# Joint Multi-scale Cross-lingual Speaking Style Transfer with Bidirectional Attention Mechanism for Automatic Dubbing

Jingbei Li, Sipan Li, Ping Chen, Luwen Zhang, Yi Meng, Zhiyong Wu, Senior Member, IEEE, Helen Meng, Qiao Tian, Yuping Wang, Yuxuan Wang

Abstract—Automatic dubbing, which generates a corresponding version of the input speech in another language, could be widely utilized in many real-world scenarios such as video and game localization. In addition to synthesizing the translated scripts, automatic dubbing needs to further transfer the speaking style in the original language to the dubbed speeches to give audiences the impression that the characters are speaking in their native tongue. However, state-of-the-art automatic dubbing systems only model the transfer on duration and speaking rate, neglecting the other aspects in speaking style such as emotion, intonation and emphasis which are also crucial to fully perform the characters and speech understanding. In this paper, we propose a joint multi-scale cross-lingual speaking style transfer framework to simultaneously model the bidirectional speaking style transfer between languages at both global (i.e. utterance level) and local (i.e. word level) scales. The global and local speaking styles in each language are extracted and utilized to predicted the global and local speaking styles in the other language with an encoder-decoder framework for each direction and a shared bidirectional attention mechanism for both directions. A multi-scale speaking style enhanced FastSpeech 2 is then utilized to synthesize the predicted the global and local speaking styles to speech for each language. Experiment results demonstrate the effectiveness of our proposed framework, which outperforms a baseline with only duration transfer in both objective and subjective evaluations.

Index Terms—Automatic dubbing, cross-lingual speaking style transfer, multi-scale speaking style transfer, bidirectional attention mechanism, text-to-speech synthesis.

# I. INTRODUCTION

EXT-to-speech (TTS) synthesis which aims to generate natural speech from given text [1], has been widely researched and utilized in many real-world application. With the

Manuscript received April 19, 2021; revised August 16, 2021. This work is supported by National Natural Science Foundation of China (62076144), Shenzhen Science and Technology Innovation Committee (WDZC20220816140515001), AMiner.Shenzhen SciBrain fund and Shenzhen Key Laboratory of next generation interactive media innovative technology (ZDSYS20210623092001004). (Corresponding author: Zhiyong Wu)

Jingbei Li, Sipan Li, Ping Chen, Luwen Zhang, Yi Meng and Zhiyong Wu are with Tsinghua-CUHK Joint Research Center for Media Sciences, Technologies and Systems, Shenzhen International Graduate School, Tsinghua University, Shenzhen, China (e-mail: lijb19@mails.tsinghua.edu.cn; lisp20@mails.tsinghua.edu.cn; p-chen21@mails.tsinghua.edu.cn; zlw20@mails.tsinghua.edu.cn; my20@mails.tsinghua.edu.cn; zywu@sz.tsinghua.edu.cn). Jingbei Li and Sipan Li equally contributes to this work.

Helen Meng is with Department of Systems Engineering and Engineering Management, The Chinese University of Hong Kong, Hong Kong SAR, China (e-mail: hmmeng@se.cuhk.edu.hk).

Qiao Tian, Yuping Wang and Yuxuan Wang are with ByteDance, Shanghai, China. (e-mail: tianqiao.wave@bytedance.com; wangyuping@bytedance.com; wangyuxuan.11@bytedance.com).

development of speech processing and neural network technologies, state-of-the-art TTS systems [2]–[6] have achieved end-to-end speech synthesis by merging different components in conventional TTS systems into one trainable framework to synthesize high quality speeches while requiring less feature engineering. Such end-to-end neural network based TTS models have been successfully implemented in various languages [7], and widely used as the backbones for downstream researches such as emotional speech synthesis [8], [9], speaking style transfer [10]–[12], cross-lingual TTS system [13]–[15] and automatic dubbing [16].

Among these downstream researches of TTS, automatic dubbing [16] which converts the speeches in films, televisions or games to their corresponding versions in a different language rendition, is a potential research area and could be utilized in film and game localization to simplify the laborious human dubbing process. Differing from standard TTS synthesis [2]–[6] which directly synthesize speech from the given text, automatic dubbing need to further consider the speaking styles in speech and transfer them to the dubbed speech during synthesis. In film or game production, actors are using various speaking styles to present the personalities, emotions and intentions of the different characters, including the speaking styles at the global (i.e. utterance level) and local scale (i.e. word level). Global speaking style [10] is used to control the global emotion and intention for each utterance, while local speaking style [17] is used to control the emphasis and intonation for each word to highlight the details in each utterance. Both kinds of speaking style are crucial for speech understanding and should be transferred in automatic dubbing to give the audiences the impression that the characters are speaking in their native tongue.

State-of-the-art automatic dubbing systems [18] have successfully transferred the duration and speaking rate in local speaking style to dubbed speech. These researches employ algorithms based on attention mechanism [16] or hidden Markov model (HMM) [19], [20] to match the prosodic phrases in the two languages. Then several prosodic phrase alignment methods [16] are proposed to adjust the duration [18] and speaking rate for each prosodic phrase [21] to match the duration of the corresponding prosodic phrase in the speech in the original language.

However, these existing automatic dubbing systems are only applicable to few simple dubbing scenarios and may cause pauses and duration in other scenarios. These approaches re-



Fig. 1. Cross-lingual speaking style transfer between two languages at multiple scales.

quire that the same numbers of prosodic phrases in the source and the dubbing language. For those complicated scenarios that the number of prosodic phrases are often different such as dubbing between Chinese and English, these approaches may synthesize improper pauses in the dubbed speeches. Furthermore, these approaches can only adjust the duration and speaking rate of each prosodic phrase according to the prosodic phrases in the other language at the same position, ignoring if they have same semantic meanings. Such design could produce improper duration and speaking rate when the word orders are significantly different in the original and dubbed languages.

Moreover, existing approaches in automatic dubbing have insufficient modeling on the speaking style transfer. At the local scale, the modeling on the other aspects of local speaking styles rather than duration and speaking rate, such as pitch, energy and emotion which are also crucial to present the character is largely missing. In addition, the modeling on the speaking style transfer at the global scale is also rarely considered. The transfer of global speaking style is vital for utterances that are sense-for-sense translation in which the meanings of each words in the two languages are complete different. Such insufficient modeling on the transfer of both local and global speaking styles will synthesis speeches without those particular emotions and intentions and seriously decrease the expressiveness of the dubbed speech.

In this paper, to address these issues and improve the speaking style transfer in automatic dubbing, we propose a multi-scale cross-lingual speaking style transfer framework which jointly model and optimizes the speaking style transfer for both dubbing directions between two languages with multitask learning. The global and local speaking styles of the speeches in each language are extracted and utilized to predict the corresponding global and local speaking styles in the other language. The predicted global and local speaking styles for the other language are then synthesized to speech by a corresponding multi-scale speaking style enhanced FastSpeech 2 (hereafter, MST-FastSpeech 2) [5], [17] for each language. The source code of our work will be published at GitHub when the paper is accepted.

Experiments results demonstrated the effectiveness of our proposed model. The proposed approach outperform the baseline approach with only duration transfer in both objective and subjective evaluations, with MOS increased by 0.2 and 0.013,

and the preference rate exceeded by 39.64% and 3.58% on the two dubbing directions.

The rest of the paper is organized as follows. We introduce related work in Section II. We then conduct data observation in Section III. In Section IV, we introduce the details of proposed approach. Experimental results and ablation studies are presented in Section V. We discuss our work in Section VI. Finally, Section VII concludes the paper.

#### II. RELATED WORK

# A. Text-to-speech synthesis

Text-to-speech synthesis is still a challenging task despite decades of investigation [1]. Conventional TTS systems usually employ complicated pipelines [22], including linguistic feature generation, duration prediction, acoustic feature prediction and vocoder [23], [24]. These components complete the respective subtasks in the conventional TTS pipelines, but are developed and trained in separate, suffering from errors compounding in steps [2], [25].

With the development of deep learning, end-to-end TTS techniques are proposed to integrate the components in conventional TTS systems [2], [3] into one trainable framework. Such end-to-end TTS systems, such as Tacotron [2], [3] and FastSpeech [5], are benefiting from joint training to alleviate the errors compounding and provide more robust synthesized speeches with less feature engineering. These end-to-end TTS systems are powered by the encoder-decoder structure [26] with attention mechanism [27], using encoder to produce linguistic encodings and decoder to directly generate raw spectrogram. Attention mechanism such as location-sensitive attention in [28] is applied with decoder to increase both performance and interpretability by learning the alignment between the text and spectrogram. Then neural vocoder is utilized to generate waveform from the spectrogram to further improve the overall natural ness and quality of the synthesized speech [3].

The improvement of end-to-end TTS systems reveals a growing opportunity for a number of applications, such as audiobook narration, news readers, and conversational assistants, which also brings the challenge to end-to-end TTS systems to improve the controllablity of choosing appropriate speaking style for different application scenarios. Global style token [10] is firstly proposed to represent the attributes that related to the speaking style among the whole utterance such as

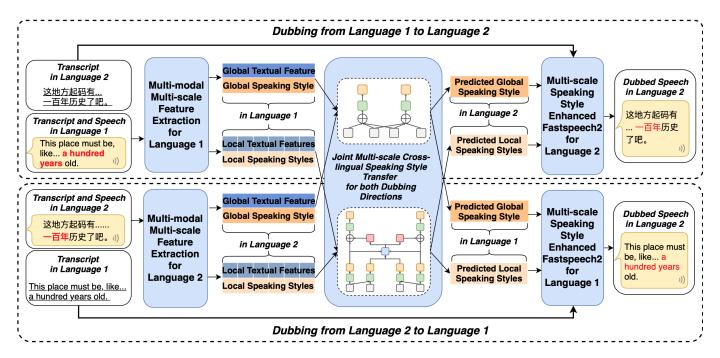


Fig. 2. Architecture of proposed joint multi-scale cross-lingual speaking style transfer framework.

emotion and intention as a single vector, which have been widely utilized in robust emotion and global speaking style transfer [10]. An adversarial branch [29] is further proposed to disentangle the speaker information from global style tokens for cross-speaker global speaking style transfer [10]. At the word level, local style token [17] is proposed to represent the attributes related to the speaking style of each word such as emphasis, rhythm and intonation with the help of a neural network based force aligner [30].

# B. Automatic dubbing

Dubbing is a complex process that converts speeches in films or games into another language while preserving the speaking styles in the original language, which can be regarded as a special kind of speech-to-speech translation [31]–[33]. Traditionally, such dubbing process are all done by professional teams and voice talents. However, with such amount of manpower spent, some dubs are still controversial among the audiences due to the unsatisfied speaking style performance in dubbed speeches.

With the development of TTS synthesis, neural network based automatic dubbing is of possibility to be developed on the top of end-to-end TTS synthesis technologies to simplify and standardize such dubbing process in film and game production. Several automatic dubbing systems have been proposed to transfer the duration and speaking rate to the dubbed speech. A prosodic alignment based automatic dubbing system is firstly proposed [16] to transfer the duration of each prosodic phrase. This approach employs a prosodic alignment algorithm to extract the mapping between the prosodic phrases in two languages from the attention weights extracted from a pretrained machine translation model. Then it adjusts the duration of each prosodic phrase to be same to the duration of its mapped prosodic phrase in the original language. However,

such design could generate too long or too short duration when the numbers of phonemes are largely different between the mapped prosodic phrases in two languages.

An hidden Markov model (HMM) [34] based prosodic alignment algorithm [35] is further proposed to segment the dubbed speech into prosodic phrases that match the pauses in the original speech by maximize the probability of pause positions in the dubbed speech. An improvement [21] to this HMM based prosodic alignment algorithm is proposed to also transfer the speaking rate. An additional phoneme level duration predictor is proposed [18] to further improve the predicted duration and speaking rate in both prosodic alignment and the following TTS system. But these approaches ignore the semantic meaning of each word when segment the prosodic phrases. So it's very likely that the original and corresponding segmented prosodic phrases have completely different semantic meanings. In this case, forcibly transfer the duration and speaking rate in the original language to an unrelated prosodic phrase in the dubbed language may seriously lowering the naturalness of the synthesized speech.

Moreover, the existing automatic dubbing systems have insufficient modeling on the speaking style transfer between two languages. Speaking styles are how people speak an utterance and each word in it to express their emotions and intentions which should be also transferred in automatic dubbing. Traditionally, speaking style could be only represented as the combination of many features defined with prior knowledge. With the development of neural network technology, global style token [10] is firstly proposed to represent all those attributes that related to the speaking style among the whole utterance such as emotion and intention as a single vector. Such global style tokens extracted from well-trained models have been widely utilized in many researches [10] for robust emotion and global speaking style transfer. An

adversarial branch [29] is further proposed to disentangle the speaker information from global style tokens for cross-speaker global speaking style transfer [10]. Local style token [17] is further proposed to represent the attributes related to the local speaking style such as emphasis, rhythm and intonation as a vector for each word with the help of a neural network based force aligner [30].

#### C. Contributions

Compared with the previous works, the contributions of our work include: (1) to our best knowledge, this is the first work that introduces speaking style transfer to automatic dubbing, in which we advocate the modeling of speaking style transfer at both global and local scales to significantly improve the expressiveness in automatic dubbing; (2) this is also the first work that employs multi-task learning to jointly optimize the modeling of cross-lingual speaking style transfer for both dubbing directions between two languages; (3) we propose an effective approach to infer the speaking styles at both global and local scales for automatic dubbing.

#### III. DATA OBSERVATION

We first conduct subjective observation to analyze the speaking style transfer among the real-world professional dubs. We randomly collect 25 pairs of parallel utterances in the English and Chinese dubs of the game Borderlands 3 for the observation, which is a well-known game with excellent and highly acclaimed dubs in many languages. 25 listeners are invited to listen to the English and Chinese speeches of each pair of these collected utterances and answer the following questions: (1) Is there a *special* global speaking style in each utterance which differs to the normal speaking style in declarative sentences? (2) Are the global speaking styles of this pair of utterances in the two languages same, similar, irrelevant or opposite? (3) Is there any special local speaking style in the words of each utterance which differs to the normal speaking style in the words of declarative sentences? (4) If a word has a word in the other language which have same or similar meaning and local speaking style to this word, we call that this word can be matched to the corresponding word in the other language. Then for each language, about how much words can be *matched* to the words in another language?

The first two question aim to demonstrate the necessity and possibility of modeling the global speaking style transfer in automatic dubbing. The aggregated responses from the listeners (by averaging) indicate that 76.13% and 78.06% of the dubbed utterances in English and Chinese have global speaking styles different to the speaking style in common declarative sentences. This shows that various global speaking styles are commonly used in dubbing which should be considered and transferred to other languages. Besides, the aggregated responses further indicate that in 96.76% of the pairs of the parallel utterances in these two languages, their global speaking styles are same or similar to the global speaking style to each other. This demonstrate the possibility of modeling the global speaking style transfer in automatic dubbing.

On the other side, the last two question are designed to demonstrate the necessity and possibility of modeling the speaking style transfer at local scale. The aggregated responses to the third question show that 83.12% and 83.68% of the dubbed utterances in English and Chinese have words with local speaking styles different to the speaking style in common declarative sentences, which reflects the importance of modeling the local speaking style transfer for automatic dubbing. And in the final question, the aggregated responses show that 86.7% of the words in the English dubs can be *matched* to the words in Chinese, which means that they have similar semantic information and local speaking styles. And for the other direction, 87.09% of the words in the Chinese dubs can also be matched to the words in English. This reveals that the similarity on the semantic meanings is related to the similarity of local speaking styles between parallel utterances in different languages, and shows the possibility of modeling local speaking style transfer across languages.

The above observation demonstrates the need to consider the both global and local speaking styles in automatic dubbings (Question 1, 3), and the possibility to model the speaking style transfer between the utterances at the global scale (Question 2) and local scale (Question 4).

## IV. METHODOLOGY

Based on the phenomenon found in data observation, we propose a multi-scale cross-lingual speaking style transfer framework for automatic dubbing, which jointly learns the speaking style transfer between two languages at both global and local scales.

#### A. Multi-scale feature extraction

To support the modeling of multi-scale cross-lingual speaking style transfer, the textual features and multi-modal features that fuse the textual and speaking style information in the two languages are extracted at both the global and local scales.

1) Textural feature extraction: A pretrained BERT model is employed for each language to extract the sentence level and word level BERT embeddings. The sentence level BERT embedding is directly used as the textual feature at global scale for each language. The word level BERT embeddings are converted by a local text encoder for each language as the textual features at local scale, which consists of the pre-net and CBHG networks in Tacotron [2]. The above process can also be formulated as:

$$g_1^t = SBERT_1 \tag{1}$$

$$g_2^t = SBERT_2 \tag{2}$$

$$s_1^t = E_1^t \left( BERT_1 \right) \tag{3}$$

$$s_2^t = E_2^t \left( BERT_2 \right) \tag{4}$$

where  $SBERT_1$  and  $SBERT_2$ ,  $BERT_1$  and  $BERT_2$ ,  $E_1^t$  and  $E_2^t$ ,  $g_1^t$  and  $g_2^t$ ,  $s_2^t$  and  $s_1^t$  are the sentence level BERT embeddings, word level BERT embeddings, local text encoder, global textual feature and local textual features, for each language.

2) Speaking style extraction: Global and local speaking style encoders [17] are then employed to extract the speaking styles at global and local scales for each language. The global speaking style encoder consists of 6 strided convolutional neural networks (CNNs) composed of  $3\times3$  kernels with 32, 32, 64, 64, 128, 128 filters respectively and  $2\times2$  stride, a 256 dimensional GRU layer and a 128 dimensional style attention layer. The mel-spectrograms of the input speech are first processed by CNNs and GRU. The final state of GRU is further sent to the style attention layer to derive the global speaking style vector GST as the weights for 10 automatically learnt base global speaking style embeddings. The process can be formulated as:

$$q = final(GRU(CNN(speech)))$$
 (5)

$$GST = softmax \left( q^T GST^{table} \right) \tag{6}$$

where final returns the final state of GRU, q is the query for the style attention layer,  $GST^{table}$  contains the 10 automatically learnt base global speaking style embeddings.

The architecture of the local speaking style encoder is same to the global speaking style encoder, except the stride is now  $1 \times 2$ , and the GRU layer now returns the output for each input frame. The outputs of GRU are then summarized for each word in the utterance by multiplying them with the speech-to-text attention weights extracted from a pretrained neural network based forced aligner (NeuFA) [30]. NeuFA employs bidirectional attention mechanism [30] to learn the bidirectional information mapping between a pair of text and speech. The learnt attention weights at the speech-to-text direction could be used to summarize the frame-level information for each word in the utterance, deriving the local speaking style sequence LST. The process of local reference encoder can be formulated as:

$$q' = W_{ASR}^T GRU(CNN(speech)) \tag{7}$$

$$LST = softmax \left( q'^T LST^{table} \right) \tag{8}$$

where  $W_{ASR}$  is the attention weights at the speech-to-text direction obtained by NeuFA, q' is the query for the local style attention layer,  $LST^{table}$  contains 10 automatically learnt base local speaking style embeddings.

3) Multi-modal feature fusion: To fuse the extracted textual and features, The sentence level BERT embedding and the global speaking style of each language are then concatenated as the multi-modal feature at the global scale. The word level BERT embeddings and local speaking styles are concatenated and consumed by a local encoder for each language to produce the multi-modal feature sequence at the local scale, which has the same architecture to the local textual encoder. The above process can also be formulated as:

$$g_1^m = [SBERT_1; GST_1] \tag{9}$$

$$g_2^m = [SBERT_2; GST_2] \tag{10}$$

$$s_1^m = E_1([BERT_1; LST_1])$$
 (11)

$$s_2^m = E_2^l([BERT_2; LST_2])$$
 (12)

where  $GST_1$  and  $GST_2$ ,  $LST_1$  and  $LST_2$ ,  $E_1$  and  $E_2$ ,  $g_1^m$  and  $g_2^m$ ,  $s_1^m$  and  $s_2^m$  are the global speaking style, local speaking

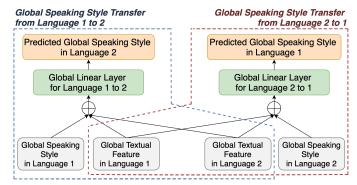


Fig. 3. Joint cross-lingual speaking style transfer at global scale.

styles, local encoder, global multi-modal feature and local multi-modal features, for each language.

# B. Joint multi-scale cross-lingual speaking style transfer

1) Speaking style transfer at global scale: As shown in Figure 3, the global multi-modal feature of each language is concatenated to the global textual feature of the other language and consumed by a global linear projection to predict the global speaking style in the other language:

$$GST_1' = f_{2to1}^g([g_2^m; g_1^t])$$
(13)

$$GST_2' = f_{1to2}^g([g_1^m; g_2^t])$$
 (14)

where  $f_{2to1}^g$  and  $f_{1to2}^g$ ,  $GST_1'$  and  $GST_2'$  are the global linear projection for each dubbing direction and the predicted global speaking style for each language.

2) Speaking style transfer at local scale: As shown in Figure 5, an architecture with two encoder-decoder frameworks and a shared bidirectional attention mechanism is employed to learn the speaking style transfer between two languages at the local scale.

The bidirectional attention mechanism is extended from conventional attention mechanism [36] to learn the bidirectional relations between two sets of key-value pairs [30], which is also shown in Figure 4. With two sets of key-value pairs are given as the inputs, each set of keys serves as the queries for the other set of key-value pairs. Then a shared compatibility function are modeled for both sets of keys to calculate the attention weights for each direction which

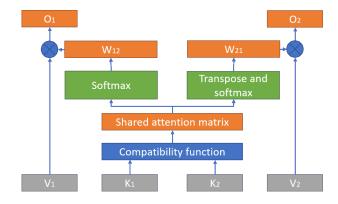


Fig. 4. Bidirectional attention mechanism [30].

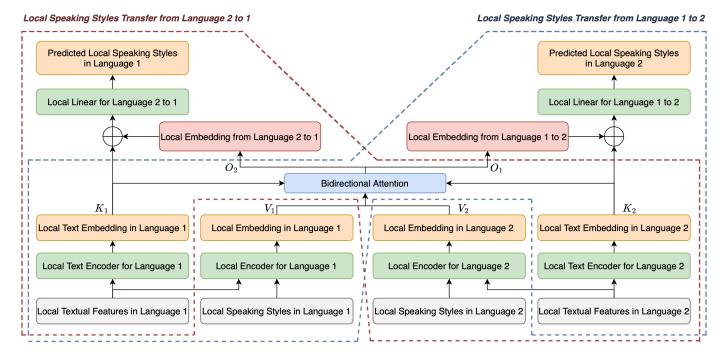


Fig. 5. Joint cross-lingual speaking style transfer at local scale.

are further utilized to summarize the two sets of values as the outputs for both directions. The bidirectional attention mechanism is formulated as:

$$A = f(K_1, K_2) (15)$$

$$W_{12} = softmax(A) \tag{16}$$

$$W_{21} = softmax(A^T) (17)$$

$$O_1 = W_{12}^T V_1 (18)$$

$$O_2 = W_{21}^T V_2 (19)$$

where  $K_1 \in R^{n_1 \times d_{k_1}}$ ,  $V_1 \in R^{n_1 \times d_{v_1}}$  and  $K_2 \in R^{n_2 \times d_{k_2}}$ ,  $V_2 \in R^{n_2 \times d_{v_2}}$  are the two sets of key-value pairs,  $n_1$  and  $n_2$  are the numbers of the key-value pairs,  $d_{k_1}$ ,  $d_{v_1}$ ,  $d_{k_2}$  and  $d_{v_2}$  are feature dimensions, f is the compatibility function,  $A \in R^{n_1 \times n_2}$  is the shared attention matrix,  $W_{12} \in R^{n_1 \times n_2}$  and  $W_{21} \in R^{n_2 \times n_1}$  are the attention weights for two directions respectively,  $O_1 \in R^{n_2 \times d_{v_1}}$  is the weighted sum of  $V_1$  for each key in  $K_2$  and  $O_2 \in R^{n_1 \times d_{v_2}}$  is the weighted sum of  $V_2$  for each key in  $K_1$ .

We employ the multiplicative form of bidirectional attention mechanism to jointly model speaking style transfer at the local scale and summarize the multi-modal features for both dubbing directions. Particularly, the local textual features and the local multi-modal features of the two languages are respectively used as the the two sets of keys and values, and the calculation of the attention weights and outputs are formulated as:

$$A_{1to2} = f_1(s_1^t) \times f_2(s_2^t)^T \tag{20}$$

$$A_{2to1} = f_2(s_2^t) \times f_1(s_1^t)^T = A_{1to2}^T \tag{21}$$

$$W_{1to2} = softmax(A_{1to2}) \tag{22}$$

$$W_{2to1} = softmax(A_{2to1}) \tag{23}$$

$$O_{1to2} = W_{1to2}^T s_1^m (24)$$

$$O_{2to1} = W_{2to1}^T s_2^m (25)$$

where  $f_1$  and  $f_2$  are two linear projections,  $A_{1to2}$  and  $A_{2to1}$  are the shared attention matrices,  $W_{1to2}$  and  $W_{2to1}$  are the learnt attention weights for the two dubbing directions,  $O_{1to2}$  and  $O_{2to1}$  are the summarized the multi-modal features of each language.

The summarize the multi-modal features of each language are then concatenated with the local textual features of the other language, and consumed by a local linear projection to the predicted local speaking styles of the other language:

$$LST_1' = f_{2to1}^l([O_{2to1}; s_1^t])$$
 (26)

$$LST_2' = f_{1to2}^l([O_{1to2}; s_2^t])$$
 (27)

where  $f_{2to1}^l$  and  $f_{1to2}^l$ ,  $LST_1'$  and  $LST_2'$  are the local linear projection for each dubbing direction and the predicted local speaking style for each language.

# C. Speech synthesis with predicted multi-scale speaking styles

A MST-FastSpeech 2 [17] is trained for each language to synthesize speeches with global and local speaking styles inferred by the proposed framework.

The speaker embedding and the predicted global and local speaking styles of each utterance are upsampled to phoneme level and concatenated with the encoder outputs of FastSpeech 2. Then the pitch, duration and energy of each phoneme are inferred from the concatenated encoder outputs by the variance adaptor, and further converted to Mel-spectrogram by the decoder of FastSpeech 2.

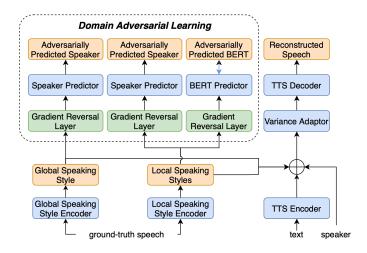


Fig. 6. Pretraining the global and local speaking style encoders and Fast-Speech 2 for each language [17].

A well-trained HiFi-GAN [24] is used as the vocoder to synthesize speech from the predicted Mel-sprectrogram with desired speaking styles transferred from the other language.

# D. Training strategy

Before the training of the proposed joint cross-lingual multi-scale speaking style transfer framework, the global and local speaking style encoders and their corresponding MST-FastSpeech 2 for each language are previously trained to ensure the extracted global and local speaking styles are compatible with the TTS backbone. To improve the robustness of extracted speaking styles and their cross-lingual transfer, the text and speaker information are also disentangled from the global and local speaking styles with gradient reversal layer (GRL) [37] and domain adversarial learning [29], [38] at this stage, which are also formulated as:

$$speaker'_{GST} = f^{GST}_{speaker} (GRL(GST))$$
 (28)  
$$speaker'_{LST} = f^{LST}_{speaker} (GRL(LST))$$
 (29)

$$speaker'_{LST} = f^{LST}_{speaker} (GRL(LST))$$
 (29)

$$BERT' = f_{BERT} (GRL(LST))$$
 (30)

where  $f_{speaker}^{GST}$ ,  $f_{speaker}^{LST}$  and  $f_{BERT}$  are linear projections serving as the adversarial speaker predictors and text predictor, GRL reverses the gradients of these adversarial predictors,  $speaker'_{GST}$ ,  $speaker'_{LST}$  are the adversarially predicted speaker embeddings, BERT' is the adversarially predicted textual embedding of this utterance. The loss for pretraining is the sum of reconstruction loss and adversarial losses, where the former one is the mean squared error (MSE) between the predicted and ground-truth mel-spectrograms, and the latter ones are the MSEs between the predicted and ground-truth speaker and BERT embeddings.

The pretrained global and local encoders and FastSpeech 2 of each language are then frozen and utilized to extract the speaking styles and synthesize speech with predicted speaking styles in the proposed framework. The proposed joint cross-lingual multi-scale speaking style transfer framework is then trained and back-propagated with the sum of the

MSEs between the predicted and ground-truth global and local speaking styles on the two languages:

$$loss = MSE(GST_1, GST'_1) + MSE(LST_1, LST'_1)$$

$$+ MSE(GST_2, GST'_2) + MSE(LST_2, LST'_2)$$
 (31)

#### V. Experiments

#### A. Baselines

To demonstrate the effectiveness of the proposed joint crosslingual multi-scale speaking style transfer framework, we employ 2 approaches with different speaking style transfer methods as the baselines, which also employ FastSpeech 2 as the TTS backbone.

- 1) No speaking style transfer: The first baseline approach is a vanilla FastSpeech 2 [5] with no speaking style transfer, which is also a representative of state-of-the-art conventional TTS and speech-to-speech translation systems with ideal translated scripts.
- 2) Duration transfer: Based on the proposed approach, we implement another approach with only duration transfer as the second baseline. This approach is inspired by a state-of-theart automatic dubbing system [18] and should have similar or better performance with the encoder-decoder frameworks and attention mechanism.

In this approach, the modeling on global speaking styles transfer is omitted, and only the duration of each word is transferred to the speech in the other language. Specifically, a sequence of the duration for each word is used to replaced the local speaking style in the proposed approach. And Equation (11), (12), (26) and (27) are respectively changed to:

$$s_1^m = E_1([BERT_1; d_1])$$
 (32)

$$s_2^m = E_2^l([BERT_2; d_2])$$
 (33)

$$d_1' = f_1^l([O_{2to1}; s_1^t]) (34)$$

$$d_2' = f_1^l([O_{1to2}; s_2^t]) (35)$$

where  $d_1$ ,  $d_2$ ,  $d'_1$ ,  $d'_2$  are the sequences of duration and predicted duration for each word in the each language. Then the sequence of predicted duration for each language is utilized by a FastSpeech 2 with precise duration control for each language to synthesize the dubbed speech.

# B. Training setup

We collect more parallel utterances from the English and Chinese dubs of the game Borderlands 3 as the corpus for our research. As introduced in Section III, the game Borderlands 3 is an action role-playing first-person shooter video game from the Borderlands game franchise in a space Western science fiction setting, which provides excellent and highly acclaimed dubs in many languages with various speaking styles. Borderlands 3 has 4 playable characters and dozens of non-playable characters (NPCs) in which there are about 20 main NPCs who are frequently speaking with each other to tell the background stories or guide the players in the missions. Each one of these playable and non-playable characters has their unique speaking style to present their different personality. Moreover,

TABLE I
Subjective and objective evaluations for different approaches. \*The predicted mel-spectrograms are resized to the size of ground-truths with nearest-neighbor interpolation.

Speaking style transfer method	Direction	MSE*	MOS±95%CI	Preference rate
No speaking style transfer [5] Duration transfer [18] Multi-scale speaking style transfer (Proposed)	en-zh	4.694 3.695 <b>1.392</b>	$3.161 \pm 0.075$ $3.923 \pm 0.073$ $4.123 \pm 0.071$	7.67% $25.83%$ $65.47%$
No speaking style transfer [5] Duration transfer [18] Multi-scale speaking style transfer (Proposed)	zh-en	5.385 3.301 <b>2.140</b>	$3.358 \pm 0.077$ $3.992 \pm 0.069$ $4.005 \pm 0.073$	$14.83\% \\ 40.41\% \\ 43.99\%$

the characters are further changing their speaking styles for different scenarios during the 35 gameplay hours of main along with other side missions.

We collect 4,914 pairs of parallel utterances from *Borderlands 3*, including 5 hours of English speeches and 5 hours of Chinese speeches along with their corresponding subtitles. The sample rate of all the speeches in the corpus is 48,000Hz. For the English speeches in the corpus, the length of each utterance is ranged from 0.212s to 12.629s, with a mean of 3.801s and a standard deviation of 2.350s. And the number of the words of each utterance is ranged from 1 to 46, with a mean of 11.397 and a standard deviation of 7.715. For the Chinese speeches in the corpus, the length of each utterance is ranged from 0.309s to 12.630s, with a mean of 3.913s and a standard deviation of 2.439s. And the number of the words of each utterance is ranged from 1 to 70, with a mean of 17.360 and a standard deviation of 11.918.

We extract Mel-spectrogram for each utterance in the corpus with a window length of 25ms and a shift of 10ms, which will be used as the inputs for the global and local speaking style encoders and the ground-truths for the MST-FastSpeech 2. We employ a pretrained BERT [39] model to extract the sentence and word level BERT embeddings, in which the BERT embedding of each word is the average of the BERT embeddings of the corresponding sub-words.

We then employ the whole corpus to pretrain the MST-FastSpeech 2 and the global and local speaking style encoders for both languages. We follow the training setups of Fast-Speech 2 [5] to train the model of each language for 1,000,000 iterations with a batch size of 32.

We randomly employ 4,414 pairs of parallel utterances in the two languages as the training set to train the proposed multi-scale speaking style transfer framework. The proposed framework is trained for 10 epochs with a batch size of 32 and a learning rate of  $10^{-4}$ .

All the models are implemented with PyTorch [40] and trained on an NVIDIA Tesla V100 GPU.

## C. Evaluation

We employ the rest 500 pairs of parallel utterances as the test set for evaluation. We adopt the mean squared error (MSE) between the predicted and ground-truth mel-spectrograms as the metric for the objective evaluation. The predicted melspectrogram is resized to match the length of the ground-truth mel-spectrogram with the nearest-neighbour interpolation.

For the subjective evaluation, 20 conversation chunks<sup>1</sup> are further randomly selected and evaluated by 25 listeners. The listeners are asked to rate on how the speaking styles of synthesized speeches are transferred from the speech in the other language on a scale from 1 to 5 with 1 point interval, from which subjective mean opinion scores (MOS) are calculated. Meanwhile, the listeners are asked to choose a preferred dubbed speech from the speeches generated by different approaches, from which preference rates are calculated.

## D. Experiment results

The results of the objective and subjective evaluations are shown in Table I. Both the approaches with duration transfer and the proposed multi-scale speaking style transfer have outperformed the baseline with no speaking style transfer. The approach with duration transfer increases the MOS by 0.762 and 0.634 for the two directions than the baseline with no speaking style transfer, and the corresponding preference rate exceeds by 18.16% and 25.58%. Compared with the baseline with duration transfer, the proposed approach further improves the MOS by 0.2 and 0.013 for the two directions, and the corresponding preference rate exceeds by 29.83% and 3.58%. Such improvements on performance demonstrate the necessity and effectiveness of modeling the transfer on all aspects in speaking style than just duration.

We illustrate the Mel spectrogram of the synthesized speech by each approach in Figure 7 for the utterance 'With this ship, we can kill bandits all over the world.' from the test set. We highlight the comparison between the words 'bandits' and 'world' in blue and red frames these utterances. In the Figure 7 (a) and (b), these words in the original English and Chinese dubs are emphasized with local speaking styles to express the excitement of the characters with the new ship. And in the Figure 7 (g) and (h), we can see their corresponding words in the other language have also been more clearly emphasized than those synthesized by the vanilla FastSpeech 2 and the baseline approach with only duration transfer.

#### E. Ablation study

Based on the proposed approach, we implement several variant approaches for ablation studies. In addition to the MSEs between the predicted and ground-truth Mel-spectrogram in both languages, we further consider the MSEs between the

<sup>1</sup>Some synthesized samples are available at https://thuhcsi.github.io/automatic-dubbing/ .

TABLE II ABLATION STUDIES.

	English to Chinese			Chinese to English			
Approach	MSE (Mel)	MSE (GST)	MSE (LST)	MSE (Mel)	MSE (GST)	MSE (LST)	
Proposed	1.392	$4.220 \times 10^{-3}$	$7.983 \times 10^{-3}$	2.140	$2.012 \times 10^{-3}$	$1.075 \times 10^{-2}$	
- without local scale	1.675	$3.274 \times 10^{-3}$	-	2.699	$1.401 \times 10^{-2}$	-	
- without global scale	1.660	-	$7.373 \times 10^{-3}$	2.666	-	$1.092 \times 10^{-2}$	
- without en-zh direction	-	-	-	2.368	$2.024 \times 10^{-3}$	$1.080 \times 10^{-2}$	
- without zh-en direction	1.402	$4.228\times10^{-3}$	$8.097 \times 10^{-3}$	-	-	-	

predicted and ground-truth global and local speaking styles in ablation studies.

The first two variants respectively ignore the speaking style transfer at the global or local scale. The corresponding results are shown in the second and third lines of Table II. Although these tow variants may have MSE of global or local speaking styles which outperforms the MSE of the proposed approach, they are suffering from missing scale in speaking style transfer and resulting in poorer MSEs of the Mel-spectrograms than the proposed approach.

The last two variants respectively ignore one dubbing direction when modeling the speaking style transfer. The results of these two variant are shown in the last two lines of Table II. The proposed approach which jointly considers both directions slightly outperforms these two variants, which showing the effectiveness of jointly modeling the speaking style transfer in both directions.

## VI. DISCUSSION

Automatic dubbing is a potential research area in TTS and could be utilized to simplify the dubbing process in real world game and film production. While several efforts have been performed towards automatic dubbing and transferred the duration of each prosodic phrase to the dubbed language, no previous work has fully considered and transferred the speaking styles in automatic dubbing. In this paper, for the first time, a joint multi-scale cross-lingual speaking style transfer framework is proposed to simultaneously model the bidirectional speaking style transfer between languages at both global and local scales. Extensive experiments show that the proposed framework is able to jointly consider the speaking style of each word and the speaking style of the whole utterance in the source language and synthesize speech with appropriate speaking styles in the target language.

To demonstrate the necessity of multi-scale cross lingual speaking style transfer in automatic dubbing, subjective observation is conducted on the cross-lingual speaking style transfer in a real game, *Borderlands 3* which contains excellent dubs in different languages with rich speaking styles. The observation results reveal the the high correlation between the speaking styles of parallel utterances in different languages. Particularly, at utterance level, the global speaking styles of these parallel utterances are always same or similar. And at word level, the local speaking styles of each word could be often *matched* to a word in the other language, which means these words have both same or similar semantic information and local speaking styles.

The difficulty of collecting speeches in different languages which are parallel in both meaning and speaking styles may be a reason to why there is no approach to cross-lingual speaking style transfer modeling in automatic dubbing yet. To overcome this issue, we collect parallel speeches from the English and Chinese dubs in the game *Borderlands 3* as the corpus for our research. These speeches are performed by experienced voice talents and recorded with professional equipment, which are ideal for learning the speaking style transfer pattern across different languages. However, these speeches can only be used in private and might be a gap to reproduce our work. We wish that game companies can publicly release their dubs in different languages to support the research of automatic dubbing in the future.

It is vital to extract clean and robust speaking style information for learning speaking style transfer patterns. We employ the MST-FastSpeech 2 to extract the ground-truth global and local speaking styles for each utterance in the corpus and also build a TTS module with multi-scale speaking style control for each language at the same time. For global speaking styles, it utilizes the global style token [10] learning branch for Tacotron [2] which has been widely used in speaking style and emotion transfer. And for local speaking styles, we map the framelevel acoustic features to word-level with the help of the neural network based forced aligner, NeuFA [30]. NeuFA is a young, experimental model which could be used as a soft forced alignment model to extract the attention weights between the given text and frame-level acoustic feature sequence. To remove unwanted information and improve the robustness of the extracted speaking styles, domain adversarial learning is employed to disentangle the semantic and speaker information from speaking styles.

The relevance between the semantic and speaking style information in different languages is the key to achieve interpretive cross-lingual speaking style transfer for automatic dubbing, which has been already demonstrated in our data observation. We present a novel framework to model cross-lingual speaking style transfer in global scale, which predicts the global speaking style for the dubbed language from the global multi-modal features in the source language and the global textual features in the dubbed language. At local scale, we employ bidirectional attention mechanism to transfer the multi-modal information in the source to the dubbed language according to the attention weights learnt between the semantic meanings of the words in two languages. Moreover, we unify the learning of cross-lingual speaking style transfer for both dubbing directions with multi-task learning to jointly

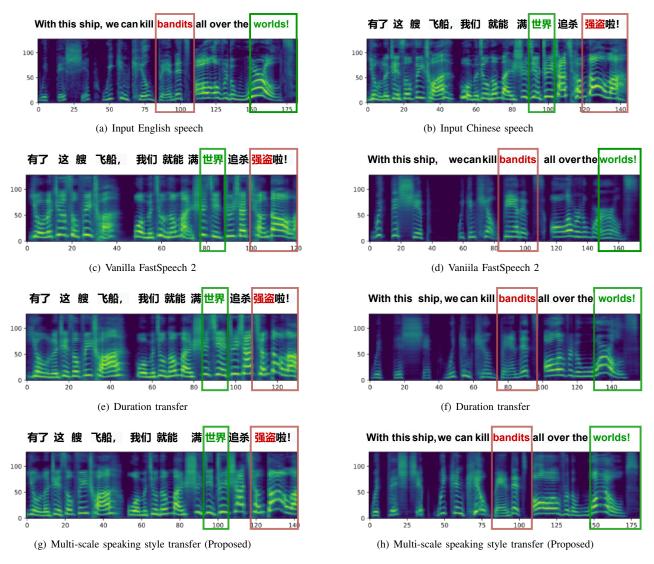


Fig. 7. Comparison between the Mel spectrograms for the words 'bandits' and 'worlds' in the synthesized speech 'With this ship, we can kill bandits all over the worlds.' of each approach in English to Chinese and Chinese to English dubbing directions.

optimize the attention weights at the local scale. However, the effectiveness of the multi-task learning for both dubbing directions may be limited by the size of the corpus. We believe such design would bring more performance enhancement with more parallel utterances.

#### VII. CONCLUSION

In this paper, to properly transfer the speaking styles at both global (i.e. utterance level) and local (i.e. word level) scales in automatic dubbing, we propose a joint multi-scale cross-lingual speaking style transfer framework to model the speaking style transfer between languages at both scales with multi-task learning. The global and local speaking styles in each language are extracted and utilized to predict the corresponding global and local speaking styles in the other language, which are further synthesized to speech by MST-FastSpeech 2. The effectiveness of our proposed framework is demonstrated by experiments and ablation studies.

# REFERENCES

- [1] P. Taylor, Text-to-speech synthesis. Cambridge university press, 2009.
- [2] Y. Wang, R. Skerry-Ryan, D. Stanton, Y. Wu, R. J. Weiss, N. Jaitly, Z. Yang, Y. Xiao, Z. Chen, S. Bengio et al., "Tacotron: Towards end-to-end speech synthesis," arXiv preprint arXiv:1703.10135, 2017.
- [3] J. Shen, R. Pang, R. J. Weiss, M. Schuster, N. Jaitly, Z. Yang, Z. Chen, Y. Zhang, Y. Wang, R. Skerrv-Ryan et al., "Natural tts synthesis by conditioning wavenet on mel spectrogram predictions," in 2018 IEEE international conference on acoustics, speech and signal processing (ICASSP). IEEE, 2018, pp. 4779–4783.
- [4] N. Li, S. Liu, Y. Liu, S. Zhao, and M. Liu, "Neural speech synthesis with transformer network," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 33, no. 01, 2019, pp. 6706–6713.
- [5] Y. Ren, C. Hu, X. Tan, T. Qin, S. Zhao, Z. Zhao, and T.-Y. Liu, "Fastspeech 2: Fast and high-quality end-to-end text to speech," arXiv preprint arXiv:2006.04558, 2020.
- [6] J. Kim, J. Kong, and J. Son, "Conditional variational autoencoder with adversarial learning for end-to-end text-to-speech," in *International Conference on Machine Learning*. PMLR, 2021, pp. 5530–5540.
- [7] J. Li, Z. Wu, R. Li, P. Zhi, S. Yang, and H. Meng, "Knowledge-based linguistic encoding for end-to-end mandarin text-to-speech synthesis." in *INTERSPEECH*, 2019, pp. 4494–4498.
- [8] X. Cai, D. Dai, Z. Wu, X. Li, J. Li, and H. Meng, "Emotion controllable speech synthesis using emotion-unlabeled dataset with the assistance of cross-domain speech emotion recognition," in ICASSP 2021-2021 IEEE

- International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2021, pp. 5734–5738.
- [9] Y. Lei, S. Yang, X. Wang, and L. Xie, "Msemotts: Multi-scale emotion transfer, prediction, and control for emotional speech synthesis," IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 30, pp. 853–864, 2022.
- [10] Y. Wang, D. Stanton, Y. Zhang, R.-S. Ryan, E. Battenberg, J. Shor, Y. Xiao, Y. Jia, F. Ren, and R. A. Saurous, "Style tokens: Unsupervised style modeling, control and transfer in end-to-end speech synthesis," in *International Conference on Machine Learning*. PMLR, 2018, pp. 5180–5189.
- [11] X. Li, C. Song, J. Li, Z. Wu, J. Jia, and H. Meng, "Towards multi-scale style control for expressive speech synthesis," arXiv preprint arXiv:2104.03521, 2021.
- [12] X. Li, C. Song, X. Wei, Z. Wu, J. Jia, and H. Meng, "Towards cross-speaker reading style transfer on audiobook dataset," arXiv preprint arXiv:2208.05359, 2022.
- [13] L. Sun, H. Wang, S. Kang, K. Li, and H. M. Meng, "Personalized, cross-lingual tts using phonetic posteriorgrams." in *INTERSPEECH*, 2016, pp. 322–326.
- [14] T. Tu, Y.-J. Chen, C.-c. Yeh, and H.-Y. Lee, "End-to-end text-to-speech for low-resource languages by cross-lingual transfer learning," arXiv preprint arXiv:1904.06508, 2019.
- [15] M. Chen, M. Chen, S. Liang, J. Ma, L. Chen, S. Wang, and J. Xiao, "Cross-lingual, multi-speaker text-to-speech synthesis using neural speaker embedding." in *Interspeech*, 2019, pp. 2105–2109.
- [16] A. Öktem, M. Farrús, and A. Bonafonte, "Prosodic phrase alignment for machine dubbing," arXiv preprint arXiv:1908.07226, 2019.
- [17] J. Li, Y. Meng, X. Wu, Z. Wu, J. Jia, H. Meng, T. Qiao, Y. Wang, and Y. Wang, "Inferring speaking styles from multi-modal conversational context by multi-scale relational graph convolutional networks," in *Proceedings of the 30th ACM International Conference on Multimedia*, ser. MM '22. Lisboa, Portugal: ACM, 2022. [Online]. Available: http://doi.acm.org/10.1145/3503161.3547831
- [18] J. Effendi, Y. Virkar, R. Barra-Chicote, and M. Federico, "Duration modeling of neural tts for automatic dubbing," in ICASSP 2022 -2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2022, pp. 8037–8041.
- [19] M. Federico, Y. Virkar, R. Enyedi, and R. Barra-Chicote, "Evaluating and optimizing prosodic alignment for automatic dubbing." in *INTER-SPEECH*, 2020, pp. 1481–1485.
- [20] Y. Virkar, M. Federico, R. Enyedi, and R. Barra-Chicote, "Prosodic alignment for off-screen automatic dubbing," arXiv preprint arXiv:2204.02530, 2022.
- [21] ——, "Improvements to prosodic alignment for automatic dubbing," in ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2021, pp. 7543–7574.
- [22] H. Zen, K. Tokuda, and A. W. Black, "Statistical parametric speech synthesis," speech communication, vol. 51, no. 11, pp. 1039–1064, 2009.
- [23] A. v. d. Oord, S. Dieleman, H. Zen, K. Simonyan, O. Vinyals, A. Graves, N. Kalchbrenner, A. Senior, and K. Kavukcuoglu, "Wavenet: A generative model for raw audio," arXiv preprint arXiv:1609.03499, 2016.
- [24] J. Kong, J. Kim, and J. Bae, "Hifi-gan: Generative adversarial networks for efficient and high fidelity speech synthesis," *Advances in Neural Information Processing Systems*, vol. 33, pp. 17022–17033, 2020.
- [25] A. Graves and N. Jaitly, "Towards end-to-end speech recognition with recurrent neural networks," in *International conference on machine* learning. PMLR, 2014, pp. 1764–1772.
- [26] K. Cho, B. Van Merriënboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, and Y. Bengio, "Learning phrase representations using rnn encoder-decoder for statistical machine translation," arXiv preprint arXiv:1406.1078, 2014.
- [27] D. Bahdanau, K. Cho, and Y. Bengio, "Neural machine translation by jointly learning to align and translate," arXiv preprint arXiv:1409.0473, 2014
- [28] J. K. Chorowski, D. Bahdanau, D. Serdyuk, K. Cho, and Y. Bengio, "Attention-based models for speech recognition," Advances in neural information processing systems, vol. 28, 2015.
- [29] Y. Ganin, E. Ustinova, H. Ajakan, P. Germain, H. Larochelle, F. Laviolette, M. Marchand, and V. Lempitsky, "Domain-adversarial training of neural networks," *The journal of machine learning research*, vol. 17, no. 1, pp. 2096–2030, 2016.
- [30] J. Li, Y. Meng, Z. Wu, H. Meng, Q. Tian, Y. Wang, and Y. Wang, "Neufa: Neural network based end-to-end forced alignment with bidirectional attention mechanism," in *ICASSP 2022-2022 IEEE International Con*ference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2022, pp. 8007–8011.

- [31] Y. Jia, R. J. Weiss, F. Biadsy, W. Macherey, M. Johnson, Z. Chen, and Y. Wu, "Direct speech-to-speech translation with a sequence-to-sequence model," arXiv preprint arXiv:1904.06037, 2019.
- [32] A. Lee, H. Gong, P.-A. Duquenne, H. Schwenk, P.-J. Chen, C. Wang, S. Popuri, J. Pino, J. Gu, and W.-N. Hsu, "Textless speech-to-speech translation on real data," arXiv preprint arXiv:2112.08352, 2021.
- [33] G. Kikui, E. Sumita, T. Takezawa, and S. Yamamoto, "Creating corpora for speech-to-speech translation," in *Eighth European Conference on Speech Communication and Technology*, 2003.
- [34] L. Rabiner and B. Juang, "An introduction to hidden markov models," ieee assp magazine, vol. 3, no. 1, pp. 4–16, 1986.
- [35] M. Federico, R. Enyedi, R. Barra-Chicote, R. Giri, U. Isik, A. Krishnaswamy, and H. Sawaf, "From Speech-to-Speech Translation to Automatic Dubbing," in *Proceedings of the 17th International Conference on Spoken Language Translation*. Online: Association for Computational Linguistics, 2020, pp. 257–264. [Online]. Available: https://aclanthology.org/2020.iwslt-1.31
- [36] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, "Attention is all you need," *Advances in neural information processing systems*, vol. 30, 2017.
- [37] Y. Ganin and V. Lempitsky, "Unsupervised domain adaptation by back-propagation," in *International conference on machine learning*. PMLR, 2015, pp. 1180–1189.
- [38] Y. Zhang, R. J. Weiss, H. Zen, Y. Wu, Z. Chen, R. J. Skerry-Ryan, Y. Jia, A. Rosenberg, and B. Ramabhadran, "Learning to Speak Fluently in a Foreign Language: Multilingual Speech Synthesis and Cross-Language Voice Cloning," arXiv:1907.04448 [cs, eess], Jul. 2019, arXiv: 1907.04448. [Online]. Available: http://arxiv.org/abs/1907.04448
- [39] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," arXiv preprint arXiv:1810.04805, 2018.
- [40] A. Paszke, S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan, T. Killeen, Z. Lin, N. Gimelshein, L. Antiga et al., "Pytorch: An imperative style, high-performance deep learning library," Advances in neural information processing systems, vol. 32, 2019.