Brain Wave and User Profile based Learning Content Type Recommendation in Interactive e-Learning Environment

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Abstract

To date, most e-learning systems have not reflected emotion of users effectively as against off-line learning (system) that has sufficiently considered it. They might cause several problems hindering e-learning from effectiveness. Overcoming this weakness, we introduce a methodology that measures user's brain wave and recommends learning content to user based on it. In this paper, we assume that a person would have similar tendency with someone whose brain wave patterns are like his, and use it for recommendation of learning content type. As a technique for our experiment, we use kNN-Recommendation, learning content type recommendation system, based on brain wave data that appears in studying. Our system can solve cold-start problem that occurs in typical recommendation system and we additionally propose harmony value for better accuracy of recommendation that is calculated with recommended values from preceding our profile based recommendation system. We check advanced performance using several experiments.

Keywords: *e-learning, Brain Wave, Recommendation, Profile*

1. Introduction

e-Learning is taking center stage as learning technique which can be used when a user study with computer one-on-one by himself/herself. But it is found to have a problem that there is a lack of the interaction between instructor and learner [1]. To overcome this, the intelligent tutoring system(ITS), recently, have achieved some desired result from adjusting the level of the question and providing the feedback by checking how much a learner have solved a question, at first, and understood it [2-4].

But for enhancing the interaction between the learner and the instructor the technique sensing the learner's emotion in real time is now required [1, 5]. To achieve it, in this paper, we have researched an algorithm that if the learner, in e-learning study, indicates the 'abnormal brain wave value', then the system recommends the other learning content type to him/her to enhancing the efficiency of study [10].

Previous research used a technique that the system predicts what content a user prefer by using the user profile. In this paper, enhancing the performance of the algorithm, we propose a method that checks learners' brain wave while he/she studies and predicts his/her preference of the 'learning content type'. In addition, we carried out a study that combines the recomendation with user's brain wave and it with user profile.

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2. Learning Content Type Recommendation Using Brain Wave and User Profile

We assume that a person would have similar tendency with someone whose brain wave patterns are like his. In the field of the recommendation system, application of this assumption has brought about good results in performance of recommendation with user profiles [6].

Learning content type recommendation using brain wave and user profile, proposed in this paper, is the combination of the two recommendation system. The system with brain wave obtains the nearest neighbor by brain wave and uses the mean value of the preference of the neighbors' learning content type for recommendation. The system with user profile has the similar sequence. Finding a user's nearest neighbor, with user profile, we use the 'Pearson Correlation Coefficient' [9]. With brain wave, we use a formula that is modified from 'Pearson Correlation Coefficient'.

In this paper, we have researched a recommendation system that uses the brain wave with the system using the profile. In chapter '2.2.1 Vector Correlation Coefficient based NN-Recommendation system', we present the recommendation system with brain wave and the harmony value by using brain wave and user profile.

2.1. Data Set

We have carried out a e-learning study with 202 experiment subjects using four learning content types, those are, 'Game type', 'Story-telling type', 'Information-presenting type', and 'Information-exploration type'. While studying these, we obtain their brain wave data, and after that, their profiles and ratings for the learning content types. But they are not data to which the recommendation system is not applied. We use them for checking performance of our recommendation system. It is the performance of our system whether the recommended learning content type is the best preference type that user rated it as the best or not.

2.1.1. Brain Wave Data and Rating Data: Analyzing the status of brain wave, we can measure the learning pattern and concentration level of each individual. This enables us to get the users' preferences of the learning content types by facilitating the analysis of checking each learner. Brain wave data classified as 21 channels are saved in the database while users learn the e-learning. Table 1 shows a sample of the brain wave channels*.

Table 1. Brain Wave Channels

	Name
Channel 6	FP2_ALPH_MEF
Channel 7	FP1_BETA_MEF
Channel 8	FP2_BETA_MEF

Table 2 is a simple example of brain wave data. In the Table 2, we select the brain wave data from Channel 4 to Channel 7 and from 4 second to 24 second. And we use the rating for each learning content type as the measure for knowing the subjects' preferences for them. Table 3 is a simple example of ratings.

Data modification is necessary for applying the brain wave to recommendation algorithm. This is for preciseness of the similarity between learners and the preference of the learning

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*** http://www.laxtha.com**

content type. Brain wave data is normalized for each channel by a formula (1). x is the brain wave value measured at an interval of 4 second, a mean value is $\bar{x}$, and σ is a standard deviation of x's. x' is the normalized brain wave value.

Table 2. Brain Wave Data

	Channel 4	Channel 5	Channel 6	Channel 7	Channel 8	Channel 9	Channel 10
4	0.97	8.75	11.00	16.00	25.75	4.61	4.86
8	-0.15	9.50	9.00	15.00	22.75	4.83	5.19
12	0.92	9.75	9.75	15.75	21.50	2.77	3.11
16	0.54	9.75	10.25	17.25	20.00	5.47	5.49
20	0.52	10.25	9.50	16.25	19.75	3.75	3.59
24	0.49	9.50	9.00	17.00	21.00	5.11	4.91

Table 3. Real Rating Data for each Learning Content Type

	Type A	Type B	Type C	Type D
User a	3	5	1	2
User b	4	4	1	3
User c	2	2	5	4
User d	2	2	1	1
User e	3	4	4	5

$$x' = \frac{\bar{x} - x}{\sigma} \tag{1}$$

And by using the same formula (formula (1)) we modified the ratings of users for each learning content type.

2.2. Recommendation Algorithm

2.2.1. Vector Correlation Coefficient based NN-Recommendation: NN(Nearest-Neighbor)-Recommendation is a system that selects nearest neighbors who have the similar brain waves and gathers the preferences of the learning content types of nearest neighbors. Neighbors are selected by similarity from heist to lowest. The brain wave data are vectors that have time-series vectors as their elements which are measured at an interval of 4 second. Therefore, the existing formula, that is, Pearson Correlation Coefficient, should be modified for calculating the similarity. We have named this modified formula 'Vector Correlation Coefficient'.

The Pearson product-moment correlation coefficient (sometimes referred to as the PPMCC or PCC, or Pearson's r, and is typically denoted by r) is a measure of the correlation (linear dependence) between two variables, giving a value between +1 and -1 inclusive. It is widely used in the sciences as a measure of the strength of linear dependence between two variables. This formula is as the formula (2).

$$PCC(X,Y) = \frac{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2}\sqrt{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}} \quad (2)$$

For pearson correlation coefficient, two vectors are used. And those have elements as real numbers. Using this formula for obtaining a similarity with brain wave, we should modify it since the vectors of brain wave consist of vectors which have elements as vectors composed with brain wave values checked at an interval of 4 second. Existing formula, pearson correlation coefficient, gives a value between +1 and -1 inclusive. The value closing to +1 means that the two variables (vectors) have similar data. The value closing to -1, by contrast, means that the two variables have opposite tendency for testing data, while closing to 0 meaning that there is no relation between the two variables.

We should maintain these properties for using the modified formula, vector correlation coefficient, with brain wave data. The modified formula is as formula (3). In

$\left(A_i - \bar{A}\right)\bullet\left(B_i - \bar{B}\right)$

$\bullet$ means the inner product. And in

$A = \left\{A_1, A_2, \cdots, A_m\right\},\ B = \left\{B_1, B_2, \cdots, B_m\right\},$

A_i, B_j are vectors.

$$PCC(X,Y) = \frac{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)\bullet\left(y_i - \bar{y}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2}\bullet\sqrt{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}} \quad (3)$$

We conducted a test for verifying the possibility of this formula and found that it can be used for obtaining similarities of the learners with brain wave data. The result of the test is as Table 4.

Table 4. Similarities by Calculating the Vector Correlation Coefficient

	Similarity
User a	-0.008105555655117929
User b	0.01690417220820031
User c	0.022942947323424712
User d	0.0

2.2.2. Finding Nearest Neighbor and Recommending Preferred Learning Content Type: We used two methods for finding the nearest neighbors for a user (‘active user’, which means that the system would recommend a learning content type to him/her). One is Threshold method, the other is k-Nearest Neighbor method. The former uses a threshold for finding nearest neighbors that the similarity is larger than it. The latter uses a value k that when other users are ranked by similarity from highest to lowest is the number to which we can select the users as nearest neighbors. When we choose the threshold method, setting the threshold as 0.1, we could select the User b and the User c as the nearest neighbors of active user. And when choose the k-Nearest Neighbor method, setting the number k as 1, we could select the User c as the only nearest neighbor since the similarity of the User c is the highest value.

We conducted a comparison test of recommendation performance between by threshold method and by k-Nearest Neighbor method. The result is shown in Table 5. Accuracy means that if the learning content type is exactly it which the active user has rated the best. When the k-value is 5 and the threshold is 0.2, the performance is the best where we changes the k-value from 1 to 10 in steps of 1 and he threshold changes from 0.1 and 0.9 in steps of 0.1.

Table 5. Accuracy by k-Value and Threshold

k-Value	Accuracy	Threshold	Accuracy
3	0.3158	0.1	0.3041
4	0.3041	0.2	0.3509
5	0.3450	0.3	0.3216
6	0.3392	0.4	0.3158
7	0.3333	0.5	0.3216

From the test we could find that the threshold method is better than the k-Nearest Neighbor for the performance of the recommendation system with brain wave data. We would select, therefore, the threshold method to calculate similarities between users.

Using Vector Correlation Coefficient (shown as formula (3)), we conducted a test where the threshold changes from 0.1 to 0.9 in steps of 0.1. From this sequence, finding nearest neighbors, we could calculate predicted rating for each learning content type by the 'Weighted Average'. It is similar to an arithmetic mean (the most common type of average) where instead of each of the data points contributing equally to the final average, some data points contribute more than others. The notion of weighted mean plays a role in descriptive statistics and also occurs in a more general form in several other areas of mathematics. The formula is as formula (4). $w_{a,u}$ is a similarity between a, active user, and u, one of the nearest neighbors, and is the rating for i, a learning content type, of u.

$$p_{a,i} = \frac{\sum_{i=1}^{n} w_{a,u} \times r_{u,i}}{\sum_{i=1}^{n} w_{a,u}} \tag{4}$$

We would use this formula to predict ratings of active user for each learning content type and the best learning content type which appears a largest rating is recommended to the active user.

3. Performance Evaluation

We conducted a test using brain wave data which consist of 21-channel and in the course of the test we use vector correlation coefficient to calculate similarities between users'. And we use the threshold method to find users' nearest neighbors by the similarities. The result of this is as in Figure 1.

We use the method Mean Absolute Error (MAE) for evaluating of the performance of this algorithm. The Mean Absolute Error is as formula (5). p_i means that the predicted rating for a learning content type i and means that the real rating for i. And n is the number of the learning content types.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|p_i - r_i| \tag{5}$$

The real rating means that we use a table fully filled with ratings for each learning content types of all subjects in the research.

In the performance evaluation test, we change the threshold from 0.1 to 0.9 in steps of 0.1. We found that, as you could know from Figure 1, the performance is the best when we set the threshold as 0.2. The MAE when threshold larger than 0.6 is the same as the threshold is equal to 0.6. We found the reason is that the similarities between all subjects in this research are smaller than 0.7, mostly positioned around 0.2. From that, the nearest neighbors, setting the threshold over 0.6, are the same for the same users.

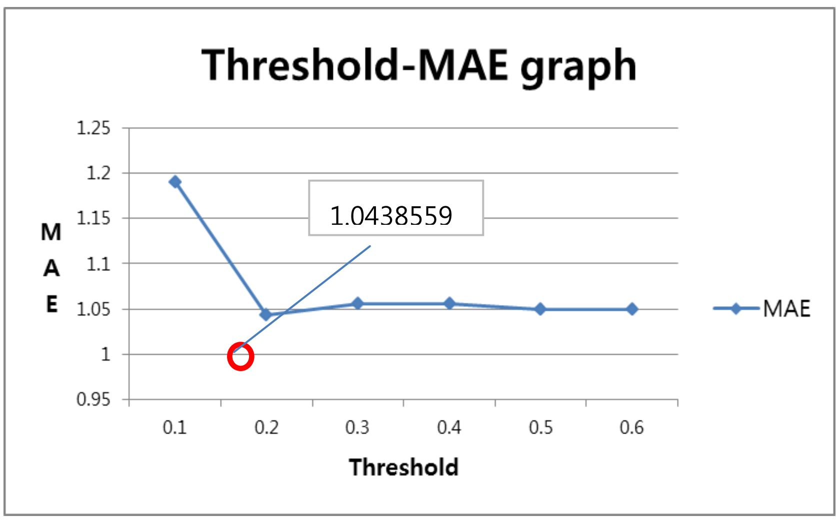

Figure 1. MAE values while the threshold changes from 0.1 to 0.9 in steps of 0.1. The MAEs where the threshold is over 0.6 are not illustrated.

And we have analyzed the brain wave data while executing an e-learning for some subjects. Then we could find that the brain wave data shows a wide variation by some slight stimulation such as tiny blink of eyes, some little noise, and so on. And the brain wave data consist of the vectors which have the time-series values at an interval of four second. This means that the input data are somewhat complex. From these reasons, the MAEs where threshold is over 0.6 are 0 because the similarities are zero.

The test that has evaluated the performance of the recommendation algorithm using user profiles has some good outcomes [9]. We have decided to conduct a test which gets the harmony value using the algorithm by user profile and the algorithm by brain wave. We use the predicted rating for the best recommended learning content type by each algorithm and it was calculated by weighted average (formula (4)).

We use a constant which changes from 0.0 to 1.0 in steps of 0.1.The reason why we test using 0.0 and 1.0 is that we could represent a graph comparing the original values, the MAE using brain wave data and it using profiles, and the harmony values of the two data used by each recommending system. In this test, we use MAE for evaluating the performance of the harmony values of the two recommendation systems. And the input data to MAE is recommended rating which consists of a rating by the system with brain wave and a rating by the system with user profile using a constant changing from 0.0 to 1.0 in steps of 0.1. The formula for MAE is as formula (6) where c = constant and r = user rating.

$$\mathrm{MAE} = \frac{1}{n} \sum_{i=1}^{n} \left| \mathrm{pre}_i - r_i \right| \tag{6}$$

$\mathrm{pre}_i = c \times r_{bi} + (1 - c) \times r_{pi}$, where

r_{bi} = rating by the system using brain wave data

r_{pi} = rating by the system using profiles

And the result of this test is as Figure 2.

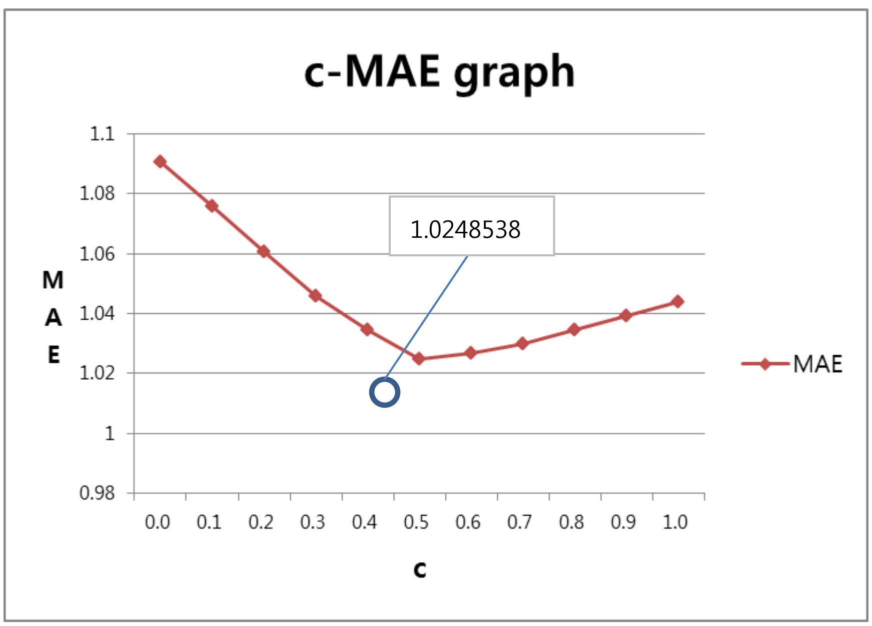

Figure 2. MAE values while the constant c changes from 0.0 to 1.0 in steps of 0.1. The MAEs where the c is over 0.7 and below 0.3 are not illustrated.

From the Figure 2, setting the constant c as 0.5, the MAE value is the smallest compared to other c values. And we already know that the c is equal to 1.0 meaning the MAE obtained by the system using brain wave data only and the c is equal to 0.0 meaning the MAE obtained by the system using profiles only. Not illustrated in Figure 2, the c that is below 0.3 and over 0.7 is almost linearly greater than 0.3 and 0.7, respectively [10]. In other words, we could know that the harmony value setting the constant c as 0.5 shows the best performance and is better than those of each system only.

4. Conclusion

In this paper, we conducted a research that uses an 'emotion recognition unit' in e-learning environment to obtain the users' brain wave data for recommendation of learning content types using the presented algorithms, and measured a performance of them. We checked the performance by the recommendation system using brain wave data only and for enhancing accuracy of the recommendation system combined it with the system using profiles. And this harmony value was verified that it could be the better method for recommendation than the system using brain wave data or that using profiles only. We selected the threshold as 0.2 and conducted the experiment which uses the user's brain wave and user profile for recommendation. And It was found that it showed the best performance.

We will develop the recommendation system that uses the brain wave data as combining other systems after collecting user profiles and brain wave data, and other data.

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