Incremental Speech Synthesis For Speech-To-Speech Translation

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Abstract

In a speech-to-speech translation (S2ST) pipeline, the text-to-speech (TTS) module is an important component for delivering the translated speech to users. To enable incremental S2ST, the TTS module must be capable of synthesizing and playing utterances while its input text is still streaming in. In this work, we focus on improving the incremental synthesis performance of TTS models. With a simple data augmentation strategy based on prefixes, we are able to improve the incremental TTS quality to approach offline performance. Furthermore, we bring our incremental TTS system to the practical scenario in combination with an upstream simultaneous speech translation system, and show the gains also carry over to this use-case. In addition, we propose latency metrics tailored to S2ST applications, and investigate methods for latency reduction in this context.

1 Introduction

Speech-to-speech translation (S2ST) (Lavie et al., 1997; Nakamura et al., 2006) is the task of translating input speech utterances into speech in another language. Compared to translating into text alone, offering speech output enriches the system’s output modality and could provide users with increased accessibility. While recently textless S2ST (Tjandra et al., 2019; Jia et al., 2019; Lee et al., 2021; Jia et al., 2021) have shown encouraging results, the text-based pipeline remains a strong baseline. In a text-based speech-to-speech translation pipeline, the text-to-speech (TTS) module is an essential component. It follows an upstream speech-to-text (ST) system and transforms the translated text to speech. For use cases with real-time constraints, such as simultaneous interpretation, users expect the output speech utterances to be delivered with a minimal latency. In this case, the speech translation system needs to produce outputs before the full input is available. Given a simultaneous ST system (Ma et al., 2020b, 2021), the corresponding TTS module must also be capable of incremental inference to deliver low-latency speech translation.

In addition to the requirement of fast computation, there are several challenges in incremental TTS. First, given limited input context, full-sentence TTS models are likely to underperform. Second, partial utterances often have different prosodic features from full utterances, such as utterance-final lengthening (Cooper and Danly, 1981; Berkovits, 1993), where articulation slows down towards the end of sentences. To produce natural-sounding speech, the model needs to account for the different prosodies. Moreover, as the TTS module outputs speech chunks incrementally, we need a reliable and accessible alignment between source tokens and target frames in order to segment the speech chunks corresponding to given input positions.

In light of these challenges, in this work, we focus on FastSpeech2 (Ren et al., 2021), a recent non-autoregressive TTS model with hard monotonous source-target alignment. We adapt the model using partial sequences and show this simple approach can largely improve incremental synthesis performance. Furthermore, we propose to measure latency tailoring to real-time constraints for S2ST, and show that our approach, when combined with an upstream simultaneous translation system, also leads to better translated speech.

2 Background: Speech Synthesis

Given an input text sequence \(X_{1:N}\), the task of speech synthesis aims to create an audio waveform \(Z_{1:M}\) containing the spoken form of the given text. Currently, the task is often decomposed into two stages (Tan et al., 2021): 1) text-to-spectrogram transformation, and 2) spectrogram-to-waveform transformation (i.e. vocoding). In the first step, we
synthesize spectrogram $Y_{1:T}$, which is a compact representation of the final waveform. Given the synthesized spectrogram $Y$, a vocoder is used to construct the final waveform $Z$.

The text-to-spectrogram transformation can be further split into steps. After the source sequence is transformed into an abstract representation, the model creates the alignment between $X$ and $Y$. Next, variance information (e.g., pitch, energy) is reconstructed to form the final spectrogram.

In the incremental use-case we consider next, the source-target alignment is essential as it indicates how the output speech corresponds to the input tokens. With encoder-decoder-attention models such as Tacotron 2 (Shen et al., 2018), the alignment is learned via source-target attention. Specifically, the alignment between source $X_i$ and target $Y_t$ is:

$$
\alpha_{i,t} = \sigma(attention(X_i, Y_{t-1})),
$$

where $\sigma(\cdot)$ is the softmax function that normalizes the attention scores over all $i \in [1, N]$.

An alternative for deriving the alignment information is by a duration predictor (Ren et al., 2021) trained using duration signals derived by forced alignment. The source-target alignment is determined by a duration prediction function $D(\cdot)$. Specifically, given $X_{1:N}$, $D(X)$ outputs the number of spectrogram frames for each input position $i \in [1, N]$. The source-target alignment between source position $i$ and target position $t$ is therefore:

$$
\alpha_{i,t} = \begin{cases} 
1, & \text{if } \sum_{j=1}^{t-i} D(j) \leq \sum_{j=1}^{i} D(j) \\
0, & \text{otherwise}.
\end{cases}
$$

By definition of Equation 2, the source-target alignment from the duration predictor is monotonic and hard, unlike source-target attention in Equation 1. An advantage of the hard, monotonic alignment is a clear correspondence between source tokens and target spectrogram frames, which allows us to decide word boundaries. More importantly, $D(\cdot)$ computes in parallel for all input positions. In contrast, with autoregressive models the frames are generated sequentially at inference time.

Given the latency constraints for incremental use-cases, non-autoregressive models are advantageous as they consume less computation time. However, most existing works (Yanagita et al., 2019; Stephenson et al., 2020; Ma et al., 2020a; Mohan et al., 2020) on incremental TTS are based on autoregressive models, notably Tacotron 2 (Shen et al., 2018). An exception is the recent work by Stephenson et al. (2021), which builds upon FastSpeech 2 (Ren et al., 2021). While we focus on the same model, our emphasis is the its application in S2ST scenarios.

## 3 Incremental TTS for S2ST

In this section, we first propose approaches to adapt offline TTS models for incremental inference. After confirming their performance on the TTS task, we apply them in combination with an upstream ST system for speech-to-speech translation.

### 3.1 Incremental TTS Framework

**Incremental Synthesis Framework** Given partial input $X_{1:j}$, a subset of full input $X_{1:N}$, the task is to synthesize and play the frames up to those corresponding to $X_j$. While the TTS task has monotonic source-target alignment and has relatively local context dependency, additional future context can still be helpful. We therefore optionally include a lookahead of some input phonemes. Given $k$ additional lookahead phonemes, we synthesize up till $X_{j+k}$ but only output those frames up to $X_j$. This is similar to the wait-$k$ method proposed by (Ma et al., 2020a). Different in our work is that we utilize the duration prediction function $D(\cdot)$ to derive word boundaries in predicted spectrogram.

Noteworthy is that synthesizing for longer utterance does not increase computation time due to parallel computation of the non-autoregressive model. Subsequently, the synthesized spectrogram is passed to vocoder, and the waveform is played.

**Prefix Augmentation** In standard training conditions, the model has only seen full sentences. When facing incomplete inputs at inference time, the output quality will likely drop. To tackle this challenge, prefix augmentation has been shown useful in simultaneous translation (Niehues et al., 2018; Arivazhagan et al., 2020). We therefore apply this technique to TTS. As FastSpeech 2 consumes time-aligned input, we can split partial sequences accordingly using this information. Furthermore, as prosodic features differ in the middle and end of sentences (Berkovits, 1993), we use the presence of the end-of-sentence (EOS) token to distinguish between partial and full sentences.

### 3.2 Measuring TTS Latency

**Current Latency Metrics** When measuring latency of incremental TTS systems, many current
works (Yanagita et al., 2019; Ma et al., 2020a; Mohan et al., 2020) discuss the amount of input text the model ingests before producing any output utterances. While this metric does correspond to the system response time, it does not fully capture the real-time constraints in speech-to-speech translation applications. As illustrated in Figure 1, although the TTS module starts with minimal delay by only waiting for the first text token, if the output speech has prolonged duration compared to the input tokens, the full speech utterance still finishes late. As multiple output utterances cannot play concurrently, the next utterance cannot play until the current utterance finishes playing. Indeed, this accumulated delay has been shown a great challenge in streaming conditions (Sudoh et al., 2020).

![Figure 1: Illustration of prolonged latency where the output speech ends much later than the last input token. While the synthesized speech is playing, no subsequent utterances can play concurrently.](image)

Chosen TTS Latency Metrics As motivated above, a more suitable latency metric is based on the time elapsed between end points of the input and output. To calculate the elapsed time, we need timestamps on input tokens. The timestamps of input tokens can be derived from forced alignment such as MFA (McAuliffe et al., 2017). When evaluating the latency of a TTS module alone, following (Ma et al., 2020a), we assume the TTS module is repeating after ground-truth input speech, and report the difference between the input end timestamp and output end timestamp. We refer to this as stand-alone TTS latency. In practice, when the TTS module consumes inputs from an upstream translation system, we have timestamps associated to incoming tokens. Furthermore, since the translation system are often subword-based, we account for the time elapsed when waiting to aggregate the subwords. We refer to this as S2ST latency.

Algorithm 1 details the calculation of the latency of an utterance. It can be seen that the resulting latency is an interplay of three factors: 1) when the input for synthesizing a given chunk arrived (EMIT\_TIME\(\cdot\)), 2) computation time for synthesizing the chunk (COMPUTE\_TIME\(\cdot\)), 3) when the previous chunk finished playing (dependent on DURATION\(\cdot\)).

### 3.3 Experimental Setup

**Data** We build incremental TTS models for English and Spanish. LJSpeech (Ito and Johnson, 2017) and CSS10 Spanish (Park and Mulc, 2019) are used respectively for model training. The phoneme durations are derived by Montreal Forced Alignment (McAuliffe et al., 2017). We use HiFiGAN (Kong et al., 2020) as vocoder. In speech-to-speech translation experiments, the upstream speech-to-text system is trained on the Fisher Spanish-English (Post et al., 2013) dataset.

**Models and Training** When training the TTS model, we follow the hyperparameters from (Ren et al., 2021) and train for 200k updates. When applying prefix augmentation, we keep an equal ratio between prefixes and full sentences. The prefixes are 1/3 or 2/3 of the full sentence lengths. In
| Test Condition | Quality | Latency |
|---------------|---------|---------|
|               | MCD↓  | CER(%)↓ | MOS*↑  | S2ST latency (s)↓ | stand-alone latency(s)↓ |
| LJSpeech      |        |         |        |
| (2) Ground truth Mel | -     | 3.2±0.0 | 3.66±0.29 | - | - |
| (3) Offline    | 3.5    | 4.8±0.1 | 3.71±0.17 | 5.8 | 6.2 |
| (4) No lookahead | 4.7   | 8.2±0.2 | 2.96±0.26 | 2.5 | 2.4 |
| (5) Lookahead 1 word | 3.9   | 5.6±0.2 | 3.43±0.27 | 1.9 | 1.4 |
| (6) Lookahead 1 phoneme | 4.2  | 6.5±0.1 | 3.41±0.33 | 1.9 | 1.8 |
| After augmentation: |        |         |        |
| (7) Offline    | 3.6    | 5.0±0.2 | 3.80±0.20 | 5.8 | 6.5 |
| (8) No lookahead | 3.8   | 5.9±0.3 | 3.27±0.40 | 1.2 | 1.1 |
| (9) Lookahead 1 word | 3.7   | 5.1±0.1 | 3.61±0.16 | 1.7 | 1.8 |
| (10) Lookahead 1 phoneme | 3.7  | 5.2±0.2 | 3.35±0.25 | 1.7 | 1.9 |
| CSS10-es      |        |         |        |
| (12) Ground truth Mel | -     | 5.2±0.0 | *       | - | - |
| (13) Offline    | 3.6    | 5.0±0.3 | *       | 7.9 | 6.4 |
| (14) No lookahead | 5.1   | 13.2±0.5 | *       | 0.8 | 2.1 |
| (15) Lookahead 1 word | 3.9   | 8.5±0.9 | *       | 0.9 | 1.5 |
| (16) Lookahead 1 phoneme | 4.5  | 8.7±0.3 | *       | 0.9 | 1.4 |
| After augmentation: |        |         |        |
| (17) Offline    | 3.6    | 5.0±0.3 | *       | 7.9 | 6.4 |
| (18) No lookahead | 3.8   | 7.1±0.5 | *       | 0.6 | 0.9 |
| (19) Lookahead 1 word | 3.6   | 5.2±0.2 | *       | 0.9 | 1.5 |
| (20) Lookahead 1 phoneme | 3.7  | 5.9±0.2 | *       | 0.9 | 1.4 |

Table 1: Summary of quality and latency on two datasets: 1) LJSpeech (100 test utterances); 2) CSS10 Spanish (107 test utterances). Results are averaged over 3 independent runs. For CER, we include 95% confidence interval (CI). For MCD and latency, the CI is less than 0.1 and therefore omitted for brevity. *: MOS scores may need further filtering of outliers as MTurk annotations are highly noisy. MOS evaluation on CSS10-es is still in progress.

Speech-to-speech experiments, the upstream simultaneous ST system is a Transformer model with wait-\(k\) policy. The model architecture is as defined in \texttt{s2t_transformer_s} model from the Fairseq S2T toolkit \cite{Wang2020}.

**Quality Evaluation** To evaluate the quality of incremental synthesis, we concatenate the incremental chunks into full utterances for evaluation. As shown in the latency calculation in Algorithm 1, depending on the input timestamps, it can occur that the TTS module stands idle waiting for input text. In this case, there will be discontinuity (silence) in the synthesized speech. When evaluating the TTS module alone, the discontinuity is minimal. When working with an upstream ST system, discontinuities occur more often. Therefore, in this scenario, we evaluate the full utterances with and without discontinuities.

Following previous works \cite{Weiss2021, Wang2021}, we use Mel cepstral distortion (MCD) and character error rates (CER) for automatic evaluation of TTS quality. MCD is computed between the HiFi-GAN vocoded utterances from the ground-truth and synthesized Mel spectrograms. The English ASR system for LJSpeech is a wav2vec 2.0 \cite{Baevski2020} model. The Spanish ASR system for CSS10-es is a XLSR-53 \cite{Conneau2020} model fine-tuned on Common Voice Spanish data\(^1\). For speech-to-speech experiments, we transcribe the final synthesized utterances with the ASR system and report BLEU scores\(^2\) against the references. For subjective evaluation, we collect mean opinion scores (MOS) on MTurk by asking annotators to rate speech naturalness on a scale of 1–5.

**Latency Evaluation** We measure latency using the metrics described in subsection 3.2. While the stand-alone TTS latency is straightforward to calculate, for the S2ST latency, we need to make some assumptions since the input text do not come from a simultaneous ST system. We segment the input text into subwords by an openly available SentencePiece model \cite{Goyal2021}. We assume the incoming subword tokens appear at a fixed rate, in accordance with the behavior of the widely-adopted

\[^1\]https://huggingface.co/jonatasgrosman/wav2vec2-large-xlmr-53-spanish
\[^2\]sacrebleu token: BLEU+case.mixed+numrefs.1+smooth.exp+tok.13a+version.1.5.1
wait-\(k\) decoding strategy (Ma et al., 2019). We assume a fixed rate of 280ms, as chosen in recent work on simultaneous speech translation (Ma et al., 2020b). Computation time is included in the latency. The outputs are synthesized one utterance at a time on an Nvidia V100 GPU.

3.4 Incremental TTS Results

In Table 1 we summarize the results of incremental decoding.

Results of Naïve Incremental Decoding First, by contrasting Rows (4) and (14) against the offline performance in Rows (3) and (13), we see naïvely decoding largely falls behind offline performance in terms of all the quality metrics. Interestingly, although this strategy directly outputs utterances without waiting for any future inputs, its latency is significantly higher than other strategies that do wait (Rows (5-6) and (15-16)). The increased latency is caused by prolonged durations of synthesized chunks, as also observed in the recent work by Stephenson et al. (2021). As every word is treated as if it were end-of-sentence, the synthesized audio carries utterance-final lengthening (Cooper and Danly, 1981; Berkovits, 1993). When manually inspecting the utterances, we also hear dropping intonations common at end of sentences. Both observations above suggest that it could be helpful to distinguish between intermediate and full input sequences.

Impact of Lookahead By allowing a lookahead to the next word (Row (5) vs (4); (15) vs (14)), we largely improve over the case of without lookahead. As the lookahead buffers away utterance-final lengthening, the predicted durations are better-regulated, hence restoring the latency. Furthermore, by looking ahead only to the next phoneme, from the automatic evaluation metrics, we still see a large quality gain compared to no lookahead. This could be explained by the TTS task having highly local context dependency.

Impact of Prefix Augmentation After training with prefix augmentation, the quality scores of incremental decoding are improved regardless of decoding strategy (Rows (8-10) vs (4-6); Rows (18-20) vs (14-16)). Notably, when looking ahead to one next phoneme, we have a small gap to offline performance (Row (10) vs (3); (20) vs (13)).

Comparison of Two Latency Metrics On LJSpeech, S2ST latency is highly correlated to stand-alone latency. By manual inspection of the samples, we observe that the words with longer durations are more often split into multiple subwords. This implicitly causes the end timestamps of words (as used in S2ST latency) to become similar to those in ground-truths speech (as used in stand-alone latency). In the CSS10-Spanish case, the two latency metrics are not always in line with each other. Compared to the English inputs in LJSpeech, our subword model more often splits words into multiple subwords, causing full words to become available relatively slowly. This highlights the impact of input speed on the final latency, which will be further investigated in subsection 4.1.

3.5 Combination with ST System

After assessing the performance of incremental TTS systems alone, we investigate the practical use-case of combining it with an upstream ST system. As described in subsection 3.3, we use an Spanish-to-English simultaneous ST system with a wait-\(k\) policy. For incremental TTS of the translated text in English, we use the systems trained on LJSpeech. The results are summarized in Table 2. We compare results based on two upstream ST systems with different latency regimes defined in recent simultaneous ST evaluation campaigns (Ansari et al., 2020; Anastasopoulos et al., 2021).

| TTS system | BLEU |
|------------|------|
| **wait-5 (low-latency)** | |
| Lookahead 1 word | 31.0 / 24.8 |
| + augmentation | 34.5 / 25.9 |
| **wait-15 (medium-latency)** | |
| No lookahead | 30.0 / 25.8 |
| + augmentation | 33.2 / 26.7 |
| Lookahead 1 word | 32.9 / 28.0 |
| + augmentation | 35.0 / 29.2 |

Table 2: Incremental TTS performance when synthesizing translated text from an simultaneous speech translation system. BLEU scores (without / with discontinuities) are calculated between ASR transcriptions of synthesized speech and reference.

Confirming the findings from subsection 3.4, the stronger incremental TTS systems (with prefix augmentation and lookahead) also lead to improved output speech as indicated by higher BLEU scores. This shows that the improvements in incremental TTS does carry over when applied in a simultaneous speech-to-speech translation pipeline.
By contrasting the BLEU scores on utterances with and without discontinuities, we see a large degradation after considering the more realistic case of including discontinuities. While this is likely related to the ASR system only being trained on fluent speech and therefore underperforming when transcribing discontinuous utterances, the discontinuities could negatively impact user experience. We leave the handling of discontinuities for next steps.

As for S2ST latency, since we measure the difference between input and output end timestamps, the additional latency of opting for a higher-latency upstream ST system is not reflected in this metric. The S2ST latency of the presented systems are all around 1.8 seconds.

4 Further Latency Reduction

As illustrated by the latency calculation in Algorithm 1, the final latency is an interplay of three factors: 1) when the synthesis process started; 2) the duration of the output speech; 3) computation time for synthesizing speech. This observation will motivate the next approach to further reduce latency for a given incremental TTS system.

4.1 Modulate Speed of Output Speech

As found in previous work (Sudoh et al., 2020), a great challenge for simultaneous speech-to-speech translation systems is the accumulated latency from the incremental TTS. Specifically, the latency accumulates as multiple input tokens queue up for the incremental TTS module to synthesize.

Table 3: Impact of input/output speed on latency. S2ST latency is highly sensitive to the speed of incoming text tokens. By scaling the speed of the output speech, we are able to largely reduce latency without sacrificing audio intelligibility.

| 1 subword per x s | Output speed scaling factor | S2ST latency (s) | CER (%) |
|-------------------|-----------------------------|------------------|--------|
| 0.28              | 1.00                        | 1.8              | 5.3    |
| 0.25              | 2.2                         | 2.2              | 5.3    |
| 0.22              | 3.1                         | 3.1              | 5.3    |
| 0.28              | 0.95                        | 1.6              | 5.7    |
| 0.25              | 1.0                         | 1.0              | 5.7    |
| 0.22              | 2.3                         | 2.3              | 5.7    |

In previous experiments, we either assumed a constant rate where input tokens stream in, or used actual timestamps from a simultaneous ST system. Here, we first investigate how much the speed of incoming text tokens influences latency. Then, to counteract the accumulated delay, we propose to modulate the speed of the output speech.

As shown in Table 3, when input tokens comes in at a higher speed, as the speed of the output utterance remains unchanged, the S2ST latency is accumulated. Notably, the latency is highly sensitive to how fast input comes in. For example, in the upper section of Table 3, a difference of 0.06s per token results in a increase of 1.3 seconds in latency.

In FastSpeech 2 (Ren et al., 2021), the duration predictor allows us to scale the output speed without altering its prosody. As shown in the lower sections of Table 3, by moderately speeding up the output speech, we are able to counteract the latency induced by faster incoming tokens. Furthermore, based on the ASR results, this does not sacrifice audio intelligibility.

5 Related Work

Incremental Speech Synthesis Before the emergence of neural TTS, several works based on traditional parametric approaches (Baumann and Schlangen, 2012; Baumann, 2014; Pouget et al., 2016; Yanagita et al., 2018) investigated incremental TTS. Recent works on incremental neural speech synthesis (Yanagita et al., 2019; Ma et al., 2020a; Stephenson et al., 2020; Mohan et al., 2020) are mostly based on autoregressive models, notably the Tacotron series (Wang et al., 2017; Shen et al., 2018).

To handle incremental input segments at inference time, Yanagita et al. (2019) propose to augment the original training data by shorter segments 1/3 of the original sentence length. While our work also utilizes partial sequence augmentation, our augmentation is based on prefixes, with the goal of promoting consistency before and after more future context is received. Ma et al. (2020a) adapt the wait-k policy (Ma et al., 2019) developed for simultaneous machine translation. Stephenson et al. (2020) investigate the impact of lookahead and report that shorter words depends more on future context than longer ones. Mohan et al. (2020) model the read-write choice in incremental TTS using the reinforcement learning framework. The afore-
mentioned works are based on Tacotron (Wang et al., 2017; Shen et al., 2018), where the autoregressive decoding is sequential and therefore time-consuming, especially given the long output sequences for speech generation. Our incremental synthesis approach is probably closest to (Stephenson et al., 2021), which is also based on FastSpeech 2 (Ren et al., 2021). While the goal in (Stephenson et al., 2021) is to predict the next word to avoid the latency from waiting for future input, our work aims to improve the incremental synthesis quality in general with a special focus on speech-to-speech translation scenarios.

Speech-to-Speech Translation

Conventional systems for S2ST consist of a cascade of ASR, MT, and TTS components (Lavie et al., 1997; Nakamura et al., 2006). While many recent efforts are devoted combining the ASR and MT steps into one end-to-end system (Inaguma et al., 2019; Di Gangi et al., 2019; Sperber et al., 2019), approaches for fully end-to-end modeling of S2ST are still rarely explored (Jia et al., 2019, 2021; Lee et al., 2021). A recent approach (Lee et al., 2021) relies on HuBERT (Hsu et al., 2021) units, where speech is translated into hidden units to and then synthesized to waveforms. While this approach enables the translation of unwritten languages, currently there remains a performance gap to speech-to-text and text-to-speech pipeline (Lee et al., 2021). The cascade of ST and TTS still being a strong baseline justifies the relevance of further exploring incremental TTS.

6 Conclusion

In this work, we investigate incremental text-to-speech with a special focus on its application to speech-to-speech translation. After showing downsides of naïve incremental decoding, we utilize prefix augmentation to largely improve the quality of synthesized speech. By assessing the developed incremental TTS modules in combination with upstream speech translation systems, we show that the improvements in TTS quality carries over to speech-to-speech translation scenarios. Furthermore, by analyzing the multiple factors affecting final latency, we propose directions to further reduce the latency of incremental TTS.

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