Handling Subjective User Feedback for Reputation Computation in Virtual Reality

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Abstract. As the interest in virtual reality is growing both from academia and industry, its new application areas emerge, one of which is the virtual marketplaces. We have previously proposed that buyers may share their experience with sellers in virtual marketplaces by exchanging their feedback. The feedback is composed of terms describing merchandise based on the users' five senses. However, some of these terms (e.g., *soft*) may be subjective and have different semantics for different buyers. Thus, alignment of the feedback containing subjective terms becomes an indispensable step before using exchanged feedback for reputation computations. In this paper, we propose a novel approach to align subjectivity in user feedback for reputation computation in virtual marketplaces. We demonstrate how sensory data in virtual reality can be exploited to handle subjectivity and describe how the aligned feedback can be used in seller reputation computation.

Keywords: Subjectivity alignment, virtual reality, five-sense, reputation system, feedback.

1 Introduction

Virtual Reality (VR) is defined as an artificial environment experienced through sensory stimuli provided by a computer. Current research on VR aims to develop a simulated reality that is realistic enough to satisfy our five senses. As this technology is getting mature, its new application areas emerge, such as virtual marketplaces. The virtual marketplaces mentioned in this paper are referred to as the environments where virtual reality is used by buyers to virtually experience products with their five senses and make shopping decisions based on the experience. Previous research has concerned about adopting virtual reality into e-commerce [2, 8] and also validated whether and how virtual reality can influence trust and thus impact consumer decision making in advance. For example, Papadopoulou [11] demonstrates that virtual marketplaces enable the formation of trust over conventional web stores. Nassiri [10] further explains that trust is improved by the mechanisms such as avatar appearance and haptic tools, while Teoh and Cyril [14] point out that presence and para-social presence assisted by virtual reality can affect trust. The weakness of their research is that they do not consider designing

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an effective trust and reputation mechanism to address the inherited trust problem in virtual marketplaces. For instance, some users may be dishonest, *e.g.*, some sellers may not deliver the products as promised. Users may also have different competency, *e.g.*, some sellers may provide only low quality products.

In order to address the trust problem in virtual marketplaces, a five-sense oriented feedback provision approach has been proposed in our previous work [4]. This approach allows buyers to share their past experience about sellers by exchanging their feedback based on five senses, namely, *vision*, *sound*, *touch*, *taste* and *smell*. Then, the reputation of sellers can be modeled based on the shared feedback. Our approach is supported by the study of Luca *et al.* [7] that, 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, such as haptic gloves, users can also sense the virtual copies similar to real objects, and can perceive the attributes (*e.g.*, *softness*) of the virtual objects. This allows the user to compare a real merchandised object with its advertised virtual copy and compose feedback based on this five-sense oriented comparison.

However, feedback based on five senses may involve users' own subjectivity because of subjective terms used in the feedback. For example, a simple concept like "soft" has different semantics for different users. The same object can be perceived as "adequately soft" by a user A while it would be perceived as "inadequately soft" by another user B. Thus, if B receives A's feedback of "adequately soft", B could be misled. Instead, the feedback of A should be translated to "may be inadequately soft" before being exposed to B. In this view, the first step before using feedback is to align the subjective terms in the exchanged feedback. Then, the aligned feedback can be used to compute reputation of sellers.

In this paper, we propose a subjectivity alignment approach by adopting virtual reality tools with the information available in human users' five senses. To do so, each user is coupled with an agent which learns the semantics of subjective terms for the user and maps the subjective terms in its user's vocabulary onto objective sensory data in the form of fuzzy membership functions. This agent 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 the buyer's own subjectivity. Then, the aligned feedback can be used to compute the reputation 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 feedback alignment approach provides an effective reputation mechanism particularly for virtual reality

The rest of this paper is organized as follows. Section 2 provides a summary of related work on subjectivity alignment. In Section 3, we describe our subjectivity alignment approach in more details and explain how we can use the aligned results to compute reputation of sellers. Finally, we conclude the current work and propose our future research in Section 4.

2 Related Work

Existing research tries to deal with the influence of ratings [9, 13, 15] provided by the third party on a subjective basis. Most previous research uses collaborative filtering tool to address the subjectivity problem in trust modeling. These approaches suffer from the risk of losing or discounting some important information. For example, from the perspective of behavioral modeling, Noorian *et al.* [16] propose a two-layered cognitive approach to filter or discount the ratings provided by others. The ratings are discounted according to the rating similarity between the user and the advisor as well as the behavior characteristics of the user and the advisor.

The information loss problem is addressed in Regan *et al.*'s work [13], which uses Bayesian learning tools to model sellers' properties and the correlations between sellers' properties and the advisor's ratings. Thus, towards a rating provided by an advisor, the buyer can infer back the seller's most possible properties and then based on the inferred result to further infer his own rating on the target seller. Sufficient shared interactions between the user and the advisor are needed for precisely modeling advisors' truth subjectivity. Koster et al. [6] claim to use clustering and Inductive Logic Programming (ILP) to align the subjective trust evaluation using objective information of the interactions. The limitations of the above mentioned approaches [6, 13, 16] mainly lie in: 1) Shared interactions are needed; 2) They generally offer limited flexibility for users to deal with the dynamic behavior of sellers and dynamic subjectivity of advisors.

Different from the above mentioned research, another approach to solve the subjectivity problem is to automatically compute the reputation value based on reviews instead of ratings. For example, Şensoy et al. [3] propose an ontology-based approach to allow agents directly interpret the reviews and thus compute trust and reputation value of sellers to eliminate undesirable products/services. However, this approach may fail if some concepts in the ontology and reviews are subjective, i.e., their meaning may change from user to user.

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.

3 Approach

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*, *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 (*e.g.*, ratings and reviews) provided by other buyers just as that in traditional e-commerce websites. As indicated in Section 1, feedback based on human users' five senses may involve advisors' own subjectivity.

In our paper, as shown in Figure 1, a *Concept Learner Engine* is attached to the agent, by which it can learn the semantics of its user's subjective terms in a shared vocabulary

[3]. The agent learns the semantics of these subjective terms over time by exploiting the correlation between the subjective product evaluation provided by its user and the 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 users. Thus, the feedback communicated among agents will be composed of only objective terms and semantic metrics. This allows the agent to clearly interpret the feedback provided by other users and transform it into its own user's subjective terms. Then, using its user's preferences, the agent can estimate the degree of satisfaction for its user based on the past transactions reported by other users.

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

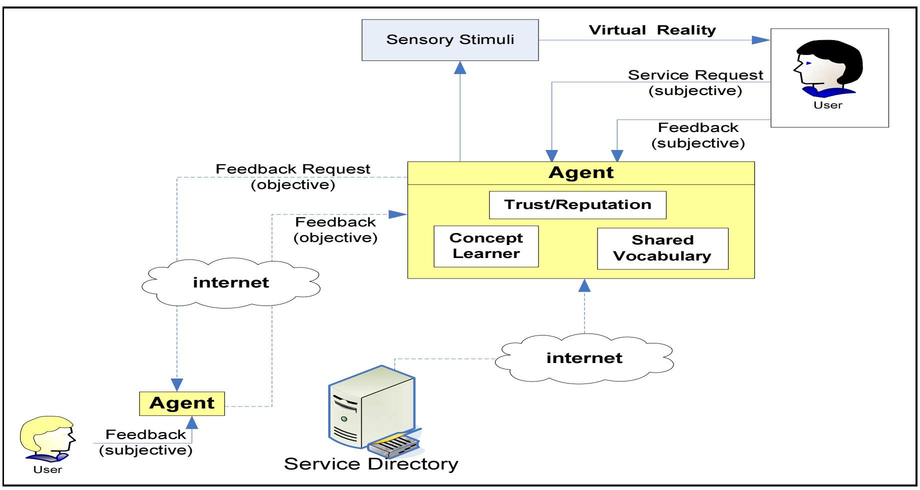

Fig. 1. The Approach Overview

3.1 Sensory Stimuli

There are five types of sensory stimuli rendered to users in virtual reality. In this paper, we focus on tactile stimuli in order to elaborate our approach clearly. Tactile stimuli is a stimuli related to the sense of *touching*. Haptic devices are used to synthesize tactile stimuli 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 stimuli.

Consider a model of virtual duck shown in Figure 2[1]. A user is equipped with some special gloves to sense trajectory of the user's hands over the virtual duck. While the

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

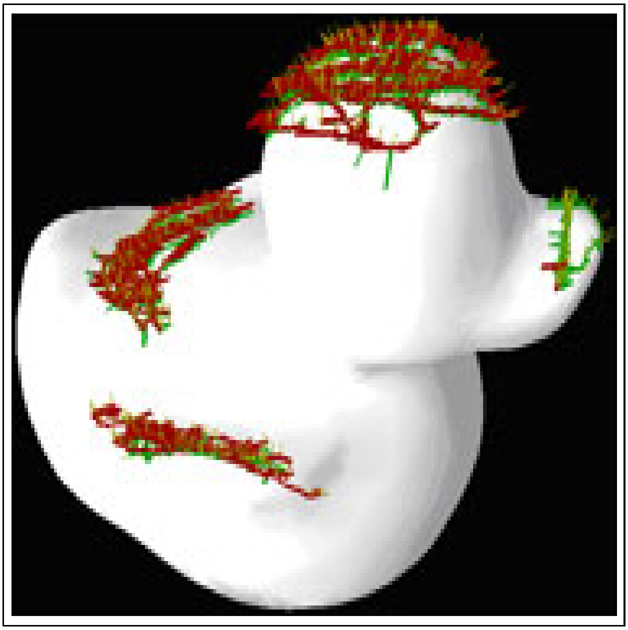

Fig. 2. A Model of a Duck and 3D Trajectories of a User on This Model

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 stimuli.

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. In order to elaborate our approach more clearly, we make following definition.

Definition 2. Objective value of subjective attributes is of simple numeric type. It means that, instead of using a vector, *i.e.*, XYZ-coordinate to represent the tactile attributes of an object, a numerical value can be a substitute as shown in the following sections. Obviously, it makes sense since a user percepts each attribute, such as *softness*, from the above mentioned force-feedback mechanism one by one. In other words, all the attributes can be identified from the same XYZ-coordinates. In this paper, for the sake of clarity and simplicity, the norm of the trajectory vector is used as objective value for subjective attributes such as *softness*. ∎

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
...	...	...	...	...	...	...

3.2 User Feedback

We assume users have a vocabulary by which a user describes what is advertised to him by the seller and what is received in reality. Two feedback examples for the same seller and the same product are shown in Figure 3 and 4. In these examples, the advisors use objective attributes such as *material*, *price*, *color*, and *delivery duration*. These attributes are *objective*, because they are interpreted in exactly the same way by different people and agents. However, the feedback also contains a subjective attribute, *softness*. Subjective attributes can be represented in the form of *visual*, *sound*, *tactile*, *smell* or *taste* information respectively. They take values that may be interpreted differently by different people and agents, and that is why these features are called *subjective*.

In Figure 3, Bob perceived the virtual duck advertised as *stiff*, and the real duck was also *stiff*. However, Jack considered the same virtual duck as *hardly soft*, while the real duck purchased turned out to be *soft*. Assume another buyer Tom wants to estimate the degree of the toy's *softness* based on Bob's and Jack's feedback. The conflicting arguments in the feedback would puzzle Tom. Hence, the semantic metrics of subjective terms in the feedback provided by *Bob* and *Jack* (see Figure 4) should be learned firstly by the agents of Bob and Jack. Then, rather than the subjective concepts, the agent of Tom collects these two semantic metrics and computes the similarities between them with Tom's own semantic metrics [12]. The subjective term *stiff* of Bob or *soft* of Jack will be aligned to the subjective term of Tom whose semantic metric is the most similar to that of *stiff* or *soft* respectively.

3.3 Subjectivity Alignment

The agent of a user is responsible for modeling semantics of the subjective terms in its user's vocabulary. Here, through virtual reality simulators, the subjective terms of

Reviewer	Bob	
Seller	xyzToyS	
Product	Toys/Duck	
	Advertised	**Actual**
Material	Rubber	Rubber
Price	$10	$12
Color	White	White
Delivery	1day	3days
Softness	*stiff*	*stiff*

Reviewer	Jack	
Seller	xyzToyS	
Product	Toys/Duck	
	Advertised	**Actual**
Material	Rubber	Rubber
Price	$10	$12
Color	White	White
Delivery	1day	1days
Softness	*hardly soft*	*soft*

Fig. 3. Two Examples of User Reviews

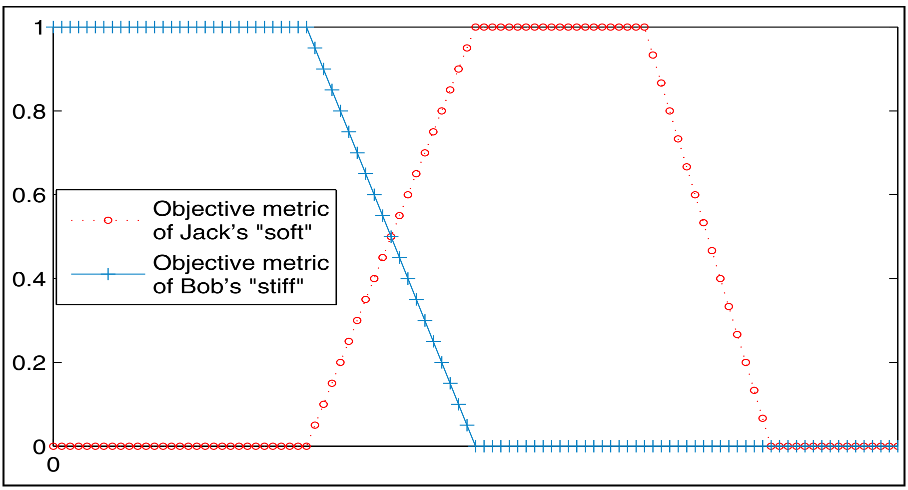

Fig. 4. Objective Semantic Metrics Communicated among Agents according to Bob and Jack's Reviews

buyers are learned and mapped onto corresponding values of objective sensory data that are numeric in our system. It should be noted that, the learning is an iterative process that requires sufficient interactions data between the agent and its user in order to obtain relatively precise mapping metrics. A basic learning unit (see Figure 5) is as follows: the agent provides a sensory stimuli to its user, and the user percepts the stimuli and provides to the agent a corresponding subjective term (*e.g.*, too soft) that best presents his perception in his vocabulary to the agent. Besides, the learning is also a continuous procedure because the perception of a user may change over time. For example, a user

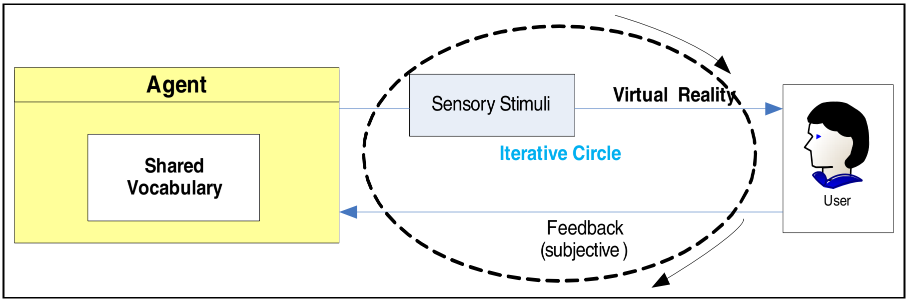

Fig. 5. Concept Learner Engine

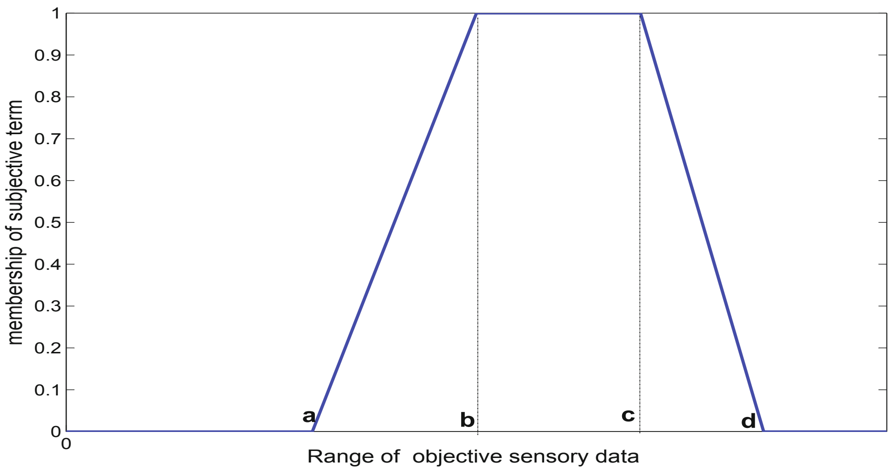

Fig. 6. Trapezoidal Membership Function for a Certain Subjective Term of a Buyer

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 similar objective sensory data as he has some fuzzy sensory zones. Hence, to better and more precisely specify the mapping metrics, we introduce the *trapezoidal membership function* with pseudo partitioning [1], ranging in the unit interval $[0, 1]$, to represent the degree of truth, μ, 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 $\rho \in (0, 1)$, it means that 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.

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

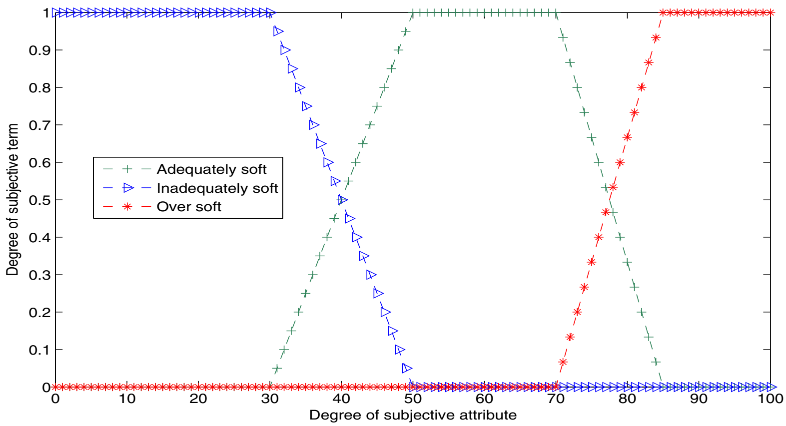

Fig. 7. Membership Functions for Example. 1

where a, b, c and d refer to the four transition points of trapezoidal membership function respectively (See Figure 6); $x \in X$ (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.

Example 1. The user describes his touching experience in subjective terms such as *adequately soft*, *inadequately soft* and *over soft*. To be specific, the sensory data of *softness* is considered in the range of [0,100], while 0 means its minimum value and 100 the maximum value. Through the *Concept Learner Engine*, his agent learns the user's semantic metrics of subjective terms related to subjective attribute *softness*, as shown in Figure 7. For *inadequately soft*, *adequately soft* and *over soft*, three corresponding trapezoidal membership functions are constructed and "30", "50", "70", "85" imply 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.

1. **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.
2. **Scenario 2:** If, for subjective attributes, only subjective terms are available in the advisor's feedback. The agent computes the similarity [12] 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 [12] 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.

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

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.

3.4 Reputation Computation

Subjectivity alignment proposed here can be used in many applications, such as recommender system, product or service selection as well as trust and reputation systems. Traditional reputation systems like eBay[2] allow consumers provide feedback in the form of ratings and simple text reviews. Generally, the ratings are aggregated by the system to compute reputation of the sellers. Then, reputation of sellers are referred by consumers to make shopping decisions. Similar ideas can also be adopted in virtual marketplaces where reputation mechanism can be more convincible on the basis of following two points: 1) Feedback in e-marketplaces is more expressive than that in traditional environments, as demonstrated in [4]; 2) Reputation of sellers can be more accurately modeled with our subjectivity alignment approach.

For the seller has been sufficiently interacted in the past, the reputation can be directly computed. In view of the subjectivity alignment approach proposed by this paper, the distributed reputation system is more appropriate[5]. In our design, each buyer can form his personal view about reputation of each seller after aligning subjectivity in others' feedback according to his own subjectivity with the assistant of his agent. That is, the agent directly collects objective semantic metrics shared by agents of other buyers, and then aligning them according to its user's own semantic metrics. Reputation of sellers are modeled using multi-dimensional reputation computation method via *Reputation Computation Engine*.

The main flow for the buyer B's actions to compute the reputation value of the seller S is illustrated as the following four steps: 1) The agent of the buyer B requests and collects a set of feedback about the seller S, where subjective terms are translated to objective semantic metrics represented as fuzzy membership functions; 2) Semantic metrics in the collected feedback are transformed into B's own semantic metrics; 3)

[2] www.ebay.com

Based on B's own preferences for different attributes and the aligned feedback of each past transaction, degrees of satisfaction are computed for the transactions; 4) The reputation of seller S is computed as the average degree of satisfaction.

4 Conclusion and Future Work

This paper proposes a novel approach to align subjective feedback for reputation computation. It takes advantages of 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 describe how the aligned feedback can be used in seller reputation computation. More specifically, the agent of each user is responsible for learning semantic metrics for 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. Besides, buyers can more accurately and stably model sellers' reputation.

This work represents an important initial step for constructing trust and reputation mechanism in virtual marketplaces. For future work, we will conduct more experiments to validate that the subjectivity alignment approach can significantly improve the efficiency and robustness of existing trust and reputation mechanisms, and compare it with other related approaches.

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References

1. Bezdek, J.C., Harris, J.D.: Fuzzy partitions and relations; an axiomatic basis for clustering. Fuzzy Sets and Systems 1, 111–127 (1978)
2. Bogdanovych, A., Berger, H., Simoff, S., Sierra, C.: Narrowing the Gap Between Humans and Agents in e-Commerce: 3D Electronic Institutions. In: Bauknecht, K., Pröll, B., Werthner, H. (eds.) EC-Web 2005. LNCS, vol. 3590, pp. 128–137. Springer, Heidelberg (2005)
3. Şensoy, M., Zhang, J., Yolum, P., Cohen, R.: Poyraz: Context-aware service selection under deception. Computational Intelligence 25(4), 335–366 (2009)
4. Fang, H., Zhang, J., Şensoy, M., Thalmann, N.M.: Design of a reputation mechanism for virtual reality: A case for e-commerce. In: Proceedings of the International Workshop on Trust in Agent Societies (2011)
5. Josang, A., Ismail, R., Boyd, C.: A survey of trust and reputation systems for online service provision. Decision Support Systems 43(2), 618–644 (2007)
6. Koster, A., Sabater-Mir, J., Schorlemmer, M.: Inductively generated trust alignments based on shared interactions. In: Proceedings of 9th International Conference on Autonomous Agents and Multiagent Systems, AAMAS 2010 (2010)
7. Luca, M.D., Knorlein, B., Ernst, M.O., Harders, M.: Effects of visual-haptic asynchronies and loading-unloading movements on compliance perception. Brain Research Bulletin (2010) (in print)
8. Mackenzie, K., Buckby, S., Irvine, H.: A framework for evaluating business lead users' virtual reality innovations in second life. Electron Commerce Research 9, 183–202 (2009)

9. Michael, B., Wrazien, S., Greenstadt, R.: 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 (2010)
10. Nassiri, N.: Increasing trust through the use of 3d e-commerce environment. In: Proceedings of the ACM Symposium on Applied Computing, pp. 1463–1466 (2008)
11. Papadopoulou, P.: Applying virtual reality for trust building e-commerce environment. Virtual Reality 11, 107–127 (2007)
12. Park, D.-H., Lee, S.H., Song, E.-H., Ahn, D.: Similarity Computation of Fuzzy Membership Function Pairs with Similarity Measure. In: Huang, D.-S., Heutte, L., Loog, M. (eds.) ICIC 2007. LNCS (LNAI), vol. 4682, pp. 485–492. Springer, Heidelberg (2007)
13. Regan, K., Poupart, P., Cohen, R.: Bayesian reputation modeling in e-marketplaces sensitive to subjectivity, deception and change. In: International Conference on Machine Learning (2006)
14. Teoh, K.K., Cyril, E.U.: The role of presence and para social presence on trust in online virtual electronic commerce. Journal of Applied Sciences 16(8), 2834–2842 (2008)
15. Yu, S., Singh, M.P.: Detecting deception in reputation management. In: Proceedings of the Second International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS), pp. 73–80 (2003)
16. Noorian, Z., Marsh, S., Fleming, M.: Multi-layered cognitive filtering by behavioural modelling. In: Proceedings of the 10th International Joint Conference on Autonomous Agents and Multiagent Systems, AAMAS (2011)