A Sentiment Analysis Method for Facial Expression Generation in Human-Robot Interactive Communication

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Abstract—**Emotion is a primary semantic component of human communication. This study focuses on automatic emotion detection in descriptive sentences and how this can be used to tune facial expression parameters for virtual character generation. Therefore, we present a classification based sentiment analysis approach to mapping a sentiment sentence into an emotional state. Each sentence is represented as a feature vector and classified using support vector machines. By considering the high dimension of the textual data, and the semantic relation between words, we introduce the distributed representation model. Results of the study indicate that our sentiment analysis method could assist automatic facial expression generation in human-robot interactive communication efficiently.**

Keywords- Sentiment analysis; Facial expression generation; Distributed representation model; Human-robot interactive communication

I. INTRODUCTION

The virtual world known as massively multiplayer online world (MMOW) is a computer-based simulated environment [1]. Second Life (https://www.second-life.com/) is one of the most popular online virtual world platforms in use, with an emphasis on social interaction [2, 3]. The users in Second Life, called Residents, can interact with each other through avatars. An avatar is a digital character that you can create and personalized customize. For instance, as shown in figure1, many companies, such as IBM, use the online world for meetings, interviews, guest speaker events and training for other employees etc [4].

In the real world, emotions play a significant role in human behavior, communication and social interaction, they always guide action, control resource usage, and shape dialogue [5, 6]. Therefore, the affective dimension also carries over its high significance for the case of human-robot interaction [7]. In recent years, emotion has increasingly been used in interface and robot design, Moreover, many studies have been performed to integrate emotions into products including electronic games, toys, and software agents [8]. However, Machinima movies created inside the virtual world like the Second Life can produce stunning visuals, but often lack character facial expressions.

The face-to-face interaction is expressed through a number of channels, including the body, the voice, and the face. While talking, people's faces are rarely still, they not only use their lips to talk, but they raise their eyebrows, move or blink their eyes, or nod and turn their head [9]. Facial signals seem to help control the flow of conversation in much the same way as intonation does, and they also express effectual signals, which may be used communicatively to influence the other participant's behavior [10, 11]. To find universal facial expressions linked to affects and attitudes were interested by some psychologists [10]. Therefore, in virtual environment, for adding realism, virtual characters need to change their facial expressions, for example, smiling or making other emotional expressions [12]. How to generate vivid facial expressions by computers has been an interesting and challenging problem for a long time, and it is considered among the core building blocks of social communication in cyberspace.

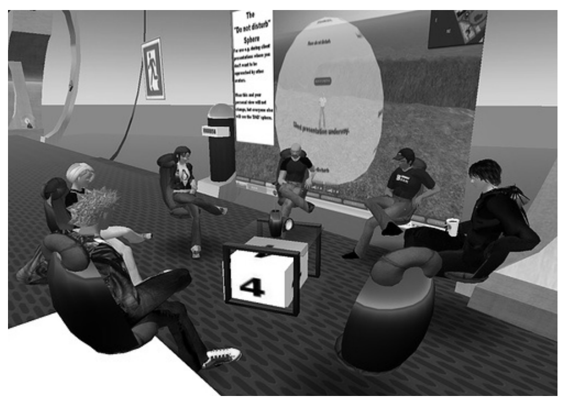

Figure 1. IBM virtual meeting using Second Life [4].

Animating the face by specifying every action manually is a very tedious task and often does not yield entirely appropriate facial expression [13], especially, it's harder to meet the requirements of real-time communication for VR applications in Internet social network. In order to improve facial animation systems, understanding linguistic semantic orientation is an important priority. Although facial expression generation has been studied for many years, by far, most research and engineering efforts on emotions in robotics have focused on facial animation [14-23]. However, little attention was paid to the study of text Sentiment Analysis approaches for facial expression generation in

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semantic level, and the correlative research in this field is rare.

Semantic orientation is a measure of subjectivity and opinion in text. It usually captures positive or negative as an evaluative factor and the strength degree to which the word, phrase, sentence, or document is positive or negative towards a specified object [24]. Text sentiment analysis [25], also referred to as emotional polarity computation, is the general method for the analysis and automatic extraction of semantic orientation. This paper studies text Sentiment Analysis approaches for facial expression generation in Human-Robot Interactive Communication. Suppose there is a conversation C scene in an Interactive environment, and c is one of the sentences belongs to C, F is a set of facial expressions, then, given a sentence c, our goal is to predict fi which is the appropriate facial expression here we expected. The formal description as: argmax $p(fi \mid c)$ and $fi \in F$.

The rest of the paper is organized as follows. Section 2 discusses related work of our study. Section 3 presents models and methodology. Empirical results and discussion are given in Section 4. Finally, Section 5 concludes the paper.

II. RELATED WORKS

A. Emotions definition

Although there is no uniformed definition, emotions are commonly described as “fairly brief but intense experiences” [26], different from the psychology fields, in the artificial intelligence literature, the term is frequently used in a broader sense to intelligent machines, it also include preferences and affective appraisals.

Facial expressions, with principally communicative purposes have revolutionized views of human emotions [27]. The most classic research has stipulated the existence of six primary emotions [28] that are expressed through facial expressions: happiness, sadness, anger, fear, disgust, and surprise. Evidence from cross-cultural studies of facial expressions [29] shows that all human expressions can be viewed as a combination of these expressions.

Because of the efficiency of human emotion cues in sending and receiving information with other humans, in order to equip robots with the ability to project emotion cues as an intuitive form of human–robot communication, varies attempt were presented.

The use of human like facial expressions, such as furrowed eyebrows may be a common example of emotion cues that simulated by a social robot. For instance, so-called baby face cues was utilized in the FLOBI humanoid head, it consist of large round eyes, and a small nose and chin. Emotions are primarily transfer through different configurations of eyebrow, eyelid, and lip movements. In addition, the diffused white or red light onto the cheek surface creates an impression of blushing [30].

B. Sentiment analysis

Sentiment analysis is the natural language processing task dealing with sentiment detection and classification from texts [31], for instance, at emotional states such as "angry," "sad," and "happy". In recent years, due to the growth in the quantity and fast spreading of user-generated contents online and the impact such information has on events, people and companies worldwide, this task has been approached in an important body of research in the field[32]. As a promising research area, text sentiment analysis has been extensively studied and it has been utilized in applications such as news tracking and summarizing, online forums, blogging etc.

Generally, sentiment analysis begins with sentiment expression with regard to a given object, and then distinguishes a lexicon of positive and negative words and phrases [33]. There are three types of lexicons: positive polarity (e.g. wonderful), negative polarity (e.g. bad, pessimistic, terrible), and contextual polarity (i.e. phrases in which a word or words can carry different meanings in different contexts).

Existing sentiment analysis approaches can be classified into two categories: word-level models such as semantic orientation Lexicon based approach, and topic-level models mainly based on machine learning approach. Turney [34] proposed a simple algorithm for classification of reviews as recommended or not recommended based on the value of the average semantic orientation of phrases containing adjectives or adverbs. Pang and Lee [35] presented a novel machine-learning method that applies text-categorization techniques to the subjective portions of a document based on minimum cuts. Beineke et al. [36] extended the traditional sentiment classification procedure by re-interpreting it as a Naive Bayes model. Additionally, many studies have employed advanced techniques to analyze sentiment at the sentence or phrase level. For example, Kamps and Marx [37] explored how the structure of the Word-Net lexicon database might be used to assess affective or emotive meaning, specifically by formulating measures based on Osgood’s semantic differential technique. Also, Wilson et al. [38] presented a new approach to phrase-level sentiment analysis that classifies whether an expression is neutral or polar and, subsequently, disambiguates the polar expressions. Meanwhile, McDonald et al. [39] constructed a model for joint classification of sentiment based on standard sequence classification techniques that utilize a constrained Viterbi algorithm, which is a dynamic programming algorithm for finding the most likely sequence of hidden states. Recently, some researchers introduced variants of a semi-supervised latent variable model for sentence-level sentiment analysis [40]. Compared to the classical sentiment analysis from writers’ perspective, Rao et al. [41] concentrate on the mining of readers’ emotions evoked by social media materials. They propose two sentiment topic models to associate latent topics with evoked emotions of readers.

So far, few studies have been reported to utilize sentiment analysis in applications of Human-Robot Interactive Communication such as facial expression generation. Therefore, our research aims to further extend the application of text sentiment analysis into facial expression generation in Human-Robot Interactive Communication.

III. METHODOLOGY

A. Overview

In order to mapping a sentiment sentence such as a microblog message into an emotional state, we present a classification based Sentiment analysis approaches. As shown in figure 2, to perform the classification task, each sentence is represented as a feature vector and classified using support vector machines (SVM). By considering the high dimension of the textual data, and the semantic relation between words, we introduce the distributed representation model (word2vec), and construct SVM multi-class classifier on the implicit sentiment sentence.

B. Word Representation

The In order to fight the curse of dimensionality, we employed the method of learning a distributed representation for words [42] which allows each training sentence to inform the model about an exponential number of semantically neighboring sentences.

A tool (https://code.google.com/p/word2vec/) was utilized to represent words, which takes a text corpus as input and produces the word vectors as output. It first constructs a vocabulary from the training text data and then learns vector representation of words. The resulting word vector file can be used as features in many natural language processing and machine learning applications. Here, we use this tool for computing continuous distributed representation of words.

In word2vec, the word representations are learned by a recurrent neural network language model [43], as illustrated in Figure 3.

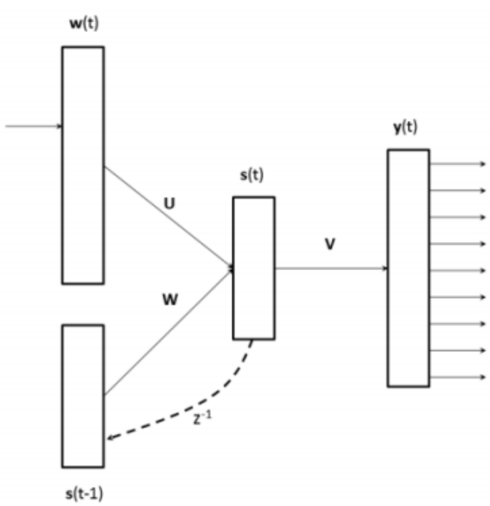

Figure 3. Recurrent Neural Network Language Model [44].

This architecture consists of an input layer, a hidden layer with recurrent connections, plus the corresponding weight matrices. The input vector *w(t)* represents input word at time *t* encoded using 1-of-N coding, and the output layer *y(t)* produces a probability distribution over words. The hidden layer *s(t)* maintains a representation of the sentence history. The input vector *w(t)* and the output vector *y(t)* have dimensionality of the vocabulary.

In this framework, the word representations are found in the columns of *U*, with each column representing a word. The RNN is trained with back propagation to maximize the data log-likelihood under the model. The model itself has no knowledge of syntax or morphology or semantics. Remarkably, training such a purely lexical model to maximize likelihood will induce word representations with striking syntactic and semantic properties.

C. Sentence Feature Representation

Here we proposed a method to transfer the word vectors into a sentence vector.

$$
VT = \begin{array}{c|cccccc}
 & t1 & t2 & \dots & tj & \dots & tn \\
\hline
v1 & \alpha_{11} & \alpha_{12} & \dots & \alpha_{1j} & \dots & \alpha_{1j} \\
v2 & \alpha_{21} & \alpha_{22} & \dots & \alpha_{2j} & \dots & \alpha_{2j} \\
. & . & . & & . & & . \\
vi & \alpha_{i1} & \alpha_{i2} & \dots & \alpha_{ij} & \dots & \alpha_{ij} \\
. & . & . & & . & & . \\
vq & \alpha_{m1} & \alpha_{m2} & \dots & \alpha_{mj} & \dots & \alpha_{mj}
\end{array}
$$

Where,

$$
\alpha_{ij} = \begin{cases} 1 & \text{If the word vi belongs to the class tj} \\ 0 & \text{else} \end{cases}
$$

The implicit word classes were used to be the features of a sentence. Assume $S = \{s1,s2,\dots,sm\}$ is a set of sentences. And $V = \{v1,v2,\dots,vn\}$ is the vocabulary, which is set of unique words in *S*. Therefore, the word2vec tool was used to word clustering in *V* firstly.

After clustering, we get the matrix *VT*, which give an index to the semantic relationship between words *vi* and class *tj*.

Let's denote the set of word cluster result by *T*, and $T = \{t1,t2,\dots,tn\}$, n is the number of word classes, as well as the dimensionality of a sentence we represented as follow.

$$
SV = \begin{array}{c|cccccc}
 & v1 & v2 & \dots & vj & \dots & vq \\
\hline
s1 & \mu_{11} & \mu_{12} & \dots & \mu_{1j} & \dots & \mu_{1j} \\
s2 & \mu_{21} & \mu_{22} & \dots & \mu_{2j} & \dots & \mu_{2j} \\
. & . & . & & . & & . \\
si & \mu_{i1} & \mu_{i2} & \dots & \mu_{ij} & \dots & \mu_{ij} \\
. & . & . & & . & & . \\
sm & \mu_{m1} & \mu_{m2} & \dots & \mu_{mj} & \dots & \mu_{mj}
\end{array}
$$

Where,

$$
\mu_{ij} = \begin{cases} tf*idf & \text{If the sentence si contains the word vj} \\ 0 & \text{else} \end{cases}
$$

Here we use augmented frequency as *tf*, to prevent a bias towards longer sentences. The *idf* is the logarithmically scaled fraction of the sentences that contain the word, obtained by dividing the total number of sentences by the number of sentences containing the word, and then taking the logarithm of that quotient.

Finally, Multiplying *SV* by *VT*, then we got *ST*, which could be used to represent all sentences in a given dimension.

$$
ST = SV \times VT = \begin{array}{c|cccccc}
 & t1 & t2 & \dots & tj & \dots & tn \\
\hline
s1 & W_{11} & W_{12} & \dots & W_{1j} & \dots & W_{1j} \\
s2 & W_{21} & W_{22} & \dots & W_{2j} & \dots & W_{2j} \\
. & . & . & & . & & . \\
si & W_{i1} & W_{i2} & \dots & W_{ij} & \dots & W_{ij} \\
. & . & . & & . & & . \\
sm & W_{m1} & W_{m2} & \dots & W_{mj} & \dots & W_{mj}
\end{array}
$$

IV. EXPERIMENTS

The experiments are carried out on a publicly available microblog datasets. The classifier used in this paper is based on support vector machine. We use extensively used measure in sentiment analysis as the performance criterion in this paper.

A. Data collections

The *Sina microblog* (http://weibo.sina.com/) has been used widely as the benchmark dataset by many papers. In this paper, we use the emotions dataset contains 700 happiness, 550 angry, 450 disgust and 400 sadness sentiment records, the whole set contains in total about 2100 records, extracted from a sina microblog dataset (which could be downloaded from http://www.datatang.com/data/45439/). The records were divided into two parts by proportion of 7:3, one for training and the other for testing.

B. The performance measure

To evaluate a sentiment analysis system, we use the precision, recall, and F1 measures in the following:

$$\text{Recall} = \frac{\text{number of correct positive predictions}}{\text{number of positive examples}}$$

$$\text{Precision} = \frac{\text{number of correct positive predictions}}{\text{number of positive predictions}}$$

$$\text{F1} = \frac{2 \times \text{Recall} \times \text{Precision}}{(\text{Recall} + \text{Precision})}$$

C. Experiments results

The existing VSM, Topic model (LDA) and the proposed distributed representation model (word2vec) are implemented for comparison. The experimental results (see figure 4) show that the LDA and the proposed model outperform the baseline VSM obviously. The performance measure of precision (%) of the VSM is 33.33%. Through the observation of the testing data, almost all of records have been classified into one emotion class by VSM, in other words, Due to the high-dimensional data are sparse, the traditional algorithm is often unable to obtain the desired results in dealing with such data.

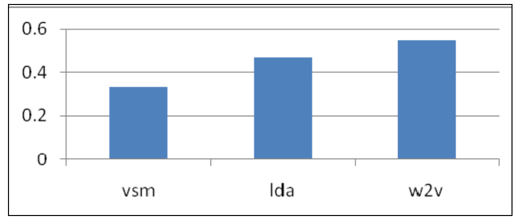

Figure 4. The comparison of existing VSM, LDA and the word2vec in the performance measure of precision.

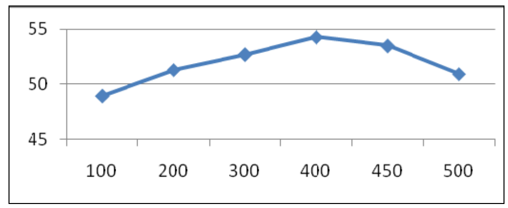

Figure 5. The performance measure of precision (%) of the distributed representation model (word2vec) in different count number of word classes.

TABLE I. THE DETAIL PERFORMANCES OF THE DISTRIBUTED REPRESENTATION MODEL (WORD2VEC) FOR EACH EMOTION WHEN THE COUNT NUMBER OF WORD CLASS N IS 400

Emotions	**Precision**	**Recall**	**F1**
HAPPINESS	56.028%	75.238%	64.228%
ANGER	49.673%	46.061%	47.799%
DISGUST	53.968%	50.370%	52.107%
SADNESS	57.971%	33.333%	42.328%

As shown in figure 5, the best performance of word2vec achieved when the count number of word class n is 400, the total precision is 54.286%. And the detail performances for each emotion are shown in table 1.

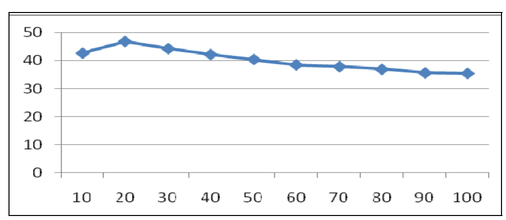

Figure 6. The performance measure of precision (%) of the Topic model (LDA) in different count number of topics.

The best performance of LDA achieved when the count number of topics k is 20, as shown in figure 6, the total precision is 46.825%. And the detail performances for each emotion are shown in table 2.

The results further explained that, compare to bag of words method like vsm, both topic model and distributed representation model could fight the sparse problem of data more efficiently.

TABLE II. THE DETAIL PERFORMANCES OF THE LDA FOR EACH EMOTION WHEN THE COUNT NUMBER OF TOPICS K IS 20

Emotions	**Precision**	**Recall**	**F1**
HAPPINESS	41.481%	80%	54.634%
ANGER	51.316%	47.273%	49.211%
DISGUST	60.345%	25.926%	36.269%
SADNESS	93.333%	11.667%	20.741%

Figure 7 shows that, although the topic model has a slight edge in the prediction of "angry", the distributed representation model still enjoy a significant edge on the whole.

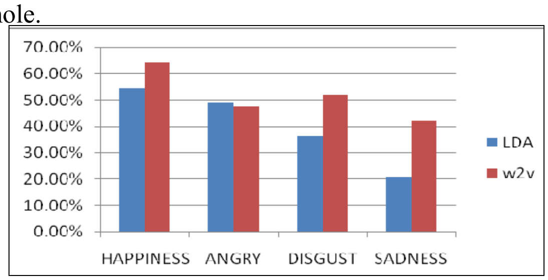

Figure 7. The comparative result of F1 measure of the Topic model (LDA) and the distributed representation model (word2vec) .

V. CONCLUSIONS

The objective of this study is to automatically identify emotional orientation in text which can be used to render facial expressions. Because of the sparseness of social communication data like microblog, the bag of words method didn't perform well. However, the Experiments results indicate that both topic model and distributed representation model could fight the high dimension of the textual data, and mining the implicit semantic relation between words. Moreover, our sentiment analysis method enjoys a significant edge on the whole and it could assist automatic facial expression generation in Human-Robot Interactive Communication efficiently. Our method currently does not use any artificial sentiment knowledge (WordNet as an example). But we believe that, by combining the knowledge-Based sentiment analysis method, the performance of this approach could be improved in semantic way. Moreover, Speech intonation is another significant factor to do sentiment analysis. In the future work, we would try to combine this factor with textual processing for facial expression generation.

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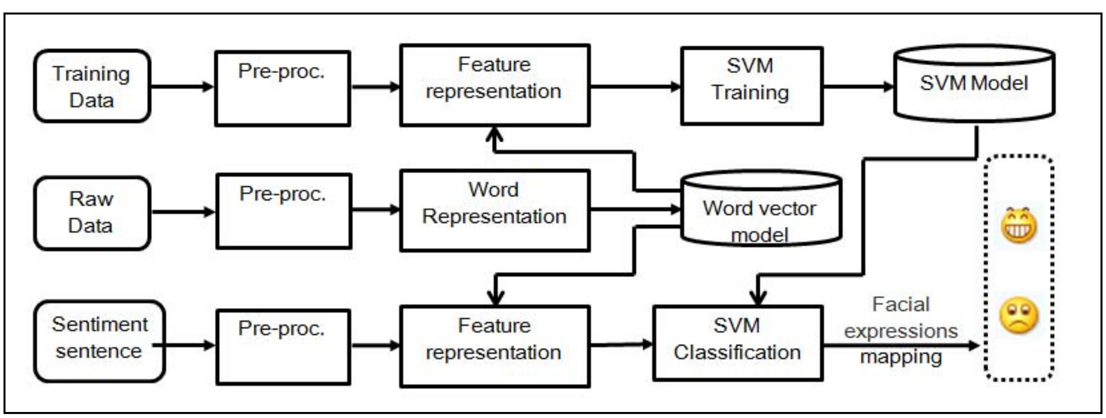

Figure 2. The framework of the classification based Sentiment analysis.