

Context Inconsistency Elimination Based on User Feedback and Modified Evidence Theory

Leitao Wang, Hongji Xu, Guoxia Sun, Zhengfeng Du, Zhigang Xie, and Lina Zheng

Abstract—In dynamic and open environment, context aware system obtains context information from the dynamic, distributed and heterogeneous sources, but the context information usually has inconsistencies which would lead to inappropriate services. We proposed a new context inconsistency elimination algorithm based on user feedback and modified evidence theory in this paper. Through user feedback, each sensor's perception precision can be acquired, and with the modified evidence theory, we can make full use of all context information and eliminate inconsistent context by adjusting the influence of every context on whole judgment based on sensor perception precision. In order to evaluate the performance of the proposed context inconsistency elimination algorithm, context aware rate is defined. The experiment results show that the proposed context inconsistency elimination algorithm can obtain the best context aware rate in most cases when the error rates of sensors are varied.

Index Terms—Adaptive service, context aware, context inconsistency elimination, user feedback

I. INTRODUCTION

Context aware technology is one of the key technologies of ubiquitous computing [1], [2]. Various sensors can be applied to deriving context. Through the consideration of contexts, the context aware systems are able to adapt their services to the continuously evolving situations without diverting human attention so as to improve the quality of human-computer interaction experience.

However, due to the precision differences of sensors, equipment isomerism and network delay, the context aware information usually has inconsistencies [3]. Thus, we should eliminate those inconsistencies so as to obtain the correct context information [4]. Otherwise the services we provide would be inappropriate.

In [5], the authors present the trust-worthiness based algorithm which selects the context information with the largest sensor perception precision among all context information. In [6] the voting algorithm is applied to select the context information by plurality. In addition, efficient context aware selection based on user feedback algorithm which takes

trust-worthiness based algorithm [5] and voting based algorithm [6] into consideration is proposed in [7]. In this algorithm, the authors set accepted threshold and rejection threshold. If there is a sensor perception precision which is larger than accepted threshold, the service provider will select the context information of this sensor as final output; or if the sensor perception precisions of all sensors are under the rejection threshold, the trust-worthiness based algorithm will be used; otherwise, voting algorithm would be applied. Nevertheless, above mentioned algorithms cannot make full use of all context information, so they could not obtain outstanding performance.

In [8]-[10], the parameter of Quality of Context (QoC) in middleware is used to manage context information. In [11], QoC is measured on context source layer, context processor layer and context consumer layer. In their work, context inconsistency would be eliminated based on one QoC parameter directly or the combination of several QoC parameters. But just through the utilization of QoC, the inconsistent context cannot be eliminated effectively. Except that, the maneuverability of their methods is also restricted.

Furthermore, the authors of [12] propose an approach to detect problematic contexts and resolve the context inconsistencies with the help of context aware application level semantics. However, it does not support real-time requirements and the error recovery would cause extra resource consumption.

In this paper, we present a new context inconsistency elimination algorithm based on user feedback and modified evidence theory. It can make full use of all context information and obtain a better performance.

The rest of the paper is organized as follows. Section II describes the proposed algorithm which is used to eliminate the inconsistent context. Section III presents the performance evaluation and experiment results. Finally we draw the conclusion in Section IV.

II. CONTEXT INCONSISTENCY ELIMINATION BASED ON USER FEEDBACK AND MODIFIED EVIDENCE THEORY

Considering smart home as a typical application scenario, various sensors are applied to deriving context.

We can acquire user feedback data from various statuses of home appliances and sensors attached to them such as on/off button or remote controller. Based on the data of user feedback, we can estimate each sensor's perception precision. For example, if the context aware system recognizes the user location context as "meeting room", the system would turn on the projector of the meeting room automatically. After a while the user operates the lamp at kitchen, and the user feedback

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indicates the real situation as “kitchen”, but the system perhaps wrongly recognizes the user location context as “meeting room”. In this case, the system would demonstrate that the current sensor perception has failed. Whenever user feedback data is acquired, an evaluation of sensor’s perception precision would be performed. With the modified evidence theory proposed by this paper, we can make full use of all context information by adjusting the influence of every context on whole judgment based on sensor perception precision. Finally, using Dempster’s basic reliability synthesis principle [13], the inconsistency of context information will be eliminated.

The procedure of proposed context inconsistency elimination algorithm is shown in Fig. 1, and the processing steps are explained as follows.

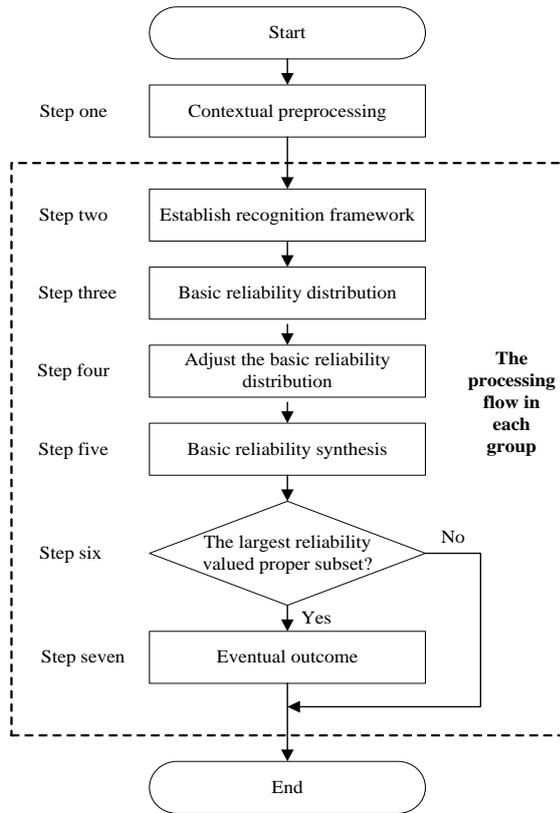


Fig. 1. The procedure of proposed context inconsistency elimination algorithm.

A. Step One: Contextual Preprocessing

In this step, we collect context information captured by all kinds of sensors, model the context information according to the context modeling mode [14], and then classify the context information according to the context awareness type. The context modeling mode is “awareness type + awareness information + awareness precision”.

By classifying the context information according to the context awareness type, context inconsistency elimination can be divided into synchronous processing parts so as to make full use of computing resources, which can improve the real-time performance of context inconsistency elimination.

Step two to Step seven are discussed in one context group.

B. Step Two: Establish Recognition Framework

We use Dempster-Shafer evidence theory [13] to establish

recognition framework. In Dempster-Shafer evidence theory, there are four definitions.

Definition 1: The recognition framework Θ is defined as an exhaustive set of mutually exclusive events or propositions of a particular experiment.

Definition 2: If for any subset A of recognition framework Θ , it satisfies $m(\phi) = 0, \sum_{A \in \Theta} m(A) = 1$, then m will be called the basic reliability distribution function of recognition framework Θ . $\forall A \subset \Theta, m(A)$ is the basic reliability value of subset A . If $m(A) > 0$, then A is the focal element of the recognition framework Θ .

Definition 3: For recognition framework Θ , the degree of belief about subset X is defined as

$$Bel(X) = \sum_{Y \subseteq X} m(Y) \quad (1)$$

where X and Y are subsets of recognition framework Θ .

Definition 4: Assume m_1 and m_2 are basic reliability distribution function on the same recognition framework. A_1, A_2, \dots, A_k are focal elements of m_1 and B_1, B_2, \dots, B_k are focal elements of m_2 . Then Dempster’s basic reliability synthesis principle can be expressed as

$$m(C) = \frac{\sum_{A_i \cap B_j = C} m_1(A_i) m_2(B_j)}{1 - K} \quad (2)$$

$$\text{Subject to: } K = \sum_{A_i \cap B_j = \phi} m_1(A_i) m_2(B_j)$$

Dempster’s basic reliability synthesis principle can be directly extended to N sensors.

In one context group, recognition framework is the exhaustive set of mutually exclusive results apperceived by every sensor.

C. Step Three: Basic Reliability Distribution

Each sensor’s sensing result in one time can be considered as a basic reliability distribution function on recognition framework and this basic reliability distribution function can be expressed as

$$m(A) = \begin{cases} 1, & A = \text{subset_awared} \\ 0, & A \neq \text{subset_awared} \end{cases} \quad (3)$$

where *subset_awared* is the focal element of the recognition framework perceived by this sensor.

For each sensor, the focal elements of the recognition framework Θ are different. In other words, each sensor’s sensing result may be inconsistent, so it is hard to make a final decision and we must take context inconsistency elimination algorithm into consideration.

D. Step Four: Adjust the Basic Reliability Distribution

We can acquire user feedback data from various statuses of home appliances and sensors attached to them. Based on the

data of user feedback, we can estimate each sensor's perception precision. The sensor perception precision r can be defined as

$$r = 1 - \frac{Mismatch_{uf}}{Total_{uf}} \quad (4)$$

where $Mismatch_{uf}$ is the number of mismatches between sensors' perception context and user feedback data, and $Total_{uf}$ is the total number of user feedback data. If there have no user feedback data in one time, we will use the last estimated sensor perception precision as the sensor perception precision of now.

Based on evidence theory, we proposed a novel algorithm which been called modified evidence theory. In this algorithm, we use (5) to readjust the basic reliability distribution function

$$m_r(A) = \begin{cases} r^n \cdot m(A) & A \subset \Theta \\ 1 - \sum_{B \subset \Theta} m(B) & A = \Theta \end{cases} \quad (5)$$

where r is sensor perception precision, n is the exponent of r and n been called weighting coefficient which can be adjusted according to the dynamic conditions.

E. Step Five: Basic Reliability Synthesis

Using Dempster's basic reliability synthesis principle [13] and (1), (5), we can calculate the belief degree about every subset of recognition framework.

F. Step Six: Select the Proper Subset Which Has the Largest Value of Belief Degree

In this step, every proper subset's belief degree value will be compared. If a subset has not the largest value of belief degree or it is not the proper subset, this subset will be neglected. On the contrary, if a proper subset has the largest value of belief degree, the content of this proper subject will be output as the final result.

G. Step Seven: Eventual Outcome

We choose the content of proper subset which be selected by step six as the eventual outcome.

For one context awareness type, there have many sensors and each sensor's sensing result may be inconsistent, so we must take context inconsistency elimination algorithm into consideration. Through the seven steps of proposed context inconsistency elimination algorithm, we can pick out one proper subset which has the largest value of belief degree from the recognition framework. Because this proper subset has only one element and the content of this subject will be chose as the final output, we eliminate the inconsistency of context information.

III. THE PERFORMANCE EVALUATION

In the experiment, we compare the performance of several context inconsistency elimination algorithms including our proposed algorithm, the trust-worthiness based algorithm [5], the voting based algorithm [6], the efficient context aware

selection based on user feedback algorithm [7].

In order to evaluate the performance of different context inconsistency elimination algorithms, we define the context aware rate [7] as follows

$$C_{ar} = \frac{Corret_{context}}{Total_{context}} \quad (6)$$

where $Corret_{context}$ is the total number of correct context, and $Total_{context}$ is the total number of context occurrence.

Table I shows the abbreviations used for context inconsistency elimination.

TABLE I: THE ABBREVIATIONS USED FOR CONTEXT INCONSISTENCY ELIMINATION

Symbols	Meaning
<i>A-trust</i>	The trust-worthiness based algorithm
<i>A-vote</i>	The voting based algorithm
<i>A-fb</i>	The efficient context aware selection based on user feedback algorithm
<i>A-ds-fd</i>	Proposed algorithm
r_i	Perception precision of sensor S_i
E_i	$1 - r_i$ i.e. Perception error rate of sensor S_i

In order to get the user feedback data and evaluate the performance of context aware rate achieved by proposed algorithms, ten human subjects and five sensors are participated in the experiment. The number of context occurrences is set to be 40,000.

In order to illustrate the influence of the weighting coefficient on performance, we evaluate the context aware rate of the proposed context inconsistency elimination algorithm with respect to various weighting coefficients. In this experiment six groups of sensors are applied. In each group, five sensors S_1, S_2, S_3, S_4, S_5 are participated in the experiment and the perception error rates of five sensors are changeless within each experiment.

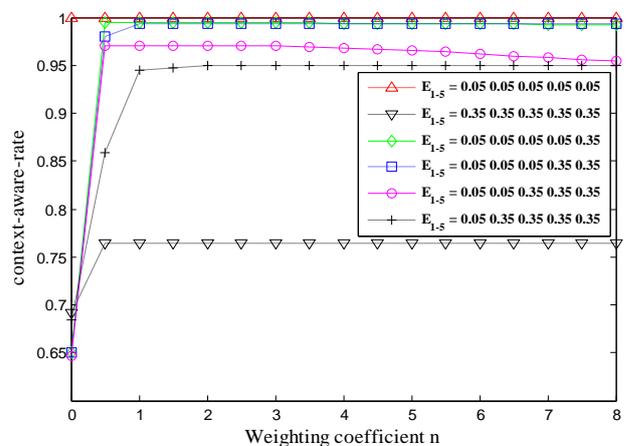


Fig. 2. The C_{ar} with respect to n .

Fig. 2 illustrates the context aware rate of the proposed context inconsistency elimination algorithm with respect to various weighting coefficients. The numerical values in the legend of Fig. 2 are perception error rates of five sensors

S_1, S_2, S_3, S_4, S_5 respectively. From Fig. 2, we can see that the performance of the proposed algorithm is superior when the weighting coefficient is 2. When the weighting coefficient is smaller than 2, particularly smaller than 0.5, the performance of the proposed algorithm drops rapidly. At the same time, when the weighting coefficient is larger than 2, there will be a slow drop of the performance. In the following experiment, we set the weighting coefficient as 2 so as to achieve the best performance.

In order to evaluate the effectiveness of our proposed context inconsistency elimination algorithm, five sensors S_1, S_2, S_3, S_4, S_5 are participated in the experiment. It is assumed that the perception error rates of sensors S_2, S_3, S_4, S_5 are changeless within each experiment, but the perception error rates of sensor S_1 vary from small to large.

Fig. 3 to Fig. 7 illustrate the context aware rate of the proposed context inconsistency elimination algorithm with the weighting coefficient equal to 2. In each experiment, we compare the performance of several context inconsistency elimination algorithms including our proposed algorithm, the trust-worthiness based algorithm [5], the voting based algorithm [6], the efficient context aware selection based on user feedback algorithm [7].

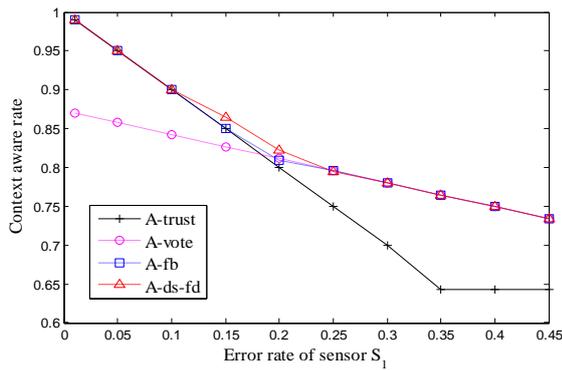


Fig. 3. The C_{ar} with respect to error rate E_1 .
($E_2 = 0.35 E_3 = 0.35 E_4 = 0.35 E_5 = 0.35$)

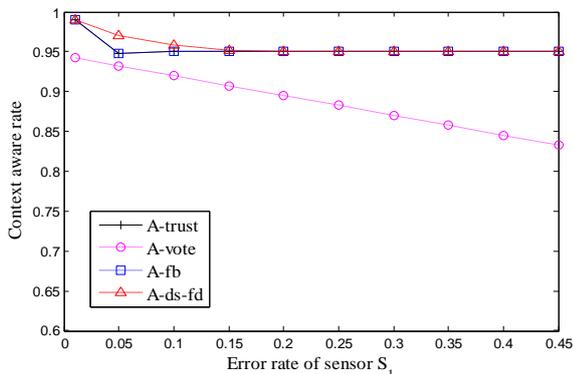


Fig. 4. The C_{ar} with respect to error rate E_1 .
($E_2 = 0.05 E_3 = 0.35 E_4 = 0.35 E_5 = 0.35$)

The context aware rate of the four algorithms with $E_2 = 0.35, E_3 = 0.35, E_4 = 0.35, E_5 = 0.35$ and different error rates E_1 of S_1 is shown in Fig. 3. When the error rate E_1 is smaller than 10%, the performance of

A_{ds_fd} is equal to A_{fb} and A_{trust} , in the meantime it is better than A_{vote} . However, when the error rate of E_1 is larger than 25%, the performance of A_{ds_fd} is equal to A_{fb} and A_{vote} , and meantime it is better than A_{trust} . In addition, A_{ds_fd} obtains a higher context aware rate when the error rate E_1 is between 10% and 25%.

Fig. 4 illustrates the context aware rate of the four algorithms with $E_2 = 0.05, E_3 = 0.35, E_4 = 0.35, E_5 = 0.35$ and different error rates E_1 of S_1 . We can see that A_{ds_fd} obtains a higher context aware rate obviously when the error rate E_1 is smaller than 20%. At the same time, when the error rate E_1 is larger than 20%, the performance of A_{ds_fd} is equal to A_{fb} and A_{trust} , moreover it is better than A_{vote} .

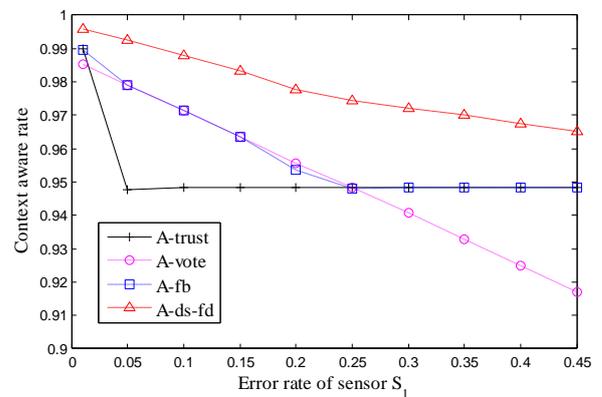


Fig. 5. The C_{ar} with respect to error rate E_1 .
($E_2 = 0.05 E_3 = 0.05 E_4 = 0.35 E_5 = 0.35$)

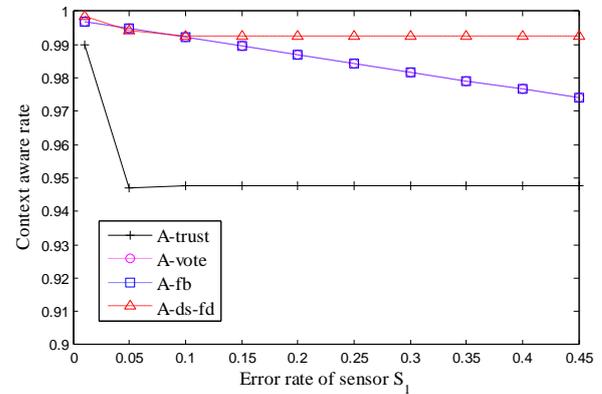


Fig. 6. The C_{ar} with respect to error rate E_1 .
($E_2 = 0.05 E_3 = 0.05 E_4 = 0.05 E_5 = 0.35$)

Fig. 5 demonstrates the context aware rate of the four algorithms with $E_2 = 0.05, E_3 = 0.05, E_4 = 0.35, E_5 = 0.35$ and different error rates E_1 of S_1 . It shows that A_{ds_fd} obtains significantly higher context aware rate than other three algorithms when the error rate E_1 are varied.

In Fig. 6, the context aware rate of the four algorithms with $E_2 = 0.05, E_3 = 0.05, E_4 = 0.05, E_5 = 0.35$ and different error rate E_1 of S_1 is compared. When the error rate E_1 is smaller than 10%, the performance of A_{ds_fd} is similar to

A_fb and A_vote , in the meantime it is larger than A_trust . When the error rate E_1 is larger than 10%, the performance of A_ds_fd is better than A_fb , A_trust and A_vote .

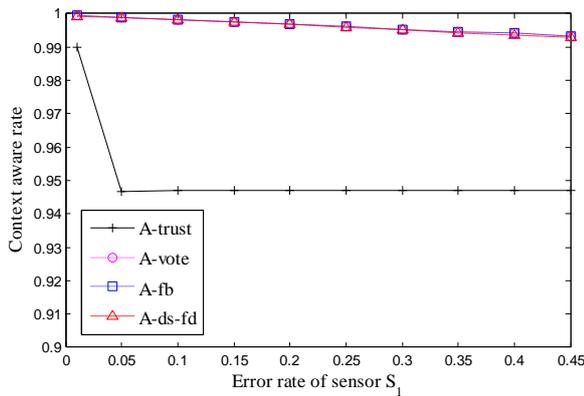


Fig. 7. The C_{ar} with respect to error rate E_1 .
($E_2 = 0.05$ $E_3 = 0.05$ $E_4 = 0.05$ $E_5 = 0.05$)

Fig. 7 shows the context aware rate of the four algorithms with $E_2 = 0.05$, $E_3 = 0.05$, $E_4 = 0.05$, $E_5 = 0.05$ and different error rates E_1 of S_1 . The performance of A_ds_fd is similar to A_fb and A_vote , but it is larger than A_trust distinctly when error rate E_1 are varied.

Through analyzing of Fig. 3 to Fig. 7, we find that the proposed context inconsistency elimination algorithm A_ds_fd can obtain the best context aware rate in most cases compared to the other algorithms. For instance, in Fig.4, the experiment results show that the proposed context inconsistency elimination algorithm improves the context aware rate by up to 3.9% compared to the trust-worthiness based method, 2.2% compared to the voting method and 2.4% compared to the efficient context-aware selection based on user feedback method when the error rate E_1 is equal to 0.2.

IV. CONCLUSION

In this paper, we presented a new context inconsistency elimination algorithm based on user feedback and modified evidence theory. By classifying the context information according to the context awareness type and building each group's recognition framework respectively, context inconsistency elimination can be divided into synchronous processing parts so as to make full use of computing resources, which can improve the real-time performance of context inconsistency elimination. Through user feedback, we can get each sensor's perception precision. Based on sensors' perception precision and modified evidence theory algorithm, we can make full use of all context information and eliminate inconsistent context by adjusting the influence of every context on whole judgment.

The experiment results show that the proposed context inconsistency elimination algorithm A_ds_fd obtains the best context aware rate in most cases compared to A_trust , A_vote and A_fb algorithms when the error rates of the sensors are varied.

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