Emotion recognition from phoneme-duration information

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1 Synopsis

The duration of each phoneme is extracted for several emotions. Information on phonemes and their duration are used to train a Variational AutoEncoder (VAE) to create a latent space z which represents emotion information. The loss functions that were used for that purpose are reconstruction loss, Kullback-Leibler (KL) divergence and multiclass N pair loss. Test samples are classified using the nearest neighbor criterion between their representation and the clusters associated to each emotion, as estimated from training data. To evaluate the models two metrics were used: emotion recognition accuracy and the consistency of the clusters of the latent space.

2 Purpose

Study the correlation of phoneme durations with emotions and illustrate the importance of phoneme duration on emotional speech production.

3 Introduction

Emotion recognition has several applications in human life, such as in assistant robots for elderly people or in call centers where it can help increase the quality of the services provided. Usually, prosodic features like pitch and energy contours are used for such tasks [1]. However, phoneme duration is also an important factor regarding the emotion of the speaker therefore it could be interesting to explore the relationship between phoneme durations and the corresponding emotion. Additionally, it could be also interesting exploring if it is possible to use the information from the relation between phoneme durations and emotion in order to create models that can profit from this knowledge in order to do emotion recognition. In this work we propose the use of phoneme information coupled with its duration to train a VAE with two different loss functions in order to 1) study the relation between phoneme durations and emotion and 2) explore the practical applications of the proposed method. The density of the clusters in the latent space was used as a metric for the first task and the emotion recognition accuracy for the second.

4 Materials and Methods

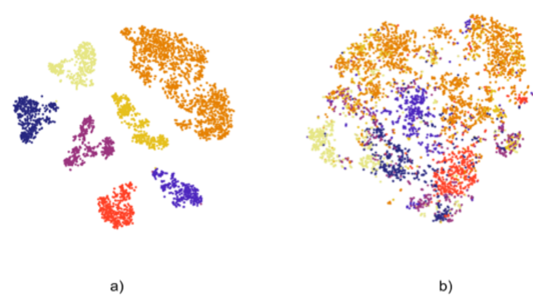
For this task, we used Caroline expressive speech corpus recorded in the French language with a female voice. Caroline's expressive speech corpus consists of several emotions, namely joy, surprise, fear, anger, sadness, and disgust (approx. 1hr for each emotion and 3hrs for neutral). For each emotion, there are approximately 500 utterances for a total of 1hr duration. All the speech signals were used at a sampling rate of 16 kHz. Each speech corpus is divided into train, validation, and test sets in the ratio of 80%, 10%, 10% respectively. We used the Soja tool [2] as a front end for context label generation. The contextual label file for the French language is designed with 1356 questions which consider the linguistic, phonetic, and prosodic details about phonemes such as phonetic category, positional information, stress, and accent information, guessed part of speech (GPOS) corresponding to the part of speech annotation of words in the text. 76 questions concern the left-left phoneme (i.e. two phonemes preceding the current one), 76 questions concern the left phoneme (i.e. phoneme preceding the current one), and so on. Contextual labels and speech waveforms are forced aligned using the HTK toolkit. For the next step, we used VAE trained with phoneme and corresponding duration information. For the VAE architecture, we implemented a BLSTM based encoder network. The input of the encoder is a sequence of context label features, x, along with duration information. The activation of hidden states of the BLSTM layer is given to feedforward layers to estimate both mean vector and variance vector, which are used to describe the encoder's latent variable, z. Similarly, the decoder network consists of BLSTM layers. The usage of BLSTM based recurrency allows the model to extract long term context from phoneme and duration information. The input of the decoder network is the latent variable z. The decoder generates the sequence of predicted duration $\hat{x}$. In the inference phase, we provide duration information and context labels as input to the encoder of the VAE model to generate the latent representation of given speech utterance. Afterward, we compute the distance between precomputed means of each emotion and generated latent representation. We classify the emotion for a given speech utterance considering the minimum distance between precomputed means for emotion. Thus, for better emotion recognition the latent space should have well-separated clusters corresponding to the various emotions. Therefore, we proposed to use multiclass N-pair loss in variational inference as deep variational metric learning. Multi-class N-pair loss has shown superior performance compared to triplet loss or contrastive loss by considering one positive sample and N-1 negative samples for N classes [3].

5 Results

In the table below, we present the accuracy for the baseline system using reconstruction and KL divergence as well as for the proposed system where we added multiclass N pair loss. The proposed system has an average accuracy of 73.18% compared to 54.84% of the baseline system. We can see that the latent space of the proposed model has more compact clusters (average standard deviation of 0.61 compared to 0.86 of the baseline model) and are clearly separated from each other without overlapping.

Emotion	Accuracy(%)	Standard Deviation
Anger	78.48 (56.78)	0.59 (0.85)
Disgust	70.27 (55.33)	0.69 (0.86)
Fear	71.60 (50.86)	0.63 (0.89)
Joy	75.06 (58.21)	0.56 (0.83)
Neutral	74.93 (50.47)	0.57 (0.89)
Sad	71.34 (54.36)	0.61 (0.87)
Surprise	70.57 (57.89)	0.65 (0.83)

Result table using VAE with multiclass N pair loss. In parenthesis are the results with the simple VAE approach



Latent space z t-SNE representation with N pair loss (a) and without (b).

6 Discussion

The t-SNE plot of the VAE N-pair model shows well-clustered emotion in latent space. The orange cluster in the t-SNE plot represents neutral speech. From the figure, addition of multiclass N-pair loss clearly indicates improvement in clustering in the latent space, which results in improved performance in emotion recognition as illustrated by numerical results. Further research could include extending the results to multispeaker experiments or using other metric losses and architectures for building the model.

7 References

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