High-Quality Automatic Voice Over with Accurate Alignment: Supervision through Self-Supervised Discrete Speech Units

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\section*{Abstract}

The goal of Automatic Voice Over (AVO) is to generate speech in sync with a silent video given its text script. Recent AVO frameworks built upon text-to-speech synthesis (TTS) have shown impressive results. However, the current AVO learning objective of acoustic feature reconstruction brings in indirect supervision for inter-modal alignment learning, thus limiting the synchronization performance and synthetic speech quality. To this end, we propose a novel AVO method leveraging the learning objective of self-supervised discrete speech unit prediction for AVO, providing more direct supervision for the alignment learning, but also alleviates the mismatch between the text-video context and acoustic features. Experimental results show that our proposed method achieves remarkable lip-speech synchronization and high speech quality by outperforming baselines in both objective and subjective evaluations. Code and sample videos are publicly available.

\textbf{Index Terms:} Text-to-speech, lip-speech synchronization, automatic voice over, discrete speech units, speech synthesis

1. Introduction

Automatic Voice Over is a cutting-edge technology that utilizes artificial intelligence to generate speech that voice-synchronizes with a pre-recorded video [1]. AVO technology enables the automatic creation of a voice track that is perfectly aligned with the lip movement, facial expression, and conversational tone of the video, provided with text transcription. As a highly efficient AI-powered solution for voice over, AVO has the potential to revolutionize video-making in various industries, including movie dubbing, online education, and marketing.

The development of neural text-to-speech synthesis has played a crucial role in the advancement of AVO technology. In light of rapid emergence of deep learning, TTS systems built upon neural networks can generate high-quality speech [2]. End-to-end TTS systems, including Tacotron 1/2 [3, 4] and FastSpeech 1/2 [5, 6], work in a simplified pipeline of mapping sequences of character or phoneme input into mel-spectrogram acoustic features. With the help of neural vocoders [7, 8, 9], they generate speech with human-level naturalness.

With the ability to generate high-quality speech, neural TTS provides a foundation for AVO systems to produce accurate and natural-sounding voice over. To model speech with precise timing in sync with the video, AVO systems generally use lip motion or facial movement to guide the rendering of phonetic duration in TTS [1, 10, 11], as illustrated in Figure 1. Existing AVO approaches use attention-based alignment modules to align multi-modal features and produce text-video context for acoustic feature decoding. However, as a learning objective of an AVO system, acoustic feature reconstruction does not provide direct supervision for the model to learn accurate inter-modal alignment, thus affecting the acoustic decoding and leading to degradation of synthetic speech quality.

Self-supervised learning (SSL) speech models trained on large amounts of unlabeled data are proved to be sufficient for capturing content information of speech [12, 13, 14, 15]. Recent studies show that discrete units derived from SSL speech models can be applied as speech content representation for speech synthesis tasks, including speech resynthesis [16] and voice conversion [17]. As speech content in AVO is modeled through the alignment of multi-modal information, content representation can provide more direct supervision for alignment learning.

Motivated by these, we propose a novel AVO approach leveraging discrete speech units: first, align multi-modal features and predict discrete speech units from the text-video context formed; then, synthesize speech conditioned on the predicted units. The main contributions of this paper include:

• We propose a new learning objective of discrete speech unit prediction for AVO, providing more direct supervision for
text-video alignment learning at the context feature level, thus improving lip-speech synchronization;
• We propose to synthesize speech directly from discrete speech units with a pretrained unit vocoder, thus alleviating mismatch between text-video context and acoustic features in acoustic decoding and improving synthetic speech quality.

2. Related work

2.1. AVO Background

The industry of video content creation calls for high-quality and cost-efficient voice over solutions. As such, AVO research, drawing upon TTS, has become increasingly important. While general-purpose TTS systems generate speech from text, AVO systems need to produce speech that is not only natural-sounding but also synchronized with visual presentation of speakers in video. With this requirement, AVO systems have to model the timing of the speech, taking visual context of the video into account.

Generally, AVO frameworks consist of text and video encoders, which encode information from multi-modal inputs, an alignment module that models inter-modal feature relationships, an acoustic decoder that constructs acoustic features such as mel-spectrogram, and a vocoder to convert acoustic features into output speech waveform [1, 10, 11]. Existing approaches of alignment module are based on attention mechanism [18]. VisualTTS [1] and Neural Dubber [10] align textual and visual features explicitly by attention-based aligners and form text-video context which serves as the input to acoustic decoder. VDTTS [11] uses a multi-source attention mechanism for selecting which outputs of video encoder and text encoder to pass to acoustic decoder at each decoding timestep, forming the alignment between modalities in an implicit manner.

The existing AVO frameworks have limitations that hinder their ability to produce high-quality voice over. Firstly, the capability of the model to learn inter-modal alignment is limited to the acoustic decoding process with the learning objective of mel-spectrogram reconstruction. To establish the alignment, the entire AVO model must be trained as a whole, which is computationally expensive and time-consuming. Secondly, the supervision on the acoustic feature level is indirect for alignment learning due to the gap between phonetic information presented in input text and the acoustic features to model. Moreover, the mismatch between the context representation modeled by the alignment module and target acoustic features can negatively impact acoustic decoder training, resulting in degradation of synthetic speech quality. In this paper, we aim to address these challenges in AVO by imposing supervision on the context representation level with a learning objective of discrete speech unit prediction, which will be introduced in Sec. 3.

2.2. Self-supervised learning in speech synthesis

Self-supervised learning has emerged as a powerful approach to learning speech representations. SSL speech models leverage large amounts of unlabeled speech data by defining auxiliary tasks and generating pseudo-labeled data to be trained using supervised learning techniques [12, 13, 14]. The pretrained models can be used for various downstream tasks [19, 20], such as automatic speech recognition (ASR) [15, 21] and speech emotion recognition [22], and speech enhancement [23].

Recent studies have also explored the use of SSL speech representations in speech synthesis tasks. Du et al. [24] propose to reduce the complexity of the acoustic model in TTS with SSL vector-quantized acoustic features as its classification target. Huang et al. [25] propose to use discrete speech representations as a bottleneck to disentangle content information from speaker information and model acoustic features on top of them for voice conversion. Polyak et al. [16] demonstrate that discrete units derived from HuBERT models [14] can serve as the input of high-quality speech waveform generation.

Inspired by these, we propose to use discrete speech units as the content representation for speech generation and the supervision of alignment learning in AVO.

3. Proposed method

We formulate the AVO problem and propose Discrete Speech Unit-AVO (DSU-AVO), with motivation of providing more direct supervision to alignment learning and establishing a strong connection between text-video context and speech in AVO.

3.1. Problem formulation

Given input phoneme sequence $X_p = (x_{p1}, x_{p2}, ..., x_{pN})$ with length $N$ and video represented by a sequence of image frames $X_v = (x_{v1}, x_{v2}, ..., x_{vT})$ with length $T_v$, the goal of AVO is to generate speech audio that accurately reflects the phonetic content and is temporally aligned with the video.

In a voiced video clip, speech audio and video are both continuous signals of the same length. In practice, they are sampled at different frame rates. This allows us to encode ground-truth speech $Y$ as a sequence of speech representation $Z$ with length $T_z$ that can be easily aligned with the video frame sequence $X_v$ by upsampling the latter, given that the length of the speech representation sequence is $n$ times that of the video frame sequence, where $n = \frac{T_v}{T_z} \in \mathbb{N}^+$. Given the temporal correspondence of speech audio and video, the synchronization between speech and lip motion can be achieved by aligning phoneme information, which determines the speech content, with the lip motion information [1, 10]. An AVO framework aims to model accurate text-video alignment and produce context representation $C = f(X_p, X_v)$ with length $T_c$. Then, conditioned on the context and given the audio-video length ratio $n$, the framework generates speech representation $\hat{Z} = g(C, n)$. Finally, $\hat{Z}$ is converted to speech waveform $\hat{Y}$ through a pretrained vocoder. Training of an AVO framework can be seen as finding the optimal context modeling $f(\cdot)$ and speech representation generation $g(\cdot)$.

3.2. Supervision at context representation level with discrete speech units

As speech representation generation in AVO is conditioned on text-video context, context modeling $f(\cdot)$ is crucial for a framework to produce speech with accurate pronunciation and timing. Since the context is formed by aligning multi-modal representations, alignment learning is an integral part of context modeling.

Existing AVO frameworks [1, 10, 11] rely on acoustic features, typically mel-spectrogram, as the speech representation $Z$ to model, utilizing acoustic decoders as $g(\cdot)$. With the learning objective of mel-spectrogram reconstruction, these frameworks guide the alignment learning through supervision at the acoustic feature level. However, mel-spectrogram does not directly capture linguistic information [4, 26], posing a gap between context and speech representation, thus providing indirect supervision for alignment learning in AVO.

We propose to guide the context modeling and alignment learning of AVO more directly by imposing discrete speech
unit prediction as the supervision at the context representation level, given that discrete speech units are closely correlated with speech content. Additionally, compared with mel-spectrogram, discrete speech units are more disentangled from nuisance variation [16] and are easier to predict. With the proposed learning objective, \( g(\cdot) \) essentially becomes a classification model instead of a regression model and gains better training efficiency. To be specific, we first encode inputs from different modalities, align inter-modal representations to form context, and predict discrete speech units; then, synthesize speech conditioned on the predicted units with a pretrained unit vocoder.

3.3. DSU-AVO system

As demonstrated in Figure 2, our proposed DSU-AVO consists of unit tokenizer, video encoder, text encoder, video-text aligner, unit predictor, and unit vocoder.

3.3.1. Unit tokenizer

A HuBERT model [14] followed by k-means clustering is used as the unit tokenizer to encode ground-truth speech into a sequence of discrete speech units as the prediction target \( Z = (z_1, z_2, ..., z_T) \), where \( z_i \in \{0, 1, ..., K - 1\} \) for \( 1 \leq i \leq T \) and \( K \) is the number of k-means centroids. The unit tokenizer is pretrained and frozen during DSU-AVO training.

3.3.2. Encoders

As speech progression is inherently linked with lip motion in real life [1, 27], we use lip image sequence cropped from the video clip as the input \( X_v \). The video encoder consists of a frozen visual feature extractor and feed-forward Transformer (FFT) [5, 10, 18] blocks. Visual features extracted by such an extractor pretrained on visual speech recognition tasks have strong correlation with phonetic information [27] and are efficient for aiding speech-related tasks [28, 29]. Input \( X_v \) is encoded into hidden visual representation \( H_v \in \mathbb{R}^{T_v \times d} \) where \( d \) is the dimension of hidden representations.

We adopt the same text encoder that is used in FastSpeech 2 [6] for TTS and in Neural Dubber [10] for AVO. It consists of an embedding layer followed by FFT blocks, to encode input phoneme \( X_p \) into hidden textual representation \( H_p \in \mathbb{R}^{T_p \times d} \).

3.3.3. Text-video aligner

We utilize a text-video aligner [1, 10] to temporarily align textual and visual representations by scaled dot-product attention [18], and produce text-video context with length \( T_v \):

\[
C = \text{softmax} \left( \frac{H_v H_p^T}{\sqrt{d}} \right) H_p + H_v
\]

\[
= AH_p + H_v \in \mathbb{R}^{T_v \times d}
\]

where \( H_v \) serves as the query, \( H_p \) serves as the key and the value, and \( A \in \mathbb{R}^{T_v \times T_p} \) is the attention weight matrix. \( H_v \) is added through residual connection to enhance alignment learning. \( C \) is then upsampled to match \( T_v \) by simply duplicating each frame of representation \( n \) times, where \( n \) is the audio-video length ratio.

We adopt the diagonal constraint loss \( L_{\text{diag}} \) following [10, 30] to shape diagonal attention.

3.3.4. Unit predictor

The accuracy of the prediction has a direct impact on the content correctness and intelligibility of the synthetic speech. A higher prediction accuracy results in a better perceptual quality of the synthetic speech. Hence, DSU-AVO focuses on predicting accurate discrete speech units.

The unit predictor consists of an FFT block that further models the context into a more deterministic representation for accurate unit prediction, followed by a softmax layer that maps output of the FFT block onto a probability distribution over a set of output classes, i.e., the discrete speech units \( \{0, 1, ..., K - 1\} \). Taking the context \( C \) produced by the text-video aligner as input, this module predicts a sequence of discrete speech units \( Z = (z_1, z_2, ..., z_T) \) with the same length of ground-truth discrete speech units \( Z \). The prediction is guided by minimizing the cross entropy loss \( L_{\text{pred}} \):

\[
L_{\text{pred}} = - \sum_{t=1}^{T_v} \sum_{k=0}^{K-1} z_{t,k} \log p_{t,k}(C)
\]

where \( z_{t,k} \) is the one-hot vector representing speech unit truth label at the \( t \)-th frame, and \( p_{t,k}(C) \) is the predicted softmax probability for unit \( k \) at the \( t \)-th frame, given context \( C \). Finally, the overall training criterion is \( L = L_{\text{pred}} + L_{\text{diag}} \).

3.3.5. Unit vocoder

We utilize Unit HiFi-GAN [16], which is pretrained on ground-truth \( < \text{units}, \text{waveform} > \) pairs without the speaker encoder and the F0 encoder in a single-speaker setting [31], as the unit vocoder. Given predicted units \( Z \), it generates speech audio as the output \( Y \) of AVO. As Unit HiFi-GAN models the mapping from discrete speech units to speech waveform without any spectrogram estimation [16], DSU-AVO does not need to model acoustic features for speech generation, thus alleviating the mismatch between context and acoustic features.

4. Experiments

4.1. Experimental setup

4.1.1. Dataset and preprocessing

We utilize Chem dataset [10] from Lip2Wave [32] to evaluate the performance of AVO frameworks. Chem dataset is a single-speaker audio-visual English speech dataset with official transcripts collected from YouTube. We use 6088 samples for train-
Table 1: Evaluation results of LSE-C, LSE-D, FD, WER, and MOS (with 95% confidence intervals). Arrows indicate whether higher or lower metric values are better.

<table>
<thead>
<tr>
<th>Method</th>
<th>LSE-C ↑</th>
<th>LSE-D ↓</th>
<th>FD ↓</th>
<th>WER(%) ↓</th>
<th>MOS ↑</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground Truth</td>
<td>7.00</td>
<td>7.51</td>
<td>NA</td>
<td>11.4</td>
<td>4.69 ± 0.06</td>
</tr>
<tr>
<td>Mel Resynthesis</td>
<td>6.89</td>
<td>7.40</td>
<td>0.66</td>
<td>11.8</td>
<td>4.58 ± 0.07</td>
</tr>
<tr>
<td>Unit Resynthesis</td>
<td>6.99</td>
<td>7.39</td>
<td>0.82</td>
<td>20.6</td>
<td>4.06 ± 0.08</td>
</tr>
<tr>
<td>FastSpeech 2 [6]</td>
<td>2.69</td>
<td>11.78</td>
<td>40.38</td>
<td>25.4</td>
<td>3.10 ± 0.09</td>
</tr>
<tr>
<td>Neural Dubber [10]</td>
<td>6.11</td>
<td>8.47</td>
<td>9.39</td>
<td>75.8</td>
<td>2.43 ± 0.12</td>
</tr>
<tr>
<td>DSU-AVO</td>
<td>6.81</td>
<td>7.56</td>
<td>3.23</td>
<td>24.7</td>
<td>3.98 ± 0.08</td>
</tr>
</tbody>
</table>

Table 2: Evaluation results of the BWS listening test on lip-speech synchronization. N/P stands for no preference.

<table>
<thead>
<tr>
<th>Method</th>
<th>Best(%)</th>
<th>Worst(%)</th>
<th>N/P(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FastSpeech 2 [6]</td>
<td>4.0</td>
<td>72.0</td>
<td>24.0</td>
</tr>
<tr>
<td>Neural Dubber [10]</td>
<td>12.0</td>
<td>26.7</td>
<td>61.3</td>
</tr>
<tr>
<td>DSU-AVO</td>
<td>84.0</td>
<td>1.3</td>
<td>14.7</td>
</tr>
</tbody>
</table>

We also conduct a Best-Worst Scaling (BWS) test [39] on lip-speech synchronization, where each subject views in total 10 scaling sets of videos and selects the best and the worst lip-speech synchronization from each set. The original pre-recorded speech samples in the test set videos are replaced with synthetic speech samples produced by system 3, 4, and 5. Table 2 shows that DSU-AVO outperforms baselines in terms of lip-speech synchronization, with the highest best votes (84.0%) and the lowest worst votes (1.3%).

4.2. Subjective evaluation

Human perception plays a crucial role in evaluating the performance of AVO, as the goal of AVO is to generate speech that appears natural to human observers. We conduct listening experiments, in which 15 listeners participate. In the mean opinion score (MOS) evaluation, each participant listens to 12 speech samples produced by each system and rates the speech audio quality on a five-point scale. As shown in Table 1, our proposed DSU-AVO produces speech with a higher level of naturalness than both baselines by achieving a MOS score of 3.98 ± 0.08.

We also conduct a Best-Worst Scaling (BWS) test [39] on lip-speech synchronization, where each subject watches in total 10 scaling sets of videos and selects the best and the worst lip-speech synchronization from each set. The original pre-recorded speech samples in the test set videos are replaced with synthetic speech samples produced by system 3, 4, and 5. Table 2 shows that DSU-AVO outperforms baselines in terms of lip-speech synchronization, with the highest best votes (84.0%) and the lowest worst votes (1.3%).

5. Conclusions

In this paper, we propose DSU-AVO, a novel AVO approach leveraging discrete speech units as the content representation. Our proposed method not only provides more direct supervision for alignment learning, but also alleviates the mismatch between context and acoustic features. Experimental results show that DSU-AVO outperforms baselines in terms of synthetic speech quality and lip-speech synchronization. In future work, we will investigate further modeling speech expressiveness with SSL speech representations for AVO.

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2. https://github.com/facebookresearch/speech-resynthesis
4. https://github.com/facebookresearch/av_hubert
6. References


