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"Research Note"

BUILDING REPUTATION FOR SERVICE-ORIENTED AMI: MODELING, ALGORITHMS, AND ANALYSIS*

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Abstract– Service reputation is a key factor for service selection and service composition in Service-Oriented Ambient Intelligence systems. Hence, service reputation computing should fully reflect the feature of multi-rating fusion and the utility value dynamic attenuation characters of the rating. The paper combines D-S evidence theory with dynamic attenuation and puts forward a service reputation computing algorithm based on multi-rating fusion, which is adapted to the Ambient Intelligence systems. First, a layered computing model of the service reputation is given. Then, a mechanism of dynamic attenuation based on time windows, an objective rating and advertisement honesty rating of service, and a user credibility computing algorithm are presented. Afterward, the rating information is combined with the D-S evidence theory to raise an aggregation algorithm of the service general reputation for the Ambient Intelligence environments. Finally, a prototype test is carried out to verify the effectiveness and availability of the model together with the algorithms.

Keywords– Service reputation, trust, evidence theory, AmI

1. INTRODUCTION

The fusion of Ambient Intelligence (AmI) and Service-Oriented Computing (SOC) is the present research trend in AmI. From the point-of-system paradigm, AmI has evolved into an open and loose coupling service-oriented system. With the rapid increase of services on the web, more and more services with similar functions can be reached by hands. Hence, how to choose an appropriate service from a variety of candidates becomes a problem. Unfortunately, some service providers may publish false information. What's worse, many service consumers are very likely to have no interactive information or prior knowledge about these services, except for those issued by the providers. Therefore, selecting an appropriate and trustworthy service is a key problem in AmI systems. An effective way of addressing this issue is to build a reputation/trust management mechanism for the services [1-4]. It can obtain the forecasting information from the past interactive activities and user rating based on reputation mechanism, and the information will influence the following operations in the future and provide trusted factors for the service selection. There have been many important works on reputation computing, but these works are not suitable for the AmI systems. Therefore, further study is essential to build a service reputation mechanism in AmI.

In order to enable the service reputation computing to meet the needs of AmI environments, first the multi-dimensional representation of service reputation concept and its computing model are studied. Then

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we design and implement related key algorithms adapted to the service-oriented AmI. Finally, we give some test results and analysis. To present our objectives, the paper is organized as follows. Related works are introduced in section 2. Section 3 presents the concept and model of reputation in AmI environment. Key algorithms of service rating and their implementation are discussed in section 4. Service reputation aggregation algorithm is detailed in section 5. Section 6 gives the analysis and test results of our study. Finally, Section 7 states the conclusions and some open issues.

2. RELATED WORKS

Reputation computing is an open problem. Several institutes have proposed some resolutions from their research domains. Audun [5] detailed relative works about the reputation and trust. In the following, we give a brief overview of the most recent research developments which are closely related to our work.

In order to design and deploy context specific and reputation-based trust model in pervasive environments, Sheikh [6] proposed a multi-hops recommendation protocol and behavioral model to describe the interaction among devices. The model established the trust relationship by using devices' interactive behavior information. Alexandre proposed the objective rating conceptual and its computing method in SOA environments, and then it provided a trustable services selection policy based on services reputation which were aggregated from the objective rating. Unfortunately, the service reputation value was for single QoS attribute, so it cannot provide an overall performance assessment for services. Chang and [7-9] adopted a temporal fading mechanism for the service reputation value. However, the fading for reputation value is a coarse granularity policy and is different from the human's cognitive process. At the same time, both Chang and Malik studied the credibility of rating entity. The latter, especially, concentrated on the research of rater credibility and achieved good theoretical results. In order to evaluate the reliability of electric power system, Ehsani employed a Markov state space model [10].

In Yu [11], the Dempster-Shafer evidence theory was introduced into reputation computing. It considered the user rating as evidence and obtained the reputation value through evidence combination. This method had important theoretical value, but it had some limitations. First, it did not consider the temporal sensitivity of user rating. Second, only the user subjective rating information was used in the reputation and it also assumed all users had the same weight. Third, the conflict evidence combine method could be improved. Malik and Bouguettaya [12] presented a complete solution which was based on subjective evaluation to calculate the service reputation in SOA environment. It considered the evaluation credibility, mainstream evaluation, the history information of evaluation body, personal assessment preference, evaluation of time decline and so on. However, this paper only considers the effect the subjective rating information has on the reputation, and this makes the foundation which, when calculated, the reputation is single. Another question was whether its dynamic attenuation mechanism could fully reflect the user experience.

3. REPUTATION COMPUTING MODEL

The study of reputation mechanism has received great attention worldwide [13-16]**.** Based on [17,18], the reputation of service in AmI can be defined as a quintuple $R=\Re$(*subjective Rating*, *objective Rating*, *advertisement Honesty*, *time*, *context*), where *subjective Rating* refers to the user's comprehensive experience after using the service in different contexts; *objective Rating* refers to the deviation of actual performance monitoring value from user requirement; *advertisement Honesty* is the deviation of service advertisement value from the actual performance monitoring value; and *time* and *context* show that the rating information is obtained in a special situation. The relationship of the quintuple can be shown in Fig. 1.

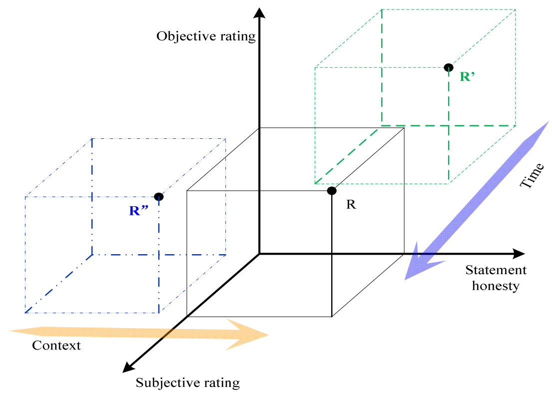

Fig. 1. Quintuple relationship of reputation

From the definition, we can see that service reputation computing involves many interactions among algorithms. Figure 2 illustrates a model of reputation computing, it abstracts all key algorithms and their interactions at each tier.

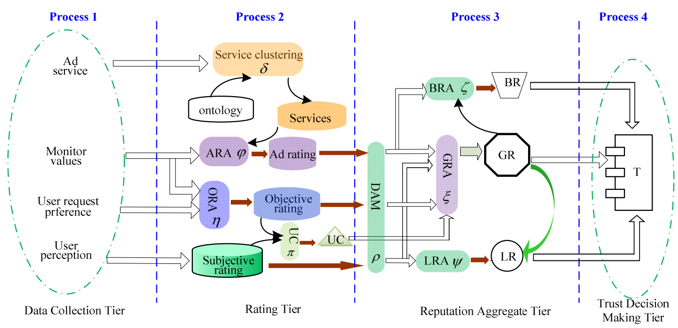

Fig. 2. A computing model of reputation

The current study focuses on the rating tier and reputation aggregation tier. The former is introduced to transform all kinds of raw data into corresponding ratings. Its core algorithms include advertisement honesty rating *(HR*), objective rating (*OR*), and user credibility assessment (*UC*). Additionally, a service clustering method is designed according to services' QoS, which classifies the candidate services into some subclasses.

The latter focuses the aggregate rating information into a corresponding reputation. Its main aggregation algorithms include user local reputation aggregation algorithm ψ, general reputation aggregation algorithm ξ, and bootstrap reputation algorithm ζ. Among these algorithms, only the user subjective rating is used to compute the user local reputation, whereas subjective rating, objective rating, service advertisement honesty, and user credibility information are used to compute the general reputation. The details of bootstrap reputation computing are discussed in [19, 20]. In addition, all kinds of rating information must be pre-processed by dynamic attenuation mechanism ρ. The attenuation mechanism transforms initial rating information into utility value, which attenuates with time.

4. RATING ALGORITHM AND ATTENUATION MECHANISM

a) Subjective rating and dynamic attenuation mechanism

In society, the rating value is dynamically attenuated. That is, with time the contribution of a rating to the reputation becomes smaller until the utility value diminishes. In AmI, the timeliness of a user's subjective rating on a service is significant. Every user gives his own subjective rating *sr* ($R=\{0.1,0.2,0.3,0.4,0.5,0.6,$

0.7,0.8,0.9,1.0}, $sr \in R$) on the performance of a service after use. The history records of subjective rating constitute a rating set *S*, and its length grows with time and user numbers. For instance, there are two rating sets *{1.0,1.0,1.0, 0.7,0.6,0.2,0.2}* and *{0.2,0.2,0.6,0.7, 1.0,1.0,1.0}* for s_1 and s_2. From the two sets, s_2 has a better reputation than s_1 because s_2 gets better ratings as time goes on, whereas s_1 gets worse. For service selection, s_2 has a higher trustworthy value. Therefore, both the good rating 1.0 and the poor rating 0.2 attenuates as time passes. The utility rating value becomes lower and closer to the median value until its reference value is gone. To express such a dynamic change process, a utility function (μ) is defined as follows:

$$sru = \mu(sr,t,w) = \begin{cases} \dfrac{\lambda w}{\lambda w + t} \bullet sr & (0 \le t \le w-1, sr \ge \mho) \\ \dfrac{\kappa w + t}{\kappa w} \bullet sr & (0 \le t \le w-1, sr \le \Omega) \\ sr & (0 \le t \le w-1, \mho < sr < \Omega) \\ \phi & (t \ge w) \end{cases} \tag{1}$$

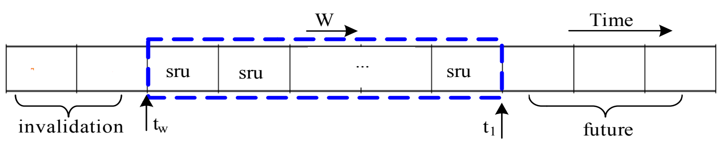

Fig. 3. Utility value sliding window

In formula (1), the user subjective rating or the average of multiple ratings is located in time frame *t*. The default value is filled if the service is not used by users in a time frame (*It is recommended to fill 0.5*). The *w* is an attenuation time window. The window goes forward with time, as shown in Fig. 3. A new rating is placed into the time window continually, and the oldest value may be slipped out of the time window. $\mho$ and Ω are two thresholds ($0.1 \le \Omega < \mho \le 1.0$). If the rating is greater than or equal to $\mho$, the corresponding service performance is satisfactory and trustable. If the rating value is less than or equal to Ω, then the corresponding service performance is unsatisfactory. The service performance cannot be determined if the rating is between $\mho$ and Ω. λ and κ are attenuation factors. A basic principle of assigning λ and κ is to guarantee that the credible utility value is greater than Ω, and the mistrustful utility value is less than $\mho$ in a time window or before the expiration of the rating information. In the paper, w =10, $\mho$ =0.6, Ω =0.3, λ=2, κ =1 and *t* represents a week's time.

b) Objective rating and advertisement honesty rating

In the AmI environment, several pieces of monitoring equipment are deployed to obtain the actual performance of the services. These monitored QoS values are used to estimate *OR* and *HR* [21].

There are three service QoS vectors: the advertisement QoS (A_{qos}) used in service registration, the required QoS (R_{qos}) for user request, and also the monitored QoS (M_{qos}) in service execution. The deviation of R_{qos} and M_{qos}, the rmd, indicates how actual performance of the service satisfied the user's requirement. *OR* is calculated using rmd. The deviation of $A_{qos}$and M_{qos}, the amd, reveals how well a service is implemented according to its advertisement. amd is used to compute the *HR*. Once a service is invoked, its *OR* and *HR* are computed using formulas 2 and 3, where A_{qos}^j, R_{qos}^j, $M_{qos}^j$are the advertisement, requirement, and monitored values of the QoS' j^{th} attribution (normalized by [0,1] operator), respectively. Compared with *SR*, the estimation of *OR* and *HR* prevents the calculation from the prejudice and malice of user's subjective rating. The utility value of *or* and *sah* are also attenuated over time, and can be computed using formula 1.

$$or = \begin{cases} \left\lceil 10 * \left(1 - \frac{1}{e^{rmd}}\right) \right\rceil * 0.1 & (\, rmd > 1.0\,) \\ \left\lfloor 10 * \left(1 - \frac{1}{e^{rmd}}\right) \right\rfloor * 0.1 & (rmd \le 1.0) \end{cases} \tag{2}$$

where $rmd = 1 - \frac{1}{n}\left(\sum_{j=1}^{n} \frac{R^j_{qos} - M^j_{qos}}{R^j_{qos}} \right)$

$$sah = \begin{cases} \left\lceil 10 * \left(1 - \frac{1}{e^{amd}}\right) \right\rceil * 0.1 & (\, amd > 1.0\,) \\ \left\lfloor 10 * \left(1 - \frac{1}{e^{amd}}\right) \right\rfloor * 0.1 & (amd \le 1.0) \end{cases} \tag{3}$$

where $amd = 1 - \frac{1}{n}\left(\sum_{j=1}^{n} \frac{A^j_{qos} - M^j_{qos}}{A^j_{qos}} \right)$

c) User rating credibility

All the *SRs* are aggregated into reputation. However, not all of the *SRs* are fair and unbiased. Even for fair users, they may give different ratings for a same service due to the different contexts or professional background. Thus, the credibility of user rating should be assessed. Generally, user credibility can be computed by using some key factors in AmI systems, such as subjective rating fluctuation (srf), subjective and majority rating similarity (sms), and the similarity of subjective rating and objective rating (sos). The user credibility is expressed as formula 4.

$$uc = 1/(\alpha * srf + \beta * sos + \varepsilon * sms) \tag{4}$$

where $0 < \alpha, \beta, \varepsilon < 1$, $\alpha + \beta + \varepsilon = 1$ and $\alpha = 0.3, \beta = 0.4, \varepsilon = 0.3$.

1. User rating fluctuations: For a service, the same user's rating may fluctuate in different contexts. This fluctuation should be kept at a reasonable range. The ratings greatly fluctuate when the user behaves irrationally or lacks professional knowledge. In the current study, the standard deviation of the user subjective rating sequence was used to define the user rating discrete degree, as shown in formula 5.

$$srf = \sqrt{\left(\sum_{t=1}^{w} (sr_t - \overline{sr})^2\right) \Big/ cw} \tag{5}$$

sr_t is the user subjective rating and $\overline{sr} = \left(\sum_{t=1}^{w} sr_t\right) \Big/ cw$. cw represents a user rating reliability window. A higher srf indicates lower user credibility, and vice versa.

2. Similarity of subjective rating and objective rating: Subjective and objective ratings measure the performance of the services from different views. Therefore, the two rating sequences should be consistent or similar, the similarity between sr=(sr_1,sr_2,…, sr_n) and or=(or_1, or_2,…,or_n) represented with Euclidean distance, as shown in formula 6.

$$sos = \sqrt{(sr_1 - or_1)^2 + (sr_2 - or_2)^2 + \ldots + (sr_n - or_n)^2} \tag{6}$$

sos represents the reciprocal of similarity and or, sr are the objective rating and subjective rating sequences respectively. $0 \le sr_i \in sr \le 1$, and $0 \le or_i \in or \le 1$.

3. Similarity of subjective rating and majority subjective ratings: The ratings of users in a time window w are clustered using the K-Means clustering algorithm. Then, the centroid of the majority cluster can be used as users' majority rating in w, as shown in formula 7 [22].

$$smr = center(max(\delta(sr_k))) \tag{7}$$

smr denotes the subjective majority ratings. The majority of users' ratings were assumed to be reasonable and credible. Therefore, taking smr as a reference, sms can be obtained by computing the Euclidean distance between the vectors sr and smr using formula 6. A smaller sms means a more credible subjective rating.

5. DYNAMIC WEIGHTED REPUTATION AGGREGATION

For meeting the needs of AmI, a novel D-S evidence theory based algorithm of service reputation aggregation is proposed. Compared with that of Yu, there are three advantages: first, the utility value was used instead of the original rating value in order to avoid the inaccuracy brought in by its time-dependent effect. Second, multi-ratings were introduced and detailed for reputation computing to revise single subjective rating, since information collected from a single subjective rating is usually unilateral due to biased or professional background. Third, the weighted evidence combined rules were adopted to aggregate the general reputation. Every subjective rating is supposed to assign a different weight to represent how important the rating is among the multi-ratings [23, 24].

a) D-S evidence theory

Dempster and Shafer [25] proposed the evidence theory, which can be applied to uncertain decisions. The knowledge, experience, and feelings of a user in certain circumstances are advantageously used as the evidence of a decision. For any subset A in the frame of discernment $\Theta = \{\theta_1, \theta_2, \cdots, \theta_N\}$, $m(A)$ is assigned as a basic support degree, which is constrainted by the following conditions:

$$\begin{cases} m(\phi) = 0 \\ \sum_{A \subset \Theta} m(A) = 1 \end{cases} \tag{8}$$

Every element of Θ is considered as an incompatible event or assumption, and *m(A)* is the basic probability assignment (*BPS*) indicating the support for set A. Different pieces of evidence E_i and E_j may have different *BSP* $m_i(A_i)$ and $m_j(A_i)$ for the same subset A_i. Hence, the basic D-S combining rule of multi-evidences can be expressed as follows (suppose $K = \sum_{A_i \cap A_j = \phi} m_i(A_i) m_j(A_j) < 1$):

$$m(A) = \begin{cases} \dfrac{\sum_{A_i \cap A_j = A} m_i(A_i) m_j(A_j)}{1-K} & A \ne \phi \\ 0 & A = \phi \end{cases} \tag{9}$$

The larger the value of K, the more conflict there is between the two evidences. The combined results are often insufficient and even lead to paradox. Moreover, the basic D-S combining rules take no account of the credibility of the evidence making the combined results different from the actual situation. To solve the conflicting evidences, some improved methods were proposed in [26].

b) BPS of the rating

BPS of the rating needs to be obtained to compute the service reputation. Contrary to that of Yu, we take the ratings utility values instead of the original ratings value as the computing evidence of *BPS*. It is assumed that the user u_i invokes service s_j n times in time window w and u_i gives the subjective rating sr_l after using the service ($sr_l \epsilon R$, $0 \leq l \leq n$). Hence, its utility value is $sru_l = \mu(sr_l, t, w)$. Threshold Ʊ and Ω are introduced to divide the ratings into three parts: trust ($sru_l \geq$ Ʊ), uncertainty (Ʊ $< sru_l < \Omega$), and distrust domains ($sru_l \leq \Omega$). Function *f(x)* is used to map *x* as its probability in time window *w*. According to the D-S evidence theory, the *BPS* of sru_l is assigned as follows:

$ms_w(\{T\}) = \sum_{sru_l=Ʊ}^{1} f(sru_l)$,

$ms_w(\{\neg T\}) = \sum_{0}^{sru_l=\Omega} f(sru_l)$,and$ms_w(\{\neg T, T\}) = \sum_{sru_l=\Omega}^{sru_l=Ʊ} f(sru_l)$. $ms_w(\{T\})$, $ms_w(\{\neg T\})$and $ms_w(\{\neg T, T\})$represent the degree of trust, distrust, and uncertainty degrees respectively. Similarly, *BPS* of *OR* can be obtained as follows: $mo_w(\{T\})$, $mo_w(\{\neg T\})$and $mo_w(\{\neg T, T\})$and *HR*: $mah_w(\{T\})$, $mah_w(\{\neg T\})$ and $mah_w(\{\neg T, T\})$.

c) General reputation aggregation

General reputation (*GRep*) indicates the trustworthiness of service in AmI environment. It can be expressed as $GRep = \zeta \cdot msr + \tau \cdot mor + \sigma \cdot msahr$, where *msr* represents the combined multi-user subjective rating, *mor* denotes the combined multi-objective ratings, *msahr* is the degree of combined multi-service honesty degree, and ζ, τ, σ represent the corresponding weights.

User u_i may call and rate a service repeatedly in a time window, and the ratings are listed in the sequence of sr_l ($sr_l \in R, 0 \leq l \leq n$). For different users u_i and u_j ($i \neq j$), the two rating sequences for the same service in an identical time window may differ. Hence, the corresponding $ms_w(\{T\})$, $ms_w(\{\neg T\})$ and $ms_w(\{\neg T, T\})$are also different. Furthermore, each user has a credibility *uc*. The user credibility can be used as the weight of *BPS* to compute *msr*. Then the weighted average of *BPS* is computed [27]. Finally, the method in [28] was adopted to combine the evidences. The computing process as follows:

i. Normalizing and obtaining the standard user credibility uc_i;
ii. Computing the multi-user weighted average (*mwa*) for attenuation-based user rating:
   $mwa(\{T\})$=$\sum_{i=1}^{N} uc_i \cdot ms_i(\{T\})$,
   $mwa(\{\neg T\})$=$\sum_{i=1}^{N} uc_i \cdot ms_i(\{\neg T\})$,
   $mwa(\{T, \neg T\})$=$\sum_{i=1}^{N} uc_i \cdot ms_i(\{T, \neg T\})$;
iii. Combing *mwa N-1* times, and obtaining the combined multi-user *BPS msc*;
iv. Computing $ms(\{T\})$ and $ms(\{\neg T\})$ using *msc.* The general user comprehensive reputation value, *msr*, is 10*($ms(\{T\}) - ms(\{\neg T\})$).

To prevent ratings (evidence) conflict caused by different contexts, Murphy's multi-evidence combing rule was used to compute *mor* and *msahr*. Its computing process is similar to the *msr* computation.

GRep can be easily worked out as soon as the values of *msr*, *mor*, and *msahr* are calculated. According to actual experience, the settings of corresponding weights are: ζ=0.4, τ=0.4, σ =0.2. The *GRep* is stored in the service register center and shared by all users. The service is continuously called and rated when the time window moves on, and the value of *GRep* is dynamically updated.

6. TEST AND ANALYSIS

To analyze the above algorithms, a prototype system based on AmI-space was designed [1]. A group of semantic web services (video player services, including QoS attributes: price, delay, jitter and image definition) were deployed on Java and Jena 2.6.2 platforms. Users, including domain experts and general users, request and rate the services. A large number of monitoring devices were deployed to measure the real-time QoS of the services.

a) Analysis of the dynamic attenuation mechanism

Figure 4 shows the results of two different methods: one is based on the dynamic attenuation time window and the other was that of Yu. Figure 4 makes it clear that there are three advantages to using D: (1) The mapping relation of reputation value and its QoS is more reasonable, and reflects the dynamic change of the QoS more accurately; (2) It agrees with the rational judgments and predictions of humans by using the dynamic attenuation mechanism; (3)It is more sensitive to the perception of the service QoS change, and is able to give an early warning when the service QoS drops.

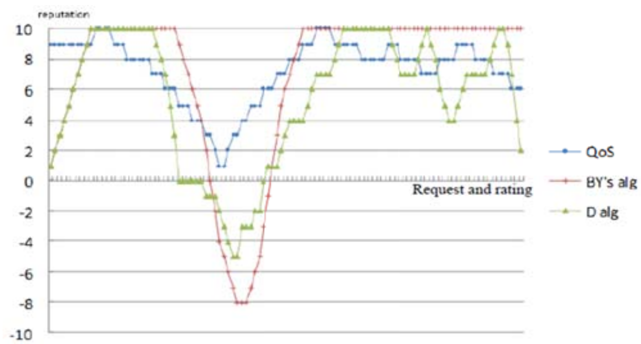

Fig. 4. Time window-based dynamic attenuation mechanism

b) Analysis of the OR and HR algorithm

Three domain experts with different requirements (SR4, SR7, and SR9 representing low, medium, and high level of QoS requirement) were selected to assess a service. The service QoS was controlled to make it dynamically changeable. According to the monitored QoS value and user requirement, the corresponding *OR* value for OR4, OR7, and OR9 can be computed. Both the *OR* sequences and the experts' *SR* sequences are shown in Fig. 5. The closer the *OR* sequences to the experts' *SR*, the better the objective rating algorithm is. From Fig. 5, the *OR* algorithm performs the best when the user requirement is medium; the performance declines when the user requirement becomes very high or very low, but still with high similarity. So, the *OR* algorithm proposed in the paper performs better. For *HR* computing, the details were not provided because they were similar to the objective rating algorithm.

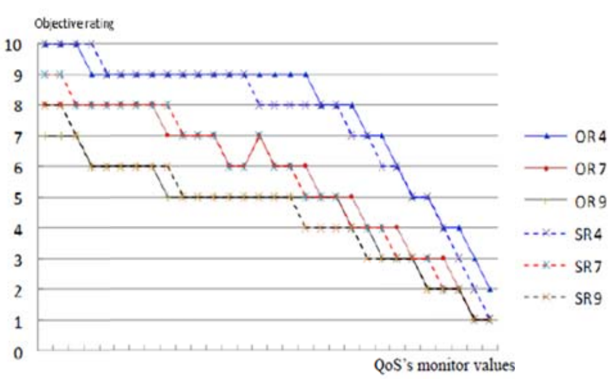

Fig. 5. Performance of objective rating

c) Analysis of the user credibility algorithm

Generally, high credibility should be assigned for the rational rating and low credibility should be assigned for the irrational or collusion ratings. Figure 6 shows the user credibility of the ratings of three groups. The results show that the user credibility is about 4:1:1. Hence, it has a good differentiation and can adapt to the requirements of AmI.

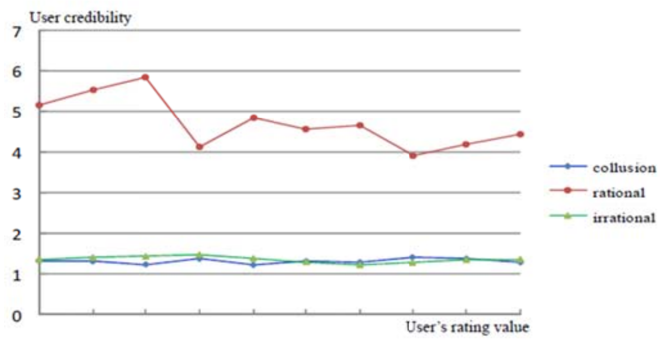

Fig. 6. Analysis of the user credibility algorithm

d) Analysis of the general reputation aggregation algorithm

Figure 7 shows the reputation values for the same service computed by different algorithms. Yu did not consider the user rating credibility factors, thus making the BY reputation (Yu) increase at an unreasonably high level (exorbitant user rating factor) and enlarging the fluctuation (irrational user factor). The reputation value computed by S reputation algorithm is more reasonable because the dynamic attenuation mechanism and user credibility factor was adopted. The G reputation was the most accurate, which can reflect the change of service QoS. It can prevent the influence of irrational subjective rating because of the combined objecting rating and user credibility. Compared with the G reputation and R reputation, the S reputation only reflects the personal feeling of the user and is restricted to the personal preference and specific context of the user, although the general reputation is more objective and accurately reflects the real changes of service QoS.

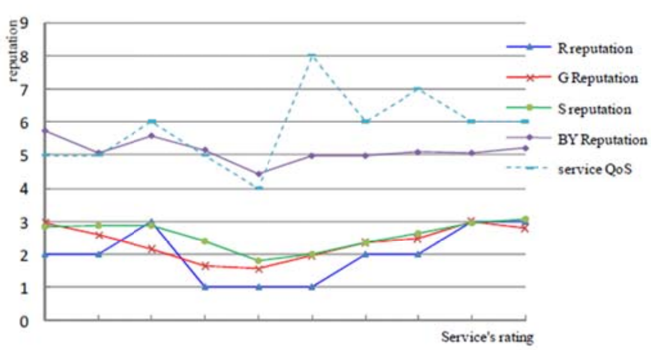

Fig. 7. Analysis of the general reputation algorithms

7. CONCLUSIONS AND FUTURE WORK

The paper presented a model of service reputation computing modeling for service-oriented AmI systems and detailed related key algorithms. Finally, the feasibility and effectiveness of the model and algorithms were tested and analyzed. The paper's main contributions include:

1) Designing a service reputation computing model for AmI systems. The model is consistent with the basic information processing: data $\rightarrow$ information $\rightarrow$ knowledge, and it summarizes the core algorithms and their interactions. Researchers can concentrate on the core algorithms design and so simplify the complexity of reputation implementation.
2) Designing and implementing the time window based dynamic attenuation mechanism, objective rating and user credibility algorithm, and also presenting a multi-ratings based service reputation aggregation algorithm. Based on these algorithms, the reputation value can better reflect the service's historical information, effectively forecast the service future behavior, and thus provide more accurate and reliable information for the service selection and composition in AmI systems.
3) Some algorithms, for instance dynamic attenuation mechanism and user credibility, are easily applied to other information systems. For example P2P, to improve the validity of reputation computing.

In the future, the rating semantic model and rating conflict combining rules for AmI system will be further studied to enhance the practicality of the service reputation mechanism in AmI environment.

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