A New Recommender System for 3D E-Commerce: An EEG Based Approach

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***Abstract*—This position paper discusses a novel recommender system for e-commerce in virtual reality environments. The system provides recommendations by taking into account prepurchase ratings in addition to traditional postpurchase ratings. Users' positive emotions are captured in the form of electroencephalogram (EEG) signals while interacting with 3D virtual products prior to purchase. The prepurchase ratings are calculated from the averaged relative power of the collected EEG signals. Prepurchase ratings are complementary to postpurchase ratings and help in alleviating two severe issues that traditional recommender systems suffer from: *data sparsity* and *cold start*. By making proper use of both pre- and postpurchase ratings, user preference can be modeled more accurately. This will improve the effectiveness of the current recommender systems and may change the traditional e-business applications.**

***Index Terms*—prepurchase ratings, recommender system, virtual reality, data sparsity, cold start, EEG signals, real-time EEG analysis.**

I. Introduction

Collaborative filtering (CF) [1] is the one of the most widely used techniques for recommender systems, aiming to recommend the products (*items*) that users may buy. The underlying heuristics is that users with similar preference in the past will have similar opinions (*ratings*) on the future products. Hence, the effectiveness of CF heavily rests on the richness of user ratings. However, a general fact is that users only rated a limited portion of items due to lack of incentives. This fact will make it difficult in finding many similar users. This problem is regarded as *data sparsity*. In addition, for those who only rated few items, it is difficult to model user preference and make accurate recommendations based on little rating information. This problem is well known as *cold start*. The empirical results shown in [1] also confirm that CF severely suffers from these two issues.

With the advent of virtual reality environments such as Second Life from www.secondlife.com and Twinity from www.twinity.com, 3D e-commerce is believed to have a promising future. For example, virtual shopping malls which integrate the advantages of 3D virtual environments and traditional online websites accommodate users with a lifelike shopping environment [2]. In these environments, users can effectively interact with virtual products by viewing from different angles, zooming in and out, touching the surface and even trying them on. The virtual product experiences enable users to form direct, intuitive and concrete comprehensions towards the quality and performance of products and make a better and informative purchase decision. However, little work has been conducted up-to-date in designing novel recommender systems for 3D e-commerce and making use of the benefits of virtual environments.

In this paper, we discuss a novel recommender system based on electroencephalogram (EEG) signals [3] to solve the aforementioned issues. Specifically, the positive emotions of users can be captured and calculated as prepurchase ratings while interacting with virtual products prior to purchase. Hence, prepurchase ratings differ from the traditional postpurchase ratings in that they are obtained based on users' virtual-product experiences prior to purchase. They are capable of capturing users' instantaneous preference during the virtual interaction with a certain product. Therefore, the consideration of prepurchase ratings in a recommender system is valuable as user's preference can be modeled more accurately.

The motivation behind this paper is to discuss the integration of prepurchase ratings (based on EEG signals) into conventional recommender systems and its benefits.

This paper is structured as follows. In the next section we discuss the traditional recommender system. Section Ⅱ elaborates on the proposed recommender system. Finally a conclusion and discussion is covered in Section Ⅲ.

II. Related Work

There have been a few recommender systems proposed in virtual reality environments. For example, Hu and Wang [4] introduce a number of ways to construct user and resource profiles based on which a prototype is

Manuscript received October 15, 2012; revised December 29, 2012.

doi: 10.12720/joams.1.1.61-65

implemented to recommend virtual furniture. Shah *et al.* [5] describe a framework combining the clustering method and item-based filtering method to suggest places of interest, helping users navigate in virtual worlds. Xu and Yu [2] design a personalized recommender system for virtual shopping malls wherein user similarity is computed by taking into account both user's purchased products and browsed products (non-purchased).

Most of these works collect raw data in virtual reality environments and utilize data mining algorithms to generate recommendations similar to the traditional recommendation methods. They do not consider the valuable features of virtual environments such as effective interactions with 3D virtual products. In this paper, we propose a recommender system that collects the prepurchase ratings during the user's interactions with 3D virtual products.

EEG has been combined with virtual shopping and used as a tool for researchers to measure brain activity [6]. Recently, emotions have received much attention in the literature. For example, Tkalcic *et al.* [7] propose an affective framework wherein emotions are shown to play an important role in three stages during the course of product inspections, and improve the quality of recommendations. However, there is no clear clue for concrete implementations based on detectable emotions.

In this position paper, we argue that EEG signals can be used and calculated as prepurchase ratings for e-business applications. Moreover, we present an adapted CF method to provide recommendations by incorporating both the pre- and postpurchase ratings.

III. The Proposed Method

Fig. 1 illustrates our proposed EEG-based recommender system for 3D e-commerce. It collects ratings at both prepurchase and postpurchase stages.

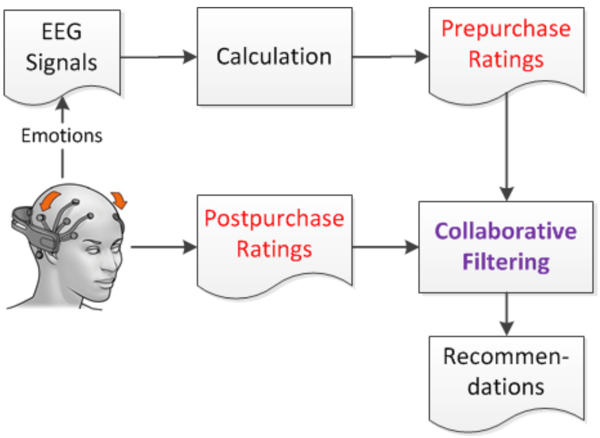

Figure 1. The proposed EEG-based recommender system. This new system considers pre-purchasing in its recommendation. Instantaneous emotions measured using EEG headset during the product experience in virtual environment (as shown in Figure 2).

The postpurchase rating is easy to measure as it comes from the users themselves after the purchasing process, while measuring the prepurchase rating is quite challenging as we do not require users to explicitly rate the products of interest. Instead, we extract their ratings automatically from the emotions when they interact with the virtual products. More specifically, the EEG signals can provide us with such a value while users interacting with 3D virtual products, prior to purchase.

As discussed above, emotions can be captured in real-time using EEG signals. The averaged relative power of the collected EEG signals has been used as a robust feature in literature that can be mapped into prepurchase ratings.

In simple words, the calculated relative power varies from 0 to 1, discussed later in Section A.1, which provides us with a range of values that corresponds to emotions. This means we can determine the percentage of likeness of a certain product during the 3D experience.

Furthermore, user ratings after experiencing real products are also gathered as postpurchase ratings. Both the pre- and postpurchase ratings are adopted, forming a new basis for CF by which product recommendations are generated.

Fig. 2 shows the user interface for a virtual t-shirt store powered by an open-source project OpenSimulator (www.opensimulator.org) which aims to provide a 3D virtual environment for people at any age. The t-shirts are randomly arranged and displayed on the walls of the virtual store. Users can click on any t-shirt, trying it on and interacting with it by viewing from different angles and distances, zooming in and out, etc. During these interactions, the emotions of users will be captured by a wireless EEG headset.

Figure 2. User interface for virtual t-shirt store. The avatar simulates the user while he or she wearing the EEG headset. The t-shirts are randomly arranged and displayed on the walls. Users can choose any T-shirt by clicking on it. The user can try any T-shirt and view himself from different angles and distances, zooming in and out. During these interactions, the emotions of users will be captured by a wireless EEG headset.

A. *Prepurchase Ratings*

In this section, we will discuss in detail the collection and significance of prepurchase ratings.

1) *Collection of prepurchase ratings*

As mentioned earlier, the EEG signals will be collected using a wireless EEG headset in real time, specifically the Emotiv EPOC wireless headset (www.emotiv.com) with a sampling frequency 128Hz. The headset has fourteen data collecting electrodes and two reference electrodes. The electrodes are placed approximately at the 10-20 locations AF3/4, F3/4, FC5/6, F7/8, T7/8, P7/8, and O1/2 as shown in Fig. 3. We use the software package BCI2000 (http://www.bci2000.org/BCI2000/Home.html) to interface with the Emotiv EPOC wireless headset. The headset transmits encrypted data to user's computer.

The system computes the relative power in two non-overlapping frequency bands (10-20Hz, and 20-30Hz) and generates rates from the computed values. Relative power is a simple measure that can readily be computed in real time. The EEG spectrum is known to depend on the mental state (e.g., relaxation, sleep).

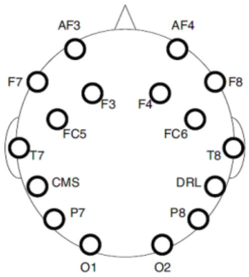

Figure 3. Electrode positions on the emotiv

Bos [3] recommends F3 and F4 channels for emotion detection, especially the alpha (α) and beta (β) bands of these two channels. Alpha waves are typical for an alert, but relaxed mental state, thus high activity is associated with meditative state, visualization, and idleness. In contrast, beta activity is related to an active state of mind during intense focused mental activity [8], and high beta activity is associated with fear and anxiety.

We now provide more details on mapping EEG features into prepurchase ratings. The power spectrum P is calculated for both EEG channels. Then relative power features f_1 and f_2 are calculated as follows:

$$f_1 = \frac{P(10-20Hz)}{P(3-40Hz)} \text{ and } f_2 = \frac{P(20-30Hz)}{P(3-40Hz)}$$

where $1 > f_1 > 0$ and $1 > f_2 > 0$, and each feature will be calculated in real-time over 5-second recording to present the user's current emotional response, i.e., f_1 represents positive emotions while f_2 represents negative emotions. Those features are averaged across both channels. The averaged features are mapped to as prepurchase ratings, with values varying from 0 to 1. We may also consider the ratio f_2 / f_1 as a mapping feature.

2) Significance of prepurchase ratings

Fuller and Matzler [9] show that interacting with virtual products enables users to express their latent needs. Since users may not purchase the products even after interactions, virtual product experiences could induce user's latent preference (via prepurchase ratings) but may not form intentions to purchase. In contrast, postpurchase ratings reflect not only users' explicit or core preferences, but also deterministic intentions to purchase.

Although the goal of recommender systems for e-commerce is to recommend products or services that users may buy, not merely of interest, user (latent) preference can help identify similar users. Therefore, prepurchase ratings can boost eliciting and completing users' preferences. As more similar users can be probed according to prepurchase ratings, it is desired that the recommendations generated will be more accurate and more products will be available for recommendations. Thus prepurchase ratings can improve the performance of traditional recommender systems. Prepurchase ratings, as an independent information source, can resolve the data sparsity to a large extent as users usually experience more products than that they actually purchase. In addition, for the cold-start users who provide little or none postpurchase ratings, we can make recommendations based on their prepurchase ratings (latent preferences). Hence, incorporating the prepurchase ratings with postpurchase ratings can greatly alleviate the problems of data sparsity and cold start. In this paper, we exclude the case in which users do not have any pre- or postpurchase ratings where other information other than ratings may be needed to model user preference. Hence, it is beyond the scope of this paper.

In addition, unlike the postpurchase ratings whose richness depends on the design of incentive mechanisms in order to encourage users to rate their purchased products, prepurchase ratings are automatically computed from users' emotional responses during their interactions with 3D virtual products. Consequently, the proposed recommender system may reduce the dependency on incentive mechanisms, and meanwhile provide accurate recommendations.

B. Adapted Collaborative Filtering

An adapted collaborative filtering is proposed to generate item recommendations using both pre- and postpurchase ratings. In this paper, the similarity $w(u,v)$ between an active user u and another user v is computed by the Pearson Correlation Coefficient [1]:

$$w(u,v) = \frac{\sum_{i=1}^{n}(r_{u,i} - \bar{r}_u)(r_{v,i} - \bar{r}_v)}{\sqrt{\sum_{i=1}^{n}(r_{u,i} - \bar{r}_u)^2}\sqrt{\sum_{i=1}^{n}(r_{v,i} - \bar{r}_v)^2}}$$

where $r_{u,i}$ denotes the rating reported by user u on item i, $\bar{r}_u$ denotes the average rating of user u, and n is the number of items commonly rated by users u and v. A set of nearest neighbors of active user u are defined as those whose similarity is greater than a predefined threshold θ, i.e., $U_u = \{v \mid w(u,v) > \theta, v \in U\}$. Generally, only positively correlated users will be adopted, i.e., $\theta = 0$.

For prepurchase ratings, $r_{u,i}$ is the positive emotional value for item i and a set of nearest neighbors U_u^b can be identified in the light of similarity $w_b(u,v)$ according to the prepurchase ratings issued by users u and v. Likewise, $r_{u,i}$ is the postpurchase rating and a set of nearest neighbors U_u^a will be probed based on computed postpurchase similarity $w_a(u,v)$. Hence, the whole set of nearest neighbors U_u for user u is the union of the two sets, i.e., $U_u = U_u^b \cup U_u^a$.

The final similarity between two users in U_u is a linear combination of pre- and postpurchase similarities:

$$w_{u,v} = (1-\lambda) w_b(u,v) + \lambda w_a(u,v)$$

where λ denotes the relative importance of postpurchase ratings. Generally, postpurchase similarity should be more reliable than prepurchase similarity, i.e., $\lambda > 0.5$. Then the system will predict the potential rating $\hat{r}_{u,j}$ for user u on an unknown item j by aggregating the ratings of nearest neighbors:

$$\hat{r}_{u,j} = \bar{r}_u + \frac{\sum_{v \in U_u} w_{u,v}(r_{v,j} - \bar{r}_v)}{\sum_{v \in U_u} | w_{u,v} |}$$

where $r_{v,j}$ is the postpurchase rating reported by a similar user v on the co-rated item i, or the prepurchase rating if the postpurchase rating is missing. Users with no pre- or postpurchase ratings on this item will not be incorporated.

IV. Conclusion

In this position paper, we discussed the idea of considering the EEG signals for a recommender system. As the number of the gaming EEG headsets increases, it is expected that the number of web applications based on such a technology will also increase. The question is if we can capture emotions with these headsets, can we utilize it for solving problems in e-business applications.

By introducing a new concept called "prepurchase ratings" for recommendations in virtual reality environments, the EEG headset becomes even more convenient for determining it. The prepurchase ratings will be calculated from the users' emotions (using EEG signals) during the virtual experience of a certain product.

We proposed an adapted collaborative-filtering method to make recommendations based on this new rating basis. The proposed generic framework incorporated both pre- and postpurchase ratings which can be potentially used for many other e-business applications.

However, there are many challenges in using the current gaming EEG headsets, especially the noise cancellation. The progress in this area is needed in order to detect emotions more accurately from users interacting with 3D virtual products prior to purchase. Intuitively, the postpurchase ratings will be provided by the users themselves after experiencing the actual products after purchase.

The main advantage of the proposed framework is its ability of overcoming two severe issues in traditional recommender systems, namely data sparsity and cold start, which ultimately enhances the effectiveness of the item rating predictions. In addition, social interactions (e.g., among trust friends) should also be considered in the future for better recommender systems since shopping *per se* is a social activity.

Acknowledgment

The authors wish to thank Jie Zhang and Daniel Thalmann from School of Computer Engineering, Nanyang Technological University for their sustainable supports for this work.

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