MIXED EMOTION MODELLING FOR EMOTIONAL VOICE CONVERSION

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ABSTRACT

Emotional voice conversion (EVC) aims to convert the emotional state of an utterance from one emotion to another while preserving the linguistic content and speaker identity. Current studies mostly focus on modelling the conversion between several specific emotion types. Synthesizing mixed effects of emotions could help us to better imitate human emotions, and facilitate more natural humancomputer interaction. In this research, for the first time, we formulate and study the research problem of mixed emotion synthesis for EVC. We regard emotional styles as a series of emotion attributes that are learnt from a ranking-based support vector machine (SVM). Each attribute measures the degree of the relevance between the speech recordings belonging to different emotion types. We then incorporate those attributes into a sequence-to-sequence (seq2seq) emotional voice conversion framework. During the training, the framework not only learns to characterize the input emotional style, but also quantifies its relevance with other emotion types. At runtime, various emotional mixtures can be produced by manually defining the attributes. We conduct objective and subjective evaluations to validate our idea in terms of mixed emotion synthesis. We further build an emotion triangle¹ as an application of emotion transition. Codes and speech samples are publicly available².

Index Terms- Emotional voice conversion, mixed emotions

1. INTRODUCTION

Emotions can coexist in human speech, creating blended emotional behaviors [1, 2, 3]. For example, excitement can be regarded as a mixed state of happiness and surprise [4]. Emotional voice conversion (EVC) seeks to modify an emotional style and infuse a desired emotion into a human voice [5]. Synthesizing mixed emotions for EVC allows us to create new emotion types that are hard to collect in real life, which could bring us one step closer to achieve emotional intelligence, and further enhance the engagement in human-computer interaction [6, 7].

Voice conversion (VC) is a task of changing the speaker identity while preserving the linguistic information [8]. Since speaker identity is characterized by the vocal tract and manifested in spectrum [9], spectrum conversion has been the major focus of VC. Unlike VC, which has attracted broadly interests, there are few studies on the synthesis of mixed emotions, which remains to be a challenging task [10]. One of the reasons is the hierarchical nature of emotions, which is inherently supra-segmental and complex with multiple acoustic cues including spectrum and prosody [11]. Therefore, it is not straightforward for us to characterize mixed emotions. Besides, current evaluation methods are inadequate to assess mixed emotions. The re-devise of current evaluation is also needed.

There are generally two types of methods for EVC to model speech emotions. One way is to learn a translation model between emotion pairs. Previous studies model the spectral and prosody mapping with statistical methods such as hidden Markov model (HMM) [12] and Gaussian mixture model (GMM) [13]. Deep learning methods such as deep neural networks (DNN) [14], deep bi-directional long-short-term memory network (DBLSTM) [15] and generative adversarial network (GAN) [16] have advanced the performance. Another way is to disentangle emotional elements from speech with auto-encoders [17, 18, 19]. Emotion conversion can be achieved by only manipulating emotional elements while keeping other speech characteristics unchanged. We note that all these methods learn emotional information either from emotion labels or reference speech. They are restricted from learning richer descriptions of emotional styles, which limits the controllability of the output emotion, resulting in an stereotypical emotional pattern at run-time. They cannot generate any emotional styles that are unseen during the training, for example, a mixture of emotions.

Despite psychological studies [20, 21] to understand the paradigm and measurements of mixed emotions, mixed emotion synthesis has only been recently studied in text-to-speech [10], but has not been given attention in EVC yet. This paper therefore marks the first study of mixed emotion synthesis for EVC, which poses two research challenges: (1) how to characterize and quantify the mixture of emotions, and (2) how to evaluate the generated results. We focus on these two challenges, and summarize our novel contributions:

- This study is the first to model and synthesize mixed emotions for emotional voice conversion;
- We propose a novel formulation to quantify the mixture of emotions. We construct a ranking function for each pair of emotions, where the ranking order represents the degree of relevance with respect to an emotion. We regard the relevance as the attribute of the emotional style, and propose to explicitly model those attributes;
- During training, the attribute can be precisely predicted by the ranking function. The EVC framework learns to associate the input emotional style with other emotions by quantifying their degree of relevance. At run-time, humans can define those attributes to generate various emotional mixtures;
- We redesign current evaluation metrics to validate our idea. We further show the application on emotion transition within an emotion triangle.

The rest of paper is organized as follows: In Section 2, we introduce the ordinal nature of emotions and motivate our study. We present our proposals to model and synthesize mixed emotions in Section3. In Section 4, we report our experimental results along with an application study. Section 5 concludes the paper.

¹Emotion Triangle: https://kunzhou9646.github.io/ Emotion_Triangle/

²Codes & Speech Samples: https://kunzhou9646.github. io/Mixed_EVC/

2. THE ORDINAL NATURE OF EMOTIONS

Studies show that humans are efficient at discriminating among options rather than giving absolute scores or assigning discrete labels to an emotion [22]. Therefore, emotions should be analyzed following the ordinal path, where the key idea is to establish a preference between samples, and construct a ranking model using training data [23]. The model can sort new objects according to their degree of relevance or preference. Ordinal methods have achieved remarkable performance in emotion recognition [24].

Current studies on emotion synthesis and conversion still rely on discrete emotion labels [25, 5] or deep emotion features [26, 27] to guide the model during the training. These methods learn to explicitly characterize the input style, but do not model the relations between different emotions. Most related studies [28, 29] explore the ordinal nature of emotions in intensity control, where emotion intensity is modelled as the ranking score between neutral and emotional speech. Inspired by these studies, we expand the idea of relative attributes [30] into mixed emotion modelling and synthesis. Since it is not straightforward to simply adding up emotions, we follow the ordinal path of emotions, and propose to model and quantify the relevance between different emotions, which will be discussed next.

3. MIXED EMOTION MODELLING AND SYNTHESIS

We introduce our proposed seq2seq emotional voice conversion framework with a novel formulation of emotion modelling, that is denoted as "*Mixed-EVC*" in short. At run-time, Mixed-EVC allows users to manipulate the source emotion to various mixture of emotions while keeping linguistic and speaker information unchanged.

3.1. Modelling Emotion Attribute with Pairwise Ranking

Most emotional speech databases group utterances into several discrete categories, thus restricts to learn richer descriptions of the emotional style [5]. Instead of predicting the presence of a specific emotional style, we propose to model the relative difference between a pair of emotional styles, which we define it as "*Emotion Attribute*". During the training, we characterize the input emotional style by measuring its relevance to other emotions by explicitly modelling emotion attributes. For example, while it is hard to give a consensus emotion label to an utterance especially when the emotions are ambiguous, we can agree that it sounds less happy than A but more angry than B. Our formulation follows the ordinal nature of emotions and offers more detailed descriptions, thus closer to human's emotional perception.

Similar with relative attributes [30] that are widely studied in computer vision, we learn a ranking function for each emotion attribute given relatively similarity constraints on paired samples. More specifically, we are given a training set $T = \{\mathbf{x}_n\}$, where \mathbf{x}_n is the acoustic feature vector of the n^{th} training sample, and a set of M emotion attributes $E = \{\mathbf{e}_m\}$. For each emotion attribute \mathbf{e}_m , our goal is to learn a ranking function f_m given as below:

$$f_m(x_n) = \mathbf{W}_m \mathbf{x}_n,\tag{1}$$

where m = 1, ..., M and **W** is a weighting matrix. As the supervision, we construct an ordered set O_m and an unodered set U_m which satisfy the following constraints:

$$\forall (x_i, x_j) \in O_m : \mathbf{W}_m \mathbf{x}_i > \mathbf{W}_m \mathbf{x}_j \tag{2}$$

$$\forall (x_i, x_j) \in U_m : \mathbf{W}_m \mathbf{x}_i = \mathbf{W}_m \mathbf{x}_j, \tag{3}$$



Fig. 1. The training diagram of our proposed Mixed-EVC, where the red boxes represent the modules that are involved in the training while the others are not. The pre-trained ranking functions automatically predict emotion attributes that indicates the degree of relevance between the input emotional style (Happy) and other emotional styles (Angry, Sad, Surprise and Neutral).

The sample x_i should have a stronger presence of emotion attribute a_m than x_j in the ordered set O_m , while their presence should be similar in the unordered set U_m . The weighting matrix **W** is estimated by solving a support vector machine problem [31]:

$$\min_{\mathbf{W}_{m}}(\frac{1}{2} \| \mathbf{W}_{m} \|_{2}^{2} + C(\sum \xi_{i,j}^{2} + \sum \gamma_{i,j}^{2}))$$
(4)

s.t.
$$\mathbf{W}_m(\mathbf{x}_i - \mathbf{x}_j) \ge 1 - \xi_{i,j}; \forall (i,j) \in O_m$$
 (5)

$$\mathbf{W}_m(\mathbf{x}_i - \mathbf{x}_j) | \le \gamma_{i,j}; \forall (i,j) \in U_m$$
(6)

$$\xi_{i,j} \ge 0; \gamma_{i,j} \ge 0, \tag{7}$$

where *C* is the trade-off between the margin and the size of slack variables $\xi_{i,j}$ and $\gamma_{i,j}$. We create pairs for all the emotions, and repeat the above ranking training in a pairwise manner. At run-time, the trained ranking function can automatically predict the emotion attribute that indicates the relevance or similarity between a pair of emotional styles. In practice, each emotion attribute is normalized into [0,1], where a smaller value represents a more similar emotional style. All the emotion attributes form an emotion attribute vector that measures the degree of relevance of an input emotional style with all other emotions.

3.2. Seq2Seq Emotional Voice Conversion Training

We incorporate our emotion attribute vector into a seq2seq EVC framework [32], as shown in Figure 1. Seq2seq-based EVC methods jointly model the feature mapping and alignment, and automatically predict the speech duration at run-time, which marks as a departure from the frame-wise modelling [33].

Given an input speech, the linguistic encoder learns to predict a sequence of linguistic embeddings ("*Linguistic Modelling*"), while the emotion encoder learns to encode the emotional style into an utterance-level emotion embedding ("*Style Modelling*"). The pre-trained relative functions further predict an emotion attribute vector indicating the relevance of the input emotional style with other emotions ("*Relevance Modelling*"). The emotion attribute vector is then projected by a fully-connected (FC) layer, resulting in a relative embedding. Finally, the decoder learns to reconstruct the input emotional style from a combination of emotion and relative embeddings.



Fig. 2. The run-time diagram of the proposed Mixed-EVC, where the green boxes represent the modules that are already trained. By assigning manually defined attributes, Mixed-EVC transfers the source emotion to a target emotional mixture while preserving the source linguistic content.

In this way, our framework does not only explicitly characterize the input emotional style, but also establish a relation with other emotions.

To overcome the instability issues in seq2seq models, we conduct emotion training with the following strategies: (1) introducing text supervision [34], and (2) pre-training with a large neutralspeaking corpus [32]. We use text transcriptions to assist the framework to disentangle the linguistic information from the speech. A text encoder predicts a sequence of text embeddings from the input text. The text and linguistic embeddings are then fed into the decoder in an alternative manner. In practice, following the previous literature [34], we employ a contrastive loss to ensure the similarity between text and linguistic embeddings, and an adversarial training with a classifier to eliminate the residual emotion information in linguistic embedding. These strategies help us to train the framework more efficiently.

3.3. Run-time Emotional Mixture

At run-time, Mixed-EVC converts the source emotion to an emotional mixture as shown in Figure 2. The linguistic encoder encodes the source linguistic content into an internal representations. The emotion encoder encapsulates a set of reference speech into an emotion embedding. The characteristics of other emotion types can be further introduced by manually defining an attribute vector. It allows us to vary the percentage to each emotion types and create different emotional mixtures.

4. EXPERIMENTS

4.1. Experimental Setup

We conduct experiments with the ESD dataset [5], where we randomly choose one female speaker ("0019") with five emotions ("*Neutral*", "*Happy*", "*Sad*", "*Angry*" and "*Surprise*"). We follow the data partition in ESD dataset, and for each emotion, we use 300, 30, 20 utterances for training, test and evaluation respectively. We train an universal EVC model for all the emotions. At run-time, we convert *Neutral* to 4 different mixtures of emotions that are:

• Outrage, Excitement, Disappointment: where we convert *Neutral* to *Angry*, *Happy* and *Sad* respectively, while introducing different percentages of *Surprise* into the mixture. These 3 mixtures have been studied in emotion theory [4];

• **Bittersweet**: where we convert *Neutral* to *Happy* while introducing different percentages of *Sad*. Even though happiness and sadness are two oppositely valenced emotions in the Russell's model [35], there are some debates that agreeing to the co-existence of happiness and sadness [2];

The training pipeline is described as below: We first pre-train the relative ranking function between each emotion pair. Each utterances is represented by a 384-dimensional feature vector defined by INTERSPEECH Emotion Challenge [36]. We then follow a 2-stage training strategy [32] to train our proposed framework: (1) Style Pretraining with the VCTK Corpus [37], and (2) Seq2Seq EVC Training with the ESD dataset. The inputs to the EVC model are acoustic features represented by 80-dimensional Mel-spectrogram extracted every 12.5 ms with a frame size of 50 ms for short-time Fourier transform (STFT), and phoneme sequences converted by the Festival [38] G2P tool. It is noted that we only use acoustic features as the inputs during the conversion.

Our proposed framework has a similar structure with that of [34]. The linguistic encoder consists of an encoder, a 2-layer 256cell BLSTM and a decoder, a 1-layer 512-cell BLSTM with an attention layer followed by a full-connected (FC) layer with an output channel of 512. The decoder has the same model architecture as that of Tacotron [39]. The text encoder is a 3-layer 1D CNN with a kernel size of 5 and a channel of 512. The text encoder is followed by a 1-layer of 256-cell BLSTM and an FC layer with an output channel of 512. The style encoder is a 2-layer of 128-cell BLSTM followed by an FC layer with an output channel of 64. The classifier is a 4-layer of FC with the channel of $\{512, 512, 512, 5\}$. We set the batch size to 64 and 4 for style pre-training and emotion training respectively. We set the learning rate to 0.001 and the weight decay to 0.0001 for style pre-training, and halve the learning rate every 7 epochs for emotion training.

4.2. Objective Evaluation

We evaluate our synthesized mixed emotions with a speech emotion recognition (SER) model that is pre-trained on the ESD dataset. The SER model has a similar structure with that of [40], which consists of 1) a 3-D CNN layer, 2) a BLSTM, 3) an attention layer and 4) a FC layer. We use the classification probabilities derived from the last softmax layer of the SER to analyze the performance of mixed emotions. We believe that classification probabilities summarize the emotion information from previous layers for decision-making, which provide us a tool to study emotional mixtures.

We report the classification probabilities in Figure 3. We first evaluate three different mixed effects that are *Outrage, Excitement* and *Disappointment*, where we convert *Neutral* to *Angry, Happy* and *Sad* respectively while gradually increasing the percentage (0%, 30%, 60% and 90%) of *Surprise*. As shown in Figure 3(a), (b) and (c), we observe that the probability of *Surprise* consistently increases when we increase the percentage of *Surprise* from 0% to 90%. In the meanwhile, the probability of *Angry, Happy* and *Sad* always remains to be the highest among the five emotions in these three different mixtures respectively. We then evaluate the mixed effect of *Bittersweet*, where *Sad* is further introduced when we convert *Neutral* to *Happy*. As shown in Figure 3(d), we find a similar observation as in Figure 3(a), (b) and (c). These observations indicate that the mixed emotions can be perceptually recognised by a pre-trained SER.



(a) Mixing Angry with Surprise (b) Mixing Happy with Surprise (Ex- (c) Mixing Sad with Surprise (Disap- (d) Mixing Happy with Sad (Bitter-(Outrage) citement) sweet)

Fig. 3. Classification probabilities derived from the pre-trained speech emotion recognition (SER) model. Each point represents an averaged probability value of 20 utterances with mixed emotions.

Table 1. Mean Opinion Score (MOS) with 95% confidence intervalto evaluate the speech quality of synthesized mixed emotions.

Configuration		MOS
Mixing Angry with Surprise	Ground truth (Angry) + 0% Surprise + 30% Surprise + 60% Surprise + 90% Surprise	$\begin{vmatrix} 4.78 \pm 0.17 \\ 3.50 \pm 0.24 \\ 3.34 \pm 0.26 \\ 3.15 \pm 0.34 \\ 3.20 \pm 0.31 \end{vmatrix}$
Mixing Happy with Surprise	Ground truth (Happy) + 0% Surprise + 30% Surprise + 60% Surprise + 90% Surprise	$\begin{vmatrix} 4.85 \pm 0.12 \\ 3.63 \pm 0.27 \\ 3.53 \pm 0.19 \\ 3.17 \pm 0.30 \\ 3.05 \pm 0.34 \end{vmatrix}$
Mixing Sad with Surprise	Ground truth (Sad) + 0% Surprise + 30% Surprise + 60% Surprise + 90% Surprise	$ \begin{vmatrix} 4.74 \pm 0.12 \\ 3.63 \pm 0.27 \\ 3.53 \pm 0.19 \\ 3.17 \pm 0.30 \\ 3.05 \pm 0.34 \end{vmatrix} $
Mixing Happy with Sad	Ground truth (Happy) + 0% Sad + 30% Sad + 60% Sad + 90% Sad	$\begin{vmatrix} 4.84 \pm 0.12 \\ 3.17 \pm 0.35 \\ 3.48 \pm 0.30 \\ 3.42 \pm 0.32 \\ 3.08 \pm 0.36 \end{vmatrix}$

4.3. Subjective Evaluation

We then conduct listening experiments to evaluate our synthesized results in terms of speech quality and emotion perception. 15 subjects participated in all the experiments and each of them listened to 112 synthesized utterances in total.

We first report mean opinion scores (MOS) results for speech quality, where all participants are asked to listen to the reference speech ("Ground truth") and the synthesized speech with mixed emotions and score the "quality" of each speech sample on a 5-point scale ('5' for excellent, '4' for good, '3' for fair, '2' for poor, and '1' for bad). As shown in Table 1, the audio quality of synthesized speech slightly decreases while we increasing the percentage of emotional mixture. We are glad to see that our synthesized speech consistently retain between fair and good.

We then conduct best-worst scaling (BWS) tests to evaluate emotion perception of the synthesized mixed emotions. All participants are asked to choose the best and the worst emotion according to their perception to the mixed emotion (*Outrage, Excitement, Disappointment* and *Bittersweet*). As shown in Table 2(a), (b) and (c), we observe that most participants can perceive the mixed feelings and choose those with 90% of *Surprise* as the "Best", and those of 0% of *Surprise* as the "Worst". We take one step further to evaluate the perception of *Bittersweet* as shown in Table 2(d). To our delight, most participants chose those with 90% *Sad* as the "Best". The results of *Bittersweet* are not as distinguishable as those of the other three mixed emotions, which suggests that it could be more challenging for listeners to perceive a *Bittersweet* feeling. These results show that we are able to create new emotion

Table 2. Best-worst scaling (BWS) test results to evaluate the perception of the mixed feelings (*Outrage, Excitement, Disappointment* and *Bittersweet*) in the converted mixed emotions.

Configuration		Best (%)	Worst (%)	
(a) Perception of Outrage				
Mixing Angry with Surprise	+ 0% Surprise	15.4	40.0	
	+ 30% Surprise	15.4	24.6	
	+ 60% Surprise	13.8	21.6	
	+ 90% Surprise	55.4	13.8	
(b) Perception of Excitement				
Mixing Happy with Surprise	+ 0% Surprise	3.1	69.2	
	+ 30% Surprise	12.3	10.8	
	+ 60% Surprise	23.1	9.2	
	+ 90% Surprise	61.5	10.8	
(c) Perception of Disappointment				
Mixing Sad with Surprise	+ 0% Surprise	13.8	53.8	
	+ 30% Surprise	16.9	12.3	
	+ 60% Surprise	21.5	27.7	
	+ 90% Surprise	47.8	6.2	
(d) Perception of Bittersweet				
Mixing Happy with Sad	+ 0% Sad	4.6	41.5	
	+ 30% Sad	20.0	12.3	
	+ 60% Sad	30.8	10.8	
	+ 90% Sad	44.6	35.4	

feelings that are subtle but do not exist in the database. We also show the effectiveness of controllability by varying the percentages of primary emotions to synthesize different emotional mixtures.

4.4. Application Study: An Emotion Triangle

Mixed emotions can be perceived during the emotion transition. As an application study, we built an emotion triangle to study emotion transition across different emotions, where the key challenge is to model the internal states between emotions. With our proposed Mixed-EVC, it is possible for us to synthesize those states by mixing with different percentages emotions. Readers are suggested to refer to the demo page. The presentation of emotion triangle further validates the controllability of Mixed-EVC.

5. CONCLUSION

We propose a seq2seq emotional voice conversion framework, Mixed-EVC, to fill the research gap of mixed emotion synthesis for EVC. We formulate emotional styles as an attribute and explicitly model the degree of relevance between different emotions through a ranking-based SVM. By manually adjusting relevance at runtime, Mixed-EVC could produce different emotional mixtures. Both objective and subjective evaluations show the effectiveness on synthesizing different mixed emotion effects. We further present emotion transition within an emotion triangle as the application study.

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