Reputation Mechanism for E-Commerce in Virtual Reality Environments

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1. RESEARCH PROGRAM

Our research is within the subfield of modeling trust and reputation in multi-agent systems for electronic commerce in virtual reality environment (virtual marketplaces, VMs). More specifically, we are interested in addressing two problems in multiagent-based VMs where a buying agent are able to model trust and reputation of sellers and other buyers:

- The trust issues in VMs with the consideration of characteristics of VMs compared to traditional e-marketplaces;
- The subjective ratings and dishonest buyers problems in multiagent-based VMs.

To clarify, the interest in 3D technology and Virtual Reality (VR) is growing both from academia and industry, promoting the quick development of VMs (*e.g.*, Second Life). Compared with traditional e-marketplaces, VMs have advanced characteristics such as stereoscopic 3D visualization, real-time interactivity, immersion and multisensory feedback [4]. However, there are also inherited trust problems in VMs, *e.g.*, sellers may advertise a perfect deal but do not deliver the promised service or product at the end. A few studies on designing reputation mechanisms for VMs [1] apply traditional reputation mechanisms where only simple numerical ratings, textual descriptions and 2D pictures are considered. They overlook the difference between traditional e-marketplaces and VMs. Besides, the same as traditional e-marketplaces, there are still a lot of subjective ratings existing in the systems because providing feedback based on advanced characteristics of VMs requires a lot of efforts from buyers. Meanwhile, buyers may also lie about experiences with sellers.

2. PROGRESS TO DATE

To effectively address the aforementioned trust issues, we design a reputation mechanism by considering the advanced characteristics of VMs. More specifically, we first study four steps for constructing the reputation mechanism, namely, five-sense oriented feedback provision, reputation computation, 3D visualization of reputation computation and automatic decision making, by incorporating novel elements related to VMs. Then, considering the scenarios where some users are reluctant or inconvenient (*e.g.*, the lack of VR devices) to provide the detailed five-sense feedback, but to provide a rating about their past experience. The ratings concluded from human users' five senses may involve users' own subjectivity. To address the user subjectivity difference problem, we also propose a subjectivity alignment approach for reputation computation in VMs.

Motivated by the advanced characteristic of VR environment, we have designed a five-sense oriented feedback provision approach especially for reputation mechanism in VMs. It is mainly built on buyers' feedback about their shopping experience with sellers and their perceptions about products delivered by the sellers. More specifically, in VMs, these kinds of feedback information can come from human users' five senses enriched by VR, namely, *vision*, *hearing*, *touch*, *taste* and *smell*. For example, with the assistance of 3D scanner and haptic devices (*e.g.*, virtual glove), a buyer can render a 3D virtual duck with its objective *softness* information to represent her purchased real duck doll, instead of describing its softness as *very soft* in text. Thus, other buyers can view and percept the virtual duck directly to assist their shopping decision making. We have also conducted a detailed user study to compare our mechanism with traditional reputation mechanisms in VMs. The comparison is based on two criterions: "institutional trust" (user's trust in the mechanism) and "interpersonal trust" (user's trust in other users with the existence of reputation mechanisms). We measure the two kinds of trust by the framework of general trust - benevolence, competence, integrity and predictability [2]. A questionnaire survey on 40 subjects is conducted. The results confirm that users prefer virtual marketplaces with our proposed reputation mechanism over traditional reputation mechanisms. Our mechanism can effectively ensure user's trust in the virtual marketplaces system and simultaneously promote user's trust in other users.

For user subjectivity difference problem, we first concluded that subjectivity difference may come from two sources by analyzing the scenario of a buyer providing a rating from both psychological and behavioral perspectives: 1) *intra-attribute subjectivity*: the subjectivity in evaluating the same attribute (*e.g.*, *softness*). For example, a product may be *inadequately soft* for buyer a, while *adequately soft* for buyer b; and 2) *extra-attribute subjectivity*: the subjectivity in evaluating different attributes. For example, a buyer with better economic conditions may consider a product's *quality* more heavily, while another buyer with worse economic conditions may concern more about the *price* of the product. These two aspects together contribute to the subjectivity differ-

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ence among buyers. To address this issue, we have proposed a subjectivity alignment approach for reputation computation (SARC).

In our approach, in a VM, each buyer is equipped with an intelligent (buying) agent and virtual reality simulators. We denote the set of buyers by $\mathcal{B} = \{b_1, b_2, b_3, \ldots\}$. The set of agents (called buying agents) equipped by corresponding buyers is denoted by $\mathcal{A} = \{a_1, a_2, a_3, \ldots\}$, and the set of sellers are referred to as $\mathcal{S} = \{s_1, s_2, s_3, \ldots\}$. The set of objective attributes for describing a transaction between a buyer and a seller is denoted as $\mathcal{F} = \{f_1, f_2, \ldots, f_m\}$, where m represents the total number of objective attributes. Each rating provided by a buyer for a seller is from a set of predefined discrete rating levels $\mathcal{L} = \{r_1, r_2, \ldots, r_n\}$, where n is the total number of different rating levels (*i.e.,* the granularity of rating scale). For a buyer $b_i \in \mathcal{B}$, the goal of her buying agent $a_i \in \mathcal{A}$ is to accurately compute the reputation value of a target seller $s_j \in \mathcal{S}$, according to b_i's subjectivity. In order to achieve this goal, the buying agent a_i needs to consider the ratings of other buyers (advisors) that evaluate the satisfaction levels about their past transactions with seller s_j. Due to the possible subjectivity difference between buyer b_i and the advisors, agent a_i also needs to align/convert ratings of each advisor (for example b_k) using our SARC approach.

More specifically, at the beginning of buyer b_i's interactions with the system, agent a_i asks b_i to provide a rating for each of her transactions with a seller (which can be any seller in $\mathcal{S}$). Buying agent a_i also asks b_i to provide detailed review[1] information about each transaction containing the values of the set of objective attributes in $\mathcal{F}$. Based on the provided information (rating-review pairs), agent a_i models a set of correlation evaluation functions (CEFs) for buyer b_i, capturing b_i's *intra-attribute subjectivity.* Each correlation evaluation function is represented by a *Bayesian conditional probability density function* that models the correlation between each rating level and each objective attribute. Thus, for each buyer, the total number of the correlation evaluation functions is equal to $m \times n$. The learned CEFs of buyers will be shared with each other buyer's agent. For a rating provided by the buyer (advisor) b_k, agent a_i can then derive a rating for each attribute, based on the CEFs shared by b_k's agent a_k and those of buyer b_i's own. Note that what is derived for an attribute is in fact a set of probability values, each of which corresponds to a rating level in $\mathcal{L}$. The rating level with the highest probability will be chosen as the rating for the attribute. Based on the provided rating-review pairs by b_i, agent a_i also learns the *extra-attribute subjectivity* of buyer b_i, which is represented by a set of weights for corresponding attributes in $\mathcal{F}$. The weight of an attribute is determined by two factors: 1) the probability value of the rating derived earlier; and 2) the importance of the attribute learned using a regression analysis model. These weights will not be shared with other buyers. Once the weights are learned, the aligned rating from that of advisor b_k can be computed as the weighted average of the derived ratings for the attributes.

Experimental results demonstrate that: 1) SARC performs better than the the representative competing approaches of BLADE [3] and TRAVOS [5], and can more accurately and stably model sellers' reputation; 2) SARC is capable of coping with environments with deception and dynamic buyer and seller behavior; 3) the requirement of detailed reviews and objective attributes is not very restrictive.

[1] The review can consist of both textual information and virtual objects (rendered by virtual reality simulators) with corresponding five-sense information.

3. FUTURE RESEARCH

In conclusion, our current work for VMs has two major contributions: 1) the reputation mechanism takes advantages of the characteristics of virtual reality environments, and advances other traditional reputation mechanisms in VMs; and 2) addresses the users subjectivity difference problem in their satisfactory evaluations of past transactions, and complements the proposed reputation mechanism.

For the future, we plan to build a concrete and complete reputation system for VMs based on current work. On the one hand, we will implement the 3D visualization for reputation representation. Because the rating for each of five senses is needed to present the micro-view of sellers' reputation, we can consider extend the current one layer Bayesian learning in SARC to two-layer Bayesian learning by adding a hidden layer for learning the rating of each of the five senses based on identified objective attributes related to corresponding sensory. On the other hand, we will also address the dishonest buyers problem considering that some buyers may lie about their experience with sellers by providing untruthful feedback, but Our SARC model can not address this problem. By adopting the characteristics of VMs, we can build a trust model based on the concept of users' *"personal social network"* for buyers to model the trustworthiness of other buyers (called advisors). Specifically, a buyer's *personal social network* can be formed from multiple information sources enriched by VR environments, *e.g.*, the buyer's environment exploration experience (*e.g.*, the avatar of the buyer and those of advisors have previously met or chat in the same shopping store or public environments). Moreover, a prototype (*i.e.*, demo) of our reputation mechanism (four parts included) needs to be built for further studying user's responses to VMs with reputation systems. Based on this prototype, more comprehensive user study, considering age diversity, shopping background and cultural differences can be conducted.

4. REFERENCES

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