On the Impact of Word Error Rate on Acoustic-Linguistic Speech Emotion Recognition: An Update for the Deep Learning Era

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Abstract

Text encodings from automatic speech recognition (ASR) transcripts and audio representations have shown promise in speech emotion recognition (SER) ever since. Yet, it is challenging to explain the effect of each information stream on the SER systems. Further, more clarification is required for analysing the impact of ASR’s word error rate (WER) on linguistic emotion recognition per se and in the context of fusion with acoustic information exploitation in the age of deep ASR systems. In order to tackle the above issues we create transcripts from the original speech by applying three modern ASR systems, including an end-to-end model trained with recurrent neural network-transducer loss, a model with connectionist temporal classification loss, and a WAV2VEC framework for self-supervised learning. Afterwards, we use pre-trained textual models to extract text representations from the ASR outputs and the gold standard. For extraction and learning of acoustic speech features, we utilise OPENSMILE, OPENXBOW, DEEPSPECTRUM, and AUDEEP. Finally, we conduct decision-level fusion on both information streams – acoustics and linguistics. Using the best development configuration, we achieve state-of-the-art unweighted average recall values of 73.6% and 73.8% on the speaker-independent development and test partitions of IEMOCAP, respectively.

Index Terms: emotion recognition, automatic speech recognition, computational paralinguistics

1. Introduction

As technology is becoming increasingly ubiquitous, speech input is gaining popularity as an accessible interaction modality. The rise of voice assistants, e.g., Amazon’s Alexa, exemplifies this trend. While today’s technologies may understand speech commands well, the conversation quality is still far from what we as humans experience in interpersonal communication. Emotional expressions are a key part of interpersonal communication. They are embodied in our gestures, body posture, and speech. Humans typically express and recognise emotional speech effortlessly, while, for machines, recognising emotions in speech is still a hard challenge.

In this paper, we present an update to previous research (i.e., [1]) on the trade-off between automatic speech recognition (ASR) accuracy (i.e., Word error rate (WER)) and linguistic emotion recognition, and the impact thereof on the later fusion with voice based emotion recognition. Such an update is urgently required, as I) most papers analysing the fusion of acoustics and linguistics use human transcripts and not actual ASR (e.g., [2], [3], [4]), hence, oversimplifying the problem, and II) practically no systematic investigation of the WER on linguistic speech emotion recognition (SER) exists, besides [1] – however, more than a decade since this investigation has witnessed massive improvements in ASR in the era of deep ASR approaches, and III) the modelling of linguistic information itself has changed dramatically with the advent of deep text modelling and the existence of large pre-trained according models. Hence, a re-investigation is urgently needed. To provide a comprehensive and ecologically valuable overview, we juxtapose and contrast variations of contemporary solutions for ASR and feature sets for emotion recognition from both text and voice. We highlight the best performing fusion solution, that to the best of our knowledge sets a new state-of-the-art. Further, we describe in detail the overall system that we use for our experiments. Moreover, we provide different variations of every system’s component.

2. Methodology

In this section, we introduce feature extraction methods that are well suited to process acoustic and linguistic cues. The features are used as inputs to Support Vector Machines (SVMs) and, therefore, build the basis for our SER analysis. We further introduce several ASR approaches, which will be investigated with respect to their WER and corresponding suitability in the SER context.

2.1. Audio Features

We examine four different audio feature sets. The first feature set is extracted with the OPENSMILE toolkit using the ComParE_2016.conf configuration file [5]. It contains 6,373 static features resulting from the computation of functionals (statistics) over low-level descriptor (LLD) contours [5, 6]. A full description of the feature set can be found in [7].

https://github.com/audeering/opensmile
In addition to the default Computational Paralinguistics Challenge (ComParE) feature set, we provide Bag-of-Audio-Words (BoAW) features by using OPENXBOW [8]. These have been applied successfully for, e.g., acoustic event detection [9] and speech-based emotion recognition [10]. After a quantisation based on a codebook, audio chunks are represented as histograms of acoustic LLDs. One codebook is learnt for 65 LLDs from the COMPARE feature set, and another one for 65 deltas of these LLDs. Codebook generation is done by random sampling from the LLDs and its deltas in the training data. Each LLD and delta is assigned to 10 audio words from the codebooks with the lowest Euclidean distance. Subsequently, both BoAW representations are concatenated. Finally, a logarithmic term frequency weighting is applied to compress the numeric range of the histograms.

The feature extraction Deep Spectrum tool kit [11] is applied to obtain deep representations from the input audio data utilising pre-trained Convolutional Neural Networks (CNNs) [11]. Deep Spectrum features have been shown to be effective, e.g., for speech processing [12,13] and sentiment analysis [14]. First, audio signals are transformed into Mel-spectrogram plots using a Hanning window of width 32 ms and an overlap of 16 ms. From these, 128 Mel frequency bands are computed. The spectrograms are then forwarded through a pre-trained DenseNet121 [15] and the activations from the ‘avg_pool’ layer are extracted, resulting in a 1024 dimensional feature vector.

Another feature set is obtained through unsupervised representation learning with recurrent sequence-to-sequence autoencoders, using AUDEEP [16,17]. This feature set models the inherently sequential nature of audio with Recurrent Neural Networks (RNNs) within the encoder and decoder networks [16,17]. First, Mel-scale spectrograms are extracted from the raw waveforms. In order to eliminate some background noise, power levels are clipped below four different given thresholds in these spectrograms. The number of thresholds results in four separate sets of spectrograms per data set. Subsequently, a distinct recurrent sequence-to-sequence autoencoder is trained on each of these sets of spectrograms in an unsupervised way, i.e., without any label information. The learnt representations of a spectrogram are then extracted as feature vectors for the corresponding instance. Finally, these feature vectors are concatenated to obtain the final feature vector. For the results shown in Table 1 the autoencoders’ hyperparameters are not fine tuned.

2.2. Text Features

DeepMoji, proposed by Felbo et al. [18], is a model pre-trained for emotion-related text classification tasks. It consists of two bidirectional long short-term memory (LSTM) layers, followed by an attention layer and yields a sentence encoding of length 2 304. Even though DeepMoji is pre-trained on emotional tweets only, the authors show that it also performs well for other kinds of emotional text data, e.g., reports of emotional experiences. We extract DeepMoji sentence encodings via the PyTorch implementation TorchMoji.

Moreover, we employ several variants of Bidirectional Encoder Representations from Transformers (BERT) [19] that has set new standards for many text processing tasks in recent years. In its base configuration, BERT consists of 12 transformer encoder layers. This network is pre-trained on large text data sets using two unsupervised language modelling tasks, namely masked word prediction and next sentence prediction. Here, we employ the pre-trained BERT-base model to obtain sentence encodings. The output of the last layer’s hidden state for the special token [CLS], followed by one tanh-activated linear layer (pooler_output) is considered as the sentence encoding.

ALBERT (A Lite BERT) [21] is a popular variant of BERT. It is of the same size as the original BERT model but comes with considerably less parameters due to parameter sharing across layers and factorisation of the embedding matrix. Furthermore, the next sentence prediction task in BERT’s pre-training has been replaced by sentence order prediction, i.e., deciding whether two sentences are given in the correct order. ALBERT has been shown to outperform BERT on many tasks. Similar to our BERT baseline, we take the pooler_output of ALBERT in its base version as our sentence encoding.

Another recent variant of the BERT language model (LM) is given by ELECTRA [22], referring to an alternative method of pre-training transformer language models. In this approach, corrupted input words are detected. First, a generator model corrupts the input sentence. Then, the discriminator, i.e., the actual language model, predicts for every word whether it has been changed by the generator or not. BERT-like transformer networks pre-trained in this fashion outperform other BERT variants on several tasks. The architecture of the model is nearly identical to BERT-base. We take the embedding of the special token [CLS] as the sentence encoding. For all three BERT variants, huggingface implementations and pre-trained weights are used to extract 768 features.

2.3. Automatic Speech Recognition

To obtain text encodings from audio waveforms, we employ several pre-trained ASR systems: a system based on QuartzNet (QN), streaming Transformer Transducer (TT) and wav2vec (W2V). Transformer Transducer (TT) [23] is an end-to-end model trained with RNN-Transducer (RNN-T) loss [24]. Its encoder implementation entails Transformer blocks with multi-headed self-attention masking future context making the network suitable for stream audio processing. The label encoder of this architecture can be interpreted as a small built-in internal LM as it takes the previous predicted output label as input. The joint network combines audio and label encoder outputs and passes them to the final softmax. Our solution is trained on LibriSpeech [25], CommonVoice [26], and Tidium [27]. Additionally, we utilise our internal audio sets with various eastern accents for model fine-tuning. In total, about 4 000 hours of speech are used for TT training. For tokenisation, we use the Byte-Pair Encoding (BPE) [28] sentence-piece model with a vocabulary size of 4 096 items. Despite the fact that the system has an internal LM, we additionally evaluate our model in combination with an external LM based on the transformer architecture. The LM is trained on 30 gigabytes of corpora that include wiki texts and books. Furthermore, cold fusion is used to connect the outputs of the LM to the external LM with the lambda parameter set to 0.2.

QuartzNet (QN) [29] is a Connectionist Temporal Classification (CTC) [30] loss based model composed of blocks with separable convolutions and residual connections between them, with a fully connected decoder at the end. The model has fewer parameters than TT while still showing near state-of-the-art accuracy. In our experiments, first, a pre-trained configuration with

https://github.com/auDeep/auDeep
https://github.com/huggingface/torchMoji
https://huggingface.co/bert-base-cased
https://huggingface.co/google/electra-base-discriminator
https://huggingface.co/OURCE
https://huggingface.co/OPEN
https://huggingface.co/OPEN
Table 1: SER comparison of linguistic features on the Interactive Emotional Dyadic Motion Capture (IEMOCAP) corpus (Chance level: 25.0% UAR). Every text feature extractor is tested with different ASR systems as input as well as with the gold standard (GS). UAR: Unweighted Average Recall. QN: QuartzNet. TT: Transformer Transducer. W2V: wav2vec. LM: Language model.

| [UAR %] | GS Text | ASR QN | ASR QN-LM | ASR TT | ASR TT-LM | ASR W2V | ASR W2V-LM |
|---------|---------|--------|-----------|--------|-----------|---------|-----------|
|         | Dev     | Test   | Dev       | Test   | Dev       | Test    | Dev       | Test      |
| DEEPMOJI| 61.7    | 63.0   | 52.2      | 49.6   | 52.3      | 48.6    | 53.8      | 54.0      | 53.8      | 45.2      | 57.4      | 58.0      | 56.3      | 55.2      |
| BERT    | 57.6    | 58.0   | 47.1      | 45.9   | 47.5      | 45.0    | 50.1      | 50.9      | 49.1      | 50.7      | 51.6      | 55.2      | 53.9      | 55.1      |
| ALBERT  | 47.9    | 52.7   | 38.1      | 40.3   | 40.8      | 42.4    | 42.2      | 43.1      | 41.4      | 44.3      | 42.7      | 46.3      | 44.3      | 49.2      |
| ELECTRA | 56.9    | 56.2   | 44.2      | 43.1   | 46.7      | 43.2    | 48.2      | 45.5      | 47.1      | 45.6      | 52.6      | 49.7      | 53.3      | 49.9      |

3.2. Automatic Speech Recognition

We evaluate each of our models on LibriSpeech test-clean with and without the external LM to compare the accuracy. We measure Word error rate (WER) and character error rate (CER). As two models are adopted for different accents, state-of-the-art results for the chosen data are not expected. On the contrary, the W2V trained on data with the same distribution as LibriSpeech and setups with this model show more precise predictions for both datasets. The evaluation on test-clean compares the accuracy of models on public and well-known data. Our measurements for IEMOCAP and LibriSpeech test-clean are demonstrated in Table 2.

Table 2: Evaluation results of ASRs on LibriSpeech test-clean and IEMOCAP waveforms. WER: Word error rate. CER: Character error rate.

| SetUp     | LibriSpeech | IEMOCAP |
|-----------|-------------|---------|
|           | WER [%]     | CER [%] | WER [%] | CER [%] |
| QN        | 15.69       | 7.26    | 41.21   | 25.43   |
| QN + LM   | 12.98       | 7.35    | 42.14   | 31.21   |
| TT        | 4.98        | 1.89    | 31.81   | 22.30   |
| TT + LM   | 4.93        | 1.86    | 31.47   | 22.08   |
| W2V       | 2.16        | 0.57    | 25.71   | 13.56   |
| W2V + LM  | 2.24        | 0.63    | 22.23   | 13.37   |

3.3. Late Fusion

We apply late fusion in form of majority voting on the basis of SVM predictions on the individual feature sets (cf. Figure 1). We evaluate all combinations of at least three feature sets from the audio, Gold Standard (GS) human transcribed spoken content, and ASR-based spoken content transcription. Table 3 summarises our results. Taking into account a high number of feature set combinations, we restrict our evaluation of the ASR-based text

Table 3: SER Results of audio features on IEMOCAP. The best resulting model of DEEPSPECTRUM is a DENSENET201 with 128 Mel bins and the viridis colour map.

| [UAR %] | Dev | Test |
|---------|-----|------|
| OPENSIMILE (ComParE_2016) | 57.8 | 58.5 |
| OPENXBOW (N = 2 000) | 55.7 | 59.1 |
| DEEPSPECTRUM | 53.2 | 59.8 |
| AUDEEP (X = −60 dB) | 55.0 | 53.3 |

https://github.com/pytorch/fairseq/tree/master/examples/wav2vec
features to the ASR system with the best overall baseline performance which is W2V with LM. Feature set combinations, based on the GS text only, clearly outperform those, which are based on ASR-generated text. Considering the fact that this result is in line with the performance of the individual feature sets (showed in Table 1), most likely, this behaviour is caused by the WER of the ASR system. However, when combining audio and text features, both ASR-based and GS-based feature sets lead to a similar performance, being higher than any individual information stream, both on average and for the best performance. Combinations of ASR-based and GS-based features show no improvement in the average Unweighted Average Recall (UAR) compared to the GS feature sets, most likely due to the similarity of the features. When considering all combinations of available feature sets the average and best performance can be further increased, which can most reasonably be explained by the vast number of combinations. Several combinations consisting of audio, GS-TEXT and ASR-TEXT features – including the combination GS-BERT, GS-DEEPMOJI, ASR-BERT, ASR-DEEPMOJI, ASR-ELECTRA, AUDEEP, DEEPSPECTRUM, OPENSIMILE, BOAW – achieve the best observed performance of 73.6% UAR on the development set and a corresponding UAR of 73.8% on the test set.

Table 4: Results of the majority voting late fusion. The possible number of feature set combinations (#), as well as the mean UAR and standard deviation are reported. We further provide the UAR of the best performing feature set combination on the development set, as well as the corresponding performance of said combination on the test set.

| [UAR %] | #  | Mean Dev | Max Dev | Test |
|---------|----|----------|---------|------|
| AUDIO   | 5  | 59.9 ± 0.1 | 60.8    | 63.3 |
| GS-TEXT | 5  | 60.3 ± 1.5 | 61.7    | 63.0 |
| ASR-TEXT| 5  | 54.6 ± 1.0 | 55.8    | 56.2 |
| AUDIO + GS-TEXT | 219 | 65.0 ± 3.5 | 71.0    | 69.9 |
| AUDIO + ASR-TEXT | 219 | 63.4 ± 3.2 | 69.5    | 70.5 |
| ASR-TEXT + GS-TEXT | 219 | 58.8 ± 3.6 | 63.3    | 64.8 |
| ALL SYSTEMS | 4017 | 66.2 ± 3.8 | 73.6    | 73.8 |

4. Discussion

When comparing the performance of different ASR systems in Table 2 and Table 1, a correlation between low WER values and high UAR values becomes obvious. Accordingly the Gold Standard System using human annotations, which is considered to have a much lower WER than any of the ASR systems, clearly achieves the highest UAR. A similar effect has previously been observed in [1], however, utilising a – from today’s point of view – outdated ASR systems with a much more limited vocabulary size. Table 4 suggests that a higher number of considered feature sets leads to a higher UAR on average. This effect is known in general, however, it should be noted that the pairwise dependence of classifiers plays a considerable role in such a late fusion system [24]. A pairwise dependence of ASR-based and GS-based feature sets could therefore explain why combinations of both sets perform worse than combinations which combine either ASR-based or GS-based feature sets with audio-based feature sets. Assuming a high dependence between ASR-based and GS-based feature sets would further suggest that a well-suited weighted fusion method combining only audio-based and ASR-based features might further increase results towards the best-performing configuration introduced in [23] which combines two instances of BERT and DeepMoji features.

5. Conclusions

In this paper, we presented current ASR systems to create transcriptions for the linguistic SER. Without adapting the ASR systems to the target database IEMOCAP, we were able to achieve state-of-the-art results by fusing acoustic and linguistic information. We further observed that higher WERs on the ASR systems lead to higher UAR values for emotion recognition.

For future work, the number of feature sets and the respective feature set sizes can be reduced in order to increase computational efficiency. Furthermore, evaluation could be performed on more natural or in-the-wild databases. We mainly chose IEMOCAP as it is widely established and thereby suitable for comparison with state-of-the-art approaches. Moreover, IEMOCAP contains transcriptions making it easier to evaluate the impact of WER achieved by the ASR on the final emotion classification. Finally, the fusion with ASR could be implemented on the levels of the embeddings instead of the text.

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