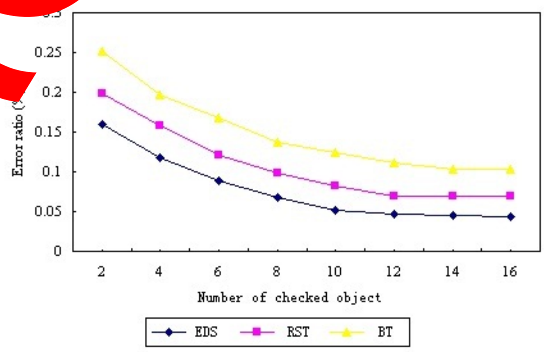

Figure 2 Comparison result of RST, EDS and BT

From the comparisons in Figure8.2, we can see that EDS is the most efficient, but Bayesian (probability) Theory (BT) is worst. The reason is that Bayesian (probability) Theory method is only depended on basic probability assignment set by the user, so it has drawbacks about other impact factors, such as, reliability, time-efficiency and relativity. Therefore it is larger than EDS and RST. RST method is also ignored the reliability, relativity of service context of mobile application. At the same time, RST is used more space and time than EDS when it do computing process. By comparisons, as we know, the more validity of new service-aware computing approach based on

EDS with uncertainty information has been tested successfully.

9. DISCUSSIONS

As we know, many researchers [41, 42] have recognized that service-aware process with uncertainty must be considered in pervasive mobile applications. Service-aware computing approach mentioned about is an important method of pervasive computing for Web-based mobile application with uncertainty. But many methods for service-aware computing have their shortcomings, such as first-order probabilistic logic, Bayesian Network, classical D-S Evidence Theory [43, 44]. The following research examples are about the introduction of their shortcomings [45].

Mori [20] studied the shortcoming of context-aware computing with uncertainty based on probability model with Bayesian network. Mahler [17] studied the shortcoming of Random Set theory in information with uncertainty. Paul Castro [21] studied reasoning of context parameters and relative state based on Bayesian network, the shortcoming of Bayesian network is slow. Saha [19] studied the shortcoming of classical Dempster-Shafer Evidence Theory in service-aware process with multi-sensor track fusion.

In D-S Evidence Theory, there is a belief degree function mass to process the combination computing, which is more freedom than traditional Probability Theory, that is $m(\Theta)$ may not be 1, if $X \subseteq Y$, $m(X)$ may not be less than $m(Y)$, meanwhile , $m(X)$ and $m(X')$ may not have a certain amount relationship. But the sensed multi-source data as dynamic evidence service-aware information is with noise and uncertainty, the application in fact requires high reliability, we must consider context reliability factor during service-aware computing, it means if the classical D-S Evidence Theory is used as service-aware computing method and reasoning theory, we must modify it.

10. CONCLUSIONS AND FUTURE WORKS

In order to support Web-based pervasive mobile application with uncertainty based on pervasive computing, in this paper, we have discussed a [illegible] of service-aware computing approach. Our approach called EDS. It is considered the reliability, time-efficiency and relativity of service context. It is based on combination rule suggested by classical D-S Evidence Theory, but we have improved it and give the new fusion computing approach.

We have selected "Smart Meeting Room" as our test bed and set up a prototype system, which is supported by NSFC, "863" High-tech Plan, The Ministry of Education, China. We have selected the scenes of prototype system to do application practices and testing of the modified approach. Three scenes have demonstrated them in the prototype system. The results have shown their correctness, so they have overcome the shortcomings of classical D-S computing approach.

In order to compare with other relative methods, we have reexamined the theory of Random Set and Bayesian Theory. At the same time, we argued the drawbacks of these approaches. Based on the comparisons, the validity of our new service-aware computing approach for pervasive Web-based mobile application with uncertainty has been tested successfully. In fact, our approach is general, so it can be used in many domains.

Of course, although we have verified our approach in our prototype system and [illegible] correct results on our projects, some work must be continued and going on, such as how to determine the reliability factor, how to select better time-efficient function and how to decide the relativity factor, etc. These are several significant works to be done.

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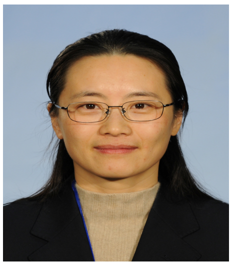

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