# RECOGNIZING REAL EMOTIONS THROUGH INDUCTIVE WRITING TEACHING

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**ABSTRACT**

It is of great importance to identify students' negative emotions so as to avoid accidents. However, most of the students with mental problems seldom express their emotions in some ways, which makes it more difficult for the emotion recognition system to obtain the emotional data of these students. To solve the problem of the lack of data acquisition approaches in emotional monitoring of special student groups, this paper proposes a method to obtain students' real emotions based on emotion-induced writing teaching. First, the channel for acquiring emotion data of the special students is established through writing teaching. Second, students are guided to express their emotions through essays by purposeful writing exercises. At last, this paper proposes an emotion calculation method, which comprehensively analyzes a student's real emotion according to the emotions of a group of essays on positive, neutral and negative themes. The experimental results show that the proposed method can obtain students' real emotions effectively and is much better for students with optimistic and pessimistic personalities.

**KEYWORDS**

Emotion Recognition, Writing Teaching, Mental Health.

## 1. INTRODUCTION

The COVID-19 pandemic is sweeping the world. The fear of the virus, the depression of isolation and the pressure of employment have affected many people's emotions. Comparatively speaking, college students, a special group, have weak emotional control ability, and psychological breakdown will lead to more serious consequences. It is of great significance for students' healthy development and social stability to accurately perceive students' negative emotions and effectively ease them so as to avoid unexpected situations.

The emotion recognition task mainly includes two sub-tasks. First, obtaining raw data for emotion recognition. It is usually obtained through conversations, social media, audio and video surveillance. These data include conversations, texts, tones, facial expressions, body movements, web behaviors, etc., which may explicitly or implicitly contain the emotions of the subjects. Second, emotion recognition. It is mainly achieved by emotion dictionary (Kim, 2004), statistical machine learning method (Wang, 2012) or deep learning method (Liu, 2015; Ouyang, 2015). Current studies mainly focus on the second sub-task, while the first task is rarely studied.

In the context of COVID-19, the primary problem faced by college student emotion recognition task is that it is difficult to obtain emotion data. Due to the necessity of fighting against the epidemic, there are fewer group activities in school and less face-to-face communication between students. In particular, for the special emotional students, they are not good at communicating with others or active on social networks. They lack the way of emotional release, and are more prone to have some psychological problems, which makes it difficult for us to obtain emotional data of the special student group through traditional means.

In order to solve the above problems, we propose English writing teaching as a channel for perceiving students' emotions. Because of the special status of English writing teaching in Chinese universities, it is a compulsory course for freshmen and sophomores in almost all majors. Some third and fourth grade students also need to take English writing courses because of the Graduate Entrance Examination, TOEFL and so on. Therefore, student essay as emotion recognition data is a possible approach. Compared with social media and other ways of expressing emotions directly, the emotions expressed by essay are not necessarily students' current emotions, so it is more difficult to identify students' real emotions based on essays. To solve the

problem, we propose an emotion-guided writing exercise, which allows students to write essays on different emotion topics in a short period, and integrates the emotions expressed by students in essays on positive, negative and neutral emotion topics, so as to better acquire students' real emotions.

The main contributions of this paper are as follows:

1) This paper proposes a method to acquire students' emotion data based on English writing teaching, and establishes a channel for acquiring emotion data of the special emotional students.
2) This paper puts forward a method of obtaining students' emotions by emotion-guided writing training, which improves the ability to obtain students' real emotions from essays.

## 2. METHOD

The proposed framework to induce and recognize students' real emotions based on writing exercises is shown in Figure 1. The framework mainly includes a writing task generation module, an essay emotion recognition module, and a student emotion recognition module. The modules and the work process of the framework are shown as follows.

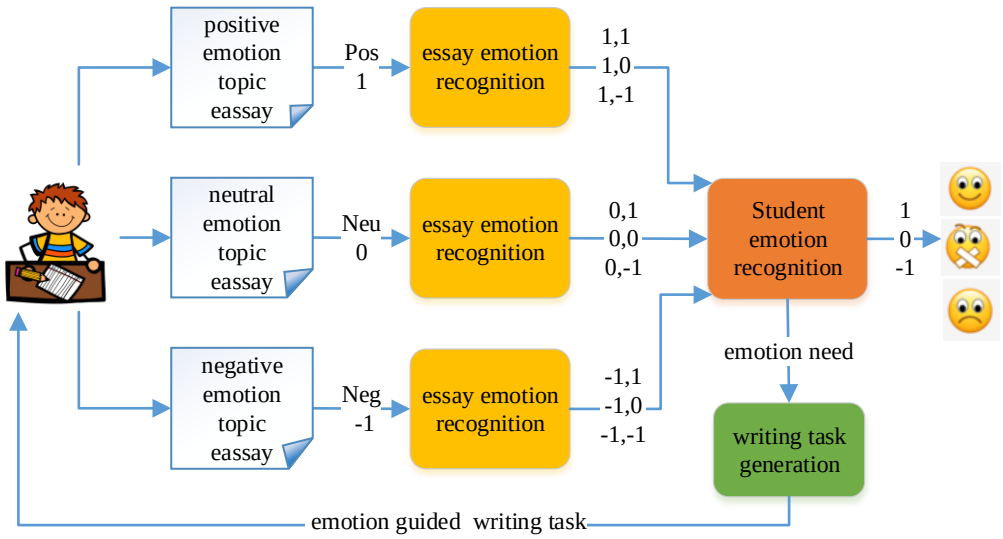


Figure 1. Real emotion recognition framework of a student

## 2.1 Writing Task Generation Module

The writing task generation module generates three different writing tasks which involve positive, negative and neutral topics for a student. An effective way is to label each writing task in the existing writing practice database with an emotion, and then randomly select writing tasks according to the task requirements and emotion labels in the database. The number of writing tasks is relatively limited, so we make the emotional labeling of writing tasks manually to obtain a more accurate result.

## 2.2 Essay Emotion Recognition Module

The essay emotion recognition module classifies the emotion of each essay. When the essays are completed by the student, emotion recognition module obtains the emotion of each essay based on emotion classification method. The text emotion classification method based on deep learning has become the mainstream, and there exist many methods with good effect, such as RNN (Recurrent Neural Network) (Topbaş, 2021; Zhang, 2016), BI-LSTM (Bi-directional Long-Short Term Memory) (Tareq, 2021). This module directly employs the BI-LSTM + CRF model as the emotion classifier.

## 2.3 Student Emotion Recognition Module

The student emotion recognition module identifies the real emotion of a student by comprehensively considering the emotions of three essays belonging to three writing tasks. This module is the key to the proposed method. We use three categories of emotions, among which positive emotion is 1, neutral emotion is 0, and negative emotion is -1. Each essay may be classified as positive, neutral, or negative emotion by the essay emotion recognition module. There are nine possible combinations shown in matrix (1), each of which is represented by a two-tuples. For example, (1, -1) indicates that a student writes an essay on a positive emotion topic into a negative emotion essay, which may indicate that the student has severe negative emotions.

$$\begin{bmatrix} (1,1) & (1,0) & (1,-1) \\ (0,1) & (0,0) & (0,-1) \\ (-1,1) & (-1,0) & (-1,-1) \end{bmatrix} \tag{1}$$

Each of these two-tuples is simplified by subtracting the first item from the second item to get the following matrix.

$$\text{mim} = \begin{bmatrix} 0 & -1 & -2 \\ 1 & 0 & -1 \\ 2 & 1 & 0 \end{bmatrix} \tag{2}$$

In (2), -2 means the most negative motion, 2 means the most positive motion, and the other values means middle motion. We call (2) as the motion inductive matrix for writing. Assume that the emotions of a student's three essays are -1, -1, 0 respectively, which are mapping to the mim matrix and get the position matrix, as shown in (3).

$$\begin{bmatrix} -1 \\ -1 \\ 0 \end{bmatrix} \Rightarrow \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \tag{3}$$

Finally, the emotion of the student $es$ can be gotten by (4). $es$ values range from -3 to +3 for a total of seven emotional states. We convert them to three emotional states -1, 0, and 1 as the final output of the method., namely the student's real emotion.

$$es = sum\left(\begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \circ \begin{bmatrix} 0 & -1 & -2 \\ 1 & 0 & -1 \\ 2 & 1 & 0 \end{bmatrix}\right) = -2 \tag{4}$$

## 2.4 Work Process

The real emotion recognition framework of a student works circularly. Each round of student emotion recognition works as follows.

1) According to the emotional need and the writing teaching need, the writing task generation module selects three writing tasks of positive, negative and neutral topics from the labeled writing tasks database.

2) When the essays are completed by the student, the emotion recognition module obtains the emotion of each essay based on text emotion classification method.

3) Finally, the student emotion recognition module comprehensively considers the emotions of three writing tasks and the emotions of three essays, and finally obtains the student's emotion.

To avoid the uncertainty of the single-round emotion recognition, the above emotion recognition process can be repeated many times according to the frequency of practice in writing teaching. If the recognition results of multiple rounds in a short period of time are conflicting, the result should be ignored. On the contrary, if the recognition results of multiple rounds in the short term are consistent, the recognition results are of great reference value.

# 3. EXPERIMENT

## 3.1 Experimental Design

**Experiment Participants:** We select 30 none-English major students from different majors and grades in a university as the participants. The emotions of these students can be observed. They either have social media accounts and update frequently, or they can be observed with the help of surrounding students, or they can be observed by teachers in class. These observations are transparent, and the participants are not aware of participating in the experiment, so as not to affect the experimental results.

**Experimental Process:** The processes of the experiment are as follow,

(1) Observe and obtain the real emotion of a student manually;

(2) Generate writing tasks, choose three essays which involve positive, negative and neutral topics respectively, and release them to the student one by one;

(3) Collect the three essays one by one, and recognize the emotion of each essay;

(4) Calculate the student's emotion based on the emotions of three essays.

(5) Observe and obtain the real emotion of the student again, and compare it with the emotion obtained in step1. If there is no change in emotion, this round of experiment is over and the results are available. Otherwise, the results of this round are discarded and then a new round of experiment starts. The goal of this step is to eliminate the influence of writing on student's emotions.

(6) Repeat the above steps for all 30 students to complete a complete experiment.

(7) Take the emotion of each student obtained in step (1) as reference, and calculate the correctness of the emotion of all students obtained by the method.

## 3.2 Experimental Results and Analysis

We repeated the experiment three times, and the results are shown in the first line of Table 1, with an average accuracy of 74.5%. Although there is still a lot of room for improvement in accuracy, the proposed method has been proved to be effective. Further, we try to find out whether there exists a difference of the proposed method in the emotion acquisition of different personalities. Based on the personality analysis of the participants, we classified them into optimistic, pessimistic and neutral groups. The results of the experiment are recalculated in each group. The final results are shown in lines 2, 3, and 4 in Table 1. The experimental results show that the proposed method has the best effect on optimistic student, followed by pessimistic student and neutral student.

Table 1. Results of real emotion recognition of students through essays

| Personality type | Exp1 | Exp2 | Exp3 | Average |
|---|---|---|---|---|
| all students | 0.739 | 0.786 | 0.711 | 0.745 |
| optimistic students | 0.800 | 0.900 | 0.800 | 0.833 |
| pessimistic students | 0.750 | 0.875 | 0.750 | 0.792 |
| neutral students | 0.667 | 0.583 | 0.583 | 0.611 |

To explore the reasons for the differences among different personality, we conducted a further analysis of the experimental data to observe whether a student’s emotions are consistent with the emotions expressed in his/her essays. The emotion consistency degree is equal to the ratio of the number of emotionally consistent essays to the total number of essays, which is also calculated in personality groups and the results are shown in Table 2. The results show that optimistic students have the highest emotion consistency degree, followed by neutral students, and pessimistic students have the lowest emotion consistency degree. The high emotion consistency degree means that students' emotions can be expressed more through the essay, which also makes students' emotion recognition algorithm perform better.

Table 2. Comparison of emotion consistency of different personality students

| Personality type | Emotion consistency degree |
|---|---|
| All students | 0.758 |
| optimistic student | 0.853 |
| pessimistic student | 0.689 |
| neutral student | 0.734 |

Through the above analysis, it can be seen that the proposed method of obtaining students' real emotions through guided writing is effective. Although the method has a certain tendency that the emotion recognition of optimistic students is better than that of pessimistic students, the emotion acquisition of pessimistic students has also been proved to be effective.

# 4. CONCLUSION

It is meaningful to monitor the psychological impact of COVID-19 on college students by using emotion analysis systems to avoid some unexpected accidents. However, most of the students with mental problems seldom express their emotions in some ways, which makes it more difficult for the emotion recognition system to obtain the emotional data of such students. This paper proposes the method of obtaining students' real emotions based on writing exercises, which effectively solves the problem of lacking emotion data in the emotion monitoring of special student groups. The experimental results show that the proposed method can obtain students' real emotions effectively and is much better for students with optimistic and pessimistic personalities. The proposed method can be used not only in student emotion perception and analysis system, but also in feedback and evaluation of writing teaching after making little changes.

The paper presents the preliminary result of the proposed method of obtaining students' emotion through inductive writing teaching. There are still more improvements to be made in the next step of the paper, such as trying to use more methods to improve the accuracy of emotion recognition in individual essays, design more step experiments to verify the effectiveness of the proposed method.

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# REFERENCES

Kim, S., and Hovy, E., 2004. Determining the sentiment of opinions. *Proceedings of the International Conference on Computational Linguistics.* Geneva, Switzerland, pp. 1367-1373.

Liu, P. et al, 2015. Fine-grained Opinion Mining with Recurrent Neural Networks and Word Embeddings. *Proceedings of the Conference on Empirical Methods in Natural Language Processing*. Lisbon, Portugal, pp.1433-1443.

Ouyang, X. et al, 2015. Sentiment Analysis Using Convolutional Neural Network. *Proceedings of the IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing.* Liverpool, UK, pp. 2359-2364.

Tareq, A., and Hewahi, N., 2021. Sentiment Analysis of Tweets During COVID-19 Pandemic Using BLSTM. *Proceedings of the International Conference on Data Analytics for Business and Industry.* Sakheer, Bahrain, pp. 245-249.

Topbaş, A. et al, 2021. Sentiment Analysis for COVID-19 Tweets Using Recurrent Neural Network (RNN) and Bidirectional Encoder Representations (BERT) Models. *Proceedings of the International Conference on Computing, Electronic and Electrical Engineering*. Quetta, Pakistan, pp. 1-6.

Wang, S., and Manning, C. D., 2012. Baselines and Bigrams: Simple, Good Sentiment and Topic Classification. *Proceedings of the Annual Meeting of the Association for Computational Linguistics Volume 2*. Jeju Island, Korea, pp. 90–94.

Zhang, Y. et al, 2016. Sentiment classification using Comprehensive Attention Recurrent models. *Proceedings of the International Joint Conference on Neural Networks.* Vancouver, BC, Canada, pp. 1562-1569.