A Reputation System based on Computing with Words

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ABSTRACT

Reputation system is a way to maintain trust in dynamic environments by collecting, distributing and aggregating feedbacks about the service providers' past behaviors. Most existing reputation systems assume that raters evaluate the ratee by means of numerical values. However, raters sometimes cannot express their judgments with exact numerical values, especially when the raters have uncertain or ambiguous opinions on the ratee. Our paper introduces a novel reputation system based on the methodology of Computing with Words (CW), in which the ratings and reputations of computation are words and propositions drawn from a natural language instead of numerical values. Our reputation system has a sound mathematical basis. At the same time, it is convenient for the raters to express their judgments and simple for the participants to understand the integrated reputation.

Categories and Subject Descriptors

H.1.2 [**Models and Principles**]: User/Machine System – *human information processing, human factors.*

General Terms

Security, Human Factors, Languages

Keywords

Reputation System, Computing with Words, Fuzzy Logic

1. INTRODUCTION

Reputation system is a way to maintain trust in dynamic environments, where we anonymously interact with people that we might have never met, not even heard of, and that we might never meet again [1]. This is achieved by the provision of information about past performance. To be more precise, a reputation system is a system that collects, distributes and aggregates feedbacks about the service providers' past behaviors [1]. A famous example is eBay's Feedback Forum. And it was found in eBay that using reputation system can significantly increase the volume of trades since it increases both the buyer's trust and the seller's trustworthiness.

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In a reputation system, a ratee's reputation is based on the integration of the ratings given by raters who had past interactions with the ratee. Most existing methods assume that raters evaluate the ratee by means of numerical values, e.g. Person A gives a rating *0.87* on Person B. However, raters sometimes cannot express their judgments with exact numerical values. The raters may feel more convenient to use linguistic assessments to express the evaluations instead of numerical values, e.g. raters are better at giving ratings like "Person B is *very reliable*" than ratings like "Person B's rating is *0.87*". Moreover, the raters sometimes use truth qualifications or probability qualifications to express their judgments when they have uncertain or ambiguous opinions on the ratee, e.g. due to his limited knowledge on the ratee, the rater may give ratings like "it is *not very likely* that Person B is *very reliable*". Under this kind of situations, it is more difficult for the raters to evaluate the ratee with exact numerical values. To solve above problems, some literatures had tried to use linguistic variables in their models, e.g. discrete models [2, 3, 4, 5] and fuzzy models [6, 7, 8]. But it has been pointed out in [9] that the previous discrete models do not easily lend themselves to sound computational principles. Fuzzy model is in essence suitable to deal with the linguistic knowledge. However, the previous fuzzy models still suffer from the problem of the raters' inconvenience on rating providing. The reason is that in previous fuzzy models fuzzy membership functions are usually only used to categorize the imprecise inputs and integrate the ratings, but the ratings used in these models are still numerical values. E.g. in [10], fuzzy membership functions are used to categorize the numerical ratings like 0.86 and 0.83 into the same category *very reliable*.

The object of this paper is to solve the above problems of existing models by proposing a reputation system which has a sound mathematical basis and is convenient for the raters to express their judgments and simple for the participants to understand the integrated reputations. This paper sets the stage by introducing a novel reputation system based on the methodology of Computing with Words (CW), in which the objects of computation are words and propositions drawn from a natural language. The main advantage of our reputation system is that it avoids the inconvenience for the raters to evaluate the ratee by exact numerical numbers, especially when the raters' opinions are uncertain or ambiguous. The ratings in our reputation system are based on human linguistics like "It is *unlikely* that Person A is *very reliable*" in stead of exact numerical values like *0.76*. Moreover, the reputation of the ratee, i.e. the integration of ratings, is also expressed in nature language instead of numerical values, which is easier for the participants to understand.

The rest of our paper is organized as follows. We introduce the related works in section 2 and give a brief introduction to CW in section 3. Our proposed reputation system is introduced in details in section 4. A case study based on the proposed CW based reputation system is given in section 5. The last section summarizes our paper and points out the future work.

2. RELATED WORKS

A number of reputation systems have been proposed in previous literatures, in which some of them have already been used to commercial applications. The simplest reputation model is to compute the ratee's reputation by summing all the positive ratings and negative ratings. A famous example is eBay's reputation forum [11]. Some reputation systems are based on Bayesian Theory, for example [12, 13, 14, 15]. These models get a posteriori (i.e. the updated) reputation from the computing of combining the priori (i.e. previous) reputation with the new ratings. To use the Bayesian reputation systems, we need to get enough training data to get the priori knowledge. There are also some reputation systems based on Dempster-Shafter Theory (belief model) [16, 17]. Dempster-Shafter Theory is a generalization of Bayesian theory of subjective probability. Some reputation systems are based on flow models. These systems calculate reputation by transitive iteration through looped or arbitrarily long chains [9]. The ratee's reputation increases as a function of income flow and decreases as a function of outgoing flow [9]. A famous example is Google's PageRank [18]. Discrete reputation systems are proposed based on the fact that humans are often better able to rate performance in the form of discrete variables instead of continuous means, e.g. [2, 3, 4, 5]. There are also some reputation systems based on the fuzzy models, e.g. [6, 7, 8]. In fuzzy reputation systems, reputations are expressed as linguistically fuzzy concepts in which membership functions describe to what degree an agent can be described [9].

3. A BRIEF INTRODUCTION TO CW

As its name suggests, Computing with Words (CW) is a methodology in which words are used in place of numbers for computing and reasoning [19]. CW is inspired by the remarkable human capability to perform a wide variety of tasks without any computation on numerical variables, e.g. summarizing a story. Underlying this remarkable capability is the brain's crucial ability to manipulate perceptions [20].

Basically, there are four principal rationales for the use of CW [19, 20]:

(1) The don't know rationale. In this case, the values of variables and/or parameters are not known with sufficient precision to justify the use of conventional methods of numerical computing.

(2) The don't need rationale. In this case, there is a tolerance for the imprecision which can be exploited to achieve tractability, robustness, low solution cost and better rapport with reality.

(3) The can't solve rationale. In this case the problem cannot be solved through the use of numerical computing.

(4) The can't define rationale. In this case, a concept that we wish to define is too complex to admit the definition in terms of a set of numerical criteria.

The conceptual structure of CW is given in Figure 1. CW belongs to the category of fuzzy logic. It is based on fuzzy set theory and integrates fuzzy theories like possibility theory, fuzzy graphs and so on. The method CW acts as the basis of computational theory of perceptions.

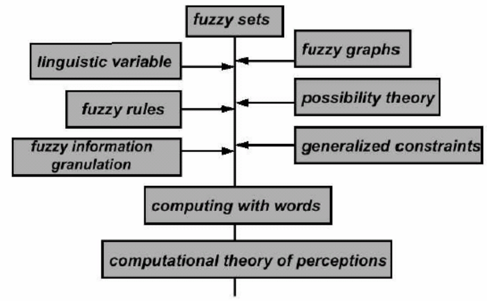

Figure 1. Conceptual structure of CW

4. OUR PROPOSED REPUTATION SYSTEM

4.1 A Scenario to use Reputation System in Ubiquitous Healthcare

An example of scenarios is given in Figure 2 to use reputation system in ubiquitous healthcare. The user, Bob, is tying to find a physician to cure the pain in his shoulder. He does not have any knowledge about the local physicians since he is a visitor to the city. He uses his cell phone to get in touch with the local ubiquitous healthcare system. In his requests, Bob gives the keyword "shoulder". The ubiquitous healthcare system detects Bob's location according to his cell phone and lists the physicians who are related to the given keyword around Bob's location. Along with the list, the system also gives the reputation of each listed physician. The reputation of each physician is calculated by the ratings given by the physician's previous patients. After the transaction with the physician, each patient is requested to give his rating on the physician. The ubiquitous healthcare system collects the ratings given by all the physician's previous patients and calculates the reputation. With the help of the reputation, it is relatively easy for Bob to find a reliable physician. Bob can then make an appointment by his cell phone and the ubiquitous healthcare system gives information on how to contact the chosen physician in details.

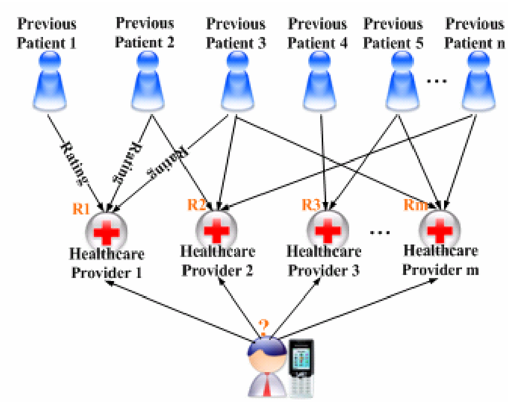

Figure 2. Using reputation system in ubiquitous healthcare

4.2 Architecture

The architecture of our reputation system is given in Figure 3. Our system first collects the ratings and put the data into Initial DB. The ratings are given by those who had past interactions with the ratee and the ratings are expressed in forms of natural language. Then the Information Translation Module makes explicit the fuzzy constrains which are implicit in the ratings expressed in natural language. After translation, the ratings are expressed in canonical form (CF) with explicit fuzzy constraints. Using Reputation Reasoning Module, the ratings expressed in CF are propagated to the conclusion. Reasoning Result Retranslation Module is an adverse procedure of Information Translations Module. In Reasoning Result Retranslation Module, the conclusion drawn from Reputation Reasoning Module which is expressed in CF will be translated to a proposition in nature language which expresses the ratee's reputation. The reputation is then stored in Terminal DB. When a user gives a request as mentioned in section 4.1, the system lists all the related service providers along with the reputations. Those reputations are expressed in forms of nature language and are distributed by the Reputation Distribution Module from the Terminal DB.

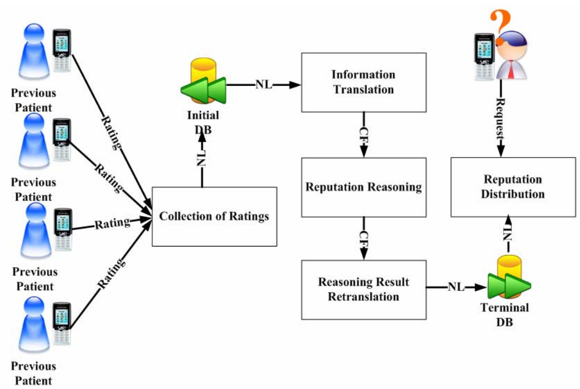

Figure 3. Architecture of our reputation system

4.3 Rating and Reputation Format

When calculating the reputation of a ratee τ, the input of our reputation system is R_τ which is the collection of ratings on τ, $R_\tau = \{r_1, r_2, ..., r_n\}$, $n \in N$, r_i is the rating given by the i^{th} rater. The output of our reputation system is τ 's reputation rep_τ. Both r_i and rep_τ are propositions expressed in forms of natural language. Since it always happens that the raters are uncertain about their opinions, probability qualifications are used in the rating and reputation format:

$$r_i = \text{It is } \delta_i \text{ that } \tau \text{ is } \omega_i$$

where δ_i is linguistic probability, e.g. unlikely; ω_i is a word which expresses the rater's judgment. ω_i acts as the label of fuzzy set and it can be atomic (e.g. reliable) as well as composite (e.g. not very reliable). An example of r_i is: r_i = It is *unlikely* that *Doctor Smith* is *very reliable*.

$$rep_\tau = \text{It is } f \text{ that } \tau \text{ is } \omega'$$

where f is a linguistic probability and ω' is a word. Both of them are induced by the integration of R_τ.

4.4 Information Translation

r_i is translated to Canonical Form (CF) with explicit fuzzy constraints by using Information Translation Module. The format of CF is:

$$r_i \to (X_\tau \quad isr \quad G_i) \quad is \quad \delta_i \tag{4.1}$$

where X_τ is the constraining variable which is a function of τ; G_i is the constraining fuzzy relation; isr is a variable copula which defines the way in which G_i constrains X_τ; the arrow → denotes explicitation.

The role of G_i in relation to X_τ is defined by the value of the discrete variable r in isr. E.g. if $r = d$, it means that G_i uses disjunctive (possibilistic) way to constrain X_τ; if $r = v$, it means that the way G_i uses to constrain X_τ is veristic. Since it has been mentioned in [19, 20] that in many cases the CFs of the propositions are constraints of the basic, possibilistic type, we choose $r = d$ in our reputation system. When r takes the value d, isd can be abbreviated to is [19, 20]. Formula 4.1 can then be expressed as:

$$r_i \to (X_\tau \quad is \quad G_i) \quad is \quad \delta_i \tag{4.2}$$

The following steps are used to make r_i explicit into the CF shown in Formula 4.2.

Step 1: To extract δ_i from r_i.

$$r_i = \text{It is } \delta_i \text{ that } \tau \text{ is } \omega_i \Longrightarrow r_i' = Prob\,(\tau \text{ is } \omega_i) \text{ is } \delta_i$$

For example, r_i = it is *likely* that *Doctor Smith* is *not very reliable*. By extracting δ_i, r_i' = *Prob* (*Doctor Smith* is *not very reliable*) is *likely*.

Step 2: To translate the part "τ is ω_i" into the form "X_τ is G_i". In this step, our reputation system acts on an explanatory database (ED) and returns the constrained variable X_τ as well as constraining relationship G_i.

ED is a collection of relations in terms of which the meaning of "τ is ω_i" is defined.

$$ED = \mathrm{Re}\,lationName_1[Attribute_{11}; Attribute_{12}]$$
$$\vee\, \mathrm{Re}\,lationName_2[Attribute_{21}; Attribute_{22}] \quad , n \in N$$
$$\vee ... \vee\, \mathrm{Re}\,lationName_n[Attribute_{n1}; Attribute_{n2}]$$

where $\vee$ means disjunction. E.g. for the propositions like "*Doctor Smith* is *not very reliable*", ED can be defined as:

$$ED = POPULATION[Name; Trustworthiness]$$
$$\vee RELIABLE[Trustworthiness; \mu]$$

Refer to the j^{th} and k^{th} ($1 \le j, k \le n$) relation defined in ED, we get X_τ and G_i respectively from r_i:

$$X_\tau = {}_{Attribute_{j2}} \mathrm{Re}\,lationName_j[Attribute_{j1} = \tau] \tag{4.3}$$

or, for simplicity:

$$X_\tau = Attribute_{j2}(\tau) \tag{4.4}$$

$$G_i = {}_{Attribute_{k2}} \mathrm{Re}\,lationName_k[Attribute_{k1} = \omega_i] \tag{4.5}$$

or, for simplicity:

$$G_i = Attribute_{k2}(\omega_i) \tag{4.6}$$

For example, for the proposition "*Doctor Smith* is *not very reliable*", we get:

$$X_\tau = {}_{Trustworthiness} POPULATION[Name = DoctorSmith]$$
$$= Trustworthiness(DoctorSmith)$$
$$G_i = {}_{\mu} RELIABLE[Trustworthiness = NotVery\,\mathrm{Re}\,liable]$$
$$= \mu(NotVery\,\mathrm{Re}\,liable)$$

The CF of proposition r_i = it is *likely* that *Doctor Smith* is *not very reliable* can then be expressed as:

$$(Trustworthiness(DoctorSmith) \text{ is } \mu(NotVery\,\mathrm{Re}\,liable)) \text{ is } likely$$

Using the same method, we can translate rep_τ in to the form:

$$rep_\tau \to (X_\tau \quad is \quad G_i^{'}) \quad is \quad \delta_i^{'} \tag{4.7}$$

4.5 Reputation Reasoning

The rules we use for reputation reasoning are the rules governing fuzzy constraint propagation. When reasoning the reputation, we first use Constraint Modification Rules in [19, 20] to simplify the constraining relationship G_i

$$G_i = mA_i = f(A_i) \tag{4.8}$$

where m is a modifier such as *not*, *very*, *more or less*; A_i is a constraining relationship. A description of some modification rules are shown in Table 1.

Table 1. Some modification rules

m	Not	Very	Not very	Very very	More or less
$f(A_i)$	$A_i^{'}$	${}^2A_i$	$1 - {}^2A_i$	${}^4A_i$	${}^{1/2}A_i$

where $A_i^{'}$ means complement; $\mu_{{}^mA_i}(u) = (\mu_{A_i}(u))^m$, μ is the fuzzy membership function.

An example for Formula 4.8 is: $G_i = \mu(NotVery\,\mathrm{Re}\,liable)$ can be simplified to $G_i = 1 - \mu^2(\mathrm{Re}\,liable)$

The reputation reasoning then calculates the Probability Qualification δ_i in Formula 4.2:

$$(X_\tau \quad is \quad f(A_i)) \quad is \quad \delta_i \Rightarrow P_i \quad is \quad \delta_i \tag{4.9}$$

where P_i is the probability of the fuzzy event X_τ.

$$P_i = prob\{X_\tau \quad is \quad G_i\} = \int_U \mu_{G_i}(u)p(u)du \tag{4.10}$$

where U is the universe of discourse in which X_τ takes value; $p(u)$ is the probability density of X_τ taking values in U ; μ_{G_i} is the fuzzy membership function of G_i.

Since we use $r = d$ in Formula 4.1, we use Possibility Theory [21] for the following calculation:

$$\prod_{prob\{X_\tau \quad is \quad G_i\}} = \delta_i$$

where $\prod_{prob\{X_\tau \quad is \quad G_i\}}$ is the possibility of the probability density of $X_\tau \quad is \quad G_i$.

$$\prod_i(P) = \prod_{prob\{X_\tau \quad is \quad G_i\}} = \mu_{\delta_i}[\int_U \mu_{G_i}(u)p(u)du] \tag{4.11}$$

where μ_{δ_i} is the fuzzy membership function of δ_i .

Use the principle of maximal restriction [21], we get the following equation for the calculation of rep_τ :

$$\begin{aligned} &\mu_{\delta_i^{'}}(X_\tau \quad is \quad G_i^{'}) = Max_P(\prod_1(P) \wedge \prod_2(P) \wedge ... \wedge \prod_n(P)) \\ &\mu_{\delta_i^{'}}[\int_U \mu_{G_i^{'}}(u)p(u)du] \\ &= Max_P(\prod_1(P) \wedge \prod_2(P) \wedge ... \wedge \prod_n(P)) \end{aligned} \tag{4.12}$$

where $\mu_{\delta_i^{'}}$ and $\mu_{G_i^{'}}$ are the fuzzy membership for $\delta_i^{'}$ and $G_i^{'}$ separately.

After get the result in Formula 4.12, we refer to the fuzzy membership of the linguistic probability, e.g. unlikely, and get $\delta_i^{'}$.

5. A CASE STUDY

$R_\tau = \{r_1, r_2, r_3\}$, r_1 = It is *unlikely* that *Doctor Smith* is *very reliable*, r_2 = It is *likely* that *Doctor Smith* is *reliable*, r_3 = It is *very unlikely* that *Doctor Smith* is *malicious*. The question is: *How likely* that *Doctor Smith is not malicious*? i.e. rep_τ = It is f that *Doctor Smith* is *not malicious*, where f is an unknown linguistic probability.

Use Formula 4.2, 4.4, 4.6 and 4.7, we translate r_1, r_2, r_3 and rep_τ in to the following format:

$$r_1 \to ((Trustworthiness(DoctorSmith) \text{ is } \mu(Very\ \mathrm{Re}\,liable) \text{ is } unlikely$$

$$r_2 \to ((Trustworthiness(DoctorSmith) \text{ is } \mu(\mathrm{Re}\,liable) \text{ is } likely$$

$$r_2 \to ((Trustworthiness(DoctorSmith) \text{ is } \mu(malicious) \text{ is } very\ \ unlikely$$

$$rep_\tau \to ((Trustworthiness(DoctorSmith) \text{ is } \mu \text{ (not malicious) is } \delta_i^{'}$$

Use Formula 4.8 and 4.11:

$$\Pi_1(P) = \mu_{likely}[1 - \int_0^1 \mu_{reliable}{}^2(u)p(u)du]$$

$$\Pi_2(P) = \mu_{likely}[\int_0^1 \mu_{reliable}(u)p(u)du]$$

$$\Pi_3(P) = \mu^2{}_{likely}[1 - \int_0^1 \mu_{malicious}(u)p(u)du]$$

Use Formula 4.12:

$$\mu_{\delta_i^{'}}[\int_0^1 (1 - \mu_{malicious}(u))p(u)du] = Max_P(\Pi_1(P) \wedge \Pi_2(P) \wedge \Pi_3(P))$$

We give the fuzzy membership functions we choose for μ_{likely}, $\mu_{malicious}$ and $\mu_{reliable}$ in Figure 4 and Figure 5. The mathematical descriptions are given in Formula 4.13, 4.14 and 4.15 separately. Figure 6 gives the possible f(Malicious) based Formula 4.8, Formula 4.14 and Table 1.

$$\mu_{likely}(u) = \begin{cases} 0 & u \in [0, \frac{1}{2}] \\ -4(u-1)^2 + 1 & u \in [\frac{1}{2}, 1] \end{cases} \tag{4.13}$$

$$\mu_{malicious}(u) = \begin{cases} 1 & u \in [0, \frac{1}{4}] \\ \dfrac{1}{1+20^2(u-\frac{1}{4})^2} & u \in [\frac{1}{4}, 1] \end{cases} \tag{4.14}$$

$$\mu_{reliable}(u) = \begin{cases} 0 & u \in [0, \frac{1}{2}] \\ \dfrac{1}{1+20^{-2}(u-\frac{1}{2})^{-2}} & u \in [\frac{1}{2}, 1] \end{cases} \tag{4.15}$$

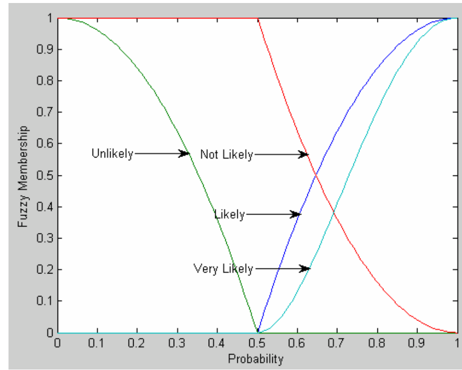

Figure 4. Fuzzy Membership function of likely

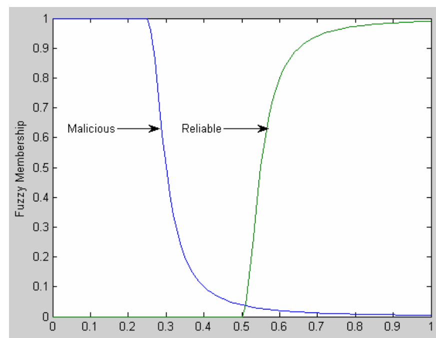

Figure 5. Fuzzy Membership function of *Reliable and Malicious*

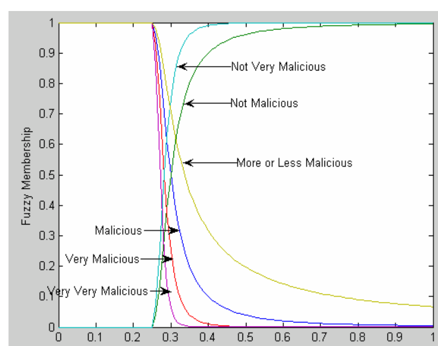

Figure 6. Fuzzy Membership function of f(Malicious)

We assume that the probability density of X_τ taking values in U is uniform distribution, i.e. $p(u) = 1$, $u \in [0,1]$. Using Formula 4.12:

$$\mu_{\delta_i'}[\int_{\frac{1}{4}}^{1}(1-\frac{1}{1+20^2(u-\frac{1}{4})^2})du] = Max_P(\mu_{likely}[1-\int_{\frac{1}{2}}^{1}(\frac{1}{1+20^{-2}(u-\frac{1}{2})^{-2}})^2 du]$$

$$\wedge\mu_{likely}[\int_{\frac{1}{2}}^{1}\frac{1}{1+20^{-2}(u-\frac{1}{2})^{-2}}du] \wedge \mu^2{}_{likely}[1-\int_0^{\frac{1}{4}}1*du-\int_{\frac{1}{4}}^{1}\frac{1}{1+20^2(u-\frac{1}{4})^2}du])$$

Refer to Figure 4, we get:

$rep_\tau \rightarrow ((Trustworthiness(DoctorSmith)$ is μ *(not malicious)* is *very likely*.

Retranslate the information use the reverse method as show in section 4.4, we get the reputation of Doctor Smith from R_τ :

rep_τ = It is *very likely* that *Doctor Smith* is *not malicious*.

6. CONCLUSIONS AND FUTURE WORK

Our reputation system is based on the computing of words and propositions drawn from natural language instead of exact numerical values. This makes our CW based reputation system more suitable to be used in real applications since it is more convenient for the raters to express their judgments and easier for the service requesters to understand the ratee's reputation. Although words are less precise than numbers, the methodology of CW has been proved to rest on a mathematical foundation [19, 20]. Moreover, compared with existing works, our reputation system is more suitable to be used in the situations where raters have limited knowledge about the ratee or have uncertain view on the ratee.

In the future work, we plan to focus on how to add different weights to each rater. And we also want to add the part of filtering out unfair raters in our reputation system. We will also make effort to integrate the reputation system with the rater's personal experience to set up a sound trust system in dynamic environment, especially in ubiquitous healthcare system. Based on our comparison between our CW based reputation system and other reputation systems, we believe that the usage of CW based reputation system in dynamic environments presents a promising path for the future research.

7. ACKNOWLEDGMENTS

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Dr. Young-Koo Lee is the corresponding author.

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