Speech-to-Speech Translation with Discrete-Unit-Based Style Transfer

Anonymous ACL submission

Abstract

Direct speech-to-speech translation (S2ST) with discrete self-supervised representations has achieved remarkable accuracy, but is unable to preserve the speaker timbre of the source speech. Meanwhile, the scarcity of high-quality speaker-parallel data poses a challenge for learning style transfer during translation. We propose an S2ST framework with style-transfer capability on the basis of discrete self-supervised speech representations and codec units. The acoustic language model we introduce for style transfer leverages self-supervised in-context learning, acquiring style transfer ability without relying on any speaker-parallel data, thereby overcoming the issue of data scarcity. By using extensive training data, our model achieves zero-shot cross-lingual style transfer on previously unseen source languages. Experiments show that our model generates translated speeches with high fidelity and style similarity. [1]

1 Introduction

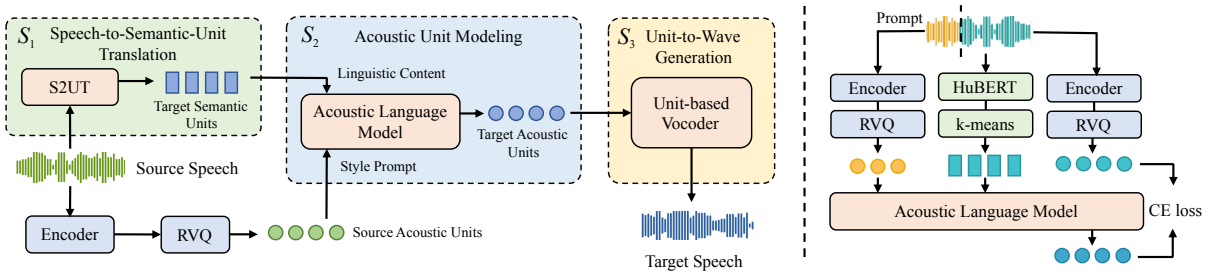
Speech-to-speech translation (S2ST) aims to translate spoken utterances from one language to another, which can bring immense convenience to international communication. Compared to conventional cascaded systems comprising ASR, text translation and TTS models (Lavie et al., 1997; Nakamura et al., 2006; Wahlster, 2013), direct S2ST models without intermediate text generation have a more concise pipeline with less computation cost and error propagation while facilitating application to unwritten languages, and thus spark widespread interest in the community.

Mainstream approaches of direct S2ST (Lee et al., 2021a,b; Huang et al., 2022; Popuri et al., 2022) utilize discrete speech representation from self-supervised models (such as HuBERT (Hsu et al., 2021)) as prediction target, and then use them to reconstruct the waveform. Such representation eliminates speaker identity and prosody of the speeches and retains only semantic contents, which simplifies the target distribution and makes the translation less challenging. However, it also has the drawback of losing the style information of the source speech. Extra voice conversion systems are needed if users want to keep the source speaker timbre, which may cause degradation in audio quality and content accuracy.

Some works propose direct S2ST with style transfer (Jia et al., 2021; Song et al., 2023). These methods depend on paired data that source and target speech share the same speaker. However, such data from the real world is extremely scarce as it requires a large number of multilingual speakers, while simulated data from multilingual TTS systems suffers from less diversity and extra data collection costs. Recent large-scale S2ST models (Rubenstein et al., 2023; Barrault et al., 2023) have also incorporated the capability of style transfer, yet their sub-modules are highly coupled and are difficult to apply to other S2ST models.

Inspired by recent progress in spoken language models (Borsos et al., 2023; Wang et al., 2023), we propose a novel approach for direct S2ST with the ability of cross-lingual style transfer, and does not rely on any speaker-parallel data. We utilize two types of discrete representations, namely semantic and acoustic units, from a self-supervised speech model and a neural codec, separately. Our method encompasses three stages: 1) speech-to-semantic-unit translation, which translates source speech to target semantic units; 2) acoustic unit modeling, which generates target acoustic units from translated semantic units using style information in the source speech; and 3) unit-to-wave generation, which reconstructs high-fidelity translated speech from the acoustic units. The modules of the three stages are trained independently and decou-

[1] Audio samples are available at http://stylelm.github.io/



(a) Overall inference pipeline

(b) Training of S_2 stage

Figure 1: We propose an S2ST approach with style transfer based on discrete representations from a self-supervised speech model and a neural codec. Figure (a) shows the inference pipeline of our method; figure (b) illustrates the self-supervised training process of the acoustic language model of S_2.

pled from each other, allowing our framework to be applied to various existing speech-to-unit translation models.

For the acoustic unit modeling stage, we introduce an acoustic language model. It employs a self-supervised training approach and learns style transfer through in-context learning, which relies on no speaker-parallel data, and thus addresses the issue of data scarcity. By utilizing extensive training data, our model achieves zero-shot cross-lingual style transfer with source languages not included in the training. Experiments show that our model generates results with superior audio quality and style similarity while maintaining accurate content.

Our contributions can be summarized as follows:

- We propose an S2ST approach with cross-lingual style transfer capability, even on previously unseen source languages.
- By employing self-supervised training, our model does not rely on any speaker-parallel data, thus addressing the issue of data scarcity.
- The decoupling nature of the sub-modules enables our framework to be adopted by various existing speech-to-unit translation models.
- Experiments show that our method generates translated speeches with high quality and style similarity.

2 Method

The overall inference pipeline of our method is illustrated in Fig.1 (a). Our method comprises three consecutive stages, utilizing two distinct types of discrete units: 1) speech-to-semantic-unit translation stage S_1, which converts source audio into semantic units of the translated speech; 2) acoustic unit modeling stage S_2, generating target acoustic units conditioned on the semantic output from the preceding stage and the acoustic units of the source speech as style prompt; 3) unit-to-wave generation stage S_3, producing translated speech that maintains consistent style with the source. We provide details about these two types of units and the three stages in the following subsections.

2.1 Semantic and Acoustic Units

Discrete HuBERT (Hsu et al., 2021) units obtained from the clustering of self-supervised speech representations are shown (Lee et al., 2021b; Huang et al., 2022) to be effective in providing semantic content information and are widely adopted in S2ST as prediction target (Lee et al., 2021a,b; Huang et al., 2022; Popuri et al., 2022). HuBERT encodes the target speech into continuous representations with a frame length of 20 ms, and these representations are then discretized with the k-means algorithm to get the semantic units.

On the other hand, audio codec models with encoder-decoder architecture such as SoundStream (Zeghidour et al., 2021) have recently shown outstanding performance in learning acoustic information. Such a codec model can produce discrete representations (i.e. the acoustic units) of audio by employing a convolutional encoder followed by a residual vector quantizer. These representations contain detailed acoustic information and can be used to reconstruct waveforms with the corresponding decoder or an additional vocoder.

2.2 Speech-to-Semantic-Unit Translation

The speech-to-semantic-unit translation stage generates translated semantic units conditioned on source speech input, achieving translation of linguistic content. Various models (Lee et al., 2021a;

Huang et al., 2022; Popuri et al., 2022) have been proposed for this procedure. These models share a common basic architecture of a convolutional speech encoder followed by an encoder-decoder architecture based on a transformer or conformer. Due to the decoupling nature of the sub-modules of the three stages, we have the flexibility to adopt different S2UT models in this stage, and we attempted two of them in our experiments (See Section 3.1).

2.3 Acoustic Unit Modeling

The acoustic unit modeling stage S_2 generates translated acoustic units from semantic tokens and style prompts. The core component of S_2 is an acoustic language model, which is basically a decoder-only transformer. The model takes a prefix sequence formed by concatenating acoustic unit sequence $\mathbf{a_p}$, which serves as a style prompt, and the target semantic sequence $\mathbf{s}$, and generates the target acoustic sequence $\mathbf{a}$ autoregressively. This procedure can be formulated as

$$p\left(\mathbf{a} \mid \mathbf{a_p}, \mathbf{s}; \theta_{AR}\right) = \prod_{t=1}^{T} \prod_{c=1}^{C} p\left(\mathbf{a}_t^c \mid \mathbf{a}_{<t}, \mathbf{a}_t^{<c}, \mathbf{a_p}, \mathbf{s}; \theta_{AR}\right) \tag{1}$$

The entire sequence is in the format of $[\mathbf{a_p}|\mathbf{s}|\mathbf{a}]$, with a separator token between each pair of adjacent parts. 3 codebooks are used for $\mathbf{a_p}$ and $\mathbf{a}$.

The training procedure of S_2 is illustrated in Figure 1(b). It adopts a self-supervised training paradigm, where the first three seconds of each audio sample is truncated as prompt, and the acoustic language model is trained to predict the acoustic units of the remaining part conditioned on its semantic units and the prompt acoustic units with cross-entropy loss. This in-context learning approach enables the model to grasp the correspondence in acoustic characteristics between the two parts and acquire style transfer ability. During inference, we use semantic tokens from the previous stage and acoustic units of source speech as the style prompt to realize cross-lingual style transfer.

2.4 Unit-to-Wave Generation

In the waveform generation stage S_3, we adopt a GAN-based unit vocoder to map the target acoustic units to high-fidelity waveforms. Our vocoder is derived from BigVGAN (Lee et al., 2022), with a generator built from a set of look-up tables (LUT) that embed the discrete units, and a series of blocks composed of transposed convolution and a residual block with dilated layers. Multi-period discriminator (MPD) and multi-resolution discriminator (MRD) are used for adversarial training.

3 Experiments

3.1 Setup

Datesets We use two language pairs in the CVSS dataset (Jia et al., 2022) as the translation benchmark, which are French-English (Fr-En) and Spanish-English (Es-En). For S_2 and S_3 stages, we use the *unlab-60k* subset of Libri-Light (Kahn et al., 2020) to train the acoustic language model, and use LibriTTS (Zen et al., 2019) a to train the SoundStream model and the vocoder. All audio is processed at a 16 kHz sampling rate. We provide more details about the datasets in Appendix A.

Model Configurations We apply the publicly available multilingual HuBERT (mHuBERT) model with the k-means model of 1000 clusters for the 11th-layer features and train a SoundStream model with a size of 1024 for each codebook and an overall downsampling rate of 320. For stage S_1, we train an S2UT-conformer for Fr-En following (Lee et al., 2021a), and an xm-transformer for Es-En following (Popuri et al., 2022) but without mbart-decoder initialization. The decoder-only transformer of S_2 has about 760M parameters, with details of its architecture provided in Appendix B.

Baselines Considering that previous S2ST models with style transfer (Jia et al., 2021; Song et al., 2023; Rubenstein et al., 2023; Barrault et al., 2023) either differ from ours in settings or are not open-sourced, we mainly compare our model with S2UT models used in S_1 followed by a single-speaker vocoder, and cascaded pipelines formed by appending various voice conversion models after the vocoder, which are PPG-VC(Liu et al., 2021), NANSY(Choi et al., 2021) and YourTTS(Casanova et al., 2022).

Evaluation Metrics We employ both objective and subjective metrics to measure the model performance in terms of translation accuracy, speech quality, and style similarity with the source speech. For objective evaluation, we calculate the BLEU score between the ASR-transcripts of the translated speech and reference text as well as speaker cosine similarity (Cos). For subjective metrics, we use crowd-sourced human evaluation with 1-5 Likert scales and report mean opinion scores on speech quality (MOS) and style similarity (SMOS) with 95% confidence intervals (CI). More details are provided in Appendix C.

Table 1: Translation Quality and Audio Similarity on CVSS Dataset.

ID	Model	BLEU (Fr-En) (↑)	BLEU (Es-En) (↑)	MOS (↑)	SMOS(↑)	Cos (↑)
1	S2UT	18.08	23.78	3.73 ± 0.05	/	/
2	S2UT + PPG-VC	17.05	23.03	3.37 ± 0.07	3.30 ± 0.06	0.65
3	S2UT + NANSY	17.21	23.36	3.56 ± 0.06	3.47 ± 0.05	0.68
4	S2UT + YourTTS	16.73	22.09	3.74 ± 0.05	3.60 ± 0.06	0.69
5	Ours	17.64	23.41	3.86 ± 0.06	$\mathbf{3.69 \pm 0.05}$	**0.74**
6	GT (CVSS-C)	84.52	88.54	3.92 ± 0.05	/	/
7	GT (CVSS-T)	81.48	84.81	3.95 ± 0.05	3.56 ± 0.06	0.68

Table 2: Ablation on Training Data Volume and Sizes of S_2 Model.

ID	Model	BLEU (Fr-En) (↑)	BLEU (Es-En) (↑)	MOS (↑)	SMOS (↑)	Cos (↑)
Ablation on Traing Data Volume						
1	LibriTTS	17.62	23.37	3.84 ± 0.05	3.55 ± 0.05	0.67
2	Libri-Light unlab-60k	17.64	23.41	3.86 ± 0.05	3.69 ± 0.05	0.74
3	+ CVSS source	17.25	23.49	3.85 ± 0.05	3.71 ± 0.05	0.76
Ablation on Model Size						
4	Small (160M)	16.55	21.78	3.73 ± 0.06	3.58 ± 0.05	0.70
5	Base (430M)	16.87	22.36	3.81 ± 0.05	3.64 ± 0.05	0.73
6	Large (760M)	17.64	23.41	3.86 ± 0.05	3.69 ± 0.05	0.74

3.2 Results and Analysis

Table 1 summarizes the main experiment results. We observe a comprehensive decrease in BLEU scores for 2-5 compared to 1, indicating that additional style transfer processes lead to a loss in semantic content. Nevertheless, our model achieves the slightest decrease of 0.44 and 0.37 in BLEU, together with the highest MOS of 3.86. This indicates that in comparison to cascaded voice conversion, our style transfer mechanism based on discrete intermediate representations can mitigate quality and content losses during the transfer and produce higher-quality audio.

On the other hand, our model achieves the highest speaker similarity, with SMOS being 3.69 and Cos being 0.74, which surpasses all three cascaded systems and even the CVSS-T target, demonstrating the outstanding performance in zero-shot cross-lingual style transfer of our model. This can be attributed to the large model size and extensive training data, through which our model acquires strong zero-shot style transfer capability and can generalize effectively to unseen source languages.

3.3 Ablation Studies

We further conduct ablations on the training data volume and model size of S_2, and the results are summarized in Table 2. We observe that when using LibriTTS with shorter duration and fewer speakers, there is a significant decrease in SMOS and Cos of 0.14 and 0.07, with only a minor decrease in BLEU and MOS of 0.02, 0.04, and 0.02. This suggests that the model's style transfer performance relies on a large amount of speech data from multiple speakers, while achieving high-quality speech generation does not require as much data. We also add part of the speech from the CVSS source to the training data, obtaining a marginal improvement of 0.02 on both Cos and SMOS. This indicates that with extensive training data, the performance of S_2 on unseen source languages is close to that on seen languages. Furthermore, we observe a comprehensive improvement in all metrics as the model size increases in 4-6, proving that the superior performance of our acoustic language model is closely linked to its large parameter size.

4 Conclusions

We propose an S2ST approach with style transfer capability by adopting an acoustic language model that learns style transfer through in-context learning. By adopting self-supervised training and large-scale training data, our method addresses the scarcity of speaker-parallel data and achieves cross-lingual style transfer with unseen source languages. Experiments indicate that our approach achieves outstanding results in terms of translation accuracy, speech quality and style similarity.

5 Limitations and Potential Risks

Despite that our model excels in style transfer and generating high-quality translated speech, it still suffers from several limitations: 1) Our evaluation (especially the objective evaluation) of style transfer capability mainly focuses on the global speaker timbre, and we have not yet delved deeply into other stylistic characteristics such as prosody and emotion. We leave the exploration of these aspects for future work. 2) The large model size and the autoregressive generation paradigm may lead to efficiency issues, such as long inference latency. 3) The BLEU scores heavily depend on the ASR quality, which may not accurately reflect the speech translation performance. Future directions could be improving ASR quality or exploring other evaluation metrics without reliance on ASR models. Besides, due to the speaker timbre transfer capability of our model, it may be misused to disinform, defame, or commit fraud. We will add some constraints to guarantee people who use our code or pre-trained model will not use the model in illegal cases.

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A Datasets

In this section, we provide details of the translation benchmark dataset and the corpora for training S_2 and S_3 models.

CVSS CVSS (Jia et al., 2022) is an S2ST benchmark dataset derived from the CoVoST 2 (Wang et al., 2020) speech-to-text translation corpus by synthesizing the translation text into speech using TTS systems. It comprises two sub-versions of CVSS-C and CVSS-T, where the target speech in CVSS-C is generated by a single-speaker TTS system while that of CVSS-T is generated by a multi-speaker TTS system with speaker timbre transferred from the source speech. We use CVSS-C for training and evaluating the translation models, and provide results of ground truth target audios in CVSS-T as a reference for style transfer performance.

Libri-Light Libri-Light is a large-scale corpus containing unlabelled speech from audiobooks in English. The *unlab-60k* subset we use consists of 57.7k hours of audio with 7,439 speakers.

LibriTTS LibriTTS is a multi-speaker English TTS dataset. It comprises 585.5 hours of audio with 2,456 speakers.

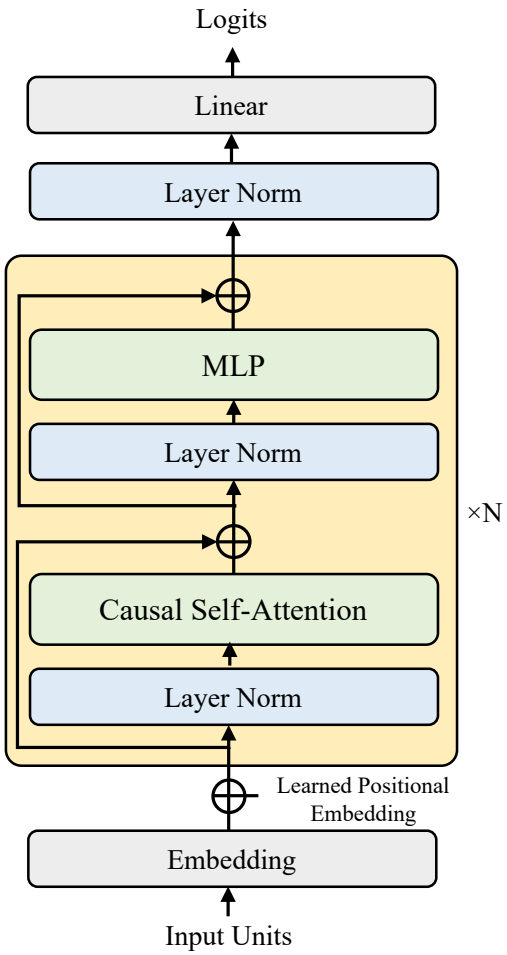

Figure 2: Structure of the Acoustic Language Model.

B Model Settings

We illustrate the structure of the acoustic language model in Figure 2, and provide hyperparameters of our S_2 and S_3 stage models in Table 3. We also refer the readers to the original papers (Lee et al., 2021a; Popuri et al., 2022) for details of S_1 models used. Each sub-module is trained with 4 NVIDIA-V100 GPUs for about a week.

Hyperparameter		Prompt-Singer
Acoustic Language Model (Small)	Layers	22
	Hidden Dim	768
	Attention Headers	12
	FFN Dim	3,072
	Number of Parameters	160.5M
Acoustic Language Model (Base)	Layers	26
	Hidden Dim	1,152
	Attention Headers	16
	FFN Dim	4,608
	Number of Parameters	420.2M
Acoustic Language Model (Large)	Layers	26
	Hidden Dim	1,536
	Attention Headers	16
	FFN Dim	6,144
	Number of Parameters	763.1M
Unit Vocoder	Upsample Rates	[5,4,2,2,2,2]
	Hop Size	320
	Upsample Kernel Sizes	[9,8,4,4,4,4]
	Number of Parameters	121.6M

Table 3: Hyperparameters of S_2 and S_3 Stage Models.

C Evaluation Metrics

For translation accuracy, we use an open-sourced ASR model in *fairseq* [2] (Ott et al., 2019) framework to transcribe the audios and then calculate the BLEU score between the transcripts and the reference text. For speaker similarity, we use Resemblyzer[3], which is a public-available speaker encoder to extract speaker embeddings of the synthesized and source speech and calculate their cosine similarity.

Our subjective evaluation tests are crowdsourced and conducted via Amazon Mechanical Turk. For audio quality evaluation, we ask the testers to examine the audio quality and naturalness. For style similarity, we instruct the testers to evaluate the style similarity between the synthesized and source speech while ignoring the content. The testers rate scores on 1-5 Likert scales. We provide screenshots of the testing interfaces in Figure 3 and 4. Each data item is rated by 2 testers, and the testers are paid $8 hourly.

We calculate BLEU scores over the entire test split and randomly sample 500 items from each language pair for other metrics, which represents approximately 3% of the test set.

[2] https://github.com/facebookresearch/fairseq/tree/main/examples/speech_to_speech/asr_bleu

[3] https://github.com/resemble-ai/Resemblyzer

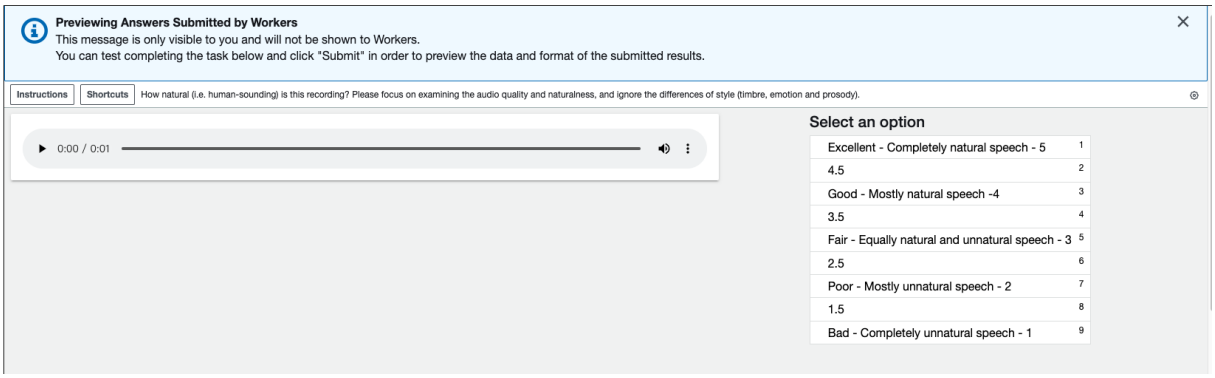

Figure 3: Screenshot of MOS testing.

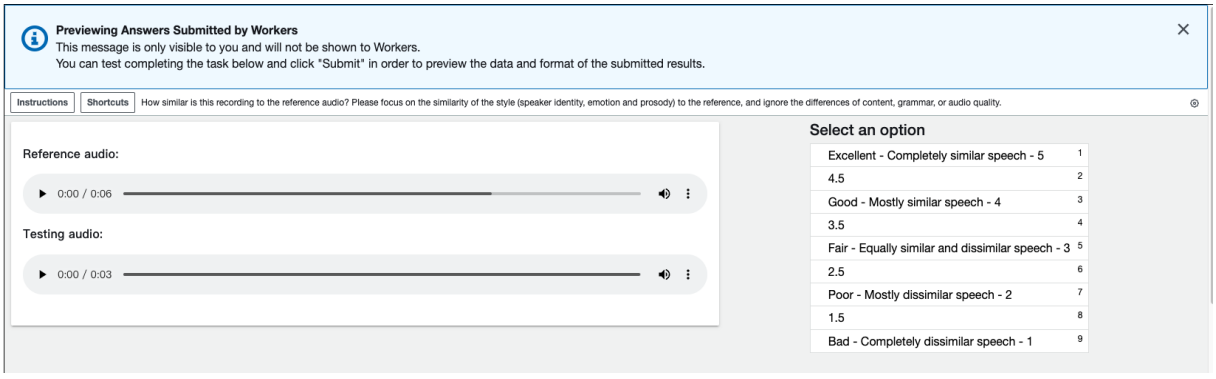

Figure 4: Screenshot of SMOS testing.