EXPRESSIVE VOICE CONVERSION: A JOINT FRAMEWORK FOR SPEAKER IDENTITY AND EMOTIONAL STYLE TRANSFER

Zongyang Du\textsuperscript{1,2}, Berrak Sisman\textsuperscript{1}, Kun Zhou\textsuperscript{2}, Haizhou Li\textsuperscript{2,3}

\textsuperscript{1}Singapore University of Technology and Design, Singapore
\textsuperscript{2}National University of Singapore, Singapore
\textsuperscript{3}The Chinese University of Hong Kong (Shenzhen), China

ABSTRACT

Traditional voice conversion (VC) has been focused on speaker identity conversion for speech with a neutral expression. We note that emotional expression plays an essential role in daily communication, and the emotional style of speech can be speaker-dependent. In this paper, we study a technique to jointly convert the speaker identity and speaker-dependent emotional style, that is called expressive voice conversion. We propose a StarGAN-based framework to learn a many-to-many mapping across different speakers, that takes into account speaker-dependent emotional style without the need for parallel data. To this end, we condition the generator on emotional style encoding derived from a pre-trained speech emotion recognition (SER) model. The experiments validate the effectiveness of our proposed framework in both objective and subjective evaluations. To our best knowledge, this is the first study on expressive voice conversion.

Index Terms— Voice conversion, emotion style features, StarGAN

1. INTRODUCTION

Traditional voice conversion (VC) aims to modify one’s voice to sound like that of another while keeping linguistic content and emotional style unchanged \cite{1}. VC is an enabling technology for various tasks, such as conversational assistants, cross-lingual speech synthesis \cite{2}, and speaker verification \cite{5}. In this paper, we formulate a new research topic denoted as Expressive Voice Conversion, and propose a solution that jointly performs speaker identity and emotional style transfer for emotional speakers.

It is known that human speech is expressive and emotive in nature, and people usually express themselves with various emotional states such as happy and sad \cite{6}. Studies also reveal the fact that emotional speech style contains speaker-dependent elements which has never been studied in traditional voice conversion \cite{7,9}. The study of expressive voice conversion is motivated to fill the gap.

Speech Samples: https://zy-du.github.io/ASRU21/

![Fig. 1. An example of expressive voice conversion which aims to convert the happy utterances expressed by speaker A to sound like those of speaker B without changing the speaking content. We note that an individual expresses the happiness in one’s own style.](https://zy-du.github.io/ASRU21/)
In traditional voice conversion, we seek to convert the speaker identity while preserving the linguistic information. As speaker identity is determined by the vocal timbre that is manifested in spectrum [22], early voice conversion studies are mainly focused on modeling the spectral mapping between the source and target with statistical parametric methods such as Gaussian mixture model (GMM) [23,25]. Recent deep learning methods such as deep neural network (DNN) [26], and recurrent neural network (RNN) [27] have significantly improved the performance. We note that these methods require parallel data, that limits the scope of real-life applications. To enable non-parallel voice conversion, many frameworks based on generative models such as variational auto-encoders (VAE) [28,31] and generative adversarial network (GAN) [32,38] are proposed in recent years. Among the GAN-based methods, StarGAN-VC [39,40] extends non-parallel VC from two domains to multiple domains. It allows for sharing of knowledge across multiple pairwise mapping, and represents one of the successful attempts in non-parallel VC, which motivates our study. We would like to study the use of a StarGAN architecture to learn a translation model across multiple spectral domains from different speakers with different emotional styles.

Our proposed framework consists of two stages for training: 1) emotional style descriptor training, where we train a SER network to learn emotion-related information such as emotional style features through acoustic features; 2) StarGAN training, where we condition the generator with both speaker label and emotional style features. We believe that emotional style features serve as an excellent tool to describe the emotional style in a continuous space, thus more suitable for speaker-dependent emotional style transfer.

The main contributions of this paper include: 1) we formulate a novel research topic, expressive voice conversion, as an extension of voice conversion research; 2) we propose an expressive voice conversion framework based on StarGAN without the need for parallel data, and that is flexible for many-to-many conversion; 3) we conduct experiments on a publicly available multi-speaker database under different emotional states, and show the effectiveness of our proposed expressive voice conversion framework for both emotional style and speaker identity transfer. To our best knowledge, this is the first paper to study expressive voice conversion.

The rest of this paper is organized as follows: In Section 2, we introduce the related work. In Section 3, we investigate the speaker-dependent emotional style with deep emotional style features, which motivates our study. In Section 4, we introduce our proposed voice conversion framework with StarGAN. In Section 4, we report the experiments. Section 5 concludes the study.

2. RELATED WORK

2.1. Traditional voice conversion and datasets

Traditional voice conversion is studied for speech with a neutral expression, where voice quality has been the main focus. The most widely used speech databases for voice conversion include VCTK database [41], CMU-Arctic database [42], and Voice Conversion Challenge (VCC) corpus [43,45]. Since these speech databases are emotion-free, it is straightforward to pay attention to the vocal timbre when conducting voice conversion research.

We note that voice conversion with emotional speech data has never been studied before, mostly due to the lack of suitable databases. Recently, ESD database [16] is released for emotional voice conversion studies, which includes multi-speaker and multi-lingual parallel speech data with different emotions, and makes possible emotion-related studies, such as expressive voice conversion.

2.2. StarGAN for voice conversion

StarGAN [46] is first proposed to multi-domain image-to-image translation in computer vision, and then adopted to voice conversion [39]. StarGAN [39] and its variants [33,37,40] have shown promising results in many-to-many voice conversion without the need for parallel data. A StarGAN consists of a generator, a discriminator, and a domain classifier. The generator takes both spectral features and domain information such as one-hot label, and translates the spectral features into the corresponding domain while the discriminator distinguishes whether the input features are real or fake. A domain classifier is used to further verify the label correctness of both real and generated spectral features. StarGAN also has been applied to other tasks such as affect generation [47] and emotional voice conversion [48]. Motivated by the success of StarGAN in many-to-many voice conversion, we extend the idea and propose a many-to-many VC framework that can jointly transfer both speaker identity and emotional style, which will be further introduced in Section 4.

3. SPEAKER-DEPENDENT EMOTIONAL STYLE

Emotional feature extraction has been a research hotspot in speech emotion recognition (SER) [49]. With the advent of deep learning, there has been a shift from traditional hand-crafted emotional features such as those extracted by low level descriptors (LLDs) [50] or openSMILE [51], to the features automatically learned by deep neural networks (DNN) [52]. Many studies [52,53] have shown that DNNs are capable of extracting hierarchical feature representations from expressive speech, which are more suitable for SER. Meanwhile, recent speech synthesis studies [54,56] also propose to leverage those deep emotional features to characterize different emotional styles over a continuum [57]. These successful attempts have served as the source of motivation for this paper.
We propose to study a scenario for expressive voice conversion, where source and target speakers are expressing the same emotion in their own styles, that we refer to as speaker-dependent emotional styles. As emotional styles are hierarchical in nature, they are difficult to describe. We believe that deep emotional features bear a huge potential to describe both speaker-dependent and speaker-independent attributes for emotional styles. Therefore, we would like to investigate the use of deep emotional features for expressive voice conversion.

We first train a SER network and use the emotional style features before the last projection layer as illustrated in Fig. 4(a). We then use t-SNE algorithm [58] to visualize the emotional style features of two female speakers (0016, 0018) and two male speakers (0013, 0020). As shown in Fig. 3, we observe that the emotional style features form emotional groups for each speaker. These results suggest that these emotional style features characterize well the emotional states.

We further look into how emotional style features differ between speakers. We measure the similarity of the emotional style features between speaker pairs in terms of euclidean distance and root mean square error (RMSE). From Fig. 2, we observe the euclidean distance and RMSE within a speaker are lower than those between two speakers, which indicates that emotional style features from SER carry speaker-dependent information.

The above analysis shows that we may use emotional style features to encode both speaker-dependent and speaker-independent emotional styles in expressive voice conversion.

4. A JOINT SPEAKER IDENTITY AND EMOTION STYLE TRANSFER FRAMEWORK

We propose a joint emotional style and speaker identity conversion framework using StarGAN, which is referred to as JES-StarGAN. We next discuss JES-StarGAN in three stages: 1) emotional style descriptor training, 2) StarGAN training, and 3) run-time conversion. In stage I, we train an auxiliary SER network to act as an emotion descriptor. In stage II, we train a StarGAN network to learn the mapping of both spectral features and emotional style features across different speakers. In stage III, JES-StarGAN performs voice conversion towards target speaker identity and emotional style.

4.1. Stage I: Emotional style descriptor training

As emotional style presents both speaker-dependent and speaker-independent characteristics at the same time, it is insufficient for us to use a discrete representation to represent different emotional styles, such as one-hot emotion label [56]. Therefore, we propose to use deep emotional features that learnt from a large emotional speech corpus to describe different emotional styles.

We propose to train an SER model to learn the emotional style features for different speakers with various emotions. The model architecture is the same as that in [59], as illustrated in Fig. 4(a). The SER network consists of the following layers: 1) a three-dimensional (3-D) CNN layer; 2) a BLSTM layer; 3) an attention layer; and 4) a fully-connected (FC) layer. The Mel-spectrum input is first projected into a fixed size latent representation by the 3-D CNN, which preserves the useful emotional information while reducing the influence
4.2. Stage II: JES-StarGAN training

StarGAN has been widely used for many-to-many voice conversion and does not need parallel data. We propose a StarGAN-based architecture as shown in Fig. 4(b), which consists of three modules: a generator G, a discriminator D, and a domain classifier C. During stage II, the proposed framework learns a feature mapping of speaker identity and speaker-dependent emotional style information from different speakers.

Given the source acoustic feature sequence $x$, target speaker label $c_y$, and target emotional style feature $E_y$, the generator learns to translate the source acoustic feature sequence $x$ to the target domain by conditioning on the emotional style feature $E_y$ and target speaker label $c_y$. The converted acoustic feature $\hat{y}$ can be represented as:

$$\hat{y} = G(x, E_y, c_y)$$  \hspace{1cm} (1)

where $c_y$ is a one-hot vector to represent each speaker. In this way, the generator jointly learns the speaker identity information and speaker-dependent emotional style information from the input features.

The discriminator D is designed to judge whether the input is real or not, while the classifier C judges whether the input acoustic features belong to the target speaker. The training process of our proposed method is illustrated in Fig. 4(b). The training losses for our proposed method are described as follows:

1) **Adversarial loss:** An adversarial loss is applied to train G and D as follows:

$$L_{adv}^{G} = -E_{x,y,c_y} \left[ \log D(G(x, E_y, c_y), c_y) \right]$$  \hspace{1cm} (2)

$$L_{adv}^{D} = -E_{x,c_x} \left[ \log(D(x, c_x)) \right] - E_{x,y,E_y,c_y} \left[ \log(1 - D(G(x, E_y, c_y), c_y)) \right]$$  \hspace{1cm} (3)

where $E[\cdot]$ represents the expectation operation, $c_x$ and $E_x$ represent the speaker label and the emotional style features of the source speaker respectively. During training, D tries to minimize $L_{adv}^{D}$, and G tries to minimize $L_{adv}^{G}$. To G, a smaller value of the adversarial loss indicates a higher similarity between the converted speech and the target emotional speech in terms of both speaker similarity and emotional style.

2) **Domain classification loss:** A domain classification loss is applied to train the C and G, which is defined as:

$$L_{dom}^{C} = -E_{x,c_x} \left[ \log p_C(c_x | x) \right]$$  \hspace{1cm} (4)

$$L_{dom}^{G} = -E_{x,y,E_y,c_y} \left[ \log p_C(c_y | G(x, E_y, c_y)) \right]$$  \hspace{1cm} (5)

where $p_C$ represents the output probability distribution from C. During training, C learns to classify a real acoustic feature sequence $x$ to its corresponding speaker label $c_x$ by minimizing Equation (4). G learns to generate acoustic feature sequence $G(x, E_y, c_y)$ with higher classification accuracy for the target domain $c_y$ by minimizing $L_{dom}^{G}$ in Equation (5). The additional input $E_y$ in $G(x, E_y, c_y)$ encourages $G(x, E_y, c_y)$ to carry speaker-dependent emotional style information, so that C can more easily classify $G(x, E_y, c_y)$ with high accuracy in target domain.

3) **Cycle-consistency loss:** A cycle-consistency loss is proposed to guarantee the consistency of the contextual information between input and output while converting the speaker.
identity and emotional style. It is defined as:

\[
L_{\text{cyc}}^G = E_{x,E_y,c_y,E_x,c_x} \| G(G(x, E_y, c_y), E_x, c_x) - x \|_1
\]  

(6)

Since the emotional style of source speaker is different from that of target speaker, it is necessary to input \( E_x \) as an additional condition for the G to make \( G(G(x, E_y, c_y), E_x, c_x) \) closer to the source acoustic features.

4) **Identity mapping loss**: An identity mapping loss is used to preserve the linguistic information between the same source and target speaker when inputting \( x, E_x \) and \( c_x \) for G. It is defined:

\[
L_{\text{id}}^G = E_{x,E_x,c_x} \| G(x, E_x, c_x) - x \|_1
\]  

(7)

Both speaker identity \( c \) and \( E_x \) are speaker-dependent features for the same speaker. \( L_{\text{id}}^G \) helps G to generate the acoustic feature sequences from the same speaker be consistent by considering these speaker-dependent features.

The full objective functions of our proposed method are given as follows:

\[
L_D = L_{\text{adv}}^D, \quad L_C = L_{\text{dom}}^C
\]  

(8)

\[
L_G = L_{\text{adv}}^G + \lambda_{\text{dom}} L_{\text{dom}}^G + \lambda_{\text{cyc}} L_{\text{cyc}}^G + \lambda_{\text{id}} L_{\text{id}}^G
\]  

(9)

where \( \lambda_{\text{dom}}, \lambda_{\text{cyc}} \) and \( \lambda_{\text{id}} \) are trade-off factors to control the relevance of the domain classification loss, the cycle consistency loss and the identity mapping loss to the overall adversarial losses.

At training stage, we condition the generator on emotional style encoding derived from a pre-trained SER model from stage I. JES-StarGAN optimizes the distribution of the generated acoustic features to match that of the target features from emotional data. With the additional input emotional style features, JES-StarGAN learns to project both emotional style and speaker identity into the converted speech.

4.3. Stage III: Run-time conversion

During the run-time conversion, we can convert the acoustic feature sequence \( x \) of an input utterance: \( y = G(x, E_y', c_y) \). Since the real target emotion style features are not available from stage I, we calculate the mean of emotion style features collected from the corresponding reference utterances as \( E_y' \), which can be defined as \( E_y' = mean(E_y^u) \), where \( y_e \) represents target speaker with a certain emotion state.

5. EXPERIMENTS

We conduct objective and subjective evaluations to assess the performance of our proposed framework in terms of speaker identity and emotional style. We use a multi-speaker emotional speech dataset, ESD [16], to conduct all the experiments. ESD consists of multi-lingual and multi-speaker parallel emotional speech data with five emotions (neutral, happy, sad, angry and surprise), and has been used in emotional voice conversion [60] and emotional text-to-speech [61].

We randomly choose three emotions (neutral, happy and sad) and four speakers (two male and two female) from ESD. For each speaker and each emotion, we use 300 utterances for training, 20 utterances for evaluation, and the rest 30 utterances are used as the reference set. As a comparative study, we choose StarGAN-VC [39] as the baseline.

5.1. Experimental setup

All the speech data is sampled at 16 kHz and encoded with 16 bits. We extract 36-dimensional Mel-cepstral coefficients (MCEPs), fundamental frequency (F0), and periodicity (APs) every 5 ms using WORLD vocoder [62]. 36-dimensional MCEPs are used as spectral features, F0 is converted through the logarithm Gaussian (LG) normalized transformation [63], and APs are directly copied from the source without any modifications.

We first train the SER network with IEMOCAP dataset [64] and then fine-tune it with ESD. We follow the model architecture and training configuration in [59] for SER training. We obtain the 64-dimensional emotional style features as in Fig 4(a). We then merge the emotion style features together with 36-dimensional MCEPs using a fully-connected layer, which is later used as the input to the generator.

The proposed JES-StarGAN has the following architecture: G consist of an encoder and a decoder. The encoder consists of 5 layers of CNN, and each is followed by a batch normalization layer and a gated linear unit. The output channel of the encoder is \{64, 128, 256, 128, 10\}. The decoder consists of 4 layers of CNN followed by a batch normalization layer and a gated linear unit, and a transposed convolution layer. Its output channel is \{64, 128, 64, 32\}. D consists of four CNN layers (each layer is followed by a batch normalization layer and a gated linear unit), a CNN layer, a sigmoid layer and product pooling layers. The output channel for D is \{32, 32, 32, 32, 1\}. C consists of a slice layer, four CNN layers (each layer is followed by a batch normalization layer and a gated linear unit), a CNN layer, a soft-max layer and product pooling layers. The output channel of C is \{8, 16, 32, 16\}.

During training, JES-StarGAN is trained using ADAM optimizer with a learning rate of 0.0001. The batch size is 4 and the training process takes 200k iterations. We set \( \lambda_{\text{dom}}=2, \lambda_{\text{cyc}}=10 \) and \( \lambda_{\text{id}} = 5 \).

5.2. Objective evaluation

We conduct objective evaluation to assess the performance of our proposed framework for neutral, happy and sad utterances. We calculate Mel-cepstral distortion (MCD) [65] to measure the spectral distortion between the converted and target speech. A smaller value of MCD indicates a smaller spectral distortion and a better conversion performance.
Table 1. Average MCD [dB] values for 2 male and 2 female speakers with an intra-gender setting.

|            | StarGAN-VC | JES-StarGAN |
|------------|------------|-------------|
| Neutral    |            |             |
| M-M        | 6.187      | 5.419       |
| F-F        | 5.917      | 5.928       |
| Happy      |            |             |
| M-M        | 6.656      | 6.534       |
| F-F        | 6.190      | 6.105       |
| Sad        |            |             |
| M-M        | 6.739      | 6.333       |
| F-F        | 7.240      | 7.113       |

Table 2. Average MCD [dB] values for 2 male and 2 female speakers with an inter-gender setting.

|            | StarGAN-VC | JES-StarGAN |
|------------|------------|-------------|
| Neutral    |            |             |
| M-F        | 7.646      | 7.444       |
| F-M        | 7.655      | 7.023       |
| Happy      |            |             |
| M-F        | 7.051      | 6.698       |
| F-M        | 7.479      | 7.185       |
| Sad        |            |             |
| M-F        | 8.227      | 7.860       |
| F-M        | 8.222      | 7.906       |

Table 3. Mean opinion score (MOS) results, where 15 groups of utterances are evaluated by 13 subjects.

| Framework   | Mean Opinion Score |
|-------------|--------------------|
| StarGAN-VC  | 2.898 ± 0.36       |
| JES-StarGAN | 3.044 ± 0.38       |

We first report the MCD results for intra-gender combinations in Table 1: 1) from male to male (denoted as M-M); 2) from female to female (denoted as F-F), and then report the MCD for inter-gender in Table 2: 3) from male to female (denoted as M-F) and 4) from female to male (denoted as F-M). From these results, we observe that the proposed method JES-StarGAN consistently outperforms the baseline StarGAN-VC in both inter-gender and intra-gender conversion, which indicates the effectiveness of our proposed framework.

5.3. Subjective evaluation

We conduct three listening tests to assess speech quality, speaker similarity and emotional style similarity. 13 subjects participate in all listening tests, in which each listens to 90 converted utterances in total.

We first report the mean opinion score (MOS) results to evaluate the speech quality. 15 sentences are randomly selected from the evaluation set. A higher MOS score indicates better speech quality. As shown in Table 3, JES-StarGAN outperforms the StarGAN-VC baseline.

We further conduct two ABX preference tests to evaluate speaker similarity and emotional style similarity respectively. First, we report the results for ABX tests for speaker similarity, where all the subjects are asked to choose the one which sounds closer to the target speech samples in terms of the speaker similarity. As shown in Fig 5, we observe that the proposed JES-StarGAN significantly outperforms the baseline StarGAN-VC in speaker similarity. Benefiting from the joint transfer of speaker identity and emotional style, the proposed JES-StarGAN has a much better performance on the speaker identity conversion than the baseline, which further validates our idea on expressive voice conversion.

We then report the ABX test results for emotional style similarity, where all the subjects are asked to choose the one which sounds closer to the reference target speech samples in terms of the emotional style. As shown in Fig 6, the proposed JES-StarGAN still outperforms the baseline StarGAN-VC in terms of emotional style similarity. It shows the effectiveness of the deep emotional features on emotional style transfer.

6. CONCLUSIONS

This paper marks as the first study for expressive voice conversion. We formulate the problem of expressive voice conversion and propose a novel solution based on StarGAN to jointly transfer speaker identity and speaker-dependent emotional style without the need for parallel data. We propose to use deep emotional features from SER to characterize different emotional styles in a continuous space. By conditioning the generator with deep emotional features, the framework jointly learn a mapping of speaker-dependent features across different speakers. Experiments show that the proposed JES-StarGAN consistently outperforms the baseline.

7. ACKNOWLEDGMENT

The research is funded by SUTD Start-up Grant Artificial Intelligence for Human Voice Conversion (SRG ISTD 2020 158) and SUTD AI Grant - Thrust 2 Discovery by AI (SG-PAIRS1821).
8. REFERENCES

[1] Berrak Sisman, Junichi Yamagishi, Simon King, and Haizhou Li, “An overview of voice conversion and its challenges: From statistical modeling to deep learning,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, 2020.

[2] Yi Zhou, Xiaohai Tian, Haihua Xu, Rohan Kumar Das, and Haizhou Li, “Cross-linguistic voice conversion with bilingual phonetic posteriorgram and average modeling,” in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 6790–6794.

[3] Berrak Sisman, Mingyang Zhang, Minghui Dong, and Haizhou Li, “On the study of generative adversarial networks for cross-linguistic voice conversion,” in 2019 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU). IEEE, 2019, pp. 144–151.

[4] Zongyang Du, Kun Zhou, Berrak Sisman, and Haizhou Li, “Spectrum and prosody conversion for cross-linguistic voice conversion with cycle-gan,” in 2020 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC). IEEE, 2020, pp. 507–513.

[5] Zhizheng Wu, Nicholas Evans, Toni Kinnunen, Junichi Yamagishi, Federico Alegre, and Haizhou Li, “Spoofing and countermeasures for speaker verification: A survey,” Speech Communication, vol. 66, pp. 130–153, 2015.

[6] Klaus R Scherer, Rainer Banse, Harald G Wallott, and Thomas Goldbeck, “Vocal cues in emotion encoding and decoding,” Motivation and emotion, vol. 15, no. 2, pp. 123–148, 1991.

[7] Dewight R Middleton, “Emotional style: The cultural ordering of emotions,” Ethos, vol. 17, no. 2, pp. 187–201, 1989.

[8] Magda B Arnold, “Emotion and personality..” 1960.

[9] Sheldon Cohen, William J Doyle, Ronald B Turner, Cuneyt M Alper, and David P Skoner, “Emotional style and susceptibility to the common cold,” Psychosomatic medicine, vol. 65, no. 4, pp. 652–657, 2003.

[10] Paul Ekman, “An argument for basic emotions,” Cognition & emotion, 1992.

[11] Julia Hirschberg, “Pragmatics and intonation,” The handbook of pragmatics, pp. 515–537, 2004.

[12] Keshi Dai, Harriet Fell, and Joel MacAuslan, “Comparing emotions using acoustic and human perceptual dimensions,” in CHI’09 Extended Abstracts on Human Factors in Computing Systems. 2009.

[13] Margarita Kotti and Fabio Paternò, “Speaker-independent emotion recognition exploiting a psychologically-inspired binary cascade classification schema,” International journal of speech technology, vol. 15, no. 2, pp. 131–150, 2012.

[14] Kun Zhou, Berrak Sisman, Mingyang Zhang, and Haizhou Li, “Converting anyone’s emotion: Towards speaker-independent emotional voice conversion,” Proc. Interspeech 2020, pp. 3416–3420, 2020.

[15] Carl Robinson, Nicolas Ohin, and Axel Roebel, “Sequence-to-sequence modelling of f0 for speech emotion conversion,” in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 6830–6834.

[16] Kun Zhou, Berrak Sisman, Rui Liu, and Haizhou Li, “Emotional voice conversion: Theory, databases and esd,” arXiv preprint arXiv:2105.14762, 2021.

[17] Kun Zhou, Berrak Sisman, and Haizhou Li, “Transforming Spectrum and Prosody for Emotional Voice Conversion with Non-Parallel Training Data,” in Proc. Odyssey 2020 The Speaker and Language Recognition Workshop 2020, pp. 230–237.

[18] Jian Gao, Deep Chakraborty, Hamidou Tentime, and Olaitan Oalaye, “Nonparallel emotional speech conversion,” Proc. Interspeech 2019, pp. 2858–2862, 2019.

[19] Kun Zhou, Berrak Sisman, and Haizhou Li, “Vaw-gan for disentanglement and recomposition of emotional elements in speech,” in 2021 IEEE Spoken Language Technology Workshop (SLT). IEEE, 2021, pp. 415–422.

[20] Chi-Chun Hsia, Chung-Hsien Wu, and Te-Hsien Liu, “Duration-embedded bi-hmm for expressive voice conversion,” 01 2005, pp. 1921–1924.

[21] Chi-Chun Hsia, Chung-Hsien Wu, and Jian-Qi Wu, “Conversion function clustering and selection for expressive voice conversion,” in 2007 IEEE International Conference on Acoustics, Speech and Signal Processing-ICASSP’07. IEEE, 2007, vol. 4, pp. IV-689.

[22] S Ramakrishnan, Speech Enhancement, Modeling and Recognition- Algorithms and Applications, BoD-Books on Demand, 2012.

[23] Mikiko Mashimo, Tomoki Toda, Hiromichi Kawanami, Kiyohiro Shikano, and Nick Campbell, “Cross-language voice conversion evaluation using bilingual databases,” 2002.

[24] Tomoki Toda, Alan W Black, and Keiichi Tokuda, “Voice conversion based on maximum-likelihood estimation of spectral parameter trajectory,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 15, no. 8, pp. 2222–2235, 2007.

[25] Hsin-Te Hwang, Yu Tsao, Hsin-Min Wang, Yih-Ru Wang, and Sin-Hong Chen, “Incorporating global variance in the training phase of gm-gmm-based voice conversion,” in 2013 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference, 2013, pp. 1–6.

[26] Geoffrey E Hinton, Simon Osindero, and Yee-Whye Teh, “A fast learning algorithm for deep belief nets,” Neural computation, vol. 18, no. 7, pp. 1527–1554, 2006.

[27] Toru Nakashika, Tetsuya Takiguchi, and Yasuo Ariki, “High-order sequence modeling using speaker-dependent recurrent temporal restricted boltzmann machines for voice conversion,” in Fifteenth annual conference of the international speech communication association, 2014.

[28] Chin-Cheng Hsu, Hsin-Te Hwang, Yi-Chiao Wu, Yu Tsao, and Hsin-Min Wang, “Voice conversion from non-parallel corpora using variational auto-encoder,” in 2016 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA). IEEE, 2016, pp. 1–6.

[29] Benjamin van Niekerk, Leanne Nortje, and Herman Kamper, “Vector-quantized neural networks for acoustic unit discovery in the zerospeech 2020 challenge,” arXiv preprint arXiv:2005.09409, 2020.

[30] Kaizhi Qian, Zeyu Jin, Mark Hasegawa-Johnson, and Gautham J Mysore, “Fb-consistent many-to-many non-parallel voice conversion via conditional autoencoder,” in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 6284–6288.

[31] Wen-Chin Huang, Hsin-Te Hwang, Yu-Huai Peng, Yu Tsao, and Hsin-Min Wang, “Voice conversion based on cross-domain features using variational autoencoders,” in 2018 11th International Symposium on Chinese Spoken Language Processing (ICSLP). IEEE, 2018, pp. 51–55.

[32] Chin-Cheng Hsu, Hsin-Te Hwang, Yi-Chiao Wu, Yu Tsao, and Hsin-Min Wang, “Voice conversion from unaligned corpora using variational autoencoders,” in 2018 11th International Symposium on Chinese Spoken Language Processing (ICSLP). IEEE, 2018, pp. 51–55.

[33] Rafael Ferro, Nicolas Ohin, and Axel Roebel, “Cyclegan voice conversion of spectral envelopes using adversarial weights,” in arXiv preprint arXiv:1704.00849, 2017.

[34] Berrak Sisman, Mingyang Zhang, Sakriani Sakti, Haizhou Li, and Satoshi Nakamura, “Adaptive wavelet vocoder for residual compensation in gan-based voice conversion,” in 2018 IEEE Spoken Language Technology Workshop (SLT). IEEE, 2018, pp. 282–289.
[35] Takuhiro Kaneko and Hirokazu Kameoka, “Cycle-vcgan: Non-parallel voice conversion using cycle-consistent adversarial networks,” in 2018 26th European Signal Processing Conference (EUSIPCO). IEEE, 2018, pp. 2100–2104.

[36] Takuhiro Kaneko, Hirokazu Kameoka, Kou Tanaka, and Nobukatsu Hojo, “Cycle-vcgan2: Improved cycle-gan-based non-parallel voice conversion,” in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 6820–6824.

[37] Takuhiro Kaneko, Hirokazu Kameoka, Kou Tanaka, and Nobukatsu Hojo, “Cycle-vcgan3: Examining and improving cycle-vcgan-vcs for mel-spectrogram conversion,” Proc. Interspeech 2020, pp. 2017–2021, 2020.

[38] Takuhiro Kaneko and Hirokazu Kameoka, “Parallel-data-free voice conversion using cycle-consistent adversarial networks,” ArXiv, vol. abs/1711.11293, 2017.

[39] Hirokazu Kameoka, Takuhiro Kaneko, Kou Tanaka, and Nobukatsu Hojo, “Stargan-vc: Non-parallel many-to-many voice conversion using star generative adversarial networks,” in 2018 IEEE Spoken Language Technology Workshop (SLT). IEEE, 2018, pp. 266–273.

[40] Takuhiro Kaneko, Hirokazu Kameoka, Kou Tanaka, and Nobukatsu Hojo, “Stargan-vc2: Rethinking conditional methods for stargan-based voice conversion,” arXiv preprint arXiv:1907.12279, 2019.

[41] Junichi Yamagishi, Christophe Veaux, Kirsten MacDonald, et al., “Csr vctk corpus: English multi-speaker corpus for csr voice cloning toolkit (version 0.92),” 2019.

[42] John Kominick and Alan W Black, “The cmu arctic speech databases,” in Fifth ISCA workshop on speech synthesis, 2004.

[43] Tomoki Toda, Ling-Hui Chen, Daisuke Saito, Fernando Villavicencio, Mirjam Wester, Zhizheng Wu, and Junich Yamagishi, “The voice conversion challenge 2016,” in Interspeech, 2016, pp. 1632–1636.

[44] Jaime Lorenzo-Trueba, Junichi Yamagishi, Tomoki Toda, Daisuke Saito, Fernando Villavicencio, Tomy Kinnunen, and Zhenhua Ling, “The voice conversion challenge 2018: Promoting development of parallel and nonparallel methods,” arXiv preprint arXiv:1804.04262, 2018.

[45] Y. Zhao, Wen-Chin Huang, Xiaohai Tian, Junichi Yamagishi, Rohan Kumar Das, Tomi Kinnunen, Zhenhua Ling, and Tomoki Toda, “Voice conversion challenge 2020: Intra-lingual semi-parallel and cross-lingual voice conversion,” arXiv preprint arXiv:2008.12527, 2020.

[46] Yunjey Choi, Minje Choi, Munyoung Kim, Jung-Woo Ha, Sunghun Hojo, and Jaegul Choo, “Stargan: Unified generative adversarial networks,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2018, pp. 8789–8797.

[47] Dimitrios Kollias and Stefanos Zafeiriou, “Vo-stargan: Continuous affect generation,” in International Conference on Advanced Concepts for Intelligent Vision Systems. Springer, 2020, pp. 227–238.

[48] Georgios Rizos, Alice Baird, Max Elliott, and Björn Schuller, “Stargan for emotional speech conversion: Validated by data augmentation of end-to-end emotion recognition,” in ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2020, pp. 3502–3506.

[49] Mehmet Berkehan Akçay and Kaya Oğuz, “Speech emotion recognition: Emotional models, databases, features, preprocessing methods, supporting modalities, and classifiers,” Speech Communication, vol. 116, pp. 56–76, 2020.

[50] Matthias Wimmer, Björn Schuller, Dejan Arsic, Bernd Radig, and Gerhard Rigoll, “Low-level fusion of audio and video feature for multimodal emotion recognition,” in Proc. 3rd Int. Conf. on Computer Vision Theory and Applications VISAPP, Funchal, Madeira, Portugal, 2008, pp. 145–151.

[51] Florian Eyben, Martin Wöllmer, and Björn Schuller, “Opensmile: the munich versatile and fast open-source audio feature extractor,” in Proceedings of the 18th ACM international conference on Multimedia, 2010, pp. 1459–1462.

[52] Dagmar M Schuller and Björn W Schuller, “A review on five recent and near-future developments in computational processing of emotion in the human voice,” Emotion Review, p. 1754073918898526, 2020.

[53] Siddique Latif, Rajib Rana, Sara Khalifa, Raja Jurdak, Junaid Qadir, and Björn W Schuller, “Deep representation learning in speech processing: Challenges, recent advances, and future trends,” arXiv preprint arXiv:2001.00378, 2020.

[54] Se-Yun Um, Sangshin Oh, Kyungguen Byun, Inseo Jang, ChungHyun Ahn, and Hong-Goo Kang, “Emotional speech synthesis with rich and granularized control,” in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 7254–7258.

[55] Rui Liu, Berrak Sisman, Guang lai Gao, and Haizhou Li, “Expressive tts training with frame and style reconstruction loss,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, 2021.

[56] Kun Zhou, Berrak Sisman, Rui Liu, and Haizhou Li, “Seen and unseen emotional style transfer for voice conversion with a new emotional speech dataset,” in ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2021, pp. 920–924.

[57] Eesung Kim and Jong Won Shin, “Dnn-based emotion recognition based on bottleneck acoustic features and lexical features,” in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 6720–6724.

[58] Laurens Van der Maaten and Geoffrey Hinton, “Visualizing data using t-sne,” Journal of machine learning research, vol. 9, no. 11, 2008.

[59] Mingyi Chen, Xuanji He, Jing Yang, and Han Zhang, “3-d convolutional recurrent neural networks with attention model for speech emotion recognition,” IEEE Signal Processing Letters, vol. 25, no. 10, pp. 1440–1444, 2018.

[60] Kun Zhou, Berrak Sisman, and Haizhou Li, “Limited data emotional voice conversion leveraging text-to-speech: Two-stage sequence-to-sequence training,” Interspeech 2021, 2021.

[61] Rui Liu, Berrak Sisman, and Haizhou Li, “Reinforcement learning for emotional text-to-speech synthesis with improved emotion discrimination,” arXiv preprint arXiv:2104.01408, 2021.

[62] Masanori Morise, Fumiya Yokomori, and Kenji Ozawa, “World: a cross-lingual voice conversion,” arXiv preprint arXiv:2008.12527, 2020.

[63] Kun Liu, Jianping Zhang, and Yonghong Yan, “High quality voice conversion leveraging text-to-speech: Two-stage sequence-to-sequence training,” Interspeech 2021, 2021.

[64] Eesung Kim and Jong Won Shin, “Dnn-based emotion recognition based on bottleneck acoustic features and lexical features,” in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 6720–6724.

[65] Laurens Van der Maaten and Geoffrey Hinton, “Visualizing data using t-sne,” Journal of machine learning research, vol. 9, no. 11, 2008.

[66] Mingyi Chen, Xuanji He, Jing Yang, and Han Zhang, “3-d convolutional recurrent neural networks with attention model for speech emotion recognition,” IEEE Signal Processing Letters, vol. 25, no. 10, pp. 1440–1444, 2018.

[67] Kun Zhou, Berrak Sisman, and Haizhou Li, “Limited data emotional voice conversion leveraging text-to-speech: Two-stage sequence-to-sequence training,” Interspeech 2021, 2021.

[68] Rui Liu, Berrak Sisman, and Haizhou Li, “Reinforcement learning for emotional text-to-speech synthesis with improved emotion discrimination,” arXiv preprint arXiv:2104.01408, 2021.

[69] Masanori Morise, Fumiya Yokomori, and Kenji Ozawa, “World: a vocoder-based high-quality speech synthesis system for real-time applications,” IEICE TRANSACTIONS on Information and Systems, vol. 99, no. 7, pp. 1877–1884, 2016.

[70] Kun Liu, Jianping Zhang, and Yonghong Yan, “High quality voice conversion through phoneme-based linear mapping functions with straight for mandarin,” in Fourth International Conference on Fuzzy Systems and Knowledge Discovery (FSKD 2007). IEEE, 2007, vol. 4, pp. 410–414.

[71] Carlos Busso, Murtaza Bulut, Chi-Chun Lee, Abe Kazemzadeh, Emily Mower, Samuel Kim, Jeannette N Chang, Sungbok Lee, and Shrikanth S Narayanan, “Iemocap: Interactive emotional dyadic motion capture database,” Language resources and evaluation, vol. 42, no. 4, pp. 335, 2008.

[72] Robert Kubichek, “Mel-cepstral distance measure for objective speech quality assessment,” in Proceedings of IEEE Pacific Rim Conference on Communications and Signal Processing. IEEE, 1993, vol. 1, pp. 125–128.