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A Reputation Mechanism for Virtual Reality

— Five-Sense Oriented Feedback Provision and Subjectivity Alignment

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***Abstract*—In this paper, we propose a reputation mechanism for virtual marketplaces. The proposed approach is based on five-sense oriented feedback provision with the support of existing virtual reality technologies. We have conducted user studies to analyse users' attitude towards this new approach. These studies reveal that users prefer virtual marketplaces with our proposed reputation mechanism over that with traditional reputation mechanisms, and that our mechanism can effectively ensure user's trust in the virtual marketplaces and simultaneously promote user's trust in other users. Our approach is based on feedback from other users. Feedback from users could be very subjective and misleading for other users. Hence, we propose a novel mechanism to align subjective user feedback before reputation computations in virtual marketplaces. Results of our experiment demonstrate that with our feedback alignment approach, buyers can more accurately model sellers' reputation.**

***Keywords*-reputation mechanism; virtual reality; subjectivity alignment; five senses; virtual marketplaces;**

I. Introduction

The Internet has become an inseparable part of our daily life. Nowadays, people prefer online stores over brick and mortal stores for various reasons. Unfortunately existing e-commerce systems provide only a simple, browser-based interface to acquire details of products and services. This kind of interfaces have been confirmed to be difficult for customers to use, and thus result in the low user satisfaction and online shopping revenue [1]. One reason is the lack of effective interaction approaches, including communication channels and coordination methods between e-commerce systems and customers. Apart from these, another critical limitation of existing systems is the limited understanding of social contexts, including social and behavioral issues, among which trust is one of the most important ones.

On the other hand, 3D technology and virtual reality are gaining popularity. Forrest report [2] claims that "within five years, the 3D Internet will be as important for work as the web is today." A technology guru at Intel Corp also predicts that "the Internet will look significantly different in 5 to 10 years, when much of it will be three dimensional or 3D" [3]. As one of the important applications of virtual reality, virtual marketplaces are referred to as the environments where virtual reality is used by buyers to virtually experience products with their five senses, make shopping decisions based on the experience and present the experience with the aid of virtual reality tools. They are one of the approaches proven to be effective in handling the above mentioned problems in traditional e-commerce. Some industrial representatives of virtual marketplaces are IBM's VR-commerce program [4], Second Life (www.secondlife.com), Active World (www.activeworlds.com), Twinity (www.twinity.com) and Virtual Shopping (virtualeshopping.com), etc. Previous research on virtual marketplaces has concerned about adopting virtual reality into constructing e-commerce, and validated whether and how virtual reality can influence trust and thus impact user decision making in advance [5].

However, the same as traditional e-commerce systems, there are also inherited trust problems for virtual marketplaces. For instance, some sellers may be dishonest (*e.g.*, fail to deliver the products as what they promised), or some sellers may have different competency (*e.g.*, produce only low quality products). As reported by Luca *et al.* [6], virtual objects can be created by copying the real products, such as using the 3D scanner to record visual information and using haptic devices to collect tactile information. With the aid of special equipments (e.g., haptic gloves), users can also sense the virtual copies similar to the real objects, and can have the similar perceptions towards the attributes (e.g., softness) of objects as in the real life. Thus, buyers can sense virtual products without time and space limitation compared to shopping markets in reality. However, this property of virtual marketplaces does not solve the trust problems. For example, some sellers may cheat on the quality of products. They can always provide virtual objects copied from high quality products to attract buyers, but deliver lower quality real products. A few studies on designing reputation mechanisms for virtual marketplaces [7] apply traditional reputation mechanisms where only simple numerical ratings, textual descriptions and 2D pictures are considered. They overlook the difference between traditional and virtual marketplace environments.

To effectively address the trust issues in virtual marketplaces, we design a five-sense oriented feedback provision approach especially for reputation mechanism in virtual marketplace environments. It is mainly built on buyers' feedback about their shopping experience with sellers and their subjective perceptions about products delivered by them. More specifically, in virtual marketplaces environments, these kinds of feedback information can come from human users' five senses enriched by virtual reality, namely, *vision*, *sound*, *touch*, *taste* and *smell*. We also study the other steps of constructing the mechanism, including reputation computation, reputation representation and decision making, by incorporating novel

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elements related to e-commerce in virtual reality. We then conduct a detailed user study to compare our mechanism with traditional reputation mechanisms in virtual marketplaces. 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.

Another important problem addressed in this paper is that feedback based on human users' five senses may involve users' own subjectivity because of the subjective evaluations represented by various subjective terms in the feedback. For example, a simple concept like "soft" has different semantics for different users. The "adequately soft" perception of a user A may be interpreted as "inadequately soft" by another user B in some situations. Thus, if user B receives user A's feedback of "adequately soft", user B cannot use it directly. Instead, user B should interpret the feedback to "inadequately soft" according to B's own subjectivity. In this view, the step to firstly align the subjectivity involved in user feedback before computing reputation of sellers is indispensable and of great importance in assuring effective decision making for buyers. In order to effectively solve the above mentioned subjectivity problem in user feedback, we propose a subjectivity alignment approach by adopting virtual reality tools with the information available in human users' five senses. To do so, we envision a multi-agent system where the agent of each user maps the subjective terms in its user's vocabulary onto objective sensory data in the form of fuzzy membership functions and shares these learned metrics with the agents of other users. Thus, for each buyer, collected feedback towards a target seller can be aligned according to his own subjectivity, and then the aligned feedback is used to compute the reputation value of the target seller. We carry out experiments to demonstrate that with our subjectivity alignment approach, buyers can more accurately model sellers' reputation. Our novel proposal of the five-sense oriented feedback provision and the feedback alignment approach provides an effective reputation mechanism particularly for virtual reality.

II. Related Work

There are mainly two research directions on virtual marketplaces. The first direction concerns about adopting 3D technology and virtual reality into e-commerce, that is the construction of virtual marketplaces. This is also currently the major research towards virtual marketplaces. For example, Bogdanovych et al. [5] propose a mechanism called 3D E-Commerce Electronic Institutions and try to increase user's trust on e-commerce systems. The second direction mainly concerns about validating the effectiveness of virtual marketplaces in addressing the problems of traditional e-commerce. For example, Papadopoulou [8] demonstrates that a virtual reality shopping environment enables the formation of trust over conventional web stores, through a survey study based on a prototype virtual shopping mall. Nassiri [9] also explains the roles of virtual marketplaces environments in increasing user's trust and in improving profitability by the mechanisms such as Avatar appearance and Haptic tools. The research conducted by Teoh and Cyril [10] mainly focuses on the trust of virtual mall. They point out that presence and para-social presence assisted by virtual reality can affect trust, and users perceive the features of a 3D immersive online e-commerce store as being useful and practical but not a mere novelty. The weakness of the research mentioned above is that they focus only on enhancing trust through virtual reality. They do not consider how to improve trust in virtual marketplaces by designing effective trust and reputation mechanisms. This is the focus of our current work.

In recent years, a lot of research have been carried out on reputation mechanisms in traditional e-commerce, and have achieved a huge success, while one of well known reputation systems is run by eBay (www.ebay.com). EBay's reputation system, also as one of the earliest online reputation systems, gathers feedback from buyers of each transaction in the simple form of numerical ratings together with a short text description. There are other successful commercial and live reputation systems [11], such as expert sites like Askme (www.askmecorp.com), products review sites like Epinions (www.epinions.com), and scientometrics related sites. However, there are only a few studies on designing reputation mechanisms specifically for virtual marketplaces. Huang et al. [7] propose a reputation mechanism based on peer-rated reputation for 3D P2P game environments where the reputation of each user is computed based on other users' subjective opinions during their interactions, which is similar to eBay's reputation mechanism. It earns some advantages on reputation evaluation, storage, query and reliability, but no simulation has been conducted to validate its advantages. Its major weakness lies in the fact that there is no consideration of differences between virtual marketplaces and traditional environments. In contrast, our reputation mechanism makes good use of virtual reality to allow the provision of feedback information from human users' five senses. The other components of our reputation mechanism also follow such a design principle of fully utilizing the important features offered by virtual reality and 3D technology.

For the subjectivity issue in feedback provision, several approaches [12]–[14] have been proposed to deal with subjective bias in ratings provided by the third party. For example, from the perspective of behavioral modeling, Noorian et al. [15] propose a two-layered cognitive approach to filter or discount the ratings provided by other buyers (advisors). The ratings are filtered or discounted according to the similarity between the ratings provided by a buyer and those of an advisor. This kind of approaches suffer from the risk of losing some important information. Another kind of approaches is to align subjective ratings. For example, the work of Regan et al. [13] applies Bayesian learning to model sellers' properties and the correlations between sellers' properties and the advisor's ratings. Koster et al. [16] use clustering and Inductive Logic Programming (ILP) to align the subjective trust evaluation using objective information of the interactions. The limitations of the existing alignment approaches [13], [16] mainly lie in two aspects: 1) sufficient shared interactions are needed between buyers and advisors; 2) they generally offer limited flexibility for buyers to deal with the dynamic behavior of sellers and the changes of advisors' subjectivity. In our approach, agents of users (*i.e.*, buyers and advisors) learn their users' subjectivity based on the users' own experience with sellers, and thus do not require shared interactions between buyers and advisors. This learning is a continuous process and can cope with the changes of advisors' subjectivity. Our approach aligns advisors' feedback about each interaction with sellers, and is able to deal with the dynamic behavior of sellers.

III. Five-Sense Oriented Reputation Mechanism

In this section, we present our five-sense oriented reputation mechanism, and carry out user studies to compare with traditional reputation mechanisms in a same virtual marketplace.

A. Reputation Mechanism

As mentioned in the previous section, current research focuses mainly on virtual reality technology adoption. Limited research on reputation mechanisms for virtual marketplaces however overlooks the differences between traditional and virtual marketplaces environments. For a traditional reputation mechanism, buyers' feedback often consists of only a positive, negative, or neutral rating, along with a short textual comment. Reputation of sellers is computed based on the ratings and perhaps those comments left by buyers, and is often in a form of a continuous numerical value. The computed reputation values will be used to make decisions for buyers on which sellers to do business with in the future.

Our reputation mechanism is specifically designed for virtual marketplaces environments. It is composed of four components: feedback provision, reputation computation, reputation representation and decision making. These components are supported by virtual reality and 3D technology, details of which will be explained in the subsequent subsections.

1) Feedback Provision: Feedback provision, as the key component of our reputation mechanism, tries to solve two major problems: what kind of user feedback to collect and how to collect feedback in virtual marketplaces. There are five senses - *vision*, *hearing*, *touch*, *smell* and *taste*, which express the *subjective perceptions* of human being. People have the ability to sense the environment and objects with these five senses, and further provide themselves better understanding of the environment. In traditional e-commerce mechanisms, only vision is regularly incorporated in simple forms like 2D pictures and textual descriptions. As human users' perception of an environment is influenced by all the sensory inputs, in order to accurately and completely express user's experience, all the five senses should be well expressed. With the development of virtual reality and augmented reality, the perceptions of human users not only can be realistically simulated, but also can be expanded by using instruments like 3D Glasses.

Five Senses: **Vision** is the ability to interpret information of what is seen from the environment, and can be expressed in the form of 3D pictures and videos in virtual reality. Therefore, in virtual marketplaces, buyers can present the real product they purchased in the form of 3D picture or animation with less distortion. Users can view the 3D object from various angles, which is more persuasive and vivid than simple 2D pictures or textual descriptions. **Hearing** is the ability to perceive sound from the environment, and can be simulated by auditory displays. Same as vision, there have been numerous works on auditory research. In virtual marketplaces, some characteristics such as tone quality of digital products are more appropriate to be presented in the form of audio. Audio is able to contain plentiful information at a time, and relatively favored and easily accepted by human users. In this sense, it is necessary to collect this kind of information. **Touch** is one of the sensations processed by the somatosensory system, and has been known in the physical world to increase initial trust. As a major part of research in virtual reality, it focuses on scanning the behaviors of objects in the physical world and incorporating similar behavior into virtual objects [17]. We have previously done some research on touching textile [18]. Touch perception can be simulated using instruments like Haptic device. Virtual touch can be supported in virtual marketplaces so that buyers can measure the characteristics of different materials and attach touch information to reputation feedback as guidance for other buyers. **Taste** refers to the ability to detect the flavor of substances such as food and minerals. Humans receive tastes through sensory organs called taste buds. The sensation of taste traditionally consists of some basic tastes such as sweetness, bitterness, sourness and saltiness. Taste can also be implemented in virtual environments. Iwata et al. [19] design a food simulator to simulate the multi-modal taste of food through a combination of chemical, auditory, olfactory and haptic sensation. Through this simulator, buyers can provide experience about the taste of products they purchase online. **Smell** refers to the ability to perceive odors. In 3D environments, devices like the olfactory display can be applied to generate various odors and deliver them to user's nose. For the purpose of presenting odors with a vivid sense of reality, the olfactory display, which has already been applied to 3D games and movies, is expected to generate realistic smells relevant to specific environments or scenes [20]. In virtual marketplaces, they can be realistic smells related to specific products such as fresh smell of fruits. Buyers can then sense a product's real smell through other buyers' feedback instead of textual descriptions about smells.

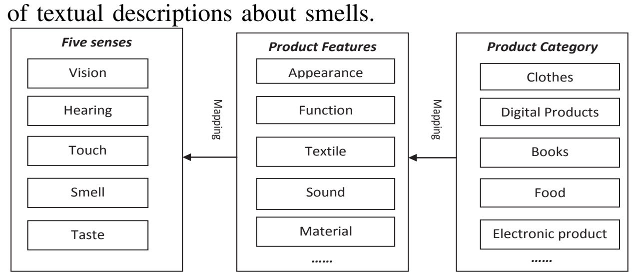

Fig. 1: Five-Sense Oriented Feedback Provision

Five-Sense Oriented Feedback Provision: As illustrated above, while concerning about buyers' historical experience with one seller, feedback can be expressed as human perceptions about the products and transaction experience. These perceptions can be simulated by virtual reality. Therefore, towards virtual marketplaces environments, we propose a five-sense orientated approach to implement feedback provision as part of our reputation mechanism. The detail of the approach is illustrated in Figure 1. Consider a virtual marketplaces providing products of different categories. According to the five-sense orientated approach, a product may belong to some specific product categories such as “Clothes” or “Books”. Products in the same category have some common product features, such as “Appearance” and “Textile”. Each product feature can be presented by some of the five senses - *Vision*, *Hearing*, *Touch*, *Smell* and *Taste* simulated by virtual reality as mentioned earlier. Thus, given a product, the necessary senses will be simulated in feedback. For example, a user has purchased a sweater from a seller in a virtual marketplaces. For feedback provision, the buyer can provide a 3D avatar model to express the appearance of the sweater sold by the seller. Besides, the touch feedback can also be simulated to show the textile and material used to make this sweater. Such information shared among buyers can be compared with the 3D avatar model of the product provided by the seller to compute reputation of the seller.

2) Reputation Computation: Feedback from other buyers about a seller contain sensory information about the received product and the buyers’ evaluations of the product. Sensory information is objective, but evaluations of subjective attributes (*e.g.*, *softness*) based on five senses such as tactile sensations are often subjective. For example, a product evaluated as *too soft* by a buyer may be evaluated as *adequately soft* by another buyer. It is thus necessary to align subjective evaluations in buyers’ feedback. Our subjectivity alignment approach will be detailed in Section IV. Based on the buyer’s own preferences for different attributes and the aligned feedback, degrees of satisfaction are computed for reported transactions. The reputation of the seller can then be computed as the average degree of satisfaction.

3) 3D Visualization for Reputation Representation: Visualization is used to present reputation results of users. Traditional reputation mechanisms use visualization of 2D objects such as a simple rating score or characteristics descriptions in the form of text or 2D pictures, which is far from being effective and provides only limited information. We apply a 3D visualization approach, aiming at presenting a rich set of reputation related information in an appealing and natural way. In this way, users will be assisted to make more informed decisions and their trust in the reputation mechanism will be increased. 3D visualization to present reputation should follow some general principles and visualization requirement [21]. First, it should support users to achieve self-efficacy. Each user has an attractive reputation model, which can be built and enhanced further with the growing reputation. The growing process should be dynamic and be expressed in real time with the assistance of the time dimension. Secondly, the reputation of users should be easily recognized that there is a common criteria for reputation comparison. Thirdly, the visualization should support micro and macro reading. It refers to that user’s overall reputation value can be easily identified. The details of user’s reputation, such as reputation of specific product categories or characteristics, should be displayed clearly.

4) Decision Making: Since a large number of sellers provide many similar products, it may take a lot of time for buyers to browse and search for the most suitable sellers. Our reputation mechanism will provide recommendations to buyers according to the computed reputation of sellers as well as buyers’ preferences. For example, some risk-taking buyers may prefer low price of products and be willing to do business with sellers who have relatively low reputation. Some other buyers may care more about sellers’ reputation.

B. User study

In this section, we present a user study on comparing our proposed reputation mechanism with traditional reputation mechanisms in the same environment of virtual marketplaces. Since reputation computation and decision making are invisible to users, our study is concentrated on the feedback provision and reputation representation components.

1) Design of the Study: The comparison was based on two criterions. One is called “institutional trust” referring to user’s trust in the mechanism, while the other is called “interpersonal trust” referring to 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 [22]. Based on this guidance, a questionnaire survey is conducted. Figure 2 presents the overall structure of the questionnaire. The questionnaire is divided into two main parts: context

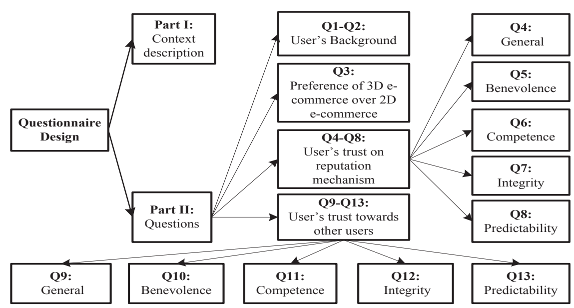

Fig. 2: Questionnaire Design for Data Collection

description part, which provides users the detailed description of our reputation mechanism and traditional reputation mechanism within virtual marketplaces; and questions part, consisting of 13 questions in total. In the context description, participants are presented with a set of images about what they will experience in the virtual marketplaces with our proposed reputation mechanism and that with the traditional reputation mechanisms. Besides, one researcher is responsible for the Q&A part in the process of questionnaire filling. Regarding the questions, Q1 and Q2 ask for the information of participant’s background, including gender, age, nationality, current residency and online shopping background; Q3 aims to study user’s preferences on virtual marketplaces versus traditional e-commerce; Q4-Q8 focus on studying user’s trust on reputation mechanisms, referring to general trust, benevolence, competence, integrity and predictability of reputation mechanism respectively. Some examples are “Do you agree that compared with traditional reputation mechanisms, the proposed reputation mechanism provides you with more confidence in believing that virtual marketplaces is well-organized and the stores are benevolent to their customers?” and “Do you agree that the proposed reputation mechanism performs better in reducing fraud behaviors than traditional reputation mechanisms?”; Q9-Q13 try to explore user’s trust in other users with the reputation mechanisms, and the structure is

TABLE I: Statistical Information about the Participants

	Gender		**Nationality**		**Current Residency**		**Often Shopping Site**			**Technology Background**		**Age Diversity**					**Attitude of Virtual Marketplaces**		
	Male	Female	Asian	American	Asia	America	Taobao	Amazon +eBay	Others	Yes	No	18-21	22-23	24	25-26	27	Positive	Neutral	Negative
Counts	21	19	24	16	21	19	16	17	7	14	26	3	14	11	11	1	26	9	5
Percents	52.5%	47.5%	60%	40%	52.5%	47.5%	40%	42.5%	17.5%	35%	65%	7.5%	35%	27.5%	26.5%	2.5%	65%	22.5%	12.5%

TABLE II: Data Analysis

(a) User Evaluation of our Reputation Mechanism over Traditional Reputation Mechanisms

Dimension		Positive		Neutral		Negative	
		Counts	Percents	Counts	Percents	Counts	Percents
User's trust in mechanism	General	29	**72.5**%	3	7.5%	8	20%
	Benevolence	24	**60**%	8	20%	8	20%
	Competence	27	**67.5**%	10	25%	3	7.5%
	Integrity	17	**42.5**%	11	27.5%	12	30%
	Predictability	23	**57.5**%	8	20%	9	22.5%
User's trust in other users	General	23	**57.5**%	8	20%	9	22.5%
	Benevolence	20	**50**%	7	17.5%	13	32.5%
	Competence	25	**62.5**%	6	15%	9	22.5%
	Integrity	16	**40**%	12	30%	12	30%
	Predictability	27	**67.5**%	8	20%	5	12.5%

(b) Comparison of People's Attitude towards our Reputation Mechanism over Traditional Reputation Mechanisms in Asia and America

Dimension		Positive		Neutral		Negative	
		Asia	America	Asia	America	Asia	America
User's trust in mechanism	General	90.4%	52.6%	0%	15.8%	9.5%	31.6%
	Benevolence	76.2%	42.1%	14.3%	26.3%	9.5%	31.6%
	Competence	76.2%	57.9%	14.3%	36.8%	9.5%	5.3%
	Integrity	61.2%	**21.1**%	19%	36.8%	19%	**42.1**%
	Predictability	57.1%	57.9%	23.8%	15.8%	19%	26.3%
User's trust in other users	General	66.7%	47.4%	23.8%	15.8%	9.5%	36.8%
	Benevolence	57.1%	42.1%	19%	15.8%	23.8%	42.1%
	Competence	76.2%	47.4%	14.3%	15.8%	14.35%	31.6%
	Integrity	42.8%	36.8%	33.3%	26.3%	23.8%	36.8%
	Predictability	85.7%	47.4%	9.5%	31.6%	4.8%	21.1%

similar to Q4-Q8. The answers for each question can be chosen from the following five levels: "5-Totally agree", "4-Partially agree", "3-Neither Agree nor Disagree", "2-Partially disagree" and "1-Totally disagree".

A total of 40 subjects with the average age of 24 years old participated in the study. They were selected based on the stratified random sampling methods with respect to their gender and current residency. 21 of them are males. 21 of them are currently living in Asia, and 19 of them in America. Besides, all of them are experienced Internet users, but only 14 of them are within technology background, while 26 of them with the background of social science, management or related. 38 of them have purchased products online at least once a year, while 30 of them at least twice a year. The e-commerce systems they went shopping most often are Taobao (www.taobao.com), Amazon and eBay. One point should be emphasized here is that since the virtual marketplaces is quite revolutionary, this study mainly focuses on the young generation mostly within the age of 22 years old to 26 years old, who are believed to be the major participants of virtual marketplaces. The basic statistical information about the participants is summarized in Table I. In addition, 26 (65%) of participants prefer virtual marketplaces over traditional e-commerce, while only 5 of them are willing to stay at traditional e-commerce sites, and 9 of them hold neutral attitude.

2) Data Analysis and Discussion: In order to comprehensively compare our proposed reputation mechanism with traditional reputation mechanisms, we explore these 40 participants' evaluation towards the four perspectives of trust typology with respect to both their trust in the reputation mechanism (Institutional trust) and their trust in other users (Interpersonal trust). For Q4-Q13, the answers of "Totally Agree" or "Partially Agree" is treated as positive evaluation of our proposed reputation mechanism, "Neither Agree nor Disagree" as neutral evaluation, and "Partially Disagree" or "Totally Disagree" as negative evaluation. Table II(a) presents the participants' specific evaluations (positive, neutral or negative) of each perspective concerned with each kind of trust regarding our reputation mechanism compared to those of conventional reputation mechanisms.

User's Trust in the Mechanism: According to the results in Table II(a), to sum up, most (72.5%) of the participants show stronger (institutional) trust in virtual marketplaces with our reputation mechanism than that with the traditional reputation mechanisms. In most of the participants' belief, our proposed reputation mechanism performs better in reducing fraud behavior (competence), provides them more confidence to believe in the virtual marketplaces (benevolence), and virtual marketplaces with our proposed reputation mechanism has greater possibility to achieve success (predictability) in the fierce competition.

User's Trust in Other Users: For the interpersonal trust, compared to traditional reputation mechanisms, users mostly hold a positive attitude towards our reputation mechanism. They are more confident that other users in our reputation mechanism are more trustworthiness (57.5%), while sellers will not only care more about buyers (50%) and more likely meet the quality requirement of the products as expected (62.5%), but also be more consistent with their behavior (67.5%) over time.

What should be noted is the integrity perspective both for institutional trust and interpersonal trust. Integrity refers to that sellers always provide high quality products and buyers always give truthful feedback. The integrity values of this study, although still positive, are relatively smaller (42.5% and 40%) compared to others, partly indicating that users worry about online shopping. Through interviewing the participants who expressed negative or neutral attitude towards our reputation mechanism, we found that they were just reluctant to use virtual marketplaces based on the technology limitations, but had less concern about reputation mechanisms.

Cultural Differences: In addition, based on the user evaluation, the cultural differences between subjects living in Asia (mostly living in Singapore) and subjects living in America was also evaluated and the result was shown in Table II(b). It demonstrates that, on the whole, both of them prefer our proposed reputation mechanism over traditional reputation mechanism, regarding the positive percents and negative percents. However, it should also be noted that people living in Asia generally hold much more confident of our proposed reputation mechanism than people living in America. This can be explained that virtual reality has been greatly developed in Singapore and has many realistic applications, such as Virtual Singapore (http://www.singaporevr.com/) and 3D Virtual World for 2010 Youth Olympic Games (http://www.singapore2010odyssey.sg/), while for America, it has profound and mature development of traditional e-commerce websites, such as Ebay and Amazon, and the applications of virtual marketplaces are relatively weak compared to those in European and some Asian countries. More cultures diversity, especially the attitude of people living in European, should be included in the further research.

IV. Feedback Alignment

In this section, we describe our feedback alignment approach. In this approach, each buyer in virtual marketplaces is assisted by a software agent and equipped with virtual reality simulators. As shown in Figure 3, a *concept learner engine* is attached to the agent, by which it can learn the semantics of its buyer's subjective terms in a shared vocabulary [23]. The agent learns the semantics of these subjective terms over time by exploiting the correlation between the subjective terms provided by its buyer and the corresponding sensory data simulated by virtual reality tools (*e.g.*, haptic tools) for products avatars. The semantic metrics in Definition 1 are specified in the form of fuzzy membership functions and shared with the agents of other buyers. Thus, the feedback communicated among agents will be composed of only objective terms and semantic metrics. This allows the agent to clearly interpret feedback provided by other buyers and transform it into its own buyer's subjective terms. Then, based on its buyer's preferences, the agent can estimate the degree of satisfaction for the buyer based on the past transactions reported by other buyers (advisors). In the next sections, we will describe our subjectivity alignment approach in more details and conduct experiments to validate its effectiveness in computing reputation of sellers.

Definition 1: A semantic metric is an objective metric that models the correlation between subjective term and corresponding objective sensory data ▮

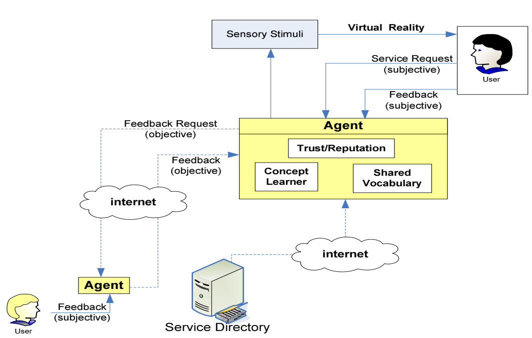

Fig. 3: An Overview of Feedback Subjectivity Alignment

A. Subjectivity Alignment

The agent of a buyer is responsible for modeling semantics of the subjective terms in its buyer's vocabulary. Here, through virtual reality simulators, the subjective terms of buyers are learned and mapped onto corresponding values of objective sensory data that are numeric in our system. The learning is an iterative process that requires sufficient interactions data between the agent and its buyer in order to obtain relatively precise mapping metrics. A basic learning unit is as follows: The agent provides a sensory stimuli to its buyer, and the buyer percepts the stimuli and provides to the agent a corresponding subjective term (*e.g.*, too soft) that best presents his perception in his vocabulary. The learning is also a continuous procedure because the perception of a buyer may change over time. For example, a buyer may become less sensitive to *tactile stimulus* as he gets older. Thus, the learned metrics should be updated regularly after a certain time interval.

Furthermore, in reality, it is common that human users cannot present their perceptions consistently. That is, more than two different but similar subjective terms may be provided by the same user for the same objective sensory data as he has some fuzzy sensory zones. Hence, to better and more precisely specify mapping metrics, we introduce the *trapezoidal membership function* with pseudo partitioning [24], ranging in the unit interval $[0, 1]$, to represent the degree of truth, μ (See Equation 1), for the subjective terms. Here, 1 indicates the full membership of a given subjective term, referring that a user is completely confident about his perception. If the degree of truth is between $(0, 1)$, the user might sometimes describe his perception using this subjective term, and at other times use other terms in his vocabulary due to the perception sensitivity.

$$\mu(x) = \begin{cases} 0 & : \quad x \leq a, x \geqslant d \\ \frac{x-a}{b-a} & : \quad a < x \leq b \\ 1 & : \quad b < x \leq c \\ \frac{d-x}{d-c} & : \quad c < x < d \end{cases} \tag{1}$$

where a, b, c and d refer to the four transition points of trapezoidal membership function respectively; $x \in X$ (universe of discourse, *i.e.*, the value range of objective sensory data). Example 1 involves the subjective attribute *softness* to demonstrate the semantic metrics of a user.

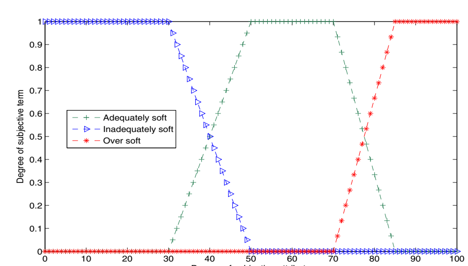

Fig. 4: Membership Functions for Example 1

Example 1: A user describes his touching experience in subjective terms such as *adequatly soft*, *inadequately soft* and *over soft*. To be specific, the sensory data of *softness* is assumed to be in the range of [0,100], where 0 means its minimum value and 100 the maximum value. Through the *Concept Learner Engine*, the agent of the user learns his semantic metrics of subjective terms related to the subjective attribute *softness*, as shown in Figure 4. For *inadequately soft*, *adequately soft* and *over soft*, three corresponding trapezoidal membership functions are constructed, and "30", "50", "70", "85" are the transition points.

After learning the semantic metrics for its own user's subjective terms and sharing the learned results with the agents of other users, the agent can then align other users' feedback according to its user's subjectivity. For feedback alignment, the following two different scenarios should be considered.

Scenario 1: If objective sensory data is available in the feedback provided by another buyer (advisor), the agent of the buyer who receives the feedback can directly map the sensory data to corresponding subjective terms based on the learned semantic metrics of its buyer. The agent first calculates truth degrees as the buyer's perceiving strengths of different subjective terms, according to Equation 1. The subjective term with the highest truth degree is chosen as the dominating perception of the buyer according to the feedback.

Scenario 2: If, for subjective attributes, only subjective terms are available in the advisor's feedback. The agent computes the similarity [25] between the learned semantic metric of each of its buyer's subjective term and that of the subjective term provided in the feedback. The subjective term with the highest similarity is considered as the buyer's perception. For example, both users A and B have different semantic metrics for the subjective terms in Example 1. Considering the case where A provides the feedback of "adequately soft" to B. The agent of A translates "adequately soft" into the objective semantic metric for "adequately soft" and shares with B the feedback after this translation. B's agent computes the similarity [25] between A's semantic metric of "adequately soft" with B's three semantic metrics for softness, *i.e.*, similarity between membership functions (See Equation 2). The subjective term of B which has the highest similarity value with A's semantic metric for "adequately soft" is considered to be B's estimated perception according to A's feedback. Thus, the feedback from A is aligned according to B's own subjectivity.

$$s(\tilde{A},\tilde{B}) = 2 - d((\tilde{A}\cap\tilde{B}),[1]) - d((\tilde{A}\cup\tilde{B}),[0]) \quad (2)$$

where $\tilde{A}$ and $\tilde{B}$ refer to user A and user B's semantic metrics respectively; d is the hamming distance between two fuzzy sets. For the fuzzy sets X_1 and X_2, $d(X_1,X_2) = \frac{1}{n}\sum_{i=1}^{n}|\mu_{X_1}(x_i) - \mu_{X_2}(x_i)|$ where $x_i \in X$ (universe of discourse) and $X = \{x_1, x_2, \cdots, x_n\}$; $\tilde{A}\cap\tilde{B}$ and $\tilde{A}\cup\tilde{B}$ correspond to fuzzy *MIN* and *MAX* operation.

B. Evaluation

We implement simulations to measure the accuracy of our approach in computing reputation of sellers, compared with the benchmark approach without the subjectivity alignment.

1) Simulation Environment: In our simulations, the characteristics of sellers and buyers are generated as follows. First, sellers provide products represented by three dimensions, namely, D_A, D_B, D_C with ranges presented in Table III. Each seller provides products within a subset of the ranges defined in Table III and provides product within this subset. A set of buyers provide ratings for the sellers according to their subjectivity. The buyers' subjectivity is set in the form of *trapezoidal membership function* towards each dimension of products, *i.e.*, each buyer has three membership functions. Specifically, four parameters (*i.e.*, transition points) are set for each function. Based on their subjectivity, the buyers provide a rating "1" or "0" for each dimension of the provided product. For each transaction, we compute the average of ratings on the three dimensions to obtain the satisfaction degree for the whole transaction. Finally, the reputation (in the range of $[0, 1]$) of the seller is modeled by computing the average satisfaction degree of the collected feedback.

TABLE III: Dimensions of the Product and their Ranges

Dimension	Type	Ranges
D_A	Double	20-90
D_B	Double	30-120
D_C	Double	40-200

Our simulation involves 60 sellers and 60 buyers. Different sellers can provide products in the same or similar quality, and different buyers can have the same or similar subjectivity. We define that each buyer previously has had 50 interactions with each seller, and consider the reputation computed from a buyer's own experience as the grounded truth of the target seller's reputation, r_t. Besides, we model reputation r based on other buyers' feedback without alignment in the benchmark approach, and r_a with alignment in our approach. Then, we compute the mean absolute error (MAE) of r and r_a compared to the ground truth r_t respectively according to Equations 3 and 4. We randomly conduct the simulation for 20 times.

$$MAE_{Aligned} = \frac{\sum_{i=1}^{60}\sum_{j=1}^{60}(|r_{a,i,j} - r_{t,i,j}|)}{60 \times 60} \quad (3)$$

$$MAE_{Benchmark} = \frac{\sum_{i=1}^{60}\sum_{j=1}^{60}(|r_{i,j} - r_{t,i,j}|)}{60 \times 60} \quad (4)$$

2) Experiment Results: Figure 5 shows the comparison results of MAEs in computing reputation value of sellers in our simulation. We can see that our subjectivity alignment approach performs better than the reputation computation approach without subjectivity alignment. It verifies that our subjectivity alignment approach can help buyers to more accurately and stably model sellers' reputation. To validate the reliability of our result, we conduct other simulations by varying the number of sellers, the number of buyers, the number of interactions or the ranges of dimensions respectively in simulation settings, and we still can attain the similar result.

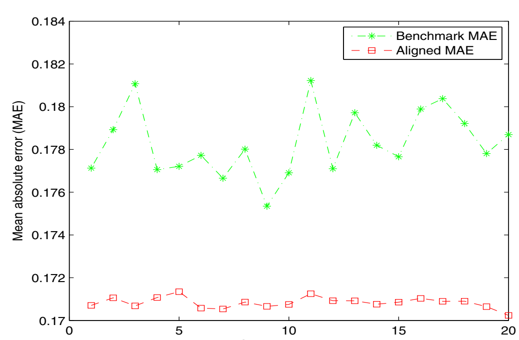

Fig. 5: MAE in Computing Reputation of Sellers

V. Conclusion and Future Work

This paper proposes a reputation mechanism for virtual marketplaces by systematically studying the four steps of constructing reputation mechanisms, namely, feedback provision, reputation computation, reputation representation and decision making. We incorporate novel elements of 3D technology and virtual reality into these steps. One major contribution of our work is a five-sense orientated approach for buyers to provide their feedback of products they have purchased in the form of five human senses simulated by virtual reality. A user study is conducted to compare our mechanism with traditional reputation mechanisms in virtual marketplaces environments. The findings illustrate that: (a) users prefer shopping in virtual marketplaces with our proposed reputation mechanism over that with traditional reputation mechanisms; (b) compared with traditional reputation mechanisms, our reputation mechanism can not only effectively ensure user's trust in the mechanism, but also greatly promote user's trust in other users. Another major contribution of our work is to address the subjectivity involved in buyers' feedback by proposing a novel approach to align subjectivity for reputation computation. It takes advantages of various virtual reality simulators in human users' five sense. We demonstrate how sensory data in virtual reality can be exploited in virtual marketplaces to handle subjectivity in user feedback and how the aligned feedback can be used in seller reputation computation. More specifically, the agent of each user is responsible for learning the subjective terms in its user's vocabulary, by mapping each subjective term into corresponding objective semantic metric. The semantic metrics are specified in the form of the trapezoidal membership function. The experiments demonstrate that buyers can more accurately and stably model sellers' reputation with our proposed approach.

Our current work represents an important initial step for confirming the necessity and value of our proposed reputation mechanism. For future work, we will develop a specific reputation computation method for our reputation mechanism and implement a 3D visualization scheme for reputation representation. A prototype of our reputation mechanism will be built to further study user's responses to virtual marketplaces with our proposed reputation mechanism. We will conduct more comprehensive user study, considering age diversity, shopping background and cultural differences. Besides, we will also conduct more experiments to compare our subjectivity alignment approach with other competing approaches.

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