DEEP NET FEATURES FOR COMPLEX EMOTION RECOGNITION

Bhalaji Nagarajan, V Ramana Murthy Oruganti

Department of Electrical and Electronics Engineering, Amrita School of Engineering, Coimbatore, Amrita Vishwa Vidyapeetham, India

ABSTRACT

This paper investigates the influence of different acoustic features, audio-events based features and automatic speech translation based lexical features in complex emotion recognition such as curiosity. Pre-trained networks – AudioSet Net, VoxCeleb Net and Deep Speech Net trained extensively for different speech based applications are studied for this objective. Information from deep layers of these networks are considered as descriptors and encoded into feature vectors. Experimental results on the EmoReact dataset consisting of 8 complex emotions show the effectiveness, yielding highest F1 score (0.85) as against the baseline of 0.69 in the literature.

Index Terms— Emotion recognition, Audio Set, Deep Speech, BoW, Speech to Text

1. INTRODUCTION

In literature, several types of verbal cues have been investigated successfully for automatic recognition of 6 basic emotions – anger, surprise, disgust, fear, happiness and sadness. These verbal cues include audio statistics such as energy, pitch, cepstral characteristics (MFCC, LPC), which are mostly extracted using OpenSmile [1] feature extractor. Deep net features [2] extracted from different layers of trained deep networks on large scale audio datasets. Complex emotions such as curiosity can be detected based on questions/inquiry related content present in the speech [3]. Transcriptions or Speech-to-text tools can be used to translate the speech into language. Searching for questions/inquiry related content such as Why, How, Does... indicate presence of curiosity. Similarly, frustration can be detected by non-language/certain sounds which are not usual words. Such sounds can be very specific to individuals and no universal model exists for such emotions. This paper investigates the affect of content – audio sounds and lexical features for detecting complex emotions using pre-trained deep nets.

Deep networks are observed to outperform handcrafted features in audio, NLP, image and vision community. Kalani et al. [4] proposed a novel phoneme sequence based lexical features for automatic emotion recognition systems where manual transcripts are not available. The proposed lex-eVector representation captures the emotional salience of both spoken content and verbal gestures when using either word level transcripts (spoken content) or phoneme sequences (spoken content and verbal gestures). They claimed superior performance than the previous lex-e-vector [5] and the standard bag-of-words features. Further, in another work Kalani et al. [6] proposed BLSTM neural networks based salient variable length phoneme sequences to represent relevant vocal gestures to overcome the limitations of Bag of Phoneme Sequences having the constraint of requiring fixed length sequences. The effectiveness of these works was demonstrated on IEMOCAP Database [7]. The database consists of 12 hours of data from 10 speakers, each session recorded between one male and one female actor. There are Four emotion classes: neutral, angry, sad and happy (excitement class is merged into happy class, to balance data distribution between classes).

The major difference of current work from the above works is in the domain of complex emotions. There are many audio, transcription, image and video based basic emotion recognition. Hence training of deep nets is feasible. Further, transfer learning, cross-corpus, cross-modal, cross-lingual techniques can further enhance the performance measure. However, complex emotion such as Curiosity, uncertainty, frustration are not common. We have come across only one such dataset – EmoReact. Direct end-to-end CNN network training is not preferred owing to the small size of dataset (735 samples for training). Hence we are investigating the effect of different pre-trained deep networks on complex emotion recognition.

2. PROPOSED FRAMEWORK

The overall framework is shown in Figure 1. Raw audio file is used to extract handcrafted local descriptors using OpenSmile tool. Further, the audio signals are converted to spectrograms using a Hamming window of 25ms width and 10ms step. These spectrograms are used as input to pre-trained net frameworks – VoxCeleb, AudioSet Net and Deep Speech. Information from different layers is used to construct feature vectors using Bag-of-Words (BoW) model. The best performing features are concatenated as early fusion to develop computational models for complex emotion recognition.
Fig. 1. Proposed layout. Audio (OpenSmile) features, Deep Speech, VoxCeleb and AudioSet features are extracted separately to build a computational model for complex emotion recognition.

2.1. OpenSmile Features

An acoustic feature set is constructed using different low level descriptors (LLDs) and their functionals. In this study, the following LLDs are used: Waveform, Signal Energy, Loudness, FFT Spectrum, ACF, Cepstrum, Bark Spectrum, Semitone, Pitch, Voice Quality, LPC, Tonal and Auditory Formants. Two standard acoustic parameter sets are used to get the required functionals. The acoustic features are extracted using OpenSMILE toolkit. The INTERSPEECH 2013 ComParE Vocalization Challenge feature set IS2013 is used to extract LLDs of 141D using 250ms frame size and 10ms step size. IS2013 consists of parameter set that is used as a test bed for social signals in speech. Extended Geneva Minimalist Acoustic Parameter Set eGeMAPs is used to extract LLDs of 25D using the same frame and step size. eGeMAPs consists of a set of voice parameters that define the affective states in voice. Thus the above configurations are used to understand the effect of acoustic features in complex emotion recognition.

2.2. Pre-trained Net Features

Often, very deep network trained on large scale datasets are made available to research community. Although these networks are trained for objectives such as speaker identification and sound classification, the information from different layers can be used as features for other applications. This is because deep nets learn generic features at the shallow layers and task specific features at the deeper layers. Using this cue, the following pre-trained Net features are extracted in the current work.

2.2.1. VoxCeleb Net

VoxCeleb is a large-scale speaker identification dataset created using a fully automated computer vision pipeline. The net is trained with real world utterances of over 1000 celebrities collected from open source media. In this work, high dimensional features from FC6 and FC7 layers which is 4096D and 1024D dimensions respectively are extracted. The information from the final convolution layer (POOL5) which is $30 \times a \times 256$, where $a$ depends on the input spectrogram is also extracted. The information is converted to two dimensional vector by flattening the first two dimensions and thus yielding descriptors of dimension $30a \times 256$. These descriptors are Bag-of-Words (BoW) encoded to reduce the descriptor dimensions.

2.2.2. Audio Set Net

AudioSet Net is a pre-trained VGG-like model trained over AudioSet, a dataset of over 2 million human-labeled 10-second YouTube video soundtracks, with labels taken from an ontology of more than 600 audio event classes. VGG-like model is a variant of the VGG model with 11 weight layers and the the input size as 96x64 for log mel spectrogram audio inputs. Only four groups of convolution/maxpool layers are there as the fifth/last group of convolutional and maxpool layers is dropped. The 1000-wide fully connected layer at the end is replaced by a 128-wide fully connected layer. In this work, high dimensional features from FC6 layer and FC7 layer both having 4096D are extracted. The information from from POOL4 layer is also extracted. The extracted information is flattened, yielding descriptors of dimension 12288D. These descriptors are encoded using BoW technique. The embedding layer with 128D dimensions is also extracted.

2.2.3. Deep Speech Net

Deep Speech at core is a recurrent neural network (RNN) composed of 5 layers of hidden units. Deep Speech is trained to generate English text transcriptions from a given speech spectrogram. The Net was trained over an extensive dataset consisting of 5000 hours of read speech from 9600 speakers. Information from the RNN fused layer of dimension 2048D and output layer information of dimensions 29D are extracted. The descriptors are similarly encoded using the BoW technique.

2.3. Dataset

EmoReact Dataset is used to conduct different experiments as explained in the proposed framework. Emoreact is a multimodal dataset, which was collected from youtube videos of children aged 4-14 years old. The dataset contains 17 different emotional states with six basic emotions, neutral, valence and nine complex emotions including curiosity, uncertainty and frustration. Labels for 8 complex emotions along with valence is available for experimentation. Standard split as explained in the literature is taken for experiments –
Training set, validation set and test set with 432 videos, 303 videos and 367 videos respectively. The training set and validation set is considered as the overall training set and the performance measures – F1 score and AUC – obtained on the test set is reported.

Radial basis function kernel SVM is used as classifier in all the experiments. Wherever BoW is used for feature encoding (POOL5, POOL4 layers, OpenSMILE features) codebook of size 256 is constructed using the training set.

3. RESULTS AND DISCUSSION

In this Section, the results obtained from the experiments conducted are presented and analyzed. The performance of handcrafted features is reported in A.1, A.2 of Table 1. In terms of F1 score, handcrafted features and deep net features fare very well as compared to the baseline [7]. An increase of 14-15% is observed. In terms of AUC, handcrafted features were on par with the baseline. But the deep net features have fared nearly 9% improvement.

| S.No. | Feature Extraction | AUC  | F1 Score |
|-------|--------------------|------|----------|
|      | OpenSMILE features |      |          |
| A.1   | IS2013 config      | 0.63 | 0.85     |
| A.2   | eGeMAPs config     | 0.68 | 0.85     |
|      | Pre-trained AudioSet Net Features | | |
| B.1   | POOL4              | 0.61 | 0.85     |
| B.2   | FC6                | 0.65 | 0.85     |
| B.3   | FC7                | 0.66 | 0.85     |
| B.4   | Embedding Layer    | 0.66 | 0.85     |
|      | Pre-trained VoxCeleb Net Features | | |
| C.1   | POOL5              | 0.68 | 0.85     |
| C.2   | FC6                | 0.73 | 0.86     |
| C.3   | FC7                | 0.73 | 0.86     |
|      | Pre-trained Deep Speech Net Features | | |
| D.1   | RNN fused layer    | 0.61 | 0.85     |
| D.2   | Output layer       | 0.60 | 0.84     |
|      | Best feature combination | | |
| E.1   | C.2 and A.2        | 0.74 | 0.86     |
| E.2   | C.2 and B.3        | 0.74 | 0.86     |
| E.3   | Audio and Video [15] | 0.64 | 0.69 |

After rounding off to two decimal places, F1 score is consistently found to be 0.85% in most cases. This may be due to the saturation of the discriminating power of different layers and type of different networks. Pre-trained VoxCeleb Net is found to perform consistently highest in terms of AUC and F1 score. This is due to the size of the training data used (1 million utterances of 7000+ speakers for 2000+ hours).

Deep Speech net performed poorer than AudioSet and VoxCeleb Net features. This is because the former’s objective is speech to Text translation. The intermediate layers information we obtained are mainly due to language content. However, complex emotions can be mostly expressed in gestures or sounds, which seems to be captured by VoxCeleb Net.

Early fusion of best performing deep net features and handcrafted features are also explored. Only slight enhancement of 1% is observed in AUC and F1 score. This shows complimentary nature of the deep net features with other features.

4. CONCLUSIONS AND FUTURE WORK

Information from deep layers of pre-trained networks – AudioSet Net, VoxCeleb Net and Deep Speech Net networks are encoded into feature vectors and their influence in complex emotion recognition is investigated extensively. Experimental results on the EmoReact dataset yielded highest performance to date in the literature.

In the current work, dataset with one speaker (child) is investigated. In a multi-person speaking set-up, emotion recognition of each person is to be investigated. Speaker diarization can be used a pre-processing step to obtain individual audio of each speaker. Then the above pre-trained networks can be applied to extract feature information. In another direction, the above pre-trained networks can be further trained (transfer learning) on the EmoReact dataset and the effect on emotion recognition should be investigated.
5. REFERENCES

[1] F. Eyben, F. Weninger, F. Gross, and B. Schuller, “Recent developments in opensmile, the munich open-source multimedia feature extractor”, *ICMI, ACM*, 2013

[2] Bhalaji Nagarajan, V. Ramana Murthy Oruganti, “Deep Learning as Feature Encoding for Emotion Recognition”, arXiv:1810.12613 [cs.LG]

[3] To Alexandra, Holmes Jarrek, Fath Elaine, Zhang Ede, Kaufmann Geoff, Hammer Jessica, “Modeling and Designing for Key Elements of Curiosity: Risking Failure, Valuing Questions”, *Proceedings of the DiGRA International Conference Melbourne*, Australia: Digital Games Research Association, Number: 1, Volume: 14, 2017

[4] Kalani Wataraka Gamage, Vidhyasaharan Sethu, Eliathamby Ambikairajah, “Salience based Lexical Features for Emotion Recognition”, *ICASSP*, 2017

[5] Q. Jin, C. Li, S. Chen and H. Wu, “Speech emotion recognition with acoustic and lexical features”, *ICASSP*, 2015.

[6] Kalani Wataraka Gamage, Vidhyasaharan Sethu, Eliathamby Ambikairajah, “Modeling variable length phoneme sequences - a step towards linguistic information for speech emotion recognition in wider world”, *ACII*, 2017

[7] C. Busso, M. Bulut, C. Lee, A. Kazemzadeh, E. Mower, S. Kim, J. Chang, S. Lee and S. Narayanan, “IEMOCAP: interactive emotional dyadic motion capture database”, *Lang Resources & Evaluation*, vol. 42, no. 4, pp. 335-359, 2008.

[8] B. Schuller, S. Steidl, A. Batliner, A. Vinciarelli, K. Scherer, F. Ringeval, M. Chetouani, F. Weninger, F. Eyben, E. Marchi and M. Mortillaro, “The INTERSPEECH 2013 computational paralinguistics challenge: social signals, conflict, emotion, autism”, *INTERSPEECH*, 2013

[9] F. Eyben, K.R. Scherer, B.W. Schuller, J. Sundberg, E. Andre, C. Busso, L.Y. Devillers, J. Epps, P. Laukka, S.S. Narayanan and K.P. Truong, “The Geneva minimalistic acoustic parameter set (GeMAPS) for voice research and affective computing”, *IEEE Transactions on Affective Computing*, vol. 7, no. 2, pp. 190-202, 2016

[10] Balaji, B., and V. Oruganti. “Multi-level feature fusion for group-level emotion recognition.” *ICMI. ACM*, 2017

[11] Nagrani, Arsha, Joon Son Chung, and Andrew Zisserman. “Voxceleb: a large-scale speaker identification dataset.” *INTERSPEECH*, 2017

[12] Shawn Hershey, Sourish Chaudhuri, Daniel P. W. Ellis, Jort F. Gemmeke, Aren Jansen, R. Channing Moore, Manoj Plakal, Devin Platt, Rif A. Saurous, Bryan Seybold, Malcolm Slaney, Ron J. Weiss, Kevin Wilson, “CNN Architectures for Large-Scale Audio Classification”, *ICASSP*, 2017

[13] Gemmeke, J. et al., “AudioSet: An ontology and human-labelled dataset for audio events”, *ICASSP* 2017

[14] Awni Hannun, Carl Case, Jared Casper, Bryan Catanzaro, Greg Diamos, Erich Elsen, Ryan Prenger, Sanjeev Satheesh, Shubho Sengupta, Adam Coates, Andrew Y. Ng, “Deep Speech: Scaling up end-to-end speech recognition”, arXiv:1412.5567v2

[15] Behnaz Nojavanasghari, Tadas Baltrusaitis, Charles. E. Hughes, and Louis-philippe Morency, “EmoReact: A Multimodal Approach and Dataset for Recognizing Emotional Responses in Children”, *ICMI, ACM* 2016