Facing Realism in Spontaneous Emotion Recognition from Speech: Feature Enhancement by Autoencoder with LSTM Neural Networks

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Abstract

During the last decade, speech emotion recognition technology has matured well enough to be used in some real-life scenarios. However, these scenarios require an almost silent environment to not compromise the performance of the system. Emotion recognition technology from speech thus needs to evolve and face more challenging conditions, such as environmental additive and convolutional noises, in order to broaden its applicability to real-life conditions. This contribution evaluates the impact of a front-end feature enhancement method based on an autoencoder with long short-term memory neural networks, for robust emotion recognition from speech. Support Vector Regression is then used as a back-end for time- and value-continuous emotion prediction from enhanced features. We perform extensive evaluations on both non-stationary additive noise and convolutional noise, on a database of spontaneous and natural emotions. Results show that the proposed method significantly outperforms a system trained on raw features, for both arousal and valence dimensions, while having almost no degradation when applied to clean speech.

Index Terms: emotion recognition, spontaneous speech, additive and convolutional noises, feature enhancement, autoencoder, LSTM Neural Networks

1. Introduction

Technology for automatic emotion recognition from speech (ERS) has gained increasing commercial attention in the last decade. Rapid progress of this technology has indeed enabled application of ERS in various domains, such as, health care [1], education [2], serious games [3], robotic [4], and call-centers [5]. However, while good performance has been reported in research papers under laboratory conditions [6], or with systems tailored towards specific databases [7], real-life applications of ERS still remain an open challenge. Indeed, various factors make this task highly challenging, which can be grouped into three main categories: (i) the contextual dependencies of the meaning and significance of affective expressions across different speakers, languages and cultures [8], (ii) the necessity to use distributed systems for client-server architecture, which introduce some latency and distortion in the data [9], and (iii) the presence of varying and degraded acoustic conditions caused by reverberation, background noise, and acoustic properties of the recording devices used.

Stationary, non-stationary, and convolutional noise severely degrade performance of systems, and affect consequently the user experience in real-life conditions [10, 11, 12]. Therefore, many studies have been performed for speech and acoustic features enhancement (FE), especially for automatic speech recognition (ASR). Recurrent Neural Networks (RNN) are widely used in this field to enhance corrupted features, which is an application of the de-noising auto-encoder [13] principle: neural networks are trained to map noisy features to clean features. This method has recently also been exploited for speech enhancement in the time domain [14, 15]. RNN have been also studied for *blind* non-linear source separation, with the aim to enhance the acoustic features by separating noise and speech sources [16, 17]. In the context of speech enhancement, [14] uses deep neural networks to map noisy to clean Mel features, but the network output is synthesised directly into a time domain signal, instead of constructing a filter based on speech and noise magnitudes. A combination of unsupervised noise estimation and Deep Neural Network (DNN) based speech power spectrum estimation is used in [15] to construct a Wiener filter. Supervised training of deep neural networks was performed to predict the ideal ratio mask in an uncertainty decoding framework for ASR [18].

Studies on noise robustness for ERS are much more sparse, despite being necessary for real-life applications of this technology. To the best of our knowledge, only a handful of studies has addressed this issue so far. Large acoustic feature sets were investigated in [10]. Adaptive noise cancellation was proposed as a front end in [11]. Speech enhancement based on spectral subtraction and masking properties was studied in [12]. Wavelet decomposition [19] and feature selection techniques [20] have also been proposed. Additionally, the impact of affective speech on ASR performance has also been investigated in [21].

One may note that all existing work on noise robustness for ERS has been performed on acted emotions, which are rarely observable in real-life. Furthermore, none of those studies have analysed the impact of reverberated noise, which is known to impact severely the performance of ASR systems [22]. In this light, this present contribution studies the impact of non-stationary additive noise and convolutional noise, on the automatic recognition of spontaneous emotions from speech. We propose the use of a FE method based on a memory-enhanced recurrent Denoising Autoencoder (rDA) as a front end, and show that this method can significantly improve the performance, while having almost no degradation when applied to clean speech.

The following paper is structured as follows: the proposed FE method based on rDA is introduced in Section 2, then extensive experiments on spontaneous emotions are described in Section 3, and a conclusion with future work is given in Section 4.

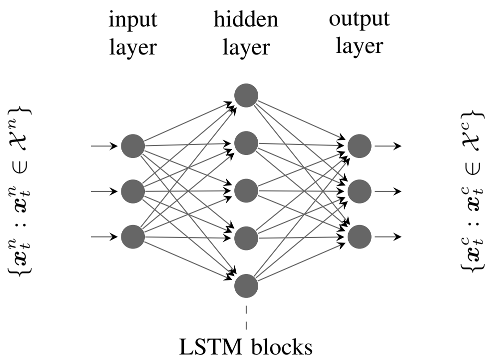


Figure 1: Structure of recurrent denoising autoencoder with LSTM neural networks.

2. Feature enhancement

In the past few years, Long Short-Term Memory (LSTM) model has been widely applied to a variety of pattern recognition tasks [23, 24], and shows a powerful capability of learning long-range contextual information. In this section, we give a quick overview of such a memory-enhanced Recurrent Neural Network (RNN), on which the rDA is built.

2.1. Memory-enhanced recurrent neural networks

Compared to conventional RNN, LSTM-RNN model proposed by Hochreiter and Schmidhuber [25] uses one or multiple LSTM blocks to replace the hidden neuron. Every memory block consists of self-connected linear memory cells c and three multiplicative gate units: an input gate i, a forget gate f , and a forget gate o, which are responsible for writing, reading, and resetting the memory cell values, respectively. Given an input $\boldsymbol{x}_t$ at the step time t, the activations of the input gate i_t, the forget gate f_t, the memory cell state c_t, and the output gate o_t are separately updated by the following formulas:

$$i_t = f_g(\boldsymbol{W}_{xi}\boldsymbol{x}_t + \boldsymbol{W}_{hi}\boldsymbol{h}_{t-1} + \boldsymbol{W}_{ci}\boldsymbol{c}_{t-1} + b_i), \quad (1)$$
$$f_t = f_g(\boldsymbol{W}_{xf}\boldsymbol{x}_t + \boldsymbol{W}_{hf}\boldsymbol{h}_{t-1} + \boldsymbol{W}_{cf}\boldsymbol{c}_{t-1} + b_f), \quad (2)$$
$$c_t = i_t \cdot f_i(\boldsymbol{W}_{xc}\boldsymbol{x}_t + \boldsymbol{W}_{hc}\boldsymbol{h}_{t-1} + b_c) + \boldsymbol{f}_t \cdot \boldsymbol{c}_{t-1}, \quad (3)$$
$$o_t = f_g(\boldsymbol{W}_{xo}\boldsymbol{x}_t + \boldsymbol{W}_{ho}\boldsymbol{h}_{t-1} + \boldsymbol{W}_{co}\boldsymbol{c}_t + b_o), \quad (4)$$
$$h_t = o_t \cdot f_o(c_t), \quad (5)$$

where f_g, f_i, and f_o denote the logistic sigmoid, tanh, and tanh activation functions, respectively; $\boldsymbol{W}$ is a weight matrix of the mutual connections; $\boldsymbol{h}_t$ presents the output of hidden block; b indicates the block bias. From the formulas mentioned above, it is observed that the values of all memory cells and block outputs in the previous time step $t-1$ will certainly affect the activations of all three gates, even the input units in the current time step t in the same layer, except the case between memory cell and output gate. More details about the memory structure can be referred to the work in [26].

The main advantage of using such a memory-enhanced block over a traditional neuron in an RNN is that the cell state in an LSTM block sums activities over time. Since derivatives distribute over sums, the backpropagated error does not blow up or decay over time (the vanishing gradient problem) [25, 26].

The general structure of rDA with memory-enhanced neural networks proposed in this paper is illustrated in Fig. 1, which includes an input layer, an output layer, and one or multiple hidden layers that are implemented by the LSTM blocks. In comparison with the conventional DA given in [13] where DA is modelled on Feedforward Neural Networks (FNN), the presented DA is structured with the above described LSTM-RNN in the hidden layers. Additionally, it also should be noticed that the recurrent autoencoder also differs from the ones demonstrated in [24, 27], where an encoder is used to map an input sequence into a fixed length representation, and a decoder is used to decode the target sequence from the representation.

2.2. Feature enhancement by autoencoder

As discussed in Section 1, the speech signal $s(k)$ is easily distorted by the environmental noise and recording devices when facing realistic application scenarios with the Acoustic Impulse Response (AIR) $r(k)$ of finite length T_{60} and the background additional noise $n(k)$. Therefore, the distorted speech signal $\hat{s}(k)$ can be expressed as

$$\hat{s}(k) = s(k) * r(k) + n(k). \quad (6)$$

The signal in the time domain $\hat{s}(k)$ can be transformed into the spectrum domain

$$|\hat{S}(f)|^2 = |S(f)|^2 \cdot |R(f)|^2 + |N(f)|^2 \quad (7)$$

by applying a Short-Time Discrete Fourier Transform (STDFT) with three assumptions: 1) The T_{60} is shorter than the analysis window size w; 2) The power spectrum of the additive noise in each analysis window w is a slowly varying process, which means that the additive noise is assumed stationary in each analysis window; 3) The phase of different analysis windows are non-correlated.

To extract the feature vectors in the ceptral domain such as Mel-Frequency Cepstrum Coefficients (MFCCs) for emotion recognition from speech, logarithms and Discrete Cosine Transform (DCT) are performed over the above spectrum. Therefore, Eq. (7) can be further formulated into

$$\begin{aligned}\mathcal{D}(ln|\hat{S}(f)|^2) =& \mathcal{D}(ln|S(f)|^2) + \mathcal{D}(ln|R(f)|^2) \\ &+ \mathcal{D}(ln(1 + \frac{|N(f)|^2}{|S(f)|^2 \cdot |R(f)|^2})).\end{aligned} \quad (8)$$

From Eq. (8), we can see that the goal of denoising is to eliminate the impact of the last two terms. For the non-stationary noise, however, its cepstrum does not only fluctuate over time, but also is involved with original speech spectrum which is non-stationary as well. Therefore, the last term in Eq. (8) can not be simply subtracted due to its non-linear property.

To tackle this non-linear problem, we choose the memory-enhance rDA as described in Section 2.1 with the purpose of exploiting its advantage of accessing long-range contextual information. The goal of the DA is to reconstruct the features $\boldsymbol{x}^c$ in the clean speech feature domain $\mathcal{X}^c$ from the corresponding features $\boldsymbol{x}^n$ in the corrupted speech feature domain $\mathcal{X}^n$, as shown in Fig. 1. When providing these corrupted features as the input $\boldsymbol{x}^n$ to the first layer, we want the output $\hat{\boldsymbol{x}}^n$ to be highly similar to the clean features $\boldsymbol{x}^c$. To learn the required mapping between noisy and clean features, an objective function is needed to minimise the Mean Squared Error (MSE) during training:

$$\mathcal{J}(\theta) = \frac{1}{T}\sum_{t=1}^{T}(\hat{\boldsymbol{x}}_t^n - \boldsymbol{x}_t^c)^2. \quad (9)$$

3. Experiments and results

In the following, we firstly describe the selected spontaneous emotion database. Then, we focus on evaluating the performance of the proposed FE method based on the rDA with LSTM neural networks for time- and value-continuous emotion recognition.

3.1. RECOLA and noise database

For the experiments, we chose the REmote COLlaborative and Affective (RECOLA) database [28] which was used as a standard database for the 5^{th} Audio/Visual^{+} Emotion Challenge (AV^{+}EC 2015) [29]. The motivation of the database collection is to study the complex phenomena, especially emotion, portrayed by humans during social interactions in daily-life.

To generate additive noisy speech, we added the CHiME15 database [30] into the clean (raw or original) speech with various levels of SNRs (i.e., 0-12 dB at a step of 3 dB). The CHiME15 database is a standard noise database for the 3rd CHiME Challenge [30], and is collected in five different locations, such as booth, bus, cafe, pedestrian area, and street junction. The goal of this database is to simulate the speech that captured in different places with additive background noise.

To generate convolution related noisy speech, we applied (convolution product) the Microphone Impulse Response (MIR) of the Google Nexus One smartphone to the recordings from RECOLA using the Audio Degradation Toolbox (ADT) [31]. The goal is to simulate how speech could be recorded with a smartphone. Moreover, other noises are further considered over the first convoluted speech, by applying the Room Impulse Response (RIR) of classroom or grand hall as the second convolutional noise and the CHiME noise as the additional additive noise. It aims to simulate the scenarios that someone speaks on the phone in different environments.

Note that when adding the CHiME noise, each noise recording was firstly normalised to 0 dB peak and concatenated as a longer one to the type of noise. Then, the recording was cut into three partitions of the same length for the training, the validation, and the test sets, respectively. Finally, for each recording of RECOLA, we randomly chose an excerpt of the concatenated noise signal from the relevant partition.

3.2. Experimental setups

At the front-end of emotion recognition system, 13 Low-Level Descriptors (i.e., MFCCs 0-12) were firstly extracted. In details, the feature vectors of $\boldsymbol{x}_t^n$ and $\boldsymbol{x}_t^c$ were separately extracted from the distorted speech signals and the original clean speech signals at every 10 ms using a window size of 25 ms. Before training rDA, the global means and variances were calculated of the noisy and clean speech. Then, standardisation was performed over the network inputs and targets using the means and variances from the corresponding training sets, respectively.

For the rDA, both input and output node numbers are equal to the dimension of the feature vector (13 in our case). Two bidirectional LSTM hidden layers were chosen, and each layer consists of 30 memory blocks. During network training, gradient descent was implemented with a learning rate of 10^{-6} and a momentum of 0.9. Zero mean Gaussian noise with standard deviation 0.1 was added to the input activations in the training phase such as to improve generalisation. All weights were randomly initialised in the range from -0.1 to 0.1. Finally, the early stopping strategy was used as no improvement of the MSE on the validation set has been observed during 20 epochs or the predefined maximum number of training epochs (200 in our case) has been executed. Furthermore, to accelerate the training process, we updated the network weights after running every mini batch of 8 sequences for computation in parallel. The training was performed with our CURRENNT toolkit [32].

After the procedure of FE, functionals of mean and variance were applied over each of the enhanced MFCCs with a window size of 8 s at a step of 0.04 s, which leads to 26 dimensional attributes for each functional window. These statistical features were then fed into the back-end of the system for emotion recognition, where L2-regularised L2-loss Support Vector Regression (SVR) implemented in LIBLINEAR toolbox [33] was used. The complexity value of SVR was optimised by the best performance of the validation set, i.e., c=0.00005 for arousal and c=0.005 for valence in our experiments.

For the performance evaluation, we choose the Concordance Correlation Coefficient (CCC) [34] as the measure. Compared to Pearson's Correlation Coefficient (PCC), CCC can estimate not only the linear correlation, but also the difference of bias between two variables. Mathematically, CCC is formulated as

$$\rho_c = \frac{2\rho\sigma_x\sigma_y}{\sigma_x^2 + \sigma_y^2 + (\mu_x - \mu_y)^2} \tag{10}$$

where ρ is the correlation coefficient between the two variables; μ_x and μ_y are the means of the two variables; and σ_x^2 and σ_y^2 are the corresponding variances. Moreover, it is worth noting that the golden standard ratings for all the recordings are posted four seconds for performance measurement. This is due to the reaction delay of human for continuous emotion annotation according to the recent study [35].

3.3. Results and Discussion

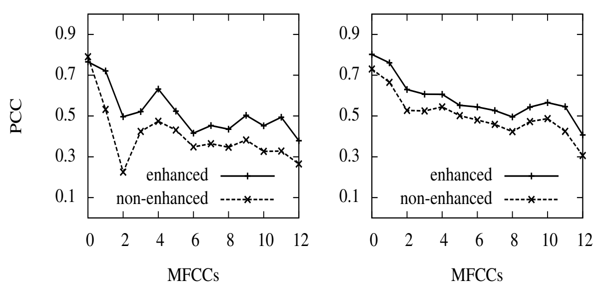
To verify the effectiveness of the rDA with LSTM Neural Networks for FE, we separately executed two experiments: 1) on the non-stationary *additive* noisy speech only, i.e., by adding *CHiME15* noise; 2) on the *smartphone* related *convolutional* noisy speech, i.e., the speech is synthesised by applying MIR only (smartphone), or additionally by applying RIR of the classroom/hall (+classroom/hall), or additionally by adding various levels of CHiME noise (+CH).

Apart from that, we carried out two FE strategies – 1) *matched* FE: Several FE models are trained separately on the data sets with different noise conditions; 2) *mixed* FE: One FE model is trained on a data set with mixed noise conditions. Therefore, the distinction between the two FE strategies is that whether the noise condition of the training data matches with the one of the denoising data.

Table 1 shows the performance of the non-enhanced speech and the enhanced speech (with the matched or mixed FE strategies) evaluated on the emotion recognition model trained on the clean speech for both arousal and valence regression. In almost all cases, the proposed FE method significantly outperforms the system trained on the non-enhanced noisy speech (baseline). Taking the additive noisy speech (CHiME15) for example, the average CCC over the speeches at different levels of SNRs on the test set is boosted from 0.563 to 0.596 and 0.594 respectively by matched and mixed FE for arousal, and from 0.124 to 0.223 and 0.199 respectively by matched and mixed FE for valence. Furthermore, it is expected that the matched FE performs better than the mixed FE, since the matched FE uses different FE models for denoising corresponding noisy data, whereas the mixed FE trains only one FE model for denoising all kinds of noisy data.

Table 1: Performance (Concordance Correlation Coefficient [CCC]) of the *validation* and *test* sets for the proposed *matched* and *mixed* feature enhancement (FE) model on the *CHiME15* noisy speech only or on the *smartphone related* noisy speech, in the evaluation of *arousal* and *valence* emotional tasks. class.: classroom; $\overline{CH.}$: the average CCC over five different 'smartphone + CHiME' noisy speeches with 0-12 dB of SNRs at a step of 3 dB.

	CHiME15							smartphone +					
CCC	clean	12dB	9dB	6dB	3dB	0dB	mean	clean	-	class.	hall	$\overline{CH.}$	mean
							arousal on the *validation* set						
baseline	0.736	0.680	0.657	0.626	0.584	0.526	0.635	0.736	0.726	0.629	0.634	0.436	0.545
matched FE	0.735	0.715	0.710	0.692	0.666	0.627	**0.691**	0.735	0.723	0.641	0.662	0.675	**0.682**
mixed FE	0.693	0.721	0.711	0.691	0.648	0.594	**0.676**	0.690	0.686	0.650	0.651	0.599	**0.630**
							arousal on the *test* set						
baseline	0.732	0.628	0.590	0.542	0.480	0.404	0.563	0.732	0.719	0.618	0.609	0.356	0.495
matched FE	0.729	0.658	0.646	0.611	0.510	0.422	**0.596**	0.729	0.713	0.614	0.694	0.682	**0.684**
mixed FE	0.717	0.683	0.651	0.598	0.499	0.418	**0.594**	0.712	0.690	0.612	0.600	0.532	**0.586**
							valence on the *validation* set						
baseline	0.402	0.304	0.276	0.246	0.213	0.180	0.270	0.402	0.359	0.306	0.302	0.156	0.239
matched FE	0.383	0.335	0.299	0.259	0.257	0.223	**0.293**	0.383	0.335	0.236	0.331	0.187	**0.246**
mixed FE	0.201	0.227	0.275	0.275	0.262	0.205	0.249	0.253	0.243	0.251	0.253	0.215	0.230
							valence on the *test* set						
baseline	0.278	0.190	0.172	0.155	0.139	0.124	0.176	0.278	0.237	0.212	0.205	0.003	0.105
matched FE	0.269	0.227	0.258	0.214	0.200	0.172	**0.223**	0.269	0.211	0.126	0.152	0.140	**0.162**
mixed FE	0.171	0.210	0.217	0.214	0.202	0.179	**0.199**	0.195	0.175	0.208	0.209	0.085	**0.135**



(a) CHiME (b) smartphone-in-the-hall

Figure 2: Pearson Correlation Coefficiency (PCC) of 13 Low-Level Descriptors (i.e., MFCC 0-12) between the enhanced/non-enhanced speech and the clean speech over the whole test set with the *CHiME* noise (a) or the *smartphone-in-the-hall* noise (b).

Specifically, the performance of the clean speech almost does not degrade when executing matched FE method, but this conclusion is not drawn again by performing the mixed FE method. This should be mainly due to huge mismatch between the clean speech and the mixed noisy speech. However, this can be easily solved by inserting a noise detector at the front-end to distinguish whether the signal is noisy or clean speech [36]. If it was clean speech, the speech signal can directly be fed into the recognition model without any procedures of FE. Moreover, for the convolutional noise of smartphone in the classroom or in the hall, we can see that our proposed methods does not work quite well, however, for the convolutional noise of smartphone with CHiME noise, the proposed methods can surprisingly improve the baseline. This may be because LSTM neural networks do not work efficiently for a linear problem, as the T_{60} of MIR or RIR used for these experiments is short and the convolutinal noise can be regarded as a constant value in the spectral domain (see Eq. (8)).

To further investigate the efficiency of the proposed FE, we calculated the PCC between the enhanced (by matched FE)/non-enhanced speech and the clean speech over the whole test set with the CHiME noise or the smartphone-in-the-hall noise, as illustrated in Fig. 2. Obviously, the enhanced speech could deliver higher correlationship with the clean speech, which possibly contributes to the better emotion recognition performance.

4. Conclusions

In this paper, we present a feature enhancement method based on the denoising autoencoder with Long Short-Term Memory neural networks for spontaneous emotion recognition from speech. Extensive experiments are carried out with non-stationary additive noise and convolutional noise. The results show that the presented feature enhancement method is significantly superior to the baseline without any enhancement methods. With the fast development of deep learning technologies, there are many possibilities that could be used to further improve the robustness performance of emotion recognition systems from speech. For example, Convolutional Neural Networks is good at reducing spectral variation for the clean speech, which could also be effective for the noisy speech. Another method combined with Deep Neural Networks as an end-to-end structure [37] is worth evaluating as well in future.

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