EMOTION RECOGNITION BY FUSING TIME SYNCHRONOUS AND TIME ASYNCHRONOUS REPRESENTATIONS

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ABSTRACT

In this paper, a novel two-branch neural network model structure is proposed for multimodal emotion recognition, which consists of a time synchronous branch (TSB) and a time asynchronous branch (TAB). To capture correlations between each word and its acoustic realisation, the TSB combines speech and text modalities at each input window frame and then uses pooling across time to form a single embedding vector. The TAB, by contrast, provides cross-utterance information by integrating sentence text embeddings from a number of context utterances into another embedding vector. The final emotion classification uses both the TSB and the TAB embeddings. Experimental results on the IEMOCAP dataset demonstrate that the two-branch structure achieves state-of-the-art results in 4-way classification with all common test setups. When using automatic speech recognition (ASR) output instead of manually transcribed reference text, it is shown that the cross-utterance information considerably improves robustness against ASR errors. Furthermore, by incorporating an extra class for all the other emotions, the final 5-way classification system with ASR hypotheses can be viewed as a prototype for more realistic emotion recognition systems.

1. INTRODUCTION

Automatic emotion recognition (AER) is an essential capability for machines to understand and interact with humans and has attracted much attention due to its wide range of potential applications in, e.g., driver monitoring, mental health analysis, spoken dialogue systems and chatbots. Although significant progress has been made [1–3], AER is still a challenging research problem since human emotions are inherently complex, ambiguous, and highly personal. Humans often express their emotions using multiple simultaneous approaches, such as voice characteristics, linguistic content, facial expressions, and body actions, which makes AER by nature a complex multimodal task [4–5]. Furthermore, due to the difficulties in data collection, publicly available datasets often do not have enough speakers to properly cover personal variations in emotion expression. Consequently, current research efforts include the use of transfer learning with speech or speaker recognition data [6–8], multi-task learning with gender or speaker classification to model the personal aspects of emotions [9], features embedded in multiple modalities, and more powerful model architectures. For instance, various types of acoustic features can be fused with text features derived either from pre-trained word embeddings [10–11] or from a jointly trained neural network component [12–13]. Context-dependent hierarchical fusion [14–15], multi-head attention mechanisms [13], and multiplicative fusion [6] have been applied to emotion recognition.

In this paper, we propose a novel deep neural network architecture for AER, which consists of a time synchronous branch (TSB) and a time asynchronous branch (TAB). To capture correlations between each word and its acoustic realisation, the TSB combines speech and text modalities at each input window frame and then uses pooling across time to form a single embedding vector. The TAB, by contrast, provides cross-utterance information by integrating sentence text embeddings from a number of context utterances into another embedding vector. The final emotion classification uses both the TSB and the TAB embeddings. Experimental results on the IEMOCAP dataset demonstrate that the two-branch structure achieves state-of-the-art results in 4-way classification with all common test setups. When using automatic speech recognition (ASR) output instead of manually transcribed reference text, it is shown that the cross-utterance information considerably improves robustness against ASR errors. Furthermore, by incorporating an extra class for all the other emotions, the final 5-way classification system with ASR hypotheses can be viewed as a prototype for more realistic emotion recognition systems.

2. PROPOSED APPROACH

2.1. Feature representation

2.1.1. Audio features

The audio representation for speech-based AER often includes log Mel filterbank features (FBKs) [19]. In this paper, 40-dimensional (-d) FBKs with a 10 ms frame duration and 25 ms frame length are used, which is denoted FBK_{25}. FBK features have information about the short-term spectrum but do not contain pitch information that can be important in describing emotional speech [20] and is often complementary to FBKs [21–22]. The log pitch frequency features with probability-of-voicing-weighted mean subtraction over a 1.5 second window are used along with FBKs [23]. In addition, we propose

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using long-term FBK features extracted in the same way as FBK\textsubscript{250} apart from a long 250ms frame length, which is denoted as FBK\textsubscript{250}.

2.1.2. Text embeddings

The use of vector representations of words and sentences has become a widely-used approach in natural language processing. The global vector (GloVe) is a commonly used method that estimates word embeddings using a global log-bilinear regression model in order to combine the advantages of both global matrix factorization and local context window methods [24]. In this paper, pre-trained 50-d GloVe embeddings are used in the TSB to encode word-level transcriptions. Recently, pre-trained sentence-level embeddings derived from a large pre-trained language model, such as BERT [16], have drawn much attention. We use the pre-trained BERT-base model without fine-tuning to encode the transcription of each single utterance into a 768-d vector, which is used as the input to the TAB.

2.2. Model structure

The proposed model structure is shown in Fig. 1 which consists of a TSB that fuses the audio features with the corresponding text information at each time step, as well as a TAB that captures the text information embedded across the transcriptions of a number of consecutive utterances. The TSB structure is similar to that which is often used for speaker embedding extraction [25]. The TSB uses a five-head self-attentive layer [17] to pool the frame-level vectors across time in the input window, and a time delay neural network with residual connections [26] is used as the encoder to derive the frame-level vectors. A modified penalty term is used for the five-head self-attentive layer, with three heads set to obtain more “spiky” attention weight distributions and the other two set to obtain “smoother” distributions [25]. In the TSB, the audio features and the corresponding GloVe-based word embeddings are combined at each time step with a simple concatenation operation. This structure exploits the alignment between each speech unit and its acoustic realisation. This could be particularly useful for modelling prosody, including the duration for each speech unit and pitch information, which is important for emotional expressions in spoken language [27]. Moreover, video information can also be included in the TSB, by simply concatenating the visual features of each video frame with the corresponding audio and text features, and ensuring that the frame rate of the audio features matches the video frame rate. Since we did not observe any performance improvement by including the visual features, possibly due to the quality and style of the videos in IEMOCAP, no video-related experiments are presented in this paper. More detail of these video-related experiments can be found in [28].

While the TSB includes modelling the temporal correlations between different modalities, the TAB focuses on capturing text information including meaning from the speech transcriptions. The BERT-derived sentence embeddings of the utterance transcriptions are used as the input vectors to TAB. The embeddings for a number of consecutive utterances were used as the input to the TAB since the emotion of each utterance is often strongly related to its context in a spoken dialogue [29]. The following text snippets illustrate the importance of context in determining emotional content:

\begin{itemize}
  \item “Did you pass the exam?”
  \item “Yes, exactly.” (happy)
  \item “Did you fail the exam?”
  \item “Yes, exactly.” (frustrated)
\end{itemize}

It is clear that the two different examples of “Yes, exactly,” convey different emotions, and hence determining the emotion from the text requires the context. Furthermore, since cross-utterance information provides extra information for the emotional content, it is possible to improve the AER system robustness when using erroneous transcriptions derived from an ASR system. In the TAB, a shared fully-connected (FC) layer is used to reduce the dimension of each input BERT embedding, and the resulting vectors are then integrated by another five-head self-attentive layer, whose attention-weight distribution reflects the extent to which sentences in the context affect the current emotion.

Finally, the output vectors from both branches are fused using an FC layer for emotion classification. The hidden and output activation functions are ReLU and softmax respectively, and a large-margin softmax loss function is used to avoid over-fitting [30].

3. EXPERIMENTS

3.1. Experiment setup

The IEMOCAP [18] corpus used in this paper is a multimodal dyadic conversational dataset. It consists of approximately 12 hours of multimodal data, including speech, text transcriptions and facial recordings. IEMOCAP contains a total of 5 sessions and 10 different speakers, with a session being a conversation of two exclusive speakers. To be consistent and to be able to compare with previous studies, only utterances with ground truth labels belonging to “angry”, “happy”, “excited”, “sad”, and “neutral” were used. The “excited” class was merged with “happy” to better balance the size of each emotion class, which results in a total of 5,531 utterances (happy 1,636, angry 1,103, sad 1,084, neutral 1,708).

Unless otherwise stated, leave-one-session-out 5-fold cross validation (CV) is used and the average result reported. At each fold of the 5-fold CV set-up, 8 speakers are used for training while the other two are used for testing. Since the test sets are slightly imbalanced between different emotion categories, both the weighted accuracy (WA) and unweighted accuracy (UA) are reported. Models were implemented using HTK [31] in combination with PyTorch. The newbob learning rate scheduler with an initial learning rate of $5 \times 10^{-5}$ was used throughout training.
3.2. TSB only results

Dialogue-level variance normalization and utterance-level mean normalization were performed on audio features. Pitch and the first differentials were appended to the 40-d FBK. The released reference transcripts of IEMOCAP were used for the text modality as most previous work on IEMOCAP takes this approach. Although [10, 11, 13] used 300-d GloVe in their experiments, 50-d GloVe was found to be most effective in our framework. As shown in Table 1, attaching GloVe to the audio features improves the accuracy by ∼5% absolute. The standard deviation across the five folds also decreases when these two features are combined, which indicates that the system is more robust to speaker variation.

| Feature     | WA (%) | UA (%) |
|-------------|--------|--------|
| Audio25     | 60.64±1.96 | 61.32±2.26 |
| GloVe       | 61.27±3.73 | 62.67±3.55 |
| Audio25+GloVe | 65.53±1.83 | 66.43±1.33 |

Table 1. Mean and std. dev. of the TSB only 5-fold CV results with different input features. “Audio25” denotes FBK25+pitch+Δ.

3.3. Results with TAB

Here we present the results with both the TSB and TAB branches. Table 2 shows the results vary with the number of context utterances from the dialogue. Comparing systems with no context ([0]) to 4 utterances before and after ([−4,4]), shows that increased context leads to improved accuracy. The best UA and WA results were obtained with context windows of [-3,3] and [-4,4] respectively. Since emotion is a long-term attribute that may last for several utterances, context utterances from the same speaker help to recognize the current emotion. As a dyadic dialogue, utterances spoken by the other speaker carry reaction information, which is also useful to infer the current speaker’s emotion. The systems with [-2,0] and [-3,0] contexts do not use information from future utterances and simulate an online streaming AER system and demonstrate the importance of the future utterance information. A [-3,3] context window is used for all future systems thereafter, unless otherwise stated.

Table 2. Results of the two-branch systems with different TAB contexts, which were trained on Session 1–4 and tested on Session 5.

| Context | UA (%) | WA (%) |
|---------|--------|--------|
| [0]     | 70.83  | 77.60  |
| [-1,1]  | 77.76  | 81.22  |
| [-2,2]  | 80.66  | 74.94  |
| [-3,3]  | 81.60  | 78.81  |
| [-4,4]  | 81.87  | 75.74  |
| [-2,0]  | 79.20  | 78.38  |
| [-3,0]  |        |        |

4.2. Use of ASR transcriptions

Although the released reference transcriptions of the IEMOCAP dataset were used in all of the previous experiments, in practice, reference transcriptions are usually not available. Therefore, here system can reduce the accuracy while adding GloVe to Audio25+BERT system can increase accuracy, which shows the importance of the prosody provided through correlations between audio and GloVe. Furthermore, by comparing the Audio25+BERT and GloVe+BERT systems, it can be seen that although GloVe itself is more useful than audio features, audio features perform better when combined with BERT, which indicates that the audio features provide complementary information to the BERT embeddings.

Next, we study the use of our proposed long-term acoustic feature FBK250. With added FBK250 features, there is a ∼0.65% increase in the classification accuracy. The best results achieve 76.12% WA and 77.36% UA for 5-fold CV. As shown in Table 4 GloVe is still useful even if the long-term acoustic features are used. Here we also found the use of long-term acoustic features requires more regularization. Dropout with a dropout rate of 0.5 was added to the output of each residual block and each self-attentive layer. Adding the dropout increases the overall performance by ∼1%, resulting in the 5-fold CV averages of 77.57% WA and 78.41% UA.

4. DISCUSSION

4.1. Cross comparisons

To compare to the best previous results published on IEMOCAP, both a single fold test with the model trained on Session 1–4 and tested on Session 5, as well as the leave-one-speaker-out test with 10-fold CV are provided for the final system, as shown in Table 5. Our systems only used emotional audio data from IEMOCAP and two pre-trained text embeddings, without any audio data augmentation. The results and modalities used in the related work are summarised in Table 5. It is worth noting that although [32] produces higher 10-CV UA, their cross validation setup is not speaker exclusive.

Table 3. Mean and std. dev. of the 5-fold CV results with different input features. “Audio25” denotes FBK25+pitch+Δ.

| Feature     | WA (%) | UA (%) |
|-------------|--------|--------|
| BERT[0]     | 58.53±4.41 | 59.20±5.57 |
| BERT[-3,3]  | 71.22±3.16 | 71.88±2.62 |
| Audio25+GloVe+BERT[-3,3] | 75.53±3.79 | 76.65±3.67 |

Table 4. 5-fold CV mean values of systems with different features. Reference transcriptions are used for all text features.
The results are shown in Table 6. The use of ASR leads to an improvement in the experiments in this section. Results from [12] were not included because the test setting was not clear. Results from [13] and [32] were not obtained using leave-one-speaker-out 10-fold CV and thus not directly comparable.

Table 6. 5-fold CV results of the 5-way system with real ASR outputs. “Ref” denotes reference transcripts provided in the dataset. “Mix” means that the system was trained on reference transcripts and tested on ASR output. “Audio25,250” denotes FBK25,250+pitch+Δ+FBK250.

| Feature | Text | WA (%) | UA (%) |
|---------|------|--------|--------|
| BERT[0] | Ref  | 58.53  | 59.20  |
| BERT[-3,3] | Ref  | 71.22  | 71.88  |
| Audio25,250+BERT[-3,3] | Ref  | 74.74  | 75.60  |
| BERT[0] | ASR  | 46.61  | 45.83  |
| BERT[-3,3] | ASR  | 64.15  | 65.73  |
| Audio25,250+BERT[-3,3] | ASR  | 70.96  | 71.90  |
| Audio25,250+BERT[-3,3] | Mix  | 61.91  | 63.47  |

Since the Google API does not provide the word-to-frame alignments, the GloVe feature was not used in the experiments in this section. The results are shown in Table 6. The use of ASR leads to an accuracy decrease of ~12.6% and ~6.6% for BERT[0] and BERT[-3,3], respectively. The decrease is reduced to ~3.7% when the audio features were included. Comparing the last two rows in Table 6, the system that is both trained and tested with ASR outputs performed better than the system trained on reference transcriptions but tested on the ASR outputs. This may reflect the fact that the system can learn to better account for the errorful ASR transcripts when they are also used in training. A major advantage of using multimodal features is that different modalities can augment or complement each other, especially when certain modalities are susceptible to noise.

Further from the results shown in Table 6, the performance loss caused by using ASR transcriptions is smaller when cross-utterance information was added, which matches the expected findings discussed in Sec. 2.2. The addition of context can help in two ways. First, it provides more information, and second, it can partly compensate for the case that ASR system gives no valid output. Analysing the 9.7% of utterances without valid ASR output and looking at AER results for only those utterances, the BERT[0] system gave 25.00% UA, which is the same as a random guess. However, BERT[-3,3] produced a much better UA of 57.34%, which shows the information lost due to ASR failures can be partly recovered with the context utterances, and hence makes the system more robust.

4.3. 5-way classification results

One of the main goals of this paper is to evaluate the performance of an emotion recognition system without making any unrealistic assumptions. Such unrealistic assumptions include assuming perfect ASR results, and that only a subset of emotion types will be seen in real applications. Papers that investigate performance on IEMOCAP normally only use a 4-way classification task based on the emotions: happy, sad, angry, neutral. However, in reality, people express many other emotions, such as fear, surprise, and disgust. In fact, IEMOCAP itself contains 10 different emotion labels, and when only 4 emotions are considered, nearly half of the utterances in the dataset are normally discarded. Therefore, in this section we investigate an alternative 5-way classification setup which has an extra class “others” to represent all the other emotions that exist in IEMOCAP. The data used for the “others” class includes utterances labelled as “frustration”, “fear”, “surprise”, “disgust”, and “other”. Note that “frustration” accounts for 92.4% of the data for the “others” category and is also the largest emotion group in IEMOCAP. In the 5-way classification setup, all of the 7,532 utterances with ground truth labels were used for training and testing. The classification accuracy of the 5-way system on the previous four emotions (happy, sad, neutral, angry) is 77.67% WA and 77.74% UA, which is similar to the results of the 4-way system given in Table 5. However, the reverse would not be the case since the 4-way system cannot correctly classify examples from the other class and the overall classification accuracy of the 4-way system drops dramatically to 57.02% WA and 62.72% UA when tested on the 5-way data. The results show that when encountering emotions that do not belong to the target four emotions, the 5-way system can classify these other emotion classes with more than 75% accuracy.

The final 5-fold CV results for the 5-class system with ASR transcriptions are shown in Table 7. Our 5-way system, combined with real ASR output transcriptions, can serve as a prototype for a more realistic emotion classification system.

| Feature | Text | WA (%) | UA (%) |
|---------|------|--------|--------|
| Audio25,250+BERT[-3,3] | Ref  | 73.34  | 74.44  |
| Audio25,250+BERT[-3,3] | ASR  | 69.44  | 70.90  |

Table 7. 5-fold CV results of the 5-way system with the 5-way training and test data with different sources for the text modality.

5. CONCLUSION

In this paper, a two-branch structure fusing time synchronous and time asynchronous features has been proposed for multimodal emotion recognition. The TSB captures the correlations between each word and its acoustic realizations at each time step, while the TAB integrates the sentence embeddings from context utterances. The two-branch system achieves state-of-the-art 4-way classification accuracy of 77.76% WA and 78.30% UA for 10-fold CV on IEMOCAP. By investigating the use of transcriptions produced by an ASR system and the alternative 5-way classification setup with an extra class representing all the other emotions, the performance of a more realistic AER system has also been demonstrated.
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