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Research on the Difficulty Points Marking System of Online Learning Process

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Abstract. There exists a notable problem in MOOCs that teachers can't find the difficulties during the learners' learning process because of their inefficiency of supervising the learners' real learning status. To solve this problem, we model the learning behavior of online learners based on facial expression information and mouse track data, and propose a method for marking learner's difficulties in online learning process based on machine learning. At same time, we design and implement a prototype system for marking difficulties based on our method. Experiments show that our method can improve the efficiency and quality of marking learner's difficulties effectively.

1. Introduction

With the continuous development of the application of machine learning and artificial intelligence in online education, a large number of online learning platforms have emerged, such as Khan Academy, Coursera, Udacity and Edx. These online learning platforms play the role of "learning resource providers" providing online learners with a large number of video resources or other forms of learning materials. However, it is necessary to strengthen the research on how to monitor the status of learners' online learning and to mark learners' difficulties in the course of learning process.

Relevant researches view problem of research of difficult points marking as problem of attention transfer. Based the inseparable connection between attention and learning, the literature [1] proposes a two-dimensional framework focusing on direction × thought content, which contains a series of attention states, so that the eye movement can be analyzed in real time to monitor whether the students' attention is transferred; Based on the recognition that attention is the key to effective learning, the literature [2] identifies the students' wandering thoughts by automatically extracting facial features using computer vision technology and the work is 31% more efficient than called opportunity model; There is a significant negative correlation between the number of thoughts wandering phenomena and reading comprehension. For this reason, the literature [3] and [4] monitor the learner's learning process through reading time and physiological signals, and study whether it is possible to predict whether the learner will be wandering in real time and also design some methods to reduce the occurrence of unconscious reading; The literature [5] uses the learner's heartbeat to monitor the wandering phenomenon of thinking in their online learners, and is 22% more effective than the original method.

Existing methods for solving difficult points marking problem includes many problems [6]. Firstly, teacher personally analyzes and summarizes the difficulties of learning content, and adds those difficulty points to "difficulties in this chapter" section which is cumbersome and inefficient. At the

same, because teachers cannot mark the personalized difficult points of different learners, this method is not adaptive for every student. Second, because of traditional learners only ask some questions in the discussion section after a certain chapter is completed, the difficult points can't be found and answered in time.

For solving the above problems, the solutions proposed in this paper are as follows: (1) Collecting the learner's facial image, current screen content and the mouse track in the online learning process; (2) Based on the above data, through emotional analysis of learners' facial images at different times, we can find the time when learner expresses "doubt, surprise" emotion. At the same time, a mouse track data corresponding to these expressions can be extracted for getting learner's learning state at that time; (3) Excluding the expression of "surprise, doubt" generated by students' non-learning factors, we can mark the learner's personalized difficult points.

2. Emotion Recognition Based on facial image

2.1 Facial Image Data
This paper selects part data in CK/CK+ dataset [7]. The CK+ dataset consists of four parts: Images, Landmarks, Emotion, and FACS. Images contain a large number of facial images, Landmarks is the facial feature point coordinates of the corresponding image, and Emotion is the expression tag. To this end, 70% of the data is used as a training dataset, and the remaining 30% of the data is used as a test dataset to support the algorithm selection experiment in Section 2.4.

2.2 Building a Face Model
Before the learner's facial expression recognition, it is necessary to build the face model. The specific practices are as follows: firstly, we use the AdaBoost algorithm with Haar features or LBP features to detect the face area, and obtain the coordinates in face image; secondly, we use the Active Appearance Model (AAM) [8] to calibrate the feature points in the picture. AAM can not only consider the local feature information, but also take the global shape and texture information into account.

2.3 Express Emotion
There are two methods of emotion representation in the field of psychology: continuous emotional dimension representation and discrete emotional representation. We use discrete emotional representation and divide people's emotion into seven categories: Anger, Joy, Sadness, Fear, Surprise, Doubt and Neutral. And we call surprise and doubt emotion as puzzled emotion which shows that learner maybe meet difficulty point.

2.4 Select Face Emotion Recognition Algorithm
For selecting the appropriate emotion classification algorithms, we compare support vector machine (SVM), k-Nearest Neighbor (KNN), decision tree and random forest as classifier in our tasks. The results of the experiment are as shown in the table 1.

Table 1. Results of different classification algorithms

Machine Learning Method	Training duration	Accuracy of training dataset	Accuracy of test dataset
SVM	long	96%	70%
KNN	very short	57%	40%
Decision tree	short	92%	50%
Random forest	long	91%	80%

According to Table 1, KNN is the least in speed, but the fitting effect is poor for both training dataset and test dataset; Decision tree takes less time, but it shows that the high accuracy in training dataset and low accuracy in the test dataset, which is an obvious over-fitting situation; SVM takes a long time, and there is also a certain over-fitting phenomenon. Time-consuming of random forest is

general, and the over-fitting situation is effectively prevented. But under the premise of larger samples, the amount of data for per decision tree under random forest is very large which will lead to a large amount of computing and time consumption. To sum up, we choose use the SVM algorithm to classify emotion.

3. Student Status Monitoring Based on mouse track

Considering the actual situation of online learning, there will be some learners who have a situation of thoughts wandering at certain times. Therefore, we use the mouse track recognition to eliminate whether puzzled emotion is generated by non-learning factors.

3.1 Classification and data acquisition of mouse track

First of all, we divide the track patterns to five categories: reading, simple reading, circle drawing, completely chaotic and almost static. In the analysis of difficult points, we find that puzzled emotion generated by reading and simple reading has high credibility. Puzzled emotion corresponding to the circle drawing and completely chaotic has low credibility. Almost static needs to be confirmed by other ways. Secondly, we divide time interval before and after a specific time into the *n* parts equally, and obtain the coordinates of equal division points to represent mouse track in the specific moment.

3.2 Mouse track dimension reduction method based on vector angle

Because a mouse track contains a large number of coordinates, if you use them to train classification algorithm in machine learning directly without reducing the dimension, it will lead to huge-scale calculations and over-fitting phenomenon. Therefore, it is necessary to reduce the dimension of the mouse track data. We propose a method for reducing the dimension of the mouse track, the specific method is: 1) A mouse track's coordinate information (x_i, y_i), $i \in (1,2,\cdots n)$ can be converted to $n-1$ vectors $v_1, v_2, \cdots v_{n-1}$; 2) Calculate the cosine's absolute value of each two adjacent vectors and relative total displacement:

$$d_i = \frac{\left| \vec{v_i} \cdot \vec{v_{i+1}} \right|}{\left\| \vec{v_i} \right\| \times \left\| \vec{v_{i+1}} \right\|}, i=1,2,\cdots,n-2 \quad , \quad S = \frac{\sum_{i=1}^{n-1} \| \mathbf{v}_i \|}{\sqrt{H^2 + W^2}}$$

H and *W* are the number of pixels of the screen height and width respectively; (3) Divide [0, 1] into *m* intervals and count the number of d_i falling into each interval. Number of each interval is divided by $n-2$ to construct *m* feature. At the same time, the relative total displacement *S* of the mouse is also taken as a feature.

3.3 Dimensionality reduction feature corresponding to the mouse track category

In the difficult point annotation, we need recognize reading and simple reading patterns. Five types of the track category features after the dimension reduction are described as follows.

(1) Reading mode. The track can be split into many similar groups. Each group include a horizontal line, a turning point, and a slightly inclined line. The angle between vectors is close to 0° or 180° (the angle of straight line is close to 0°, and the angle of the turning point is close to 180°), their cosine value is close to 1 after absolute value processing.

(2) Simple reading mode. The composition of the track is generally a number of straight line segments with a number of turning points. Different from the reading mode, the simple reading mode is for quick browsing. Generally, the slope of the straight line segment is higher than the reading, and thus the angle at the turning point will be bigger.

(3) Static mode. Judging this track mode requires a measurement of the total displacement generated by the mouse. In addition, the screen size of different devices is different, so it is necessary to divide the size of the screen to calculate the relative displacement.

(4) Circle drawing mode. The significance of studying this mouse model is that it corresponds to a so-called "boring" status of learners. The track image is basically rendered as some kind of convex

polygon. Among them, the angle between adjacent vectors is basically fixed at an angle near the range of 30º.

(5) Completely confusing mode. The vector angle of this mode is basically chaotic and disordered.

3.4 Effect of learning state monitoring algorithm based on mouse track
Based on *3.2.* and *3.3.*,student status monitoring based on mouse track algorithm is shown in algorithm 1. For evaluating the dimension reduction method designed in this paper, we choose PCA (principal component analysis) as comparison method to carry out experiment. Mouse track dataset constructed by simulation was divided as the training dataset and test dataset. Results of the two dimensionality reduction methods with SVM as classifier are shown in Table 2.

Algorithm 1: Mouse track dimension reduction algorithm based on vector angle

Input: mouse track *Track*; screen size *SIZE*

Output: dimension reduction results Re *sult*

Time complexity: constant

Start

1. For $i \leftarrow 1$ to length$(Track)$ do
2.   Generate a mouse track vector $\vec{v_i} = (X_{i+1} - X_i, Y_{i+1} - Y_i)$;
3.   If $i \geq 2$:
4.   Generate vector angles $\deg ree[i-1] = \left| \cos\left(\vec{v_i}, \vec{v_{i+1}}\right) \right|$;
5. Calculate the ratio of the number of the values in the five intervals $1 \sim \cos(\pi/6)$、 $\cos(\pi/6) \sim \cos(\pi/4)$、$\cos(\pi/4) \sim \cos(\pi/3)$、$\cos(\pi/3) \sim 0$ to the total in the $\deg ree$, respectively, and count $result[0 \sim 3]$;
6. $result[4] = \sum \left\| \vec{v} \right\| / SIZE$;

End

Table 2. Test effect of two dimension reduction methods

Method	Accuracy under training dataset (%)					Accuracy under test dataset (%)				
	0	1	2	3	4	0	1	2	3	4
PCA + SVM	93	87	88	94	83	80	60	60	40	60
Our Method + SVM	100	95	77	83	83	100	80	40	80	40

The second row of numbers in this table represents different types of mouse track: 0 for almost static; 1 for reading; 2 for circle drawing; 3 for simple reading; 4 for completely confusing. It can be seen that the accuracy of the two methods is extremely high on the training set. In the test set, the average performance of PCA is slightly worse than our method. The accuracy of our method in the three modes of reading, simple reading and almost static can be achieved 80%. Especially, the accuracy of almost static reached 100%. Therefore, our method has a good reduction effect for classifying track patters.

4. Empirical Research

4.1 Design of difficult point marking System
In order to verify the effectiveness of proposed method, we designed and developed a prototype system of difficult point marking. The main process of the system is shown in Figure 1.
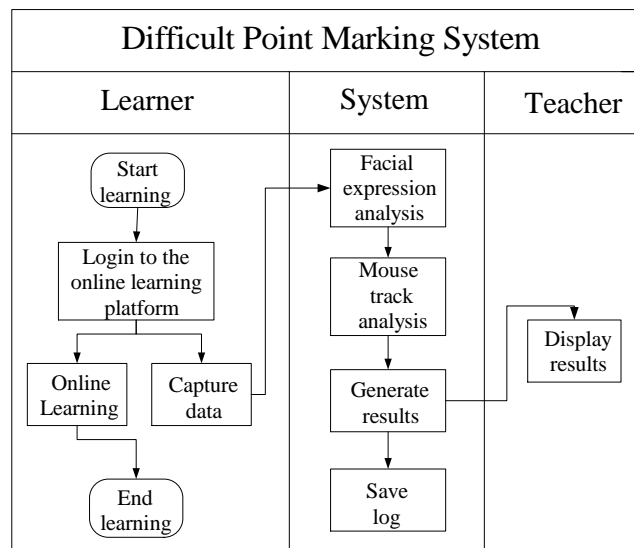
Figure 1. Design of difficult point marking System

4.2 Experimental Design

We mainly need to distinguish the following two learning states.

   1) The learner has doubts about the real learning content: Learner expresses puzzled emotion, and carefully studies the learning content.

   2) Learners express doubts because of thoughts wondering: Learner expresses puzzled emotion, but do things unrelated to learning (such as watching mobile phones).

   We collected learning trajectories from multiple volunteers on the system designed in this paper. To verify the effectiveness of the proposed method, we compare the results of the system marking with of the learner self-marking.

4.3 Experimental Result

Through experiments, degree of coincidence between marking results of our method and learner self-marking can reach 80%. We illustrate the effectiveness of the method by an example.

   We simulate a learner's learning process in a minute. In the 10th second, we simulate the situation where the learner is really confused. In the 30th second, we simulate the situation where learner has doubt caused by seeing the mobile phone. In the 50th second, we simulate the situation where learner has doubt caused by playing computer game.
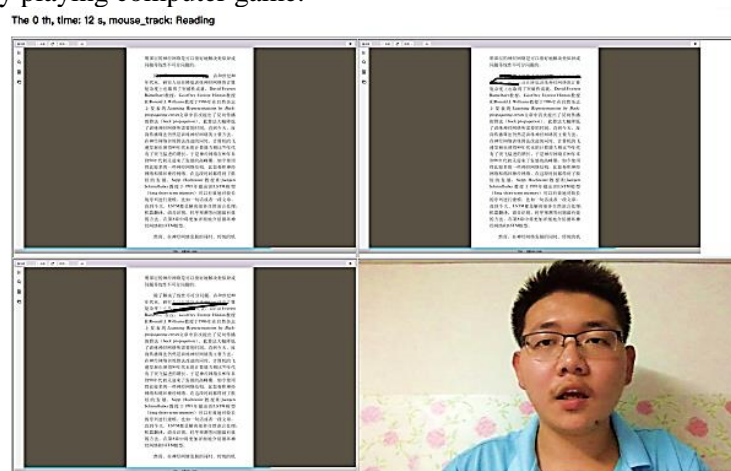

Figure 2. Case result

As shown in the Figure 2, the system accurately identify the 12th second as a doubt caused by learning. Specifically, "The 0th, time: 12 s, mouse_track: Reading" in the upper left corner indicates that this is the first doubt, and the time is the 12th second. Then, looking at the colored mouse track on the three screenshots, we can see that this is a very obvious mouse track generated by reading the text line by line carefully. The lower right picture corresponds to the facial image at 12 seconds. The learner's brow is tight and his mouth is slightly open, which is a typical doubtful expression. This example shows that the system can effectively help educators find difficult points in learners' learning.

5. Summary
This paper proposes a method of marking learner's difficulties in learning and implements a prototype system. Our method can effectively recognize when learners express puzzled emotion. At same time, through the analysis of mouse track, we can know learner's state in creating puzzled emotion, and mark related content that makes learners confused. In further research, we can merge sound text semantics and other information in our method to improve the accuracy of marking.

Acknowledgment

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