Visualizing e-Learner Emotion, Topic, and Group Structure In Chinese Interactive Texts

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***Abstract*—To help teachers know class/group members better in the case of large scale on-line textual interaction, this paper tried to display e-Learner's emotion combined with topics and group structure. For achieving this goal, a color palette of emotions based on Plutchik's color palette was presented, an extended cascaded PLSI algorithm using sliding window technique was proposed to detect and track topics in Chinese interactive texts, and multiple star-field variants were introduced to display the group structure.**

Keywords-emotion; visualization; topic detection and tracking; group structure; interactive texts;

I. INTRODUCTION

Textual interaction in e-learning applications, such as chat-room for courses, online Q&A and group discussion, serves as the most common ways to communicate between teachers and students or among students. How to display these emotional contents of interactive texts in a direct and artistic way becomes very important in the field of affective computing, which can help characterize e-Learners' negative emotions and be adopted by teachers to solve the problem of Emotional Illiteracy [1-3].

Currently, many researches focus on the topic visualization [4]. A little researchers [5] paid attentions on emotion visualization. But reports on using the Chinese vocabulary to visualize emotional contents in texts lack in literatures. And, there are new and special requirements aroused in emotion visualization of interactive texts based e-learning applications: 1) In addition to considering the general emotion states, such as happy, angry, surprise, and frustration/sadness [7], it is necessary to consider the e-learner-oriented emotion states, such as anxiety, guilty & shame, and sympathy [1]; 2) interactive texts are characterized with interactivity (turn and interaction of content and emotion), organization, and time dependence [2], besides the ambiguity and ill-formedness of natural language. Moreover, we find that short sentences (even phases), nonlinguistic symbols and Emoticons are rich in our interactive texts corpus.

We had built an emotion vocabulary collected from interactive texts and proposed a decision tree based emotion recognition method in [1]. In this paper, we discuss the issues about color palette of emotions, time related parameters, topic detection and tracking, and group structure visualization.

II. MAIN PARAMETERS OF E-LEARNER EMOTION VISUALIZATION IN TEXTUAL INTERACTION

A. Color Palette of Emotions

Currently, most researches on emotion visualization build a mapping relationship between primary emotion states and basic color based on visual perception of human on cognition in the psychological level. In this paper, we map our emotion category[1] into different colors according to Plutchik's color palette[7] (seen in Table I).

TABLE I. THE MAPPING OUR EMOTION STATES INTO PLUTCHIK'S COLOR PALETTE

No.	Emotion states	
	Our emotion states	**Plutchik's**
1	appreciation	joy + acceptance
2	sympathy	trust + sadness
3	love/adore	admiration + elation
4	relief	serenity
5	pride	anger + joy
6	hope	anticipation
7	positive surprise	surprise + joy
8	inhospitality	anger + disgust
9	anxiety	anticipation + fear
10	shame & guilt	joy + fear + disgust
11	hopeless	grief + astonishment
12	negative surprise	surprise + fear

B. Time Related Parameters

Time is an essential element of reality, especially in emotion communication based on textual interaction. In the existing interactive texts there are two types of time: absolute time and relative time. Currently, the units of timeline (absolute time) and response intervals (relative time) in a dialogue are considered. Turns occurred in timeline is shown

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in Fig. 1, where colorful squares/stars/dots/arrows mean group members' texted sentences; the histogram is for turns occurred in a time interval change over time (see Fig. 2); and users can feel the *response intervals* and the dialogue process in an animation way.

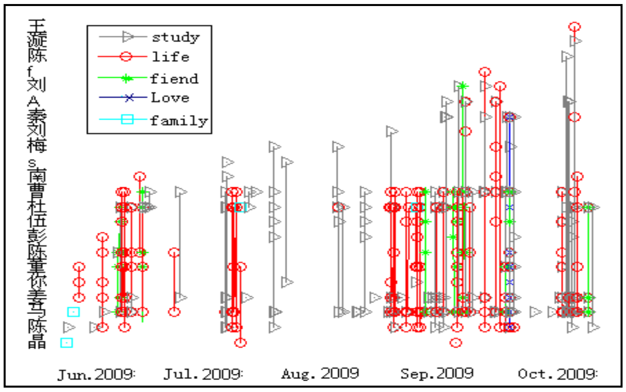

Figure 1. Topics change over time (Timeline :month)

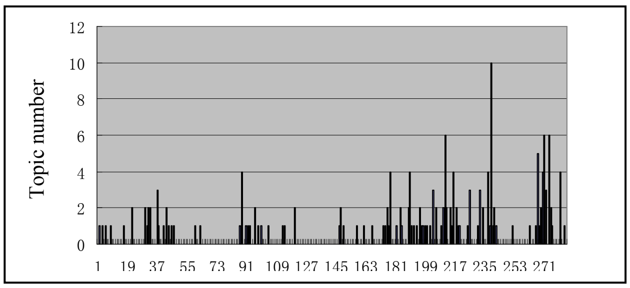

Figure 2. Turns occurred in a time interval (12 Hours) change over time

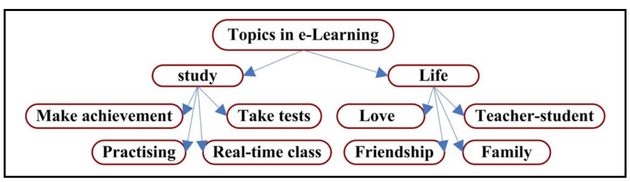

Figure 3. A partial part of a hierarchical topic in e-Learning

C. Topic Detection and Tracking

Topic detection and tracking (TDT) is a hot topic in the field of text mining. According to our experiments, current methods of topic detection and tracking failed to deal with this kind of situation (seen the experiment results using K-Means and PLSI [8] in this section), because short sentences and phases are popular in interactive text applications. For example, each turn has less than five sentences in seventy percent of dialogues in our corpus. So, there is a need to develop a new TDT method for interactive texts.

The interactive texts can be represented as seven tuples: *Its= (ID, D, Name, Role, Content, E, T)*, where *ID* is a set of the unique identifier of each turn in the dataset; *D* is a set of the date and time when a turn in the dialogue is occurred; *Name* is a set of speakers' name; *Role* is a set with two elements, one is for speaker, the other is for recipient; *Content* is a set of words and their counts obtained after parsing sentences in each turn; *E* is a set of emotion states (see Section II.B) and its intensity, which is labeled manually or marked by machines; *T* is a set of topics which in each turn are always labeled manually. As shown in Fig. 3, a topic in dialogues or interactive texts is a hierarchical concept. Topics in the upper level maybe abstract concept, such as 'Study' or 'Life'; a topic concept in the bottom level is defined as an affair/event group discussed, such as 'my technical report was criticized by my supervisor' and so on.

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An Improved Algorithm based on Cascaded PLSI:
INPUT: ITs: String Array   %a test data set of interactive texts;
       d : Array            %time array indicated that each turn occurred
       D_T: Integer         %a threshold for judging whether two nearest sentence is
                            %topic-related in the term of the response intervals.
OUPUT: T, Dialogue: Array % Marked ITs with Topic and event number, respectively.
Procedure:
Begin
  FOR i=1 to length(ITs) { level=0; T=TopLevel; T_i'=Deep-first(Content, T, level);
    IF i == 1 THEN { Dialogue[i]=1;  T[i] = T_i'; }
    ELSEIF |d[i] - d[i-1]| <= D_T THEN
       {IF T[i-1] = T_i' THEN { Dialogue[i]= Dialogue[i-1]; T[i]=T[i-1]; }
        ELSE { k=k+1; Dialogue[i] = k;  T[i] = T_i' ; } }
    ELSE  IF |d_i - d_{i-1}| > D_T  THEN { k=k+1; Dialogue[i] = k; T[i] = T_i' } }
End

FUNCTION T_i'=Deep-first(feature_set, Topic, level)
BEGIN
  IF Topic== TopLevel && level == 0 THEN { P_{T_i} = max_{T_i ∈ T_TopLevel} {P_{T_i}(feature_set)};
    IF sonof(T_i) == NULL THEN { T_i' = T_i; Return;}
    Else { T_i' =Deep-first(feature_set, T_i, level+1);  Return;} }
  Else { P_{T_i} = max_{T_i ∈ sub(Topic)} {P_{T_i}(feature_set)};
     If sonof(T_i) == NULL THEN { T_i' = T_i;  Return;}
     Else { T_i' =Deep-first(feature_set, T_i, level+1);  Return; } }
End
```

Figure 4. Procedure of an improved algorithm based on cascaded PLSI

1) An Extended cascaded PLSI algorithm: Firstly, inspired by the topic hierarchical classification, a cascaded PLSI algorithm is proposed. For example, the procedure of takes is: classify a sentence into one topic, such as 'Life' in the upper level of Fig.3, denoted as T_i. If there is a subset of T_i, denoted as $sub(T_i)$ = *{Love; Friendship; Family; Teacher-student}*, then classify the sentence into one of topics in $sub(T_i)$, denoted as $T_t \in sub(T_i)$, continually execute this classification procedure along with the hierarchical topic tree until there is no subset, then stop the algorithm.

Secondly, as shown in Fig.2, the response intervals in a dialogue can be an important index for new topic detection. So, we use a parameter, sliding time window, D_T, to control the turns that should be focused. Combining sliding time window with the cascaded PLSI algorithm, an improved algorithm for TDT in interactive texts is proposed and shown in Fig. 4. In which, if the response interval between the neighbored turns is less than D_T, then the cascaded PLSI algorithm is adopted to judge whether topics of the two turns are same; otherwise, a new topic is marked.

2) Experiments and their results: (1) Data preprocessing and training. A real world interactive text set is collected from a QQ group named 'Linux group', contains 1525 turns and 158 events, of which the span is from April 2009 to Oct. 2009, 70 percents for train, and 30 percents for test. In this dataset, each sentence is parsed by a Chinese parser, ICTCLAS [10], and each turn is labeled manually with 'Study', 'Life', 'Friendship', 'Family', and 'Love'.

To obtain probabilistic matrix of terms and topic in different levels, two trained datasets were formed, one includes all the turns, but each of which only marked with 'Study' or 'Life'; the other only includes the dataset labeled as 'Life', but of which each turn is marked with the secondary level topics, such as 'Friendship', or 'Family'.

(2) Experiments and their results. The proposed algorithm, K-Means, and PLSI algorithm are carried out on the test dataset, three algorithm precision are 61.88%, 4%, and 45%, respectively. It is obvious that the proposed extended cascaded PLSI algorithm performs better than the other two in terms of precision, which is attributed to the imbalance of topics distribution in the dataset where the number of the dataset labeled with 'Study' and 'Life' is more than 100 dialogues, and the number of dataset labeled with 'Friendship', 'Love' and 'Family' is less than 50 dialogues.

D. Group Structure Visualization

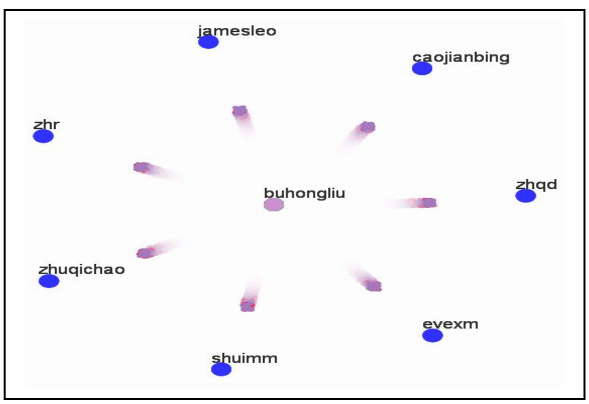

Figure 5. A star-field pattern for teacher-dominant mode

Group structure plays an important role in typical e-Learning scenario, such as on-line course, Q&A, and group discussing. According to teaching mode and role-play, group structure can be classified into three types: (1) Teacher-dominant mode. That is, a teacher plays a dominant role in teaching, and transfers the information and emotions to the students, for example, real-time classroom. So, a teacher-centered star-field pattern is adopted to display teacher-dominant mode, in which the central star represents a teacher who broadcasts his/her information to students, shown in Fig. 5; (2) Q&A mode. In which, as a one-to-one dialogue, usually one to ask questions, the other to answer it. So, a peer-to-peer based star pattern is introduced to display Q&A mode; (3) Equal mode. That is, members in a group have the same right to speak. So an equal-portion-circle pattern is used, and similar to teacher-centered star-field pattern but without the center star. During visualization, all sentences are rendered as an emotion-state-mapping-color dot set approaching from a sender to the receiver(s) in an animation fashion, according to the recognized emotion state from the sentences, word counts, intensity marker and its counts.

III. CONCLUSION

A method for e-learner emotion visualization is proposed, in which, a mapping from our emotion category to Plutchik's color palette is introduced, a cascaded PLSI algorithm with a sliding window threshold D_T is proposed for topic detection and tracking in Chinese interactive texts, and different star-field modes are adopted to visualize the group structure. In the future, combined FLEX technology with our method, a prototype system will be developed.

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