Direct simultaneous speech to speech translation

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Abstract

We present the first direct simultaneous speech-to-speech translation (Simul-S2ST) model, with the ability to start generating translation in the target speech before consuming the full source speech content and independently from intermediate text representations. Our approach leverages recent progress on direct speech-to-speech translation with discrete units. Instead of continuous spectrogram features, a sequence of direct representations, which are learned in an unsupervised manner, are predicted from the model and passed directly to a vocoder for speech synthesis. The simultaneous policy then operates on source speech features and target discrete units. Finally, a vocoder synthesize the target speech from discrete units on-the-fly. We carry out numerical studies to compare cascaded and direct approach on Fisher Spanish-English dataset.

1 Introduction

Simultaneous speech-to-speech (Simul-S2ST) translation is the task of incrementally translating speech in a source language to speech in another language given partial input only. It aims at applications where low latency is required, such as international conferences, where professional human interpreters usually serve the purpose. While a fair amount of research has been conducted on simultaneous translation, including text-to-text (Cho and Esipova, 2016; Gu et al., 2017; Ma et al., 2019a; Arivazhagan et al., 2019; Ma et al., 2019c), and speech-to-text (Ren et al., 2020; Ma et al., 2020c, 2021), few works have explored the speech-to-speech setting (Zheng et al., 2020b; Sudoh et al., 2020) which usually adopt the cascaded approach.

A cascaded Simul-S2ST system is usually composed of three parts, a streaming automatic speech recognition (ASR) system which transcribes source speech to source text, a simultaneous text-to-text system which translates source text to target text in a simultaneous fashion, and an incremental text-to-speech (TTS) synthesis system to generate target speech in real time. While the cascade systems can be built on top of existing models, it has several disadvantages. First, the pipeline of multiple models introduced extra latency. The latency can either come from the computation time of multiple models, or the delay caused by their asynchronous processing (Zheng et al., 2020b). Meanwhile, the compounding errors can be accumulated through a pipeline of systems.

Recent efforts on direct S2ST provide a new possibility for Simul-S2ST, where the intermediate representations, such as source or target text, is no longer needed. Jia et al. (2019) introduced Translatron model which generated speech spectrogram features on the target side. The gap with a cascaded system is bridged in a followup work Translatron 2 Jia et al. (2021). These approaches show potentials when there is more training data. However, the generation of continuous features in real-time can be computationally inefficient. More recently, Lee et al. (2021) proposed a direct S2ST model, where instead of spectrogram, a sequence of discrete units, learned in an unsupervised way, is directly generated from source speech, and passed to a vocoder for target speech synthesis. The vocoder can be trained separately and run on-the-fly given the discrete units.

In this work, we propose the first direct simultaneous speech-to-speech translation model, based on recent progress on speech-to-units (S2U) translation (Lee et al., 2021). The model has two characteristics at the same time. First the model is able to generate the target speech before the source speech is finished; second the model is independent from intermediate representations when generating target speech. We carry out experiments on Fisher Spanish-English dataset (Post et al., 2014) to show the differences between direct and cascaded model.
2 Task Formalization

We first formalize the task of simultaneous speech-to-speech translation (S2ST), including the definition of the task and its evaluation. Denote the $X(t)$, $Y(t)$ the amplitude of the input and output speech signal at a given time $t$. The duration of input and output speech are $T_X$ and $T_Y$. Assuming the input speech happens at $t = 0$ and the system starts generation at $t = T_0$, a system is defined as simultaneous S2ST system if $T_0 < T_X$. Note that in an offline system, $T_0 \geq T_X$. Similar to the translation task with text output, the evaluation for simultaneous S2ST includes two aspects, quality and latency. More specifically, the quality is evaluated by two aspects: the first one is the translation quality, for which an automatic speech recognition system is used to transcribe the generated speech and the transcription is then compared with reference translation.

The latency for Simul-S2ST systems, on the other hand, lacks a well defined metric. One of the most popular evaluation metrics for text-to-text simultaneous translation is average lagging (Ma et al., 2019a), which later was extended for speech-to-text translations (Ma et al., 2020c). Given a sequence of text predictions $Y = y_1, \ldots, y_N$ and corresponding timestamps $d(y_i)$ for generating $y_i$, the average lagging (AL) for a speech-to-text system is defined as

$$\text{AL} = \frac{1}{\tau(T_X)} \sum_{i=1}^{\tau(T_X)} d(y_i) - \frac{T_X}{|Y|} (i - 1) \quad (1)$$

Where the $\tau(T_X)$ is the first index of the target prediction that make use of the full source sentence. Note that the second term is the delay of an oracle system, which starts the translation at the every beginning and stops exactly when the source sentence finishes. To adapt AL to speech-to-speech task, similar to (Zheng et al., 2020b), we first run an ASR system on the target speech $Y(t)$ to generate $Y$, then use a force aligner aligner to align $Y$ with $Y(t)$ to acquire $d(y_i), i = 1, \ldots, N$. In this paper, to simulate a real world scenario, we only consider the computation-aware average lagging (Ma et al., 2020c), in which $d(y_i)$ includes computation time.

3 Background

3.1 Offline Direct S2ST with Direct Units

Recently, Lee et al. (2021) propose a method for offline direct S2ST with discrete units. First, unsupervised continuous representations at every 20-ms frame are learned on target speech corpus by a HuBERT model (Hsu et al., 2021). Then the k-means algorithm is applied to the representations to generate $K$ cluster centroids. For each window, found the it’s closest centroids index as it’s discrete label. Denote the discrete sequence as $Z = z_1, \ldots, z_L$. Given the discrete units, Lee et al. (2021) build a transformer-based (Vaswani et al., 2017) speech-to-unit (S2U) model. In the encoder, a stack of 1D-convolutional layers serve as downsampler for the speech input. Since the target sequence is discrete, the S2U model can be trained with cross-entropy loss. Finally, the vocoder converts the discrete units to speech signal. Lee et al. (2021) introduce a modified version of the HiFi-GAN neural vocoder (Kong et al., 2020) for unit-to-waveform conversion.

3.2 Wait-$k$ Policy

Wait-$k$ (Ma et al., 2019a) is a simple and commonly used policy for simultaneous translation. It first waits $k$ inputs, which can be words or characters for text inputs, and frames or fbank features for speech inputs, to collect some contextual information, then alternates between taking inputs and generating outputs.

4 Methodology

Figure 1 illustrate the architecture of the direct Simul-S2ST model with discrete units. The encoder reads the speech features with downsampling, and generates a sequence of hidden representations. Then the simultaneous policy replaces soft-attention in offline model to connect encoder and decoder. Because of the granularity of the encoder states, we follow the same setup as (Ma et al., 2020c) to use a fixed pre-decision module before applying the simultaneous policy. The policy contains two actions: READ and WRITE. The READ action indicates that the model takes another chunk of speech segment to update the encoder states. In this paper, we use the wait-$k$ policy introduced by (Ma et al., 2019a) In this work, we’re focusing on algorithmic latency and leave architectures such as emformer (Shi et al., 2021) with more efficient computation for future work.

A vocoder will be applied to the discrete units to synthesize the final speech output. Denote the emission rate $l$, the vocoder will be called every time $l$ units are predicted. Note that the vocoder is not used during training time. Because the
vocoder is trained on short speech segment in a non-autoregressive manner, as shown in the results, a small $l$ can achieve good latency without a huge sacrifice on quality.

Simultaneous translation. Simultaneous translation equips the model with the capability of live translation, generating outputs before it finishes reading complete inputs. A challenge in simultaneous translation is to find a good policy deciding when to start translation based on partial inputs, taking both the translation quality and latency into consideration.

Rule-based policies are used for reading and writing such as wait-if-diff and wait-if-worse policy (Cho and Esipova, 2016), and tunable agent policy (Dalvi et al., 2018). A simple yet efficient wait-$k$ strategy is proposed so that the model reads first $k$ inputs, and then alternate reads and writes with a given step (Ma et al., 2019b). In a simultaneous S2T model, speech segmenter splits the input streaming speech and the encoder-decoder attention adopts a wait-$k$ strategy (Ren et al., 2020).

Learned policies have attracted increasing attention due to their flexibility to balance the tradeoff between translation quality and latency. Monotonic multihead attention (MMA) is a variant of multilhead attention, enabling the model in partial input processing and incremental decoding (Ma et al., 2019c). An adaptive policy is designed via a heuristic composition of a set of fixed policies for a simultaneous S2T model (Zheng et al., 2020a).

5 Related Work

Speech-to-speech translation. The task of speech-to-speech translation translates speech in one language into speech in another. Earlier approaches are cascaded models consisting of automatic speech recognition (ASR), machine translation (MT) and text-to-speech synthesis (TTS). Recent studies make progress in direct S2S translation without relying on intermediate texts. In comparison with cascaded models, direct translation is faster in inference and free from error propagation in the pipeline. Translatron is a sequence-to-sequence model with a multitask objective to predict source and target transcripts as well as generating spectrograms of the target speech (Jia et al., 2019). Translatron2 is further proposed with improvements in voice preservation, speech naturalness and prediction robustness over Translatron (Jia et al., 2021). Instead of modeling spectrograms of the target speech, Lee et al. (2021) predicts discrete units which are learned from speech corpora in an self-supervised manner in its multitask learning framework for S2S training (Lee et al., 2021).

6 Experiments

We conduct experiments of simultaneous speech-to-speech translation on Fisher Spanish-to-English dataset (Post et al., 2014). The dataset The consists of 139k sentences from telephone conversations in Spanish, the corresponding Spanish text transcriptions and their English text translation. Same as (Lee et al., 2021), the target speech data is generated from a high-quality in-house TTS with a single female voice. We follow the same training setup as Lee et al. (2021), except that a masked attention for wait-$k$ policy is used for training (Ma et al., 2019a). As to inference, we use (Ma et al., 2020b) to simulate the real world setup with a server-client scheme.

The offline cascaded system we used as baseline consists of two components: S2T and TTS. The S2T model is the s2t_transformer_s architecture provided by FAIRSEQ S2T for speech-to-text translation (Wang et al., 2020). As for the TTS, we use a Transformer model with 6 layers, 4 atten-
|                | BLEU | CA AL (ms) |
|----------------|------|------------|
| Offline        |      |            |
| Cascaded (S2T+TTS) | 39.5 |            |
| Direct S2U     | 37.2 | -          |
| Simul          |      |            |
| Cascaded (S2T with wait-k + incremental TTS) | | |
| k=1            | 29.0 | 1317       |
| k=3            | 30.4 | 3109       |
| k=5            | 31.0 | 2004       |
| k=10           | 32.7 | 3476       |
| k=15           | 32.9 | 3803       |
| k=20           | 33.3 | 4099       |
| k=25           | 33.7 | 4460       |
| Direct S2U with wait-k | | |
| k=5            | 22.2 | 1757       |
| k=10           | 27.9 | 3520       |
| k=15           | 33.5 | 4127       |
| k=20           | 34.3 | 4409       |

Table 1: BLEU scores and latency of models on the Fisher Spanish-English dataset.

As to the simultaneous cascaded system, its S2T module has the same architecture as the offline S2T Transformer, and wait-k strategy is integrated to enable simultaneous speech-to-text translation. Meanwhile, for computational efficiency, we adapt the non-autoregressive FastSpeech 2 model (Ren et al., 2021) as the incremental TTS component. It incrementally generates utterances word-by-word, utilizing the duration predictor for segmenting output word boundaries (Stephenson et al., 2021). It further uses a lookahead of 1 word, which is equivalent to a wait-k strategy at test-time (Ma et al., 2019b, 2020a), where k is two words. When running offline inference, this cascaded system scores 38.1 BLEU on the test set.

Translation quality and efficiency are important for simultaneous translation models. Following the evaluation of speech quality (Lee et al., 2021), we transcribe the generated speech with a pre-trained ASR model, and measure the BLEU score by comparing the transcription and the reference. To have a fair comparison with offline model, discontinuities are not considered while transcribing of real-time target speech. The computation-aware (Ma et al., 2020c) version of Average Lagging (AL) (Ma et al., 2019a) is used to measure the latency as previous works of simultaneous translation.

7 Results

The full results is shown as Table 1. We include offline speech-to-speech models which provide an upper bound of the translation quality. In the offline setting, the direct S2S model falls behind the cascaded model by 2.3 BLEU. As for the simultaneous setting, latency is an important factor besides the translation quality. Comparing two models, we can find that the direct approach has higher BLEU score on the high latency setting (> 4000 ms). Considering the difference between offline and direct models, the better performance for direct model on high latency shows that it has the ability to handle the compounding errors. However, in low latency region (< 4000 ms), the translation quality for direct model drop significantly. The potential reason can be in wait-k policy, a small look-ahead of k hurts the discrete units more than characters. A direction of further work can be designing a simultaneous policy specifically for discrete units.

8 Conclusion

In this work, we propose the first direct simultaneous speech-to-speech translation model. We compare the direct approach with cascaded approach. The results show that the while the direct model can reduce the compounding errors on high latency region, the simple wait-k hurts its performance under low latency settings.

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1 Wait-(k + 1) is equivalent to lookahead-k following the definition in (Ma et al., 2020a)
References

Naveen Arivazhagan, Colin Cherry, Wolfgang Macherey, Chung-Cheng Chiu, Semih Yavuz, Ruoming Pang, Wei Li, and Colin Raffel. 2019. Monotonic infinite lookback attention for simultaneous machine translation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1313–1323, Florence, Italy. Association for Computational Linguistics.

Kyunghyun Cho and Masha Esipova. 2016. Can neural machine translation do simultaneous translation? arXiv preprint arXiv:1606.02012.

Fahim Dalvi, Nadir Durrani, Hassan Sajjad, and Stephan Vogel. 2018. Incremental decoding and training methods for simultaneous translation in neural machine translation. In NAACL-HLT (2).

Jiatao Gu, Graham Neubig, Kyunghyun Cho, and Victor OK Li. 2017. Learning to translate in real-time with neural machine translation. In 15th Conference of the European Chapter of the Association for Computational Linguistics. EACL 2017, pages 1053–1062. Association for Computational Linguistics (ACL).

Wei-Ning Hsu, Benjamin Bolte, Yao-Hung Hubert Tsai, Kushal Lakhota, Ruslan Salakhutdinov, and Abdelrahman Mohamed. 2021. Hubert: Self-supervised speech representation learning by masked prediction of hidden units. arXiv preprint arXiv:2106.07447.

Ye Jia, Michelle Tadmor Ramanovich, Tal Remez, and Roi Pomerantz. 2021. Translatotron 2: Robust direct speech-to-speech translation. arXiv preprint arXiv:2107.08661.

Ye Jia, Ron J Weiss, Fadi Biadsy, Wolfgang Macherey, Melvin Johnson, Zhifeng Chen, and Yonghui Wu. 2019. Direct speech-to-speech translation with a sequence-to-sequence model. arXiv preprint arXiv:1904.06037.

Jungil Kong, Jaehyeon Kim, and Jaekyoung Bae. 2020. HiFi-GAN: Generative adversarial networks for efficient and high fidelity speech synthesis. Advances in Neural Information Processing Systems, 33.

Ann Lee, Peng-Jen Chen, Changhan Wang, Jiatao Gu, Xutai Ma, Adam Polyak, Yossi Adi, Qing He, Yun Tang, Juan Pino, et al. 2021. Direct speech-to-speech translation with discrete units. arXiv preprint arXiv:2107.05604.

Mingbo Ma, Liang Huang, Hao Xiong, Renjie Zheng, Kaibo Liu, Baigong Zheng, Chuanqiang Zhang, Zhongjun He, Hairong Liu, Xing Li, et al. 2019b. Stacl: Simultaneous translation with implicit anticipation and controllable latency using prefix-to-prefix framework. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 3025–3036, Florence, Italy. Association for Computational Linguistics.

Mingbo Ma, Baigong Zheng, Kaibo Liu, Renjie Zheng, Hairong Liu, Kainan Peng, Kenneth Church, and Liang Huang. 2020a. Incremental text-to-speech synthesis with prefix-to-prefix framework. In Findings of the Association for Computational Linguistics: EMNLP 2020, pages 3886–3896, Online. Association for Computational Linguistics.

Xutai Ma, Mohammad Javad Dousti, Changhan Wang, Jiatao Gu, and Juan Pino. 2020b. Simuleval: An evaluation toolkit for simultaneous translation. arXiv preprint arXiv:2007.16193.

Xutai Ma, Juan Pino, James Cross, Liezl Puzon, and Jiatao Gu. 2020c. SimulMT to SimulST: Adapting Simultaneous Text Translation to End-to-End Simultaneous Speech Translation. In Proceedings of 2020 Asia-Pacific Chapter of the Association for Computational Linguistics and the International Joint Conference on Natural Language Processing.

Xutai Ma, Juan Miguel Pino, James Cross, Liezl Puzon, and Jiatao Gu. 2019c. Monotonic multhead attention. In International Conference on Learning Representations.

Xutai Ma, Yongqiang Wang, Mohammad Javad Dousti, Philipp Koehn, and Juan Pino. 2021. Streaming simultaneous speech translation with augmented memory transformer. In ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 7523–7527. IEEE.

Matt Post, Gaurav Kumar, Adam Lopez, Damianos Karakos, Chris Callison-Burch, and Sanjeev Khudanpur. 2014. Fisher and callhome spanish–english speech translation.

Yi Ren, Chenxu Hu, Xu Tan, Tao Qin, Sheng Zhao, Zhou Zhao, and Tie-Yan Liu. 2021. Fastspeech 2: Fast and high-quality end-to-end text to speech. In 9th International Conference on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3-7, 2021. OpenReview.net.

Yi Ren, Jinglin Liu, Xu Tan, Chen Zhang, QIN Tao, Zhou Zhao, and Tie-Yan Liu. 2020. Simulspeech: End-to-end simultaneous speech to text translation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 3787–3796.

Yangyang Shi, Yongqiang Wang, Chunyang Wu, Ching-Feng Yeh, Julian Chan, Frank Zhang, Duc Le, and Mike Seltzer. 2021. Emformer: Efficient memory transformer based acoustic model
for low latency streaming speech recognition. In *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 6783–6787. IEEE.

Brooke Stephenson, Thomas Hueber, Laurent Girin, and Laurent Besacier. 2021. *Alternate Endings: Improving Prosody for Incremental Neural TTS with Predicted Future Text Input*. In *Proc. Interspeech 2021*, pages 3865–3869.

Katsuhito Sudoh, Takatomo Kano, Sashi Novitasari, Tomoya Yanagita, Sakriani Šákti, and Satoshi Nakamura. 2020. Simultaneous speech-to-speech translation system with neural incremental asr, mt, and tts. *arXiv preprint arXiv:2011.04845*.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. *Attention is all you need*. In *Advances in neural information processing systems*, pages 5998–6008.

Changhan Wang, Yun Tang, Xutai Ma, Anne Wu, Dmytro Okhonko, and Juan Pino. 2020. Fairseq s2t: Fast speech-to-text modeling with fairseq. In *Proceedings of the 1st Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 10th International Joint Conference on Natural Language Processing: System Demonstrations*, pages 33–39.

Baigong Zheng, Kaibo Liu, Renjie Zheng, Mingbo Ma, Hairong Liu, and Liang Huang. 2020a. Simultaneous translation policies: From fixed to adaptive. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 2847–2853.

Renjie Zheng, Mingbo Ma, Baigong Zheng, Kaibo Liu, Jiahong Yuan, Kenneth Church, and Liang Huang. 2020b. *Fluent and low-latency simultaneous speech-to-speech translation with self-adaptive training*. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 3928–3937, Online. Association for Computational Linguistics.