Reputation Mechanism for E-Commerce in Virtual Reality Environments

Hui Fang[a,*], Jie Zhang[a], Murat Şensoy[b], Nadia Magnenat-Thalmann[a]

[a]*School of Computer Engineering, Nanyang Technological University, Singapore*
[b]*Computer Science, Ozyegin University, Turkey*

Abstract

The interest in 3D technology and Virtual Reality (VR) is growing both from academia and industry, promoting the quick development of virtual marketplaces (VMs) (*i.e.* e-commerce systems in VR environments). VMs have inherited trust problems, *e.g.* sellers may advertise a perfect deal but doesn't deliver the promised service or product at the end. In view of this, we propose a five-sense feedback oriented reputation mechanism (supported by 3D technology and VR) particularly for VMs. The user study confirms that users prefer VMs with our reputation mechanism over those with traditional ones. In our reputation mechanism, five-sense feedback is objective and buyers can use it directly in their reputation evaluation of target sellers. However, for the scenarios where buyers only provide subjective ratings, we apply the approach of subjectivity alignment for reputation computation (SARC), where ratings provided by one buyer can then be aligned (converted) for another buyer according to the two buyers' subjectivity. Evaluation results indicate that SARC can more accurately model sellers' reputation than the state-of-the-art approaches.

Keywords: Virtual Reality Environments, Reputation Systems, E-marketplaces, Five Senses, Subjectivity Alignment

1. Introduction

The Internet has become an inseparable part of our daily life nowadays. According to the Internet World Stats[1], the number of Internet users worldwide has reached 1.97 billion by the end of September 2010, accounting for almost 30 percent of the global population. Consequently, people are becoming more willing to shop online other than going to traditional solid shops. Unfortunately, current e-commerce systems only provide users with a simple, browser-based interface to acquire details of products and services. This kind of interfaces has been confirmed to be difficult for customers to use, and thus resulted in the low online shopping revenue (Hoffman et al., 1999; Qiu and Benbast, 2005). One reason is the lack of effective interaction approaches, including communication channels and coordination methods between e-commerce systems and customers. Another more important reason is the limited understanding of social contexts, including social and behavioral issues, among which trust is one of the most important ones. Besides, the design of current e-commerce systems is quite constrained and not appealing.

On another hand, 3D technology is gaining popularity. Forrest report (Drive, 2008) acclaims 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" (Gaudin, 2010). Meanwhile, applications of virtual reality, such as immersing in 3D virtual communities, watching 3D movies and playing 3D games, are becoming part of ordinary life for people. As one of the important applications of virtual reality, virtual marketplaces (VMs) are referred to as the environments where virtual reality is

---

[*]Corresponding author. Address: Institute for Media Innovation, 50 Nanyang Drive Research Techno Plaza, XFrontiers Block, Level 03-01, Singapore 637553. Tel.:+65-93734538; fax.:+65 63162994

Email address: `hfang1@e.ntu.edu.sg` (Hui Fang)

[1]http://www.internetworldstats.com/stats.htm

used by sellers to virtually present their products or service in VR environments, and 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 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 (Mass and Herzberg, 1999), Second Life (secondlife.com), Active World (activeworlds.com), Twinity (twinity.com) and Virtual Shopping (virtualeshop-ping.com), etc.

Compared with traditional e-commerce environments, VMs have advanced characteristics such as stereoscopic 3D visualization, real-time interactivity, immersion and multisensory feedback (Stanney et al., 1998; Price et al., 2013), which make them more similar to realistic worlds. However, the same as traditional e-commerce systems, since buyers can only inspect products after purchased, there are also inherited trust problems for VMs. 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. (2010), 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 VMs 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 VMs (Huang et al., 2008) apply traditional reputation

mechanisms where only simple numerical ratings, textual descriptions and 2D pictures are considered. They overlook the difference between traditional and VM environments.

To effectively address the trust issues in VMs, we design a five-sense oriented feedback provision approach (Fang et al., 2011) especially for reputation mechanisms in VM environments. It is mainly built on buyers' feedback about their shopping experience with sellers and their subjective perceptions (*e.g.*, ratings) about products delivered by them. More specifically, in VMs, these kinds of feedback information can come from human users' five senses enriched by virtual reality, namely, *vision*, *sound*, *touch*, *taste* and *smell*. For example, with the assistance of haptic devices (*e.g.*, virtual glove), a buyer can render a virtual teddy bear with its objective *softness* information to represent his purchased real teddy bear, instead of describing it as *very soft* in text, and thus other buyers can percept the virtual teddy bear directly to assist their shopping decision making. We then conduct a detailed user study to compare our mechanism with traditional reputation mechanisms in VMs. The comparison was 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 (McKnight and Chervany, 2001). A questionnaire survey on 40 subjects is conducted. The results confirm that users prefer VMs 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.

In our reputation mechanism, five-sense feedback is objective and buyers can use it directly in their reputation evaluation of target sellers. However, there may be some scenarios that users are reluctant or inconvenient (*e.g.*, the lack of virtual reality devices) to provide the detailed five-sense feedback, but to provide a rating (or a rating for each

of the five senses) about their past experience. The ratings concluded from human users'
five senses may involve users' own subjectivity. Subjectivity difference may come from
two sources if we analyze the scenario of a buyer providing a rating from both psycho-
logical and behavioral perspectives:

Intra-attribute Subjectivity When the buyer evaluates her satisfaction level with
a transaction, she considers each attribute related to that transaction. Although the in-
formation about each attribute is *objective*, the evaluation (*i.e.*, satisfactory level) of the
attribute value may be subjective and change from user to user. This is referred to as
intra-attribute subjectivity in this paper. For example, a product may be *inadequately
soft* for buyer a, while *adequately soft* for buyer b.

Extra-attribute Subjectivity When the buyer assigns a satisfaction level to a trans-
action, she may consider some attributes of the transaction more heavily than others.
This is referred to as *extra-attribute subjectivity*. For example, a buyer with better eco-
nomic 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.

The definitions and differences of these two kinds of subjectivity can be summa-
rized as follows: 1) intra-attribute subjectivity: users' subjectivity in evaluating the
same attribute; 2) extra-attribute subjectivity: users' subjectivity in evaluating different
attributes. These two aspects together contribute to the subjectivity difference among
buyers. Due to the subjectivity difference, it may not be effective if a buyer directly
takes other buyers' subjective ratings towards a seller and aggregates the ratings to com-
pute the reputation of the seller. Otherwise, the computed reputation values may then
mislead the buyer in selecting business partners.

To effectively address the subjectivity difference problem, we propose a subjectiv-
ity alignment approach for reputation computation (SARC) (Fang et al., 2012). In our
approach, each buyer is equipped with an intelligent (buying) agent and virtual reality

5

simulators. At the beginning of her interactions with the reputation system, a buyer a is required to provide her buying agent with both a single rating and a detailed review[2] containing values of the objective attributes of transactions with sellers, such as *price* and *softness*[3], for each of a few transactions. Based on these rating-review pairs, the buying agent applies a proposed Bayesian learning approach to model the correlations between buyer a's each rating level and the value of each objective attribute involved in the transactions. The learned correlation function, which represents buyer a's *intra-attribute subjectivity*, will then be shared with the agents of other buyers. The agent of buyer a also applies a regression analysis model to learn the weight of each attribute for buyer a, representing her *extra-attribute subjectivity*. This information will not be shared with other buyers. After the learning phase, buyer a only needs to provide ratings for her interactions with sellers, not detailed reviews. When another buyer b just shares a new rating (without detailed reviews) of her transaction with a seller (buyer b is acted as an advisor in our context), the agent of buyer a will first retrieve a rating level for each attribute of the transaction based on the shared rating and the *intra-attribute subjectivity* of buyer b shared by the agent of b. The rating levels of the attributes will then be aggregated according to buyer a's *extra-attribute subjectivity* learned by the agent of a. In this way, the rating shared by buyer b is aligned to that can be used by buyer a for computing the reputation of the seller. To evaluate the performance of our SARC approach, we simulate a virtual marketplace environment involving a number of buyers with different subjectivity in evaluating products and a set of sellers selling products with different attribute values. Experimental results confirm that our SARC approach provides sufficiently good performance in a general setting. It can more accu-

---

[2]The review can consist of both textual information and rendered virtual objects with corresponding five-senses information.

[3]Value of objective attributes related to touch, smell or taste sensory like softness are provided by virtual reality simulators automatically in the form of virtual stimuli.

rately and stably model sellers' reputation than the representative competing approaches of BLADE (Regan et al., 2006) and TRAVOS (Teacy et al., 2006).

The rest of this paper is organized as follows. In Section 2, we summarize the related research in the literature. In Section 3, we elaborate our proposed reputation mechanism for VMs in details, and present the user study of comparing our mechanism with traditional reputation mechanisms in VMs environments. In Section 4, we address the subjectivity difference problem for virtual marketplaces and propose our SARC algorithm. Finally, we conclude our work in Section 5.

2. Related Work

In this section, we provide an overview of related research on the trust issue and reputation mechanisms in VMs as well as the existing approaches for dealing with the subjectivity difference problem in reputation computation, clearly point out the shortcomings of these approaches, and explain how we cope with those shortcomings in our SARC approach.

2.1. Trust Issue in Virtual Marketplaces

There are mainly two research directions on VMs. The first direction concerns about adopting 3D technology and VR into e-marketplaces, i.e. the construction of VMs. This is also currently the major research towards VMs. For example, Bogdanovych et al. (2005) propose a mechanism called 3D E-Commerce Electronic Institutions which tries to increase user's trust on e-marketplaces systems. The second direction mainly concerns about validating the effectiveness of VMs in addressing the problems of traditional e-marketplaces, one of which is the trust issue. Mennecke et al. (2008) indicate that security and trust are key enablers for virtual worlds. They also insist that development of trust is one of the ten most important issues in the virtual world environments like virtual

7

marketplaces. Besides, Gajendra and Sun (2010) point out that privacy and trust should be maintained for encouraging face to face meeting, which is regarded as a significant advantage for virtual world environments.

Compared to traditional e-marketplaces, Papadopoulou (2007) demonstrates that a virtual reality shopping environment enables the formation of trust over conventional web stores, through a questionnaire-assisted survey study on a prototype virtual shopping mall of Active World. Nassiri (2008) explains the roles of virtual environments in increasing user's trust and improving profitability via the ways such as Avatar appearance and Haptic tools. Through a field study, Qiu and Benbast (2005) demonstrate that the technology like text-to-speech voice can significantly increase both consumers' emotional trust and cognitive trust towards consumer service representatives in transactions and live help interface. The research conducted by Teoh and Cyril (2008a,b) mainly focuses on the trust of 3D mall. They point out that presence and para-social presence assisted by virtual reality can affect trust, and users perceive the features of an immersive shopping store in virtual marketplaces as being useful and practical other than as merely novel. They also indicate that gender and ethnicity can affect users' trust towards VMs. Shin and Shin (2011) explore the effect of social presence on perceived trust, perceived risk and intention in virtual shopping malls as well as their pairwise relationships. The findings imply that social presence assisted by virtual reality is a key behavioral antecedent to using virtual malls, and user perception of security and trust is a focal feature of user attitude to VMs.

The weakness of the aforementioned research is that they focus only on enhancing trust through virtual reality and 3D technology. They do not consider how to improve trust in virtual marketplaces by designing effective trust and reputation mechanisms, since the difficulties of establishing trust may due to the salient characteristics of trustworthiness, such as largely experiential and greatly dependent on past experience (Men-

necke et al., 2008). By testing 20 well-known companies in Second Life on the basis of a four-dimensional measurement framework, Mackenzie et al. (Mackenzie et al., 2009) find that there is a challenge for business in virtual marketplaces to establish trust and attain authenticity and confidentiality. Thus, that to design an effective reputation mechanism to manage trust for virtual marketplaces is the focus of our current work.

2.2. Reputation Mechanisms

The VMs allow their users to select services and products among a wide range of possibilities. However, as the number of these possibilities increases, it becomes harder to make a selection. For instance, the same product is offered by a wide range of sellers with different prices and conditions in VMs. VMs are open in the sense that some sellers may leave and new ones may join. Since it is not possible to have experience with each of these sellers, a buyer could suffer from lack of knowledge about the sellers while making decisions. If a seller is dishonest, it could advertise a perfect deal but does not deliver the promised service or product at the end. Therefore, there is a significant risk for a buyer when selecting a seller among many alternatives in such uncertain and open environments.

To address these issues, various mechanisms such as reputation systems have been proposed. These mechanisms allow buyers to model trustworthiness of sellers and distinguish honest sellers from malicious ones. Such mechanisms also create incentives for sellers to be honest and remain so. In reputation systems (Resnick and Zeckhauser, 2002a; Bharadwaj and Al-Shamri, 2009), buyers who previously bought products from a seller share their experience, normally in the form of numerical ratings reflecting the level of satisfaction for the transactions with the seller. These ratings are aggregated to represent the seller's reputation. Other buyers can rely on the reputation value to make decisions on which sellers to do business with. Reputation systems are particularly use-

ful for buyers who have no or very little experience with sellers.

In recent years, lots of research has been carried out on reputation mechanisms (Jøsang and Ismail, 2002; Teacy et al., 2006; Resnick et al., 2000; Resnick and Zeckhauser, 2002a; Chang and Wong, 2011; Liu et al., 2013) in traditional e-marketplaces, and have achieved a huge success, while one of the well-known reputation systems is run by eBay (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. Previously, it owned some obvious drawbacks, such as always positive feedback (less distinguishable), reciprocal buyers and sellers, and not easy for trust prediction (Resnick and Zeckhauser, 2002b). However, as it grows mature, the eBay market rewards higher reputation value to those sellers who have accumulated a lot of positive feedback. The reputation system exhibits great robustness and seller's reputation is positively correlated with products' price (Resnick et al., 2006). There are other successful commercial and live reputation systems (Josang et al., 2007), such as expert sites like Askme (askmecorp.com) and Advogate (advogato.org), products review sites like Epinions (epinions.com) and Amazon (amazon.com), Discussion Forums like Slashdot (slashdot.org), Google's web page ranking system, supplier reputation systems and scientometrics related sites.

However, there are only a few studies on designing reputation mechanisms specifically for virtual marketplaces. Huang et al. (2008) 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 earned 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 traditional e-marketplace environments and VM environments.

10

In contrast, our reputation mechanism makes good use of virtual reality to allow the provision of feedback information from human user's five senses.

2.3. Subjectivity Alignment in Reputation Mechanisms

Quite a lot of filtering approaches have been proposed to address the problem of subjectivity difference among buyers or unfair ratings intentionally provided by dishonest buyers to mislead other buyers (Brennan et al., 2010; Yu and Singh, 2003; Whitby et al., 2004; Noorian et al., 2011; Teacy et al., 2006; Zhang and Cohen, 2008). For example, some of the approaches filter out the ratings of some buyers (advisors) whose past ratings differ significantly from the ratings of all advisors (Whitby et al., 2004), the ratings of a particular buyer (Noorian et al., 2011; Teacy et al., 2006), or the ratings of both (Zhang and Cohen, 2008). From the perspective of behavioral modeling, Noorian et al. (2011) propose a two-layered cognitive approach to filter or discount the ratings provided by others. The ratings are discounted or filtered according to the rating similarity between the user and the advisor as well as the behavior characteristics of them. These filtering approaches generally suffer from the risk of losing or discounting some important information. Our SARC approach does not filter or discount ratings provided by an advisor with different subjectivity. Instead, our approach aligns/converts the ratings of the advisor to those that can be directly used by buyers according to the buyers and advisor's subjectivity learned by their agents.

Some other alignment approaches have also been proposed to align advisors' advice about the trustworthiness of sellers (Koster et al., 2010; Regan et al., 2006). For example, Koster et al. (2010) propose a trust alignment approach based on the general framework of Channel Theory. The BLADE approach of Regan et al. (2006) applies Bayesian learning to model sellers' properties and the correlations between sellers' properties and buyers' ratings. Once a buyer receives a rating from an advisor, she can infer

11

back the target seller's properties, and then compute the rating of her own towards the seller on the basis of the inferred properties of the target seller. One shortcoming of these alignment approaches is that they ignore the intra-attribute subjectivity difference among buyers. Another shortcoming is that they require the buyer and the advisor to have interacted with a set of same sellers (shared interactions), which may not be the case in an e-commerce environment with a large population of sellers. In contrast, our SARC approach does not rely on shared interactions. Instead, the agent of each buyer makes use of the ratings and detailed reviews provided by the buyer about her transactions with any sellers, to learn the buyer's intra-attribute and extra-attribute subjectivity.

Another approach that also requires buyers to provide detailed reviews of their transactions with sellers to address the subjectivity difference problem is the POYRAZ approach of Şensoy et al. (2009). The POYRAZ approach models the reputation of sellers on the basis of detailed reviews containing values of the objective attributes of transactions with sellers, rather than numerical ratings. However, this approach requires buyers to always provide a detailed review for each transaction with sellers, which is time-consuming and tedious. In contrast, our SARC approach requires buyers to provide detailed reviews at the beginning of interacting with the reputation system. Afterwards, detailed reviews are required only once a while if need to update the learned subjectivity of buyers. We will carry out experiments in Section 4.3 to show that with limited number of detailed reviews, our approach is still able to perform effectively.

In conclusion, previous research demonstrates that VMs can encourage trust formation over traditional e-marketplaces from the behavioral and technology innovation perspective, and ignores to consider how to design an effective mechanism (*i.e.*, reputation mechanism) particulary for VMs to resolve the major difficulties in trust establishment. Thus, we try to design a reputation mechanism for VMs on the basis of reputation source information enriched by VR and 3D technology. To deal with the subjectivity problem

12

in reputation computation, collaborative filtering tools may suffer from the risk of losing or discounting some important information. Besides, both the collaborative filtering and trust alignment models need shared interactions. Although the review-based reputation mechanisms can partly deal with subjectivity problem in trust modeling, they place a responsibility for users to provide detailed reviews, which is quite time-consuming and tedious for users.

3. Reputation Mechanism For VMs

In this section, we first propose our reputation mechanism particularly for VMs by exploring their characteristics, and then conduct a user study to evaluate the necessity and value of our proposed reputation mechanism.

3.1. The Five-sense Oriented Reputation Mechanism

As summarized in the related work, current research focuses mainly on VR and 3D technology adoption. Limited research on reputation mechanisms for VMs however overlooks the differences between traditional and VM 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 VM environments. Its major component is the five-sense oriented feedback provision supported by virtual reality and 3D technology, details of which will be explained as follows.

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. virtual marketplace is a virtual environment generated by computer and other tools, such as head-mounted displays, headphones, and motion-sensing gloves, to enable users to feel realism through interaction that simulates five human senses. In traditional e-marketplaces 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 perception of human users not only can be realistically simulated, but also can be expanded by using instruments like 3D Glasses.

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 (Pai et al., 2001). We have previously done some research on touching textile (Magnenat-Thalmann et al., 2007). 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. (2004) 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 (Brkic and Chalmers, 2010). 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.

The Enabled Technologies of Five Senses Virtual Reality has been striving to create a virtual environment that enables users to feel realism through interaction that stimulates the aforementioned five senses (Price et al., 2013). VR can mimic these senses, through devices employed in human-computer interaction, with various degrees of fi-

15

delity. A wide range of hardware and software is available for the creation of VR simulations. These simulators have ability to syntheses *visual*, *tactile*, *sound*, *taste* and *smell* information. Accordingly, there are five types of sensory stimulus rendered to users in Virtual Reality. On the other hand, of all the five senses, technologies to enable vision, sound, and touch have been more maturely developed compared to the other two senses. As to the visual stimulus, Computer Graphics (CG) or photo-realistic images, light source estimation and realistic rendering are needed in order for the objects to look realistic. Auditory (or sound) stimulus for sound sense needs 3D sound technologies, so that the users can hear sound harmonized with the virtual environment, and in accordance with the real-world. With respect to the tactile or haptic stimulus for sound sense, tactile or force feedback technologies have been developed and combined with visual and auditory stimulus (Kim et al., 2006).

In the following paragraphs, we focus on tactile stimulus in order to provide an example to show sensory stimulus clearly. Tactile stimuli is related to the sense of *touch*. Haptic devices are used to synthesize tactile stimulus for the user. The input of an haptic device is the trajectory of the user's hand on a virtual object. Based on this input trajectory and the model of the virtual object, the haptic device computes an output trajectory which is used to render the tactile stimulus.
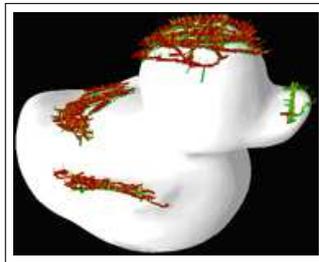
Figure 1: A Model of a Duck and 3D Trajectories of a User on This Model.

Consider a model of virtual duck shown in Figure 1[4]. A user is equipped with some special gloves to sense trajectory of the user's hands over the virtual duck. While the user moves his hands over the virtual duck, the trajectory is input to the haptic device. The input trajectory is shown in Table 1. This trajectory is composed of a set of points recorded over time. Each point has a position on real XYZ-coordinates and forces applied by the user's hand in XYZ directions. Based on the input trajectory and the model, the haptic device computes the output trajectory in Table 2, which is composed of points on the virtual XYZ-coordinates. The output trajectory also determines the forces that will be applied at each point to the users' hands by the gloves to create tactile stimulus.

Table 1: Input Trajectory for an Haptic Device for a Model of a Duck.

time(s)	X(mm)	Y(mm)	Z(mm)	Fx(N)	Fy(N)	Fz(N)
46.03	-46.3544	23.9523	-15.8292	-0.264958	-0.189902	0.768912
46.032	-45.9744	24.2482	-15.8633	-0.27005	-0.176252	0.76251
46.034	-46.024	24.2526	-15.8545	-0.253143	-0.163933	0.755568
46.036	-46.085	24.3773	-15.8643	-0.247722	-0.179404	0.764896
46.038	-46.1213	24.4051	-15.8557	-0.250062	-0.159736	0.75727
…	…	…	…	…	…	…

Table 2: Output Trajectory from the Haptic Device.

time(s)	X(mm)	Y(mm)	Z(mm)	Fx(N)	Fy(N)	Fz(N)
46.03	-46.3002	23.9834	-15.0931	0.0734185	0.0421645	0.996409
46.032	-45.9182	24.2794	-15.1348	0.0767852	0.0425608	0.996139
46.034	-45.9683	24.2835	-15.1311	0.0767852	0.0425608	0.996139
46.036	-46.0285	24.4086	-15.1318	0.0767852	0.0425608	0.996139
46.038	-46.0654	24.4361	-15.1301	0.0767852	0.0425608	0.996139
…	…	…	…	…	…	…

From Table 1 and 2, we can see that actually the tactile information of the virtual objects are presented in XYZ-coordinators, and it can be identified from the change of output trajectory with respect to input trajectory by using the gloves.

Five-Sense Oriented Feedback Provision As illustrated above, while concerning

---

[4]Both the model and the data are collected from Haptic Data Repository (http://jks-folks.stanford.edu/haptic_data/)

about buyers' historical experience with one seller, feedback can be expressed as human perceptions about the products and transaction experience. These subjective perceptions can be simulated by virtual reality. Therefore, towards VM 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 2. Consider a virtual marketplace community 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 duck doll from a seller in a virtual marketplace system. For feedback provision, the buyer can provide a 3D avatar model to express the appearance of the duck sold by the seller (as shown in Figure 1). Besides, the touch feedback can also be simulated to show the textile and material used to make this duck doll and attached to the rendered 3D avatar model. Such information shared among buyers can be perceived by buyers directly and compared with the 3D avatar model of the product provided by the seller to compute reputation of the seller. It should be noted that, our five-sense oriented reputation mechanism, besides taking the advantage of virtual reality technologies, also adopts the basic functionalities of the traditional reputation mechanism such as using *textual descriptions* to describe important product attributes or features (e.g. weight and brand of the duck doll).

3.2. 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 mar-

Five senses		Product Features		Product Category
Vision		Appearance		Clothes
Hearing	Mapping	Function	Mapping	Digital Products
Touch		Textile		Books
Smell		Sound		Food
Taste		Material		Electronic product
		......		......
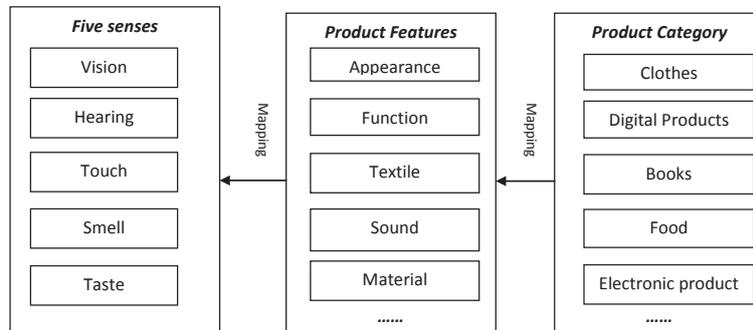
Figure 2: Feedback Provision based on an Five-Sense Oriented Approach

ketplaces.

3.2.1. 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 (McKnight and Chervany, 2001). Based on this guidance, a questionnaire survey is conducted. Figure 3 presents the overall structure of the questionnaire.

The questionnaire is divided into two main parts: context 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, all the participants are presented with a set of images about what they will experience in the virtual marketplaces with the traditional reputation mechanisms and then that with our proposed reputation mechanism. 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-marketplaces; 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 marketplace 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 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".
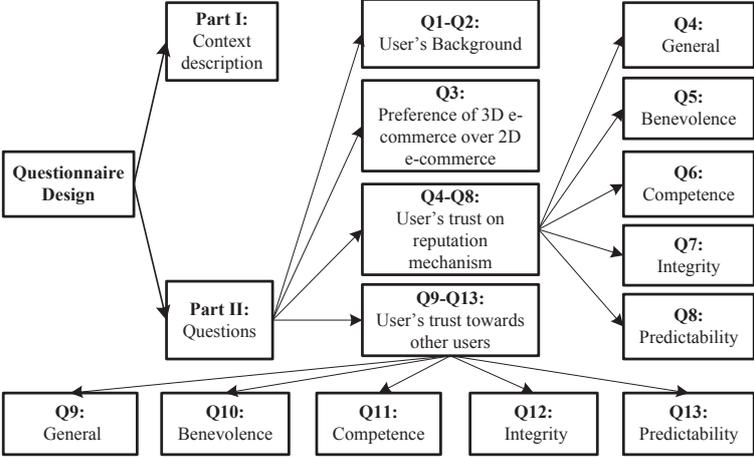

Figure 3: Questionnaire Design for Data Collection

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 liv-

ing 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 (taobao.com), Amazon and eBay. One point should be emphasized here is that since the virtual marketplace 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 Tables 3 and 4. In addition, 26 (65%) of participants prefer virtual marketplaces over traditional e-marketplaces, while only 5 of them are willing to stay at the traditional e-marketplaces sites, and 9 of them hold neutral attitude.

Table 3: Statistical Information about the Participants I

	Gender		Nationality		Current Residency		Often Shopping Site		
	Male	Female	Asian	American	Asia	America	Taobao	Amazon +eBay	Others
Counts	21	19	24	16	21	19	16	17	7
Percents	52.5%	47.5%	60%	40%	52.5%	47.5%	40%	42.5%	17.5%

Table 4: Statistical Information about the Participants II

	Technology Background		Age Diversity					Attitude of Virtual Marketplaces		
	Yes	No	18-21	22-23	24	25-26	27	Positive	Neutral	Negative
Counts	14	26	3	14	11	11	1	26	9	5
Percents	35%	65%	7.5%	35%	27.5%	26.5%	2.5%	65%	22.5%	12.5%

3.2.2. Data Analysis and Discussion

According to the trust framework of McKnight and Chervany (2001), a good reputation mechanism promoting high trust of users should also assure users' beliefs such

21

as benevolence, competence, integrity and predictability towards the reputation mechanism. Accordingly, a high degree of one perspective of the trust framework should also indicate a high degree of other perspectives. Based on these criterion and the collected data, we compute the pairwise correlation between trust and its four perspectives - benevolence, competence, integrity and predictability. Firstly, trust value of each participant is computed as the average value of Q4 and Q9. In the similar way, benevolence, competence, integrity and predictability values of each participant are computed according to participants' answers to Q5 and Q10, Q6 and Q11, Q7 and Q12, and Q8 and Q13 respectively. Each value is referred to participant's preference of our proposed reputation mechanism over traditional mechanisms. Then, the correlation analysis among each factor is conducted (See Table 5). By viewing the coefficient values, we find that trust is relatively highly correlated with each perspective (coefficients are all around 0.7000), especially for the correlation between trust and predictability (0.7449), indicating that people believe that virtual marketplaces with our proposed reputation mechanism will be competitive in the e-commerce market compared with that with the traditional reputation mechanisms. Additionally, the four perspectives are also relatively highly correlated with each other, which confirms that the trust framework in McKnight and Chervany (2001) can be applied to reputation mechanisms in virtual marketplaces.

In order to comprehensively compare our proposed reputation mechanism with traditional reputation mechanisms, we explore these 40 participants' evaluations 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 6 presents the participants' specific evaluations (positive, neutral or negative) of each perspective

22

concerned with each kind of trust regarding to our reputation mechanism compared to those of conventional reputation mechanisms.

Table 5: Correlation between Trust Related Variables

Variables	Trust	Benevolence	Competence	Integrity	Predictability
Trust	1.0000				
Benevolence	0.6970	1.0000			
Competence	0.6950	0.5939	1.0000		
Integrity	0.6985	0.7279	0.6241	1.0000	
Predictability	0.7449	0.7494	0.6441	0.6197	1.0000

User's Trust in the Mechanism According to the results in Table 6, to sum up, most (72.5%) of the participants showed 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 have greater possibility to achieve success (predictability) in the fierce competition.

Table 6: User Evaluation of Our Reputation Mechanism over Traditional Reputation Mechanisms

Dimension		Positive		Neutral		Negative	
		Counts	Percents	Counts	Percents	Counts	Percents
User's trust in the 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%

User's Trust in Other Users For the interpersonal trust, compared to traditional reputation mechanisms, users mostly hold a positive attitude towards our reputation mech-

anism. They are more confident that other users in our reputation mechanism are more trustworthiness (57.5%), while sellers would not only care more about buyers (50%) and more likely to 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.

Table 7: 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 the 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%

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 ware also evaluated and the results were shown in Table 7. It demonstrates that, on the whole, both of them prefer our proposed reputation mechanism over traditional reputation mechanism, considering the positive percents and negative percents.

24

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[1] and 3D Virtual World for 2010 Youth Olympic Games[2], while for America, it already has profound and mature development of traditional e-marketplaces websites, such as eBay and Amazon, and the applications of 3D virtual world 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.

4. Subjectivity Alignment for Reputation Computation in VMs

As introduced in Section 3, reviews based on human users' five senses (e.g. sensory stimulus) are objective and buyers can use them directly in their reputation computations of target sellers. However, there may encounter scenarios that some buyers are reluctant to provide detailed five-sense feedback, or it is inconvenient (*e.g.*, the lack of virtual reality devices) for buyers to provide the detailed reviews, but to provide a rating (or rating for each of the five senses[5]) for their past experience. A rating is subjective evaluation of a seller by a buyer within the context of a specific transaction. Therefore, different ratings could be given for the same transactions by different buyers. Hence, to effectively address the subjectivity difference problem involved in the ratings, we propose a subjectivity alignment approach for reputation computation (SARC) in virtual marketplaces.

Specifically, in our approach, each user is assisted by a software agent and equipped with virtual reality simulators. These simulators have ability to syntheses *visual*, *tactile*,

---

[1]http://www.singaporevr.com/

[2]http://www.singapore2010odyssey.sg/

[5]For clarification, we assume that buyers only provide a single rating for each of past transactions.

sound, *taste* and *smell* information. Sellers send potential buyers virtual representations of their products (*i.e.*, avatars), which are used by the simulators on buyers' side to experience virtual presentations of these products. Based on these presentations, buyers make their shopping decisions. However, some sellers may deceive buyers by sending virtual representations different from real products. Hence, in addition to virtual products, buyers may also refer to feedback (*i.e.*, detailed reviews and ratings) of the target seller provided by other buyers (referred as advisors). When only ratings are available in advisors' feedback, due to subjectivity difference among users, it may not be effective if a buyer directly takes other buyers' ratings towards a seller and aggregates the ratings to compute the reputation of the seller. Thus, we employ the buying agent of each buyer to address the buyer subjectivity difference problem.

In the following subsections, we first give an overview of our SARC approach in Section 4.1, and describe in great details how it learns buyers' subjectivity and aligns subjective ratings in Section 4.2. After that, we conduct experiments to verify the effectiveness of our approach in Section 4.3.

4.1. Overview of the SARC Approach

In an open virtual marketplace, 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 by $\mathcal{S} = \{s_1, s_2, s_3, \ldots\}$. 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). These notations are summarized in Table 8

For a buyer $b_i \in \mathcal{B}$ in the virtual marketplace, the goal of her buying agent $a_i \in \mathcal{A}$

Table 8: Summary of Notations

Notations	Description
$\mathcal{B} = \{b_1, b_2, b_3, \ldots\}$	Set of all buyers in the virtual marketplace.
$\mathcal{S} = \{s_1, s_2, s_3, \ldots\}$	Set of all sellers in the victual marketplace.
$\mathcal{A} = \{a_1, a_2, a_3, \ldots\}$	Set of all agents in the virtual marketplace.
$\mathcal{F} = \{f_1, f_2, \ldots, f_m\}$	Set of all the objective attributes. m is its total number.
$\mathcal{L} = \{r_1, r_2, \ldots, r_n\}$	Set of all the different rating levels. n is the total number.
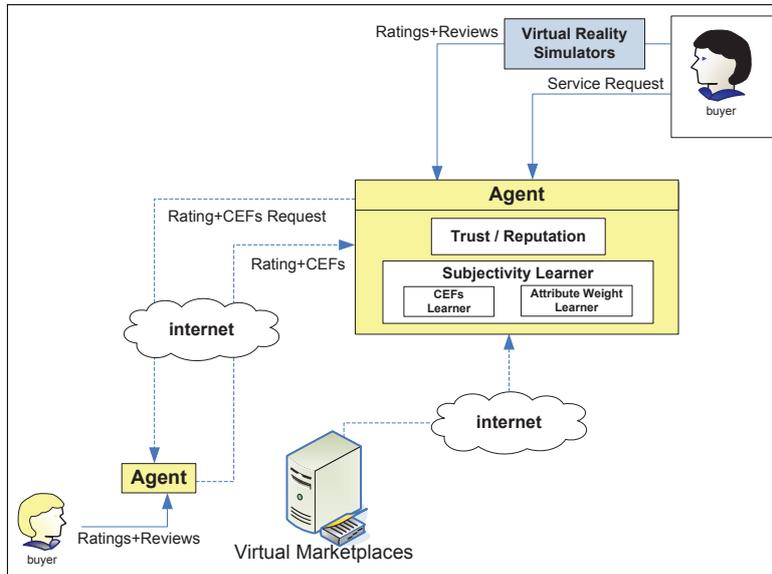
Figure 4: Overview of the SARC Approach

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.

In the SARC approach illustrated in Figure 4, a *Subjectivity Learner* is attached to agent a_i, by which it can model b_i's subjectivity. 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 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 uses the *CEFs Learner* of the *Subjectivity Learner* to model 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, the *Attribute Weight Learner* of the *Subjectivity Learner* is also used by agent a_i to learn 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.

As indicated above, each agent will only *partly* share its user's subjectivity (i.e. intra-attribute subjectivity) with other agents. By doing so, each agent can partly protect its

user's privacy in the whole community. This also ensures our approach to be practical in the real system. Besides, we acclaim that our agent architecture can be both centralized and distributed in the sense that for the distributed architecture, each agent can actively require other users' intra-attribute subjectivity if needed. Of course, other agents can refuse the agent's request. However, in turn, this kind of refusal might decrease other agents' probability of getting useful information from the system, which is similar to other distributed systems.

In the next section, we will describe in great details how our SARC approach models CEFs based on rating-review pairs, derives a rating for each attribute, learns the weights for attributes, and computes a (aligned) rating by aggregating the derived ratings for attributes. These procedures are organized as intra-attribute subjectivity alignment and extra-attribute subjectivity alignment.

4.2. Subjectivity Alignment

In this section, we describe the technical details of our SARC approach for the intra-attribute subjectivity alignment and the extra-attribute subjectivity alignment.

4.2.1. Intra-attribute Subjectivity Alignment

Given a set of rating-review pairs provided by buyer b_i, each of which is for a transaction between b_i and a seller, the rating in a pair indicates b_i's satisfaction level about the corresponding transaction, and the review in the pair is a set of values for the attributes $\mathcal{F}$ of the transaction. Buyer b_i's agent a_i learns the correlation evaluation functions (CEFs) of b_i, each of which is represented by a Bayesian conditional probability density function. Each CEF is the correlation between a rating level and the values of an attribute. More specifically, let us learn $\text{CEF}^{b_i}_{u,v}$, the correlation function between attribute f_u and rating level r_v for buyer b_i, where $1 \leq u \leq m$ and $1 \leq v \leq n$. Buying agent a_i first learns $p^{b_i}(r_v)$ (the probability that buyer b_i provides a rating r_v), $p^{b_i}(f_u)$ (the probability

29

distribution of the values for attribute f_u), and $p^{b_i}(r_v \mid f_u)$ (the conditional probability of rating level r_v given the distribution of the values for attribute f_u). By applying the Bayes' Rule, agent a_i can derive $\text{CEF}^{b_i}_{u,v}$ as the conditional probability distribution of the values for attribute f_u given rating level r_v as follows:

$$\text{CEF}^{b_i}_{u,v} = p^{b_i}(f_u \mid r_v) = \frac{p^{b_i}(r_v \mid f_u) \times p^{b_i}(f_u)}{p^{b_i}(r_v)} \tag{1}$$

In our SARC approach, the agents of buyers share the learned CEFs for their buyers with the agents of other buyers. Suppose that the agent a_k of a buyer b_k shares the learned CEF^{b_k} for b_k with the agent a_i of buyer b_i. For a rating r^{b_k} shared by the agent a_k of buyer b_k, agent a_i can then derive a rating level for each attribute in $\mathcal{F}$. We use a Naïve Bayesian Network model to learn the mapping/alignment from r^{b_k} of buyer b_k to the ratings of b_i for the attributes, as illustrated in Figure 5. Although in this model we assume that the attributes are independent given the ratings of buyers, in Section 4.2.2, we will learn the relative weights of the attributes to capture the dependency among the attributes.
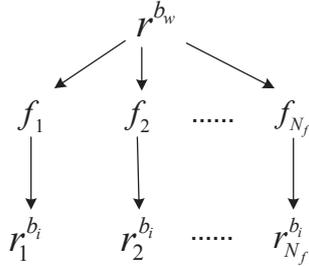

Figure 5: A Naïve Bayesian Network Model for Agent a_i of Buyer b_i to Align b_k's Rating r^{b_k}

Let us take any $f_u \in \mathcal{F}$ as an example attribute to show how agent a_i derives a rating for attribute f_u. To do so, agent a_i first estimates the conditional probability of a rating level in $\mathcal{L}$ for attribute f_u, given rating r^{b_k} provided by buyer b_k. Take any rating level r_v

as an example, agent a_i computes $p^{b_i}(r_{v,f_u}|r^{b_k})$, the conditional probability that buyer b_i will assign the rating level r_{v,f_u} to attribute f_u given the rating r^{b_k} of buyer b_k, as follows:

$$
\begin{aligned}
p^{b_i}(r_{v,f_u}|r^{b_k}) &= \frac{p^{b_i}(r_v \mid f_u, r^{b_k}) \times p^{b_k}(f_u \mid r^{b_k})}{p^{b_i}(f_u \mid r_v, r^{b_k})} \\
&= \frac{p^{b_i}(r_v \mid f_u) \times p^{b_k}(f_u \mid r^{b_k})}{p^{b_i}(f_u \mid r_v)}
\end{aligned} \tag{2}
$$

where $p^{b_k}(f_u \mid r^{b_k})$ is learned by agent a_k of buyer b_k using Equation 1 and shared by agent a_k to agent a_i, $p^{b_i}(f_u \mid r_v)$ is learned by agent a_i itself using Equation 1, and $p^{b_i}(r_v \mid f_u)$ is obtained by agent a_i from the rating-review pairs provided by its buyer b_i. In Equation 2, $p^{b_i}(r_v \mid f_u, r^{b_k})$ is equivalent to $p^{b_i}(r_v \mid f_u)$ and $p^{b_i}(f_u \mid r_v, r^{b_k})$ is equivalent to $p^{b_i}(f_u \mid r_v)$ because buyer b_i provides ratings to corresponding attributes regardless of buyer b_k's ratings. In another word, buyers evaluate transactions independently.

For attribute f_u, agent a_i learns the conditional probability of each rating level $r_v \in \mathcal{L}$ according to Equation 2. The aligned rating of attribute f_u for buyer b_i on the basis of buyer b_k's rating is then determined as the rating level with the highest probability value, as follows:

$$
r_{u,k}^{b_i} = \underset{r_v \in \mathcal{L}}{argmax}(p^{b_i}(r_{v,f_u}|r^{b_k})) \tag{3}
$$

The aligned ratings for other attributes in $\mathcal{F}$ can also be determined in the same way according to Equations 2 and 3.

For example, assume that there are five rating levels 1, 2, 3, 4 and 5, and three objective attributes f_1, f_2 and f_3. Buyer b_k provides a rating level 3 to buyer b_i. Through the intra-attribute subjectivity alignment, agent a_i gets that, for this experience, the rating level 3 of b_k means that b_i will evaluate attribute f_1 as rating level 1, attribute f_2 as 3,

and attribute f_3 as 4, respectively.

4.2.2. Extra-attribute Subjectivity Alignment

After the ratings of the attributes are obtained, agent a_i of buyer b_i then aggregates the ratings to represent an aligned rating of the rating r^{b_k} shared by buyer b_k. To do this, a_i needs to first determine a weight for each attribute in $\mathcal{F}$ as buyer b_i may concern more about one attribute over another.

The weight of an attribute f_u is determined by two factors. One factor is the confidence C_u about the rating $r^{b_i}_{u,k}$ derived for the attribute f_u using Equations 2 and 3. The confidence can be represented as the conditional probability value of the derived rating, $p^{b_i}(r^{b_i}_{u,k}|r^{b_k})$ estimated using Equation 2. A larger probability value means that it is more probable that the derived rating for attribute f_u should be $r^{b_i}_{u,k}$ according to buyer b_k's rating and the subjectivity of buyers b_i and b_k. In another word, the larger the probability is, the more reliable the derived rating $r^{b_i}_{u,k}$ is. Thus, we have:

$$C_u = p^{b_i}(r^{b_i}_{u,k}|r^{b_k}) \tag{4}$$

Another factor to determine the weight for attribute f_u is the importance I_u of f_u in buyer b_i's view. The importance I_u can be modeled as the coefficient of attribute f_u by a regression analysis model, based on the rating-review pairs provided by b_i. More specifically, given the rating-review pairs, we compute the coefficients for attributes by minimizing the aggregated difference between the true ratings in the rating-review pairs of b_i and the ratings, each of which is predicted for a review by the following equation:

$$r^{b_i}_0 = I_0 + \sum_{u=1}^{m} I_u \times V_{f_u} + \varepsilon \tag{5}$$

where $r^{b_i}_0$ is the predicted rating for a review, V_{f_u} is the value of f_u in the review, I_0 is a

constant, and ε is residual. So, the coefficients $I = [I_0, I_1, \ldots, I_m]$ can be computed by:

$$I' = (X'X)^{-1}X'Y \tag{6}$$

where if there are c rating-review pairs for buyer b_i in total,

$$X = \begin{bmatrix} 1 & f_{11} & \cdots & f_{m1} \\ 1 & f_{12} & \cdots & f_{m2} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & f_{1c} & \cdots & f_{mc} \end{bmatrix}, \quad Y = \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_c \end{bmatrix} \tag{7}$$

After the weight (confidence and importance) of each attribute is determined, the aligned rating $r_k^{b_i}$ can be computed as the weighted average of the ratings for attributes derived using Equations 2 and 3, as follows:

$$r_k^{b_i} = \frac{\sum\limits_{u=1}^{m} r_{u,k}^{b_i} \times C_u \times I_u}{\sum\limits_{u=1}^{m} C_u \times I_u} \tag{8}$$

Following the example in the previous section, based on b_i's past experience, agent a_i obtains b_i's weights of f_1, f_2 and f_3 as 0.1, 0.2 and 0.9, respectively. In this case, the final rating for b_i from b_k's rating level 3 is computed as: $(0.1 \times 1 + 0.2 \times 3 + 0.9 \times 4)/(0.1 + 0.2 + 0.9) = 3.58 \approx 4$.

After aligning all ratings shared by all buyers (advisors), the reputation value of seller s_j in the view of b_i can be computed as, for example, the average of the aligned ratings.

4.3. Experiments

In this section, we carry out experiments to evaluate the performance of our SARC approach and compare it with some representative competing approaches.

4.3.1. Experimental Environment

We simulate a VM environment involving 50 sellers and 200 buyers. In our simulations, sellers may provide different products. Their products are represented by five objective attributes, namely, *Attribute A*, *Attribute B*, *Attribute C*, *Attribute D*, and *Attribute E* with ranges presented in Table 9. For each seller, the values of the five attributes of her products are randomly chosen within the ranges.

Table 9: Product Attributes and Value Ranges

Dimension	Type	Ranges
Attribute A	Double	$100-$10,000
Attribute B	Double	1-10 GHZ
Attribute C	Char	5 types
Attribute D	Char	2 types
Attribute E	Integer	40-1000GB

Buyers may have different subjectivity in evaluating their transactions with (the products of) sellers. We simulate both buyers' intra-attribute subjectivity and extra-attribute subjectivity. To be specific, we assume that a buyer's rating for a transaction with a seller is derived as follows. First, the buyer evaluates each objective attribute according to a specific intrinsic (taste) function. In our experiments, buyers' intra-attribute subjectivity is simulated as approximate *Gaussian Distribution*. That is, for each attribute, the probability of each rating level given by a buyer is in the form of normal distribution. Second, the buyer places random weights (in the domain of [0,1]) on different attributes, and computes the weighted average of her evaluations on attributes as a single rating for the transaction. Since buyers can only give ratings under the predefined rating scale in reality, the simulated rating is chosen from the predefined rating scale that

34

is the closest to the weighted average.

In the experiments, besides our SARC approach, we implement a baseline approach without subjectivity alignment, which computes the reputation of sellers by directly averaging the ratings collected from other buyers for the sellers. We also choose to implement the TRAVOS approach (Teacy et al., 2006), which is a representative approach in the set of filtering approaches (see Section 2.3 for details). The BLADE approach (Regan et al., 2006) is chosen instead of the approach of Koster et al. (2010) because the two approaches are very similar and the approach of Koster et al. (2010) is complicated to implement.

We compare the performance of these approaches with our approach in computing the reputation of sellers. The performance of an approach is measured as the mean absolute error (MAE) between the reputation of sellers computed for each buyer using the approach, and the reputation of sellers using the ratings according to each buyer's own subjectivity (representing the ground truth about the reputation of sellers with respect to the buyer).

4.3.2. Experimental Parameters

To simulate real-world VM environments, we set several important parameters for our simulations, including information availability, and granularity of rating scale. *Information availability* refers to the amount of available information required by different approaches for subjectivity alignment. Two types of information are needed by our approach. One type of information is the detailed reviews describing the objective attributes of transactions between buyers and sellers. This information is used by our approach to model the correlation evaluation functions (CEFs) and the importance of the attributes for buyers. In the experiments, we vary the *number of detailed reviews* (N_r) to see how the performance of our approach is affected by this parameter. Another

type of information contributing to our approach is the number of objective attributes. In reality, some attributes (*e.g. appearance*) may not be objective. The total number of objective attributes in our simulations may thus be less than 5. In the experiments, we vary the *ratio of objective attributes* (R_{obj}) to be 0%, 20%, 40%, 60%, 80% and 100%, to see how much the performance of our approach will be affected. One type of information required by the BLADE approach is shared interactions where buyers and advisors have interacted with some same sellers. We vary the *ratio of shared interactions* (R_i) to see how this parameter affects the performance of BLADE. *Granularity of rating scale* (G_{scale}) refers to the number of rating levels. It may be different for different reputation systems. In our experiments, we will study the effect of the granularity of rating scale by varying G_{scale} from 2 to 10.

4.3.3. Experimental Results

Here, we present the performance of our approach and the competing approaches in different simulated environments. Various experiments are conducted by varying the other related parameters that may influence the performance of the approaches.

We first simulate a basic environment without any variation of the parameters, and compare the performance of our approach and that of the three competing approaches, including the baseline approach, TRAVOS and BLADE. We compute their mean absolute error (MAE) values for computing the reputation of sellers in different epoches. In each epoch, each buyer interacts with one seller in the marketplace. From the results shown in Figure 6, we can see that our approach performs consistently the best no matter whether buyers have more or less experience with sellers. Because both TRAVOS and BLADE require shared interactions, their performance is limited. Both TRAVOS and BLADE perform slightly better than the baseline approach. The performance difference between the different approaches is reduced when buyers have more experience with

36

sellers in the marketplace.
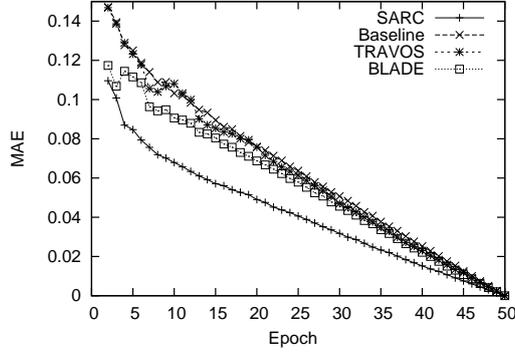
Figure 6: Performance Comparison in the Basic Environment

Based on the basic environment, we then vary some parameters to examine their effects. We first examine how the ratio of objective attributes R_{obj} affects our SARC approach. We vary R_{obj} from 0% to 100% for our SARC approach, while keep R_{obj} to be 100% for BLADE. As shown in Figure 7 (a), SARC performs slightly worse than BLADE when there is no objective attributes. However, it performs better than BLADE when there are more than 20% of objective attributes. The performance of SARC consistently increases as the ratio of objective attributes increases. But, the increment becomes smaller when $R_{obj} \geq 20\%$. The larger the granularity of rating scale (G_{scale}) is, the easier to learn buyers' subjectivity because buyers' subjectivity can be better captured by the larger granularity of rating scale. This trend is verified by our experiment. In Figure 7 (b), we plot the MAE results of the four approaches when varying G_{scale} from 2 to 10. The figure shows that the performance of SARC is significantly greater than the baseline approach, TRAVOS and BLADE. On average, the performance of SARC improves as G_{scale} increases.

We also vary the number of detailed reviews (N_r) provided by buyers from 1 to 30. We try to figure out a reasonable N_r for SARC. As shown in Figure 8 (a), when N_r

37
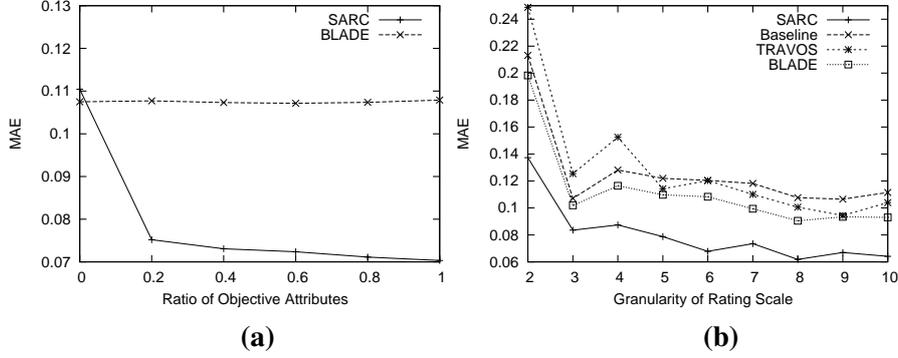
Figure 7: Performance When Varying (a) Ratio of Objective Attributes, and (b) Granularity of Rating Scale

increases from 1 to 5, the performance of SARC increases significantly. While N_r is larger than 5, as the increase of N_r, the performance of SARC also increases, but in a much smaller degree. This is simply because SARC requires only a few detailed reviews to learn buyers' subjectivity well. After that, any additional information leads to only small improvement. Thus, we can choose 6 as the acceptable minimum N_r. Besides, SARC performs better than the baseline approach and BLADE in all the cases for N_r. As discussed in Section 2.3, the BLADE model requires shared interactions in order to learn buyers' subjectivity. However, in real e-marketplaces, shared interactions are generally very sparse. In this experiment, we fix the number of past interactions for each buyer, but vary the ratio of shared interactions (R_i) from 0% to 100%. For each ratio value, MAE is computed as the average of five repeated runs. Figure 8 (b) indicates that BLADE performs significantly worse than SARC when R_i is in the range from 0% to 30%. The performance of BLADE increases with the increase of R_i.

5. Conclusions and Future Work

In this paper, we first propose a five-sense oriented reputation mechanism for VMs by incorporating novel elements of 3D technology and virtual reality. Specifically, a

38
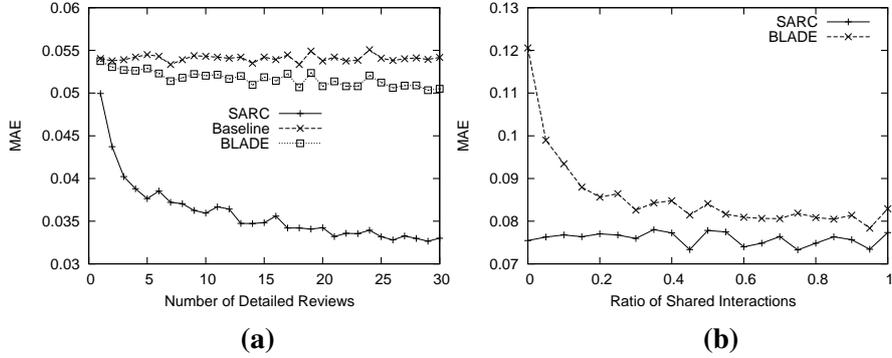
Figure 8: Performance When Varying (a) Number of Detailed Reviews, and (b) Ratio of Shared Interactions

five-sense oriented feedback provision approach is applied to provide buyers' 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 VM environments. The questionnaire survey with a stratified sampling method mainly focuses on user's trust in the mechanism (institutional trust) and user's trust in other users (interpersonal trust) respectively based on the four perspectives of trust typology - benevolence, competence, integrity and predictability. 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. Our current work represents an important initial step for confirming the necessity and value of our proposed reputation mechanism.

In Section 4, towards the scenario that only a rating is available in advisor's feedback, we propose a subjectivity alignment approach for reputation computation (SARC) to address the user subjectivity difference problem in virtual marketplaces. It takes advantages of virtual reality simulators in human users' five sense. In SARC, buyers'

39

subjectivity is learned based on the ratings and detailed reviews they provide about the objective attributes of their transactions with sellers. More specifically, SARC separately learns the *intra-attribute subjectivity* and *extra-attribute subjectivity* of buyers. Buyers' *intra-attribute subjectivity* is modeled using Bayesian learning. Their *extra-attribute subjectivity* is learned using a regression analysis model. We also conduct various experiments to compare the performance of our approach with that of other three competing models, including the baseline approach, TRAVOS and BLADE. Experimental results demonstrate that: 1) SARC performs better than the other three approaches, and can more accurately model sellers' reputation; and 2) the requirement of detailed reviews and objective attributes is not very restrictive.

The proposed reputation mechanism for virtual marketplaces has two major components: 1) the reputation mechanism takes advantages of the characteristics of virtual reality environments, and advances other traditional reputation mechanisms in virtual marketplaces; 2) SARC addresses the users subjectivity difference problem in their satisfactory evaluations of past transactions, and complements the five-sense feedback provision approach. Besides, it can also be applied in traditional e-commerce environments to cope with the subjectivity difference problem. As an initiative computational reputation mechanism for e-commerce in virtual reality environments, it will induce more attentions towards this direction.

For future work, following the current framework of our proposed reputation system, we wish to build a concrete and complete reputation system for virtual marketplaces: 1) *An extended SARC model to learn rating for each of human users' five senses*. In current work, we assume that buyers only provide a single rating for each of past transactions. However, the rating for each of five senses is needed for 3D visualization for reputation representation in our reputation mechanism to present the micro-view of sellers' reputation. In view of this, we plan to 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; 2) *A trust model to deal with buyers lying behavior in VMs*. For current work, we assume that all buyers are intended to report their past experience with sellers truthfully. However, it may not be true in real virtual marketplaces where some buyers may lie about their experience with sellers. In view of this, by adopting the characteristics of virtual reality environments, we can build a trust model based on the concept of users' *"personal social network"* for buyers to model the trustworthiness of advisors. Specifically, a buyer's *personal social network* can be computed from multiple information sources enriched by virtual reality 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); and 3) *A prototype of reputation mechanism in VMS*. A prototype (*i.e.*, demo) of our reputation mechanism needs to be built for further studying user's responses to virtual marketplaces with reputation systems. Based on this prototype, more comprehensive user study, considering age diversity, shopping background and cultural differences can be conducted.

References

Bharadwaj, K.K., Al-Shamri, M.Y.H., 2009. Fuzzy computational models for trust and reputation systems. Electronic Commerce Research and Applications 8, 37–47.

Bogdanovych, A., Berger, H., Simoff, S., Sierra, C., 2005. Narrowing the gap between humans and agents in e-commerce: 3d electronic institutions, in: Proceedings of the 6th International Conference on Electronic Commerce and Web Technologies (EC-Web), pp. 128–137.

Brennan, M., Wrazien, S., Greenstadt, R., 2010. Using machine learning to augment collaborative filtering of community discussions, in: Proceedings of the 9th International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS), pp. 1569–1570.

Brkic, B.R., Chalmers, A., 2010. Virtual smell: Authentic smell diffusion in virtual environments, in:

Proceedings of the 7th International Conference on Computer Graphics, Virtual Reality and Interaction in Africa, pp. 45–52.

Burnett, C., Norman, T.J., Sycara, K., 2010. Bootstrapping trust evaluations through stereotypes, in: Proceedings of the Eighth International Conference on Autonomous Agents and Multiagent Systems, pp. 241–248.

Chang, J.S., Wong, H.J., 2011. Selecting appropriate sellers in online auctions through a multi-attribute reputation calculation method. Electronic Commerce Research and Applications 10, 144–154.

Chen, C., 2010. Handbook of Pattern Recognition and Computer Vision (4th Edition). World Scientific Publishing Co. Pte. Ltd.

Şensoy, M., Zhang, J., Yolum, P., Cohen, R., 2009. Poyraz: Context-aware service selection under deception. Computational Intelligence 25, 335–366.

Drive, E., 2008. Getting real work done in virtual worlds. Forrest Research http://www.forrester.com/rb/Research/getting_real_work_done_in_virtual_worlds/q/id/43450/t/2.

Erickson, T., 2003. Designing visualizations of social activity: six claims, in: CHI'03 Extended Abstracts on Human Factors in Computing Systems, pp. 846–847.

Fang, H., Zhang, J., Sensoy, M., Thalmann, N.M., 2011. A reputation mechanism for virtual reality-five-sense oriented feedback provision and subjectivity alignment, in: Proceedings of the 10th IEEE International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom), pp. 312–319.

Fang, H., Zhang, J., Şensoy, M., Thalmann, N.M., 2012. Sarc: subjectivity alignment for reputation computation, in: Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems, pp. 1365–1366.

Gajendra, S., Sun, W., 2010. Second life: a computer mediated environment for communication and e-business managemnet, in: Proceedings of the 2010 International Conference on Challenges in Environmental Science and Computer Engineering, pp. 431–434.

Gaudin, S., 2010. Intel guru says 3-d internet will arrive within five years. Computer World http://www.computerworld.com/s/article/9175048/Intel_guru_says_3_D_Internet_will_arrive_within_five_years.

Hoffman, D.L., Novak, T.P., Peralta, M., 1999. Building consumer trust online. Communications of the ACM 42, 80–85.

Huang, G.Y., Hu, S.Y., Jiang, J.R., 2008. Scalable reputation management with trustworthy user selection for p2p mmogs. International Journal of Advanced Media and Communication 2, 380–401.

Iwata, H., Yano., T., Uemura, T., Moriya, T., 2004. Food simulator: A haptic interface for biting, in: Proceedings of Virtual Reality (VR), pp. 51–57.

Jøsang, A., Bhuiyan, T., 2008. Optimal trust network analysis with subjective logic, in: Proceedings of the International Conference on Emerging Security Information, Systems and Technologies, pp. 179–184.

Jøsang, A., Ismail, R., 2002. The beta reputation system, in: Proceedings of the 15th Bled Electronic Commerce Conference, pp. 324–337.

Josang, A., Ismail, R., Boyd, C., 2007. A survey of trust and reputation systems for online service provision. Decision Support Systems 43, 618–644.

Kern, S., 1974. Olfactory Ontology and Scented Harmonies: on the History of Smell. The Journal of Popular Culture 7, 816–824.

Kim, S., Suh, Y., Lee, Y., Woo, W., 2006. Toward ubiquitous VR: When VR meets ubiComp, in: Proceedings of the 4th International Symposium on Ubiquitous VR, pp. 1–4.

Koster, A., Sabater-Mir, J., Schorlemmer, M., 2010. Inductively generated trust alignments based on shared interactions, in: Proceedings of 9th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2010), pp. 1571–1572.

Liu, X., Datta, A., Rzadca, K., 2013. Trust beyond reputation: A computational trust model based on stereotypes. Electronic Commerce Research and Applications 12, 24–39.

Luca, M., Knorlein, B., Ernst, M.O., Harders, M., 2010. Effects of visual-haptic asynchronies and loading-unloading movements on compliance perception. Brain Research Bulletin .

Mackenzie, K., Buckby, S., Irvine, H., 2009. A framework for evaluating business lead users' virtual reality innovations in second life. Electronic Commerce Research 9, 149–172.

Magnenat-Thalmann, N., Volino, P., Bonanni, U., Summers, I.R., asco, M.B., Salsedo, F., Wolter, F.E., 2007. From physics-based simulation to the touching of textiles: the haptex project. The International Journal of Virtual Reality 6, 35–44.

Mass, Y., Herzberg, A., 1999. Vrcommerce- electronic commerce in virtual reality, in: Proceedings of the 1st ACM Conference on Electronic Commerce, pp. 103–109.

McKnight, D., Chervany, N., 2001. What trust means in e-commerce customer relationships: An interdisciplinary conceptual typology. International Journal of Electronic Commerce 6, 35–59.

Mennecke, B.E., McNeill, D., Roche, E.M., Bray, D.A., Townsend, A.M., Lester, J., 2008. Second life

and other virtual worlds: A roadmap for research. Communications of the Association for Information Systems 22, 371–388.

Nassiri, N., 2008. Increasing trust through the use of 3d e-commerce environment, in: Proceedings of the ACM symposium on Applied computing, pp. 1463–1466.

Noorian, Z., Marsh, S., Fleming, M., 2011. Multi-layered cognitive filtering by behavioural modelling, in: Proceedings of the 10th International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS), pp. 871–878.

Pai, D.K., v. Doel, K., James, D.L., Lang, J., Lloyd, J.E., Richmond, J.L., Yau, S.H., 2001. Scanning physical interaction behavior of 3d objects, in: Proceedings of the 28th Annual Conference on computer graphics and interactive techniques, pp. 87–96.

Papadopoulou, P., 2007. Applying virtual reality for trust building e-commerce environment. Virtual Reality 11, 107–127.

Price, S., Jewitt, C., Brown, B., 2013. The SAGE Handbook of Digital Technology Research. SAGE.

Qiu, L., Benbast, I., 2005. Online consumer trust and live help interfaces: the effects of text-to-speech voice and three-dimensional avatars. International Journal of Human-Computer Interaction 19, 75–94.

Quinlan, J.R., 1993. C4.5: programs for machine learning. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA.

Regan, K., Poupart, P., Cohen, R., 2006. Bayesian reputation modeling in e-marketplaces sensitive to subjectivity, deception and change, in: Proceedings of the 21st National Conference on Artificial Intelligence (AAAI), pp. 1206–1212.

Resnick, P., Zeckhauser, R., 2002a. Trust among strangers in internet transactions: Empirical analysis of ebay's reputation system. The Economics of the Internet and E-Commerce 11, 127–157.

Resnick, P., Zeckhauser, R., 2002b. Trust among strangers in internet transcations: Empirical analysis of ebay's reputation system. Advances in Applied Microeconomics 11, 127–157.

Resnick, P., Zeckhauser, R., Friedman, E., Kuwabara, K., 2000. Reputation systems. Advances in Applied Microeconomics 43, 45–48.

Resnick, P., Zeckhauser, R., Swanson, J., K., L., 2006. The value of reputation on ebay: a controlled experiment. Experimental Economics 9, 79–101.

Shin, D.H., Shin, Y.J., 2011. Consumers' trust in virtual mall shopping: the role of social presence and perceived security. International Journal of Human-Computer Interaction 27, 450–475.

Sirin, E., Parsia, B., Grau, B.C., Kalyanpur, A., Katz, Y., 2007. Pellet: A practical OWL-DL reasoner. Web

Semant. 5, 51–53.

Stanney, K., Mourant, R., Kennedy, R., 1998. Human factors issues in virtual environments: A review of the literature. Presence 7, 327–351.

Teacy, W.T.L., Patel, J., Jennings, N.R., Luck, M., 2006. Travos: Trust and reputation in the context of inaccurate information sources. Autonomous Agents and Multi-Agent Systems 12, 183–198.

Teoh, K.K., Cyril, E.U., 2008a. Exploring the roles of gender and ethnicity as antecedents of trust in 3d immersive electronic commerce. Communications of the IBIMA 2, 68–74.

Teoh, K.K., Cyril, E.U., 2008b. The role of presence and para social presence on trust in online virtual electronic commerce. Journal of Applied Sciences 16, 2834–2842.

W3C OWL Working Group, 2009. OWL 2 web ontology language document overview. http://www.w3.org/TR/owl2-overview.

Wang, Y., Vassileva, J., 2003. Bayesian network-based trust model, in: Proceedings of the International Workshop on Trust, Privacy, Deception and Fraud in Agent Systems, pp. 372–380.

Whitby, A., Jøang, A., Indulska, J., 2004. Filtering out unfair ratings in bayesian reputation systems, in: Proceedings of the 3rd International Joint Conference on Autonomous Agenst Systems Workshop on Trust in Agent Societies (TRUST).

Yu, B., Singh, M.P., 2003. Detecting deception in reputation management, in: Proceedings of the Second International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS), pp. 73–80.

Zhang, J., Cohen, R., 2008. Evaluating the trustworthiness of advice about selling agents in e-marketplaces: A personalized approach. Electronic Commerce Research and Applications 7, 330–340.