

A Non-autoregressive Generation Framework for End-to-End Simultaneous Speech-to-Any Translation

Zhengrui Ma^{1,3}, Qingkai Fang^{1,3}, Shaolei Zhang^{1,3}, Shoutao Guo^{1,3}
Yang Feng^{1,2,3*}, Min Zhang⁴

¹Key Laboratory of Intelligent Information Processing
Institute of Computing Technology, Chinese Academy of Sciences

²Key Laboratory of AI Safety, Chinese Academy of Sciences

³University of Chinese Academy of Sciences

⁴School of Future Science and Engineering, Soochow University

{mazhengrui21b, fengyang}@ict.ac.cn zhangminmt@hotmail.com

Abstract

Simultaneous translation models play a crucial role in facilitating communication. However, existing research primarily focuses on text-to-text or speech-to-text models, necessitating additional cascade components to achieve speech-to-speech translation. These pipeline methods suffer from error propagation and accumulate delays in each cascade component, resulting in reduced synchronization between the speaker and listener. To overcome these challenges, we propose a novel non-autoregressive generation framework for simultaneous speech translation (NAST-S2x¹), which integrates speech-to-text and speech-to-speech tasks into a unified end-to-end framework. We develop a non-autoregressive decoder capable of concurrently generating multiple text or acoustic unit tokens upon receiving fixed-length speech chunks. The decoder can generate blank or repeated tokens and employ CTC decoding to dynamically adjust its latency. Experimental results show that NAST-S2x outperforms state-of-the-art models in both speech-to-text and speech-to-speech tasks. It achieves high-quality simultaneous interpretation within a delay of less than 3 seconds and provides a 28× decoding speedup in offline generation.²

1 Introduction

Simultaneous machine translation (Cho and Esipova, 2016; Gu et al., 2017; Raffel et al., 2017; Ma et al., 2019; Arivazhagan et al., 2019) models are widely applied in communication scenarios, eliminating barriers between individuals with different linguistic backgrounds. In practice, simultaneous translation systems can be broadly categorized into speech-to-text (Simul-S2T; Ma et al., 2020c) and speech-to-speech (Simul-S2S; Zheng et al., 2020) variants. Regardless of the modality of output, simultaneous translation models initiate generation

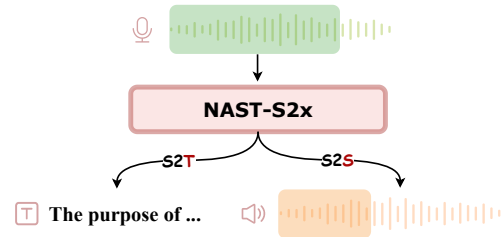


Figure 1: NAST-S2x can perform both Simul-S2T and Simul-S2S tasks within a unified end-to-end framework. The model generates speech output directly without the need to produce intermediate target text tokens

before receiving the complete input to maintain synchrony between the listener and speaker. This necessitates models to delicately balance between translation quality and latency.

Most research on simultaneous machine translation primarily focuses on either text-to-text (Ma et al., 2020d; Miao et al., 2021) or speech-to-text models (Tang et al., 2023; Zhang and Feng, 2023b), necessitating additional cascaded components such as streaming automatic speech recognition (Chiu and Raffel, 2018; Zhang et al., 2020) and incremental text-to-speech synthesis (Ma et al., 2020a) for achieving speech-to-speech interpretation (Zheng et al., 2020). However, pipeline methods often suffer from error propagation and delay accumulation. The intermediate texts serve as information bottlenecks, hindering subsequent cascade components from accessing the original information and correcting errors. Moreover, each component operates with independent streaming strategies, resulting in cumulative delays thus diminishing synchronization between the speaker and listener. Given these challenges, the emergence of end-to-end Simul-S2S models has garnered increasing attention in the research community.

Recent success of end-to-end offline speech-to-speech translation (Offline-S2S) has paved the way for the development of end-to-end Simul-S2S models. Particularly, Lee et al. (2022) construct a direct

* Corresponding author: Yang Feng

¹ $x \in \{\text{text}, \text{speech}\}$

² Project: <https://github.com/ictnlp/NAST-S2x>

speech-to-unit model (S2UT), which predicts self-supervised discrete representations of target speech. Waveforms are subsequently generated using a separate unit-based vocoder (Polyak et al., 2021). On this basis, Ma et al. (2022) builds the first end-to-end Simul-S2S model by introducing a variational version of monotonic multihead attention (Ma et al., 2020d). However, previous works are mainly limited to predicting units in an autoregressive manner, which is suboptimal for end-to-end Simul-S2S models. Considering that the acoustic unit sequence is 25 times longer than the corresponding text sequence on average, autoregressive unit prediction often leads to issues such as hallucination or truncation (Seamless Communication et al., 2023b). Moreover, the sequential prediction of long unit sequences imposes a significant computational time overhead, making it impractical for delay-sensitive Simul-S2S systems. To tackle these challenges, our focus is on developing a non-autoregressive end-to-end Simul-S2S model, aiming for enjoying the merits of an end-to-end system without the necessity of intermediate text decoding, while benefiting from the efficiency inherent in non-autoregressive generation.

In this work, we propose a non-autoregressive generation framework for end-to-end simultaneous speech-to-any translation (NAST-S2x). Inspired by recent advances in non-autoregressive generation (Shao and Feng, 2022; Ma et al., 2023), we develop a non-autoregressive decoder capable of concurrently generating multiple text or acoustic unit tokens upon receiving each fixed-length speech chunk. The entire generation adopts a chunk-to-chunk approach, while avoiding the unstable expected training method (Zhang and Feng, 2023b). The model can produce blank or repeated tokens and perform CTC decoding (Graves et al., 2006) to adjust its latency dynamically. Considering the difficulty of the speech translation task and aiming to leverage intermediate text data to assist training, we further introduce a two-step glancing and a multi-task non-monotonic training strategy, which largely enhances the translation performance while maintaining the end-to-end nature of our model.

Extensive experiments highlight the superiority of our NAST-S2x. In Simul-S2T, its performance is on par with state-of-the-art models. In Simul-S2S, it significantly surpasses cascade Simul-S2T + TTS baselines, achieving high-quality simultaneous interpretation within a delay of less than 3 seconds. In Offline-S2S, it matches the performance of the

strong autoregressive baseline while providing a $28\times$ inference speedup.

2 Preliminaries

2.1 Simultaneous Speech Translation

Simultaneous speech translation models often process a streaming sequence of acoustic features $\mathbf{x} = \{x_1, \dots, x_m\}$ as input, extracted from speech samples every T_w ms. Simultaneous translation models can be further categorized into speech-to-text (Simul-S2T) and speech-to-speech (Simul-S2S) variants based on the output modality.

2.1.1 Simul-S2T

A Simul-S2T model generates a translated text sequence $\mathbf{y} = \{y_1, \dots, y_n\}$ in a streaming fashion. To quantify the extent of source information taken into account during the generation, a monotonic non-decreasing function $g(t)$ is introduced to represent the number of observed frames when generating y_t .

To assess the latency of Simul-S2T models, Ma et al. (2020c) introduce a modified version of average lagging (AL; Ma et al., 2019) for speech-to-text task. They measure the lagging based on time instead of steps, and the metric is defined as:

$$AL = \frac{1}{\tau(|\mathbf{x}|)} \sum_{t=1}^{\tau(|\mathbf{x}|)} d(t) - \frac{|\mathbf{x}|}{|\mathbf{y}^*|} \cdot T_w \cdot (t-1), \quad (1)$$

where $|\mathbf{x}|$ and $|\mathbf{y}^*|$ represent the lengths of source frames and reference text. $\tau(|\mathbf{x}|)$ is the index of the first generated token when the source is complete, and $d(t)$ is the delay of generating y_t . Ma et al. (2020c) further defines computation-aware and non-computation-aware versions of $d(t)$. The former, $d_{CA}(t)$, is defined as the elapsed time from the beginning of the whole process, while the latter is simply calculated as $d_{NCA}(t) = g(t) \cdot T_w$. As the non-computation-aware metric is independent of implementation, most previous studies adopt this metric for comparisons, focusing on the algorithm.

2.1.2 Simul-S2S

A Simul-S2S model further synthesizes translated text into speech. To assess the translation quality of Simul-S2S models, a separate offline automatic speech recognition system is employed to transcribe the generated speech $\mathcal{Y}(t)$ into text \mathbf{y} for computing ASR-BLEU against the reference (Jia et al., 2019). To evaluate latency, a forced aligner is

usually introduced to align the transcription \mathbf{y} with $\mathcal{Y}(t)$ to acquire the delay of each token in \mathbf{y} . Subsequently, the AL metric, as defined in Simul-S2T, can be calculated for \mathbf{y} (Ma et al., 2022).³

2.2 Speech-to-Unit Translation

Recent success of self-supervised representation learning in speech has opened up a new avenue for building speech-to-speech translation systems. The discretized units derived from clustering speech representations allow models to predict speech in a manner analogous to text. Lee et al. (2022) build the first speech-to-unit (S2UT) translation model with autoregressive Transformer (Vaswani et al., 2017). They utilize a HuBERT (Hsu et al., 2021) pre-trained on an unlabelled speech corpus and perform k -means algorithm to the learned representations of each 20ms chunk to produce K cluster centroids. Each chunk is then assigned the index of its nearest centroid serving as the label. Consequently, a target utterance can be encoded as a sequence of cluster indices $\mathbf{z} = \{z_1, z_2, \dots, z_T\}$, $z_i \in \{0, 1, \dots, K - 1\}$, $\forall 1 \leq i \leq T$, where T is the number of chunks. S2UT model can be trained using cross-entropy. A separate unit-based vocoder (Polyak et al., 2021) is employed to convert the predicted acoustic unit sequence into waveform.

3 Approach

We provide a detailed introduction to our non-autoregressive generation framework for end-to-end simultaneous speech-to-any translation in this section.

3.1 Architecture

As illustrated in Figure 2, NAST-S2 x consists of a chunk-based acoustic streaming encoder and a chunk-based non-autoregressive (NAR) streaming decoder. This non-autoregressive decoder comprises stacked linguistic and acoustic components, with the two parts connected by upsampling the hidden states from linguistic part’s top layer and feeding them into the acoustic component. In contrast to previous two-pass speech-to-speech models (Jia et al., 2022a; Inaguma et al., 2023), NAST-S2 x leverages its fully non-autoregressive nature. It no longer relies on intermediate text decoding to determine the information passed to the acoustic component. This characteristic allows it to be

³A detailed description of the latency metric used in our Simul-S2S experiments is provided in Section 4.2.

trained and tested directly from speech to acoustic units, thereby circumventing issues related to error propagation.

3.1.1 Streaming Acoustic Encoder

The acoustic encoder operates by setting a chunk size T_s . We extract FBank features from the streaming speech every T_s ms, which are then fed into the encoder. The acoustic encoder consists of two layers of causal convolution for downsampling and followed by multiple standard Transformer layers. In a Transformer layer, features within each chunk are encoded bidirectionally, and the information from all previous chunks can also be attended to. Given the strong local dependencies in speech, we additionally employ Lookahead encoding (Liu et al., 2021a), which enables states in each chunk to attend to its subsequent r frames.

3.1.2 Streaming Non-autoregressive Decoder

Once the latest chunk is encoded, we use the features as input to the linguistic decoder. Given the significant discrepancy in length between the sequences of FBank and text, we downsample the encoded features before feeding them into the decoder:

$$\text{DownSample}(\tilde{\mathbf{s}}_i^e, r_{\text{down}}), \quad (2)$$

where $\tilde{\mathbf{s}}_i^e$ represents the encoded features in the i -th chunk and r_{down} is the downsampling ratio. We use MeanPooling applied to every r_{down} encoded features in our experiments.

The linguistic decoder also works in a chunk-by-chunk manner. The decoding of current chunk relies solely on hidden states in the previous chunks rather than any generated token:

$$\begin{aligned} &\text{SelfAttn}(\mathbf{s}_i^{ld}, \mathbf{s}_{\leq i}^{ld}), \\ &\text{CrossAttn}(\mathbf{s}_i^{ld}, \tilde{\mathbf{s}}_{\leq i}^e), \end{aligned} \quad (3)$$

where \mathbf{s}_i^{ld} denotes the hidden states in the i -th chunk in the linguistic decoder. Optionally, the linguistic decoder can generate text translation from the chunks. The text logits are derived by projecting the last layer states.

Meanwhile, hidden states in the last layer of linguistic decoder serve as input to the acoustic decoder after upsampling. This upsampling is designed to bridge the length gap between the sequences of text and acoustic unit:

$$\text{UpSample}(\tilde{\mathbf{s}}_i^{ld}, r_{\text{up}}), \quad (4)$$

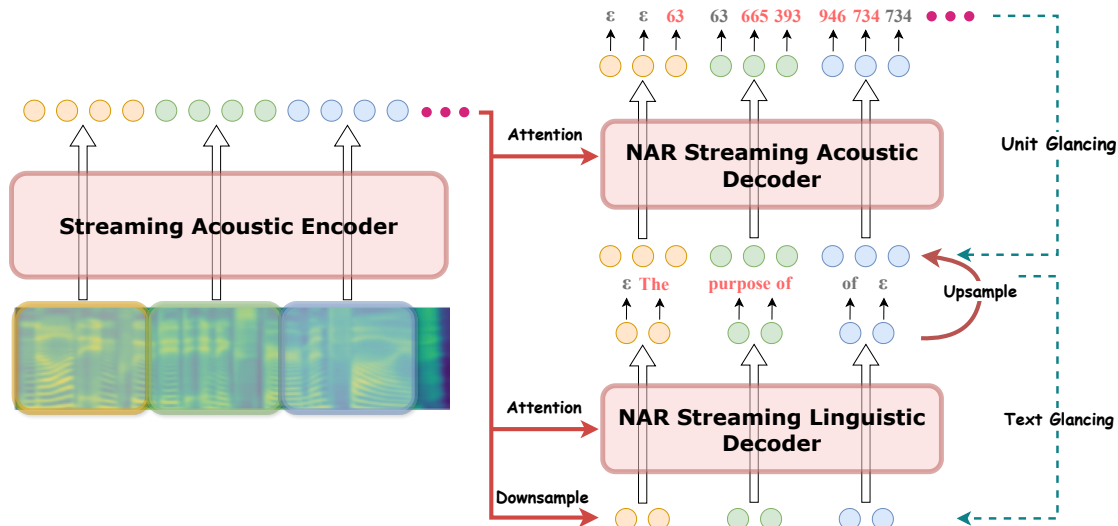


Figure 2: Overview of the proposed non-autoregressive generation framework for end-to-end simultaneous speech-to-any translation (NAST-S2 x , $x \in \{\text{text, speech}\}$). Different colors indicate different chunks.

where \tilde{s}_i^{ld} denotes the last layer states of the linguistic decoder in the i -th chunk and r_{up} is the upsampling ratio. We simply copy each state in the chunk r_{up} times.

The acoustic decoder operates similarly to the linguistic decoder. Compared with previous two-pass models, our non-autoregressive acoustic decoder can directly attend to the acoustic encoder. This capability enables it to incorporate a broader range of acoustic information (e.g., rhythm, pitch, and energy) and helps in recovering from potential mistakes made by the linguistic decoder:

$$\begin{aligned} & \text{SelfAttn}(\mathbf{s}_i^{ad}, \mathbf{s}_{\leq i}^{ad}), \\ & \text{CrossAttn}(\mathbf{s}_i^{ad}, \tilde{\mathbf{s}}_{\leq i}^e), \end{aligned} \quad (5)$$

where \mathbf{s}_i^{ad} denotes the hidden states in the i -th chunk in the acoustic decoder. We use the states in the top layer to predict acoustic units.

When predicting text and unit sequences, an additional blank token is included in the vocabulary. The model dynamically adjusts the output length of each chunk by generating repeated or blank tokens. Subsequently, the collapse function in CTC (Graves et al., 2006) is employed for online deduplication and removal of blanks to generate the final output. The generated chunk of units is sent directly to a separate unit-based HiFi-GAN vocoder (Polyak et al., 2021) for synthesizing the waveform, which is then played immediately to the listener.

3.2 Latency Control

In this subsection, we explore various techniques for controlling the latency of NAST-S2 x .

Chunk Size Given that NAST-S2 x operates at a chunk level, a straightforward approach to controlling latency is to adjust the chunk size. Specifically, when the chunk size exceeds the utterance length, our model transitions into an offline model, conducting bidirectional encoding and bidirectional non-autoregressive decoding.

Lookahead Chunk lookahead decoding resembles Lookahead encoding. When a feature chunk is sent to the decoder, it is allowed to wait for its subsequent k chunks before starting decoding:

$$\begin{aligned} & \text{CrossAttn}(\mathbf{s}_i^{ld}, \tilde{\mathbf{s}}_{\leq i+k}^e), \\ & \text{CrossAttn}(\mathbf{s}_i^{ad}, \tilde{\mathbf{s}}_{\leq i+k}^e). \end{aligned} \quad (6)$$

This allows the model to obtain more source-side information through an additional delay of $(k \cdot T_s)$ ms, without changing the chunk size.

3.3 Training

While NAST-S2 x benefits from various advantages of non-autoregressive generation, training it is challenging. Previous studies (Huang et al., 2022a; Shao et al., 2023) have highlighted that NAR generation struggles to capture multi-modal distributions. Regrettably, speech-to-speech translation encounters this multimodality problem. This challenge

stems from two aspects: First, the mapping from speech input to text translation can be one-to-many, as different word choices and grammar structures may convey the same semantics. Secondly, the distribution of speech when the text is given can be multi-modal, with variations in pitch, rhythm, and energy. To mitigate these challenges, we propose the following strategies to train NAST-S2x.

3.3.1 Multi-task Non-monotonic Training

Due to the performance decline observed in NAR models when trained with maximum likelihood estimation, we train NAST-S2x using CTC-based non-monotonic latent alignment loss (Shao and Feng, 2022)

$$\mathcal{L}_o(\theta) = -\frac{2 \cdot \sum_{g \in G_2} \min\{C_g(\mathbf{o}), C_g(\theta)\}}{\sum_{g \in G_2} (C_g(\mathbf{o}) + C_g(\theta))}, \quad (7)$$

where $\mathbf{o} \in \{\mathbf{y}, \mathbf{z}\}$ is the target for either S2T or S2U task. $C_g(y)$ denotes the occurrence count of bigram g in target, $C_g(\theta)$ represents the expected count of g for model, and G_2 denotes the set of all bigrams in target. This training objective maximizes the F1 score of expected bigram matching between target and the uncollapsed output, and guides NAST-S2x towards convergence to a concentrated distribution, thereby alleviating the multimodality problem in speech-to-speech translation. We utilize multi-task learning to integrate the losses from both text and acoustic unit prediction tasks into our training process:

$$\mathcal{L} = \mathcal{L}_y(\theta) + \mathcal{L}_z(\theta). \quad (8)$$

3.3.2 Two-Step Glancing

To further simplify the learning complexity for both linguistic and acoustic decoders, we further introduce the concept of glancing (Qian et al., 2021) to our NAST-S2x training. As depicted in Figure 2, we find the most probable sequence that can be collapsed to the target within the current distribution of text and acoustic unit in the model:

$$\begin{aligned} \mathbf{a}_{\text{unit}}^* &= \arg \max_{\mathbf{a}_{\text{unit}} \in \beta^{-1}(\mathbf{z})} p_{\theta}(\mathbf{a}_{\text{unit}} | \mathbf{x}), \\ \mathbf{a}_{\text{text}}^* &= \arg \max_{\mathbf{a}_{\text{text}} \in \beta^{-1}(\mathbf{y})} p_{\theta}(\mathbf{a}_{\text{text}} | \mathbf{x}), \end{aligned} \quad (9)$$

where \mathbf{a}_{unit} and \mathbf{a}_{text} represent the predicted uncollapsed sequence of text and acoustic unit, and β^{-1} is the inverse of collapse function. We then randomly substitute the features fed to both the

linguistic and acoustic decoders with token embeddings corresponding to positions in the most probable text or unit sequences.

This strategy simplifies the complexity of S2S mapping by providing cues during both decoding stages. This induces the NAR model to learn a deterministic conditional distribution, mitigating the issue of insufficient capacity for tasks with multi-modal distributions.

4 Experiments

4.1 Speech-to-Text

Datasets We conduct experiments on two MuST-C⁴ language pairs: English to German (En→De) and English to Spanish (En→Es) (Di Gangi et al., 2019). We use the dev set for validation and report performance on the tst-COMMON set.

Pre-processing The input speech is represented as 80-dimensional log mel-filterbank coefficients computed every 10ms with a 25ms window. Global channel mean and variance normalization is applied to the input speech. In training, SpecAugment (Park et al., 2019) data augmentation with the LB policy is additionally employed. We use SentencePiece (Kudo and Richardson, 2018) to generate a unigram vocabulary of size 10000 for the source and target text jointly.

Model Configurations In the Simul-S2T experiments, we exclusively utilize the linguistic component of the decoder. We set the downsampling ratio⁵ to 2 and explore chunk sizes within the set {160, 320, 640, 1280} ms. The offline results are obtained by setting the chunk size to be longer than any utterance in the corpus. The number of additional frames the encoder can attend to is set equal to the size of a chunk. When employing lookahead decoding, we vary the lookahead number k within the range {0, 2, 6} while maintaining a fixed chunk size of 320ms. More implementation details can be found in Appendix A.

Baselines We compare our NAST-S2T with several strong Simul-S2T baselines. Further details regarding baselines are available in Appendix B.1.

⁴<https://ict.fbk.eu/must-c>

⁵For details on the analysis of the downsampling ratio, see Appendix D.

	<i>ms</i>	320	640	1280
Chunk (# = 0)	BLEU	26.48	27.02	28.05
	AL	1114	1396	2180
	#	0	2	6
Lookahead (320ms)	BLEU	26.48	27.02	26.99
	AL	1114	1762	2781

Table 1: Results of the quality-latency trade-off with increasing the chunk size or implementing lookahead decoding. Experiments are conducted on En→Es Simul-S2T task.

Evaluation We use SimulEval⁶ toolkit (Ma et al., 2020b) for evaluation. Translation quality is assessed using case-sensitive detokenized BLEU (Papineni et al., 2002; Post, 2018), while latency is measured by word-level Average Lagging (AL; Ma et al., 2020c). Numerical results with more latency metrics are provided in Appendix C.1.

4.1.1 Preliminary Experiment

We first conduct a preliminary experiment to compare latency control strategies. Employing NAST-S2T with a baseline chunk size of 320ms, we examine the trade-off between latency and quality by adjusting the chunk size and implementing lookahead decoding. As depicted in Table 1, both strategies enhance quality at the sacrifice of latency. Nevertheless, increasing the chunk size yields superior quality with reduced latency over lookahead decoding. Notably, there appears to be a quality plateau when utilizing lookahead decoding. Waiting for an extra 6 source chunks versus 2 extra ones results in nearly identical quality, despite an additional delay of almost 1000ms. This implies that the amount of source information alone does not solely dictate translation quality. By adopting the strategy of increasing chunk size, we not only enable the model to attend to more source information but also facilitate bidirectional non-autoregressive decoding of longer sequences within a chunk. This enhancement significantly improves the translation quality. Therefore, we only vary the chunk size in the main experiment.

4.1.2 Main Results and Analysis

Figure 3 illustrates the main results of Simul-S2T task. Detailed numerical results are available in Table 5 and 6. It can be observed that NAST-S2T achieves competitive or superior translation quality compared to strong baselines across various

⁶<https://github.com/facebookresearch/SimulEval>

latency constraints. At lower latency, its performance is only inferior to CAAT (Liu et al., 2021a). Meanwhile, it performs better or comparably as the autoregressive models under higher latency or offline conditions. Both datasets demonstrate that as the chunk size T_s increases from 160ms to 320ms, there is a significant improvement in translation quality with only a minor increase in latency. We attribute this phenomenon to the average duration of each word, estimated to be approximately 280ms (Ma et al., 2020c). The model’s performance tends to degrade when the chunk size falls below it. Furthermore, we find that NAST-S2T achieves a better balance when the chunk size T_s is 640ms (AL \approx 1200ms), after which the quality gain from further increasing the chunk size diminishes.

4.2 Speech-to-Speech

Datasets We conduct experiments on CVSS-C⁷ French to English (Fr→En) dataset (Jia et al., 2022b).

Pre-processing For the source speech, we resample the audio to 16kHz and apply identical preprocessing steps as those used in the Simul-S2T experiments. For the target speech, we also downsample the audio and extract discrete units utilizing the publicly available pre-trained mHuBERT model and K-means quantizer.⁸

Model Configurations The downsampling and up-sampling ratio are set to 2 and 6. We explore different settings for chunk sizes within the set {320, 640, 1280, 1920, 2560} ms. The offline results are obtained by setting the chunk size to be longer than any utterance. The number of additional frames the encoder can attend to is set equal to the size of a chunk. We also experimented with fixing the duration of additional frames to 1280ms when the chunk size is larger. More details can be found in Appendix A.

Baselines

Wait- k -Stride- n : We employ Wait- k strategy (Ma et al., 2019) for S2UT model (Lee et al., 2022) to build an end-to-end Simul-S2S baseline. Since the input is speech audio, a pre-decision module

⁷<https://github.com/google-research-datasets/cvss>

⁸https://github.com/facebookresearch/fairseq/blob/main/examples/speech_to_speech/docs/textless_s2st_real_data.md

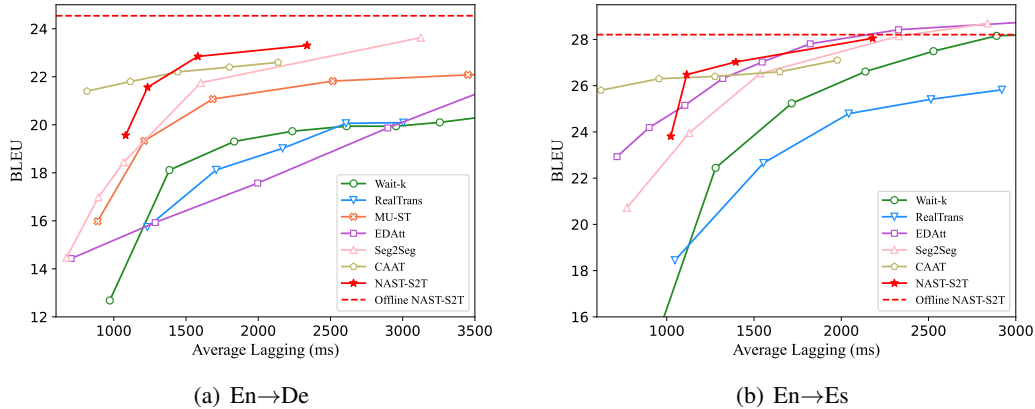


Figure 3: Results of translation quality (BLEU) against latency (Average Lagging, AL) on MuST-C En→De and En→Es datasets. The red solid line and dashed line illustrate the performance of NAST-S2T under different chunk sizes T_s or in an offline condition. The numerical results are presented in Table 5 and Table 6.

is needed to segment the utterance into multiple chunks to execute Wait- k (Ma et al., 2020c). Furthermore, the translation of a speech chunk can consist of multiple acoustic units to form the pronunciation of a word. It is reasonable to generate multiple unit tokens upon receiving a speech chunk. Therefore, we adopt Wait- k -Stride- n strategy (Zeng et al., 2021) to construct an end-to-end Simul-S2S baseline, varying the speech chunk size and the hyperparameters k and n . The numerical results can be found in Table 13.

EDAtt + Tacotron2: We further provide the results of cascade systems (Simul-S2T + TTS) for comparison. We choose EDAtt (Papi et al., 2023b) as the Simul-S2T model. According to the recommendation in Papi et al. (2023b), we train a Conformer + CTC compression model (Gaido et al., 2021) with a total of $\sim 120M$ parameters using speech-text parallel pairs of CVSS-C Fr-En dataset as the offline model to implement EDAtt algorithm. For TTS part, we use a Tacotron2 model trained on LJSpeech⁹. Whenever the Simul-S2T model generates a complete word, we send it to the TTS model and generate a speech chunk as output. The numerical results can be found in Table 14.

We also compare NAST-S2S with several strong Offline-S2S models to assess its performance in offline scenarios. Further details regarding baselines are available in Appendix B.2.

Evaluation We also use SimulEval toolkit for evaluation. Following Ma et al. (2022), we keep discontinuities between generated speech chunks to sim-

ulate real-world scenarios. Translation quality is assessed using ASR-BLEU. We also employ BLASER 2.0¹⁰ (Seamless Communication et al., 2023a) to assess the quality. The results for BLASER 2.0 are presented in Table 12. Regarding latency, we report AL and AL_EOW (Ma et al., 2022). AL measures time delay of waveform chunks, while AL_EOW assesses the delay of text transcribed from generated speech. The generated time of each word is considered as the end time of its corresponding segment. Numerical results with more latency metrics are provided in Appendix C.2.

4.2.1 Main Results

Figure 4 illustrates the main results of Simul-S2S task. Detailed numerical results are presented in Table 9. We observe a trend where the translation quality of NAST-S2S generally improves as latency increases, with a notable improvement from 3000ms to 4000ms. Even under extremely low latency conditions (AL ≈ 1000 ms), NAST-S2S still achieves acceptable translation quality (ASR-BLEU > 19). This result even surpasses the performance of wait- k -stride- n and cascade baselines at 4000ms latency. Furthermore, we discover that in offline scenarios, the quality achieved by NAST-S2S exceeds that of the current leading NAR Offline-S2S model DASpeech (Fang et al., 2023) by nearly 1 ASR-BLEU, with translation quality only slightly inferior to two-pass autoregressive model UnitY¹¹ (Inaguma et al., 2023).

¹⁰<https://huggingface.co/facebook/blaser-2.0-ref>

¹¹Two-pass models are not strictly end-to-end, as they must generate target text before producing the speech output.

⁹<https://huggingface.co/speechbrain/tts-tacotron2-ljspeech>

Model	#Params	End-to-End	Streamable	ASR-BLEU	Speedup
S2UT (Lee et al., 2022)	58M	✓	✗	24.80	1.00×
UnitY (Inaguma et al., 2023)	67M	✗	✗	26.90	1.60×
DASpeech (Fang et al., 2023)	93M	✗	✗	25.03	16.29×
Offline NAST-S2S	79M	✓	✓	25.82	28.30×

Table 2: Comparison of strong Offline-S2S baselines and our NAST-S2S in offline conditions. The speedup is measured using a GeForce RTX 3090 GPU with a batch size of 1.

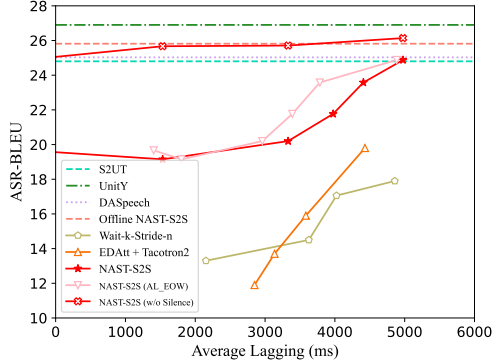


Figure 4: Results of translation quality in offline conditions and simultaneous scenarios (ASR-BLEU or ASR-BLEU (Silence Removed) against AL or AL_EOW). The numerical results of NAST-S2S are presented in Table 9 and Table 11.

4.2.2 Analysis on Inference Efficiency

Speech-to-speech translation imposes strong demands on inference efficiency. In Offline-S2S, efficiently generating long sequences of acoustic unit is crucial to minimize waiting time. In Simul-S2S, reducing computational time overhead is essential to avoid extra latency. Benefiting from end-to-end non-autoregressive generation, NAST-S2S offers appealing advantages in both scenarios. Table 2 presents the comparison in Offline-S2S. NAST-S2S achieves a $28\times$ speedup compared to S2UT and a $17\times$ speedup compared to UnitY at decoding. In Simul-S2S, the advantage in inference speed becomes more critical. Table 3 presents the comparison of non-computation-aware and computation-aware latency. The gap between AL and AL_CA and the average computation time per chunk generation are both less than 300ms when the chunk size is larger than 640ms, indicating that NAST-S2S’s latency in practical use is similar to the theoretical latency of its simultaneous translation policy.

4.2.3 Analysis on Discontinuity

We observed notable differences in the performance of NAST-S2 x between Simul-S2S and Simul-S2T tasks. NAST-S2T achieves satisfac-

tory quality when the chunk size T_s is set to 640ms (AL < 2000ms). However, to attain translation quality comparable to offline condition, NAST-S2S requires an increase in the chunk size T_s to 2560ms. This discrepancy may stem from the differing nature of text and speech streaming generation. In text generation, appending newly generated chunk directly after the historical sequence is straightforward. However, in speech generation, there may be silence intervals between each speech chunk, particularly when the chunk size T_s exceeds the duration of the last generated speech chunk. Therefore, we speculate that as the chunk size decreases, increased silence between generated speech chunks may lead to discontinuity in speech, thereby decreasing the overall quality.

To validate this hypothesis, we further analyze the trends of the following metrics as the chunk size varies: ASR-BLEU (Silence Removed), representing ASR-BLEU score after removing the added silence between generated chunk; Unit-BLEU, representing BLEU score of the generated unit sequences against the reference; S2T-BLEU, where we conduct additional decoding of the linguistic decoder to evaluate quality in Simul-S2T. We also provide statistics on the number of discontinuities (DCNum), the average silence duration per discontinuity (DCAve), and the total silence duration (DCSum) in the generated streaming speech.

Table 4 presents the statistics. We observed minor degradation in the values of Unit-BLEU and S2T-BLEU even at a chunk size of 320ms, showing NAST-S2S’s capability in streaming text and unit generation. However, there exists a significant increase in the number of discontinuities as the chunk size decreases. Although the duration of silence per discontinuity is relatively short when the chunk size is small, the increase in their number results in a longer total silence duration, thus intensifying the degree of discontinuity and impacting its overall quality (ASR-BLEU).

Moreover, if the added silence were removed, the measured ASR-BLEU (Silence Removed) sig-

T_s (ms)	ASR-BLEU	Average Lagging (ms)			Start Offset (ms)			End Offset (ms)			ACT (ms)
		NCA	CA	Δ	NCA	CA	Δ	NCA	CA	Δ	
320	19.67	-392	347	739	655	712	57	562	1550	988	555
640	19.15	1532	1824	292	1294	1350	56	863	1344	481	297
1280	20.20	3330	3500	170	2566	2642	76	1648	1901	253	192
2560	24.88	4975	5097	122	4691	4781	90	2753	2879	126	120

Table 3: Results of translation quality (ASR-BLEU), latency (Average Lagging, Start Offset & End Offset) and average computation time per chunk generation (ACT) during NAST-S2S simultaneous inference. All latency metrics report both the computation-aware (CA) version and the non-computation-aware (NCA) version, as well as their differences (Δ).

T_s (ms)	320	640	1280	2560
S2T-BLEU	28.04	28.28	28.23	28.78
Unit-BLEU	33.41	33.97	34.04	34.40
ASR-BLEU	19.67	19.15	20.20	24.88
ASR-BLEU (Silence Removed)	24.90	25.67	25.71	26.14
DCNum	7.3	4.7	2.1	0.4
DCAve (ms)	355	450	685	360
DCSum (ms)	2220	1952	1420	395

Table 4: Statistics of NAST-S2S generation across varying chunk sizes T_s .

nificantly increased and the gap between streaming and offline scenarios becomes small. This suggests that ASR-BLEU may underestimate speech quality here. The decline in ASR-BLEU scores is primarily due to the *playback timing*. For example, consider the word "Richardson", which consists of multiple syllables. If the "Richard" part of the waveform is generated in the previous chunk and played immediately, and the "son" syllable is generated in the subsequent chunk, the potential silence period (which equals to the chunk size minus the length of the waveform generated in the previous chunk) could cause the listener to perceive a *stuttering* effect, leading to a decrease in ASR-BLEU scores.

5 Related Work

Researches in simultaneous speech translation can be roughly categorized into Simul-S2T (Ma et al., 2020c) and Simul-S2S (Zheng et al., 2020) variants.

Simul-S2T With the rise of neural networks, Simul-S2T models no longer rely on the transcription as a bridge (Ma et al., 2020c; Iranzo-Sánchez et al., 2020). Given the difference between speech and text input, some researchers focus on how to divide speech chunks and then execute strategies. Ma et al. (2020c) employed fixed-length segmentation and

implemented Wait- k (Ma et al., 2019) and MMA (Ma et al., 2020d) based on that; Ren et al. (2020); Zeng et al. (2021); Chen et al. (2021) utilized ASR results to partition and execute Wait- k or its variants. Zhang et al. (2022) trained a segmentation model to detect semantic units. Zhang and Feng (2023a) trained a model to dynamically segment with differentiable approach, then extending it to a segment-to-segment framework (Zhang and Feng, 2023b). Additionally, some researchers have also attempted to use Transducer (Graves, 2012) and incorporate attention mechanisms to enhance its performance (Liu et al., 2021a; Tang et al., 2023). Besides, some researchers are leveraging offline models for simultaneous inference. Liu et al. (2020) considered the agreeing prefixes of two consecutive chunks as stable hypotheses. Papi et al. (2023b,c) used attention as guidance, allowing the model to generate output for the current step if its attention is not focused on the most recently received frames.

Simul-S2S There have been limited prior studies exploring Simul-S2S. Zheng et al. (2020) and Sudoh et al. (2020) both developed cascade models by integrating streaming ASR, Simul-T2T, and incremental TTS components. Additionally, Liu et al. (2021b) proposed latency reduction strategies for incremental TTS in Simul-S2S. Moreover, Ma et al. (2022) introduced a variational version of MMA to S2UT (Lee et al., 2022) and constructed the first end-to-end Simul-S2S model.

6 Conclusion

In this paper, we present a non-autoregressive streaming generation framework for simultaneous speech-to-any translation, which integrates both Simul-S2T and Simul-S2S tasks into a unified framework. Experimental results on various benchmarks showcase the superiority of our model.

Limitation

Our NAST-S2 x exhibits greater latency in Simul-S2S compared to Simul-S2T tasks. This discrepancy arises due to NAST-S2S’s reliance on an external vocoder, typically trained on offline tasks and not adapted for streaming scenarios, thereby constraining NAST-S2S’s performance. Additionally, our method requires a parallel speech-to-speech translation corpus for end-to-end training, which can be challenging to obtain. Existing datasets are typically based on synthesized target speech. The lack of such corpora may hinder the development of simultaneous speech-to-speech translation models.

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A Implementation Details

A.1 Configuration

We incorporate both cosine positional encoding (Vaswani et al., 2017) and relative positional attention (Shaw et al., 2018) into the acoustic encoder, and utilize learned positional encoding for non-autoregressive decoder. A separate learned positional encoding is applied to the acoustic decoder. The acoustic encoder comprises two layers of causal convolution followed by six standard Transformer layers. Both the non-autoregressive linguistic and acoustic decoders consist of six Transformer layers each. All Transformer layers are configured with a 512 embedding dimension, 8 attention heads, and a 2048 FFN dimension. The total number of parameters for NAST-S2T and NAST-S2S are 52M and 79M.

A.2 Training

NAST-S2T Considering the inherent complexity of speech-to-text translation, we leverage the concept of curriculum learning. We initialize the encoder of NAST-S2T with an ASR-trained model and conduct pretraining using CTC loss (Graves et al., 2006). Subsequently, we employ non-monotonic training to further refine NAST-S2T. During the CTC loss pretraining, we set the dropout rate to 0.3, weight decay to 0.01, and incorporate label smoothing with a value of 0.01. The dropout rates for activation and attention are both set to 0.1. The pretraining process spans 100k updates with a batch size of 320k tokens. The learning rate gradually warms up to $1 \cdot 10^{-3}$ within 10k steps, while the text glancing ratio linearly anneals from 0.5 to 0.3 over 50k steps. In non-monotonic training, we adjust the dropout rate to 0.1 while keeping other hyperparameters unchanged. This stage involves training NAST-S2T for 20k updates. The learning rate warms up to $3 \cdot 10^{-4}$ within 4k steps, and the text glancing ratio is maintained at 0.3. Throughout the training, we optimize models using the Adam optimizer (Kingma and Ba, 2015) with parameters $\beta = (0.9, 0.98)$ and $\epsilon = 10^{-8}$. We utilize sequence-level knowledge distillation (Kim and Rush, 2016) solely during the CTC pretraining stage to facilitate model warmup, while NAST-S2T is trained directly on raw data during non-monotonic training.

NAST-S2S Similar to the training of NAST-S2T, a curriculum learning approach is also devised for NAST-S2S. We initialize the encoder

of NAST-S2S with an ASR-trained model and conduct multi-task pretraining using the CTC loss. Subsequently, we employ multi-task non-monotonic training to further refine NAST-S2S. During the pretraining, the hyperparameters are consistent with those used in NAST-S2T, with the exception of incorporating label smoothing for both text and unit targets, set at a value of 0.01. The multi-task pretraining process spans 50k updates with a batch size of 320k tokens. The text glancing ratio linearly anneals from 0.5 to 0.3 over 50k steps, while the unit glancing ratio linearly decreases from 0.3 to 0.1 over the same number of steps. In multi-task non-monotonic training, we adjust the dropout rate to 0.1 while keeping other hyperparameters unchanged. This stage involves training NAST-S2S for 30k updates. The learning rate warms up to $3 \cdot 10^{-4}$ within 4k steps. We maintain a text glancing ratio of 0.3 and a unit glancing ratio of 0.1 in this stage. Knowledge distillation is not utilized during the entire training of NAST-S2S.

B Baselines

B.1 Speech-to-Text

We compare our NAST-S2T with the following strong Simul-S2T baselines.

Wait- k (Ma et al., 2020c): It executes Wait- k policy (Ma et al., 2019) by setting the pre-decision window size to 280 ms.

RealTrans (Zeng et al., 2021): It detects word number in the streaming speech by counting blanks in CTC transcription and applies Wait- k -Stride- n strategy accordingly.

MU-ST (Zhang et al., 2022): It trains an external segmentation model, which is then utilized to detect meaningful units for guiding generation.

Seg2Seg (Zhang and Feng, 2023b): It alternates between waiting for a source segment and generating a target segment in an autoregressive manner.

CAAT (Liu et al., 2021a): It utilizes the Transformer Transducer (Graves, 2012; Zhang et al., 2020) as its foundational architecture for streaming generation and incorporates a cross-attention mechanism within the joiner module to alleviate the strong monotonic constraint.

EDAtt (Papi et al., 2023b): It computes the attention scores towards the latest received speech frames, serving as guidance for an offline-trained speech translation model during simultaneous inference. The experimental results reported in their

paper were obtained using a 112M parameter Conformer (Gulati et al., 2020; Papi et al., 2023a). To ensure a fair comparison with our method, we re-trained a Conformer¹² of similar size to NAST-S2T on the same dataset to perform EDAtt decoding (52M parameters, achieved by reducing the encoder embedding dimension from 512 to 256 and keeping the number of encoder layers at 12). The numerical results of our re-implemented EDAtt can be found in Tables 7 and 8.

B.2 Speech-to-Speech

We compare our NAST-S2S with several strong Offline-S2S and Simul-S2S baselines.

Offline-S2S

S2UT (Lee et al., 2022): A direct speech-to-unit model, which predicts acoustic units in a standard autoregressive manner.

UnitY (Inaguma et al., 2023): A two-pass speech-to-unit model, which first generates a sub-word sequence in an autoregressive manner and then feeds the last hidden states into another autoregressive model to generate unit sequence.

DASpeech (Fang et al., 2023): A two-pass non-autoregressive speech-to-spectrogram model. It initially employs a directed acyclic graph layer (Huang et al., 2022b) to generate a phoneme sequence, followed by utilizing FastSpeech2 (Ren et al., 2021) to synthesis the phonemes into mel-spectrograms.

Simul-S2S

Wait- k -Stride- n : We employ Wait- k strategy (Ma et al., 2019) for S2UT model (Lee et al., 2022) to build an end-to-end Simul-S2S baseline. Since the input is speech audio, a pre-decision module is needed to segment the utterance into multiple chunks to execute Wait- k (Ma et al., 2020c). Furthermore, the translation of a speech chunk can consist of multiple acoustic units to form the pronunciation of a word. It is reasonable to generate multiple unit tokens upon receiving a speech chunk. Therefore, we adopt Wait- k -Stride- n strategy (Zeng et al., 2021) to construct an end-to-end Simul-S2S baseline, varying the speech chunk size and the hyperparameters k and n . The numerical results can be found in Table 13.

EDAtt + Tacotron2: We further provide the results of cascade systems (Simul-S2T + TTS) for comparison. We choose EDAtt (Papi et al., 2023b)

as the Simul-S2T model. According to the recommendation in Papi et al. (2023b), we train a Conformer + CTC compression model (Gaido et al., 2021) with a total of ~ 120 M parameters using speech-text parallel pairs of CVSS-C Fr-En dataset as the offline model to implement EDAtt algorithm. For TTS part, we use a Tacotron2 model trained on LJSpeech. Whenever the Simul-S2T model generates a complete word, we send it to the TTS model and generate a speech chunk as output. The numerical results can be found in Table 14.

C Numerical Results

C.1 Speech-to-Text

In addition to Average Lagging (AL; Ma et al., 2020c), we also incorporate Average Proportion (AP; Cho and Esipova, 2016), Differentiable Average Lagging (DAL; Arivazhagan et al., 2019) and Length Adaptive Average Lagging (LAAL; Papi et al., 2022) as metrics to evaluate the latency of NAST-S2T. AL, DAL and LAAL are reported with milliseconds. The trade-off between latency and quality is attained by adjusting the chunk size T_s . The offline results are obtained by setting the chunk size to be longer than any utterance in the dataset ($T_s = \infty$). We use SimulEval v1.1.4 for evaluation in all the experiments. The numerical results of NAST-S2T are presented in Table 5 and 6.

C.2 Speech-to-Speech

In addition to AL and AL_EOW, we also present results for AL_BOW, StartOffset, and EndOffset, as measured by the SimulEval toolkit. AL_BOW is analogous to AL_EOW but considers the generation time of each word as the beginning time of the corresponding speech. StartOffset and EndOffset measure the offset of the beginning and ending of the generated speech compared with the input speech. We also employ BLASER 2.0 to assess the quality of translated speech. The trade-off between latency and quality is attained by adjusting the chunk size T_s and the additional frames T_a . The offline results are obtained by setting the chunk size to be longer than any utterance in the dataset ($T_s = \infty$). We use SimulEval v1.1.4 for evaluation. The numerical results of NAST-S2S are presented in Table 9, 10, 11 and 12.

D Analysis on Length Ratio

We present the ablation study of model hyperparameter r_{down} and r_{up} in Table 15 and 16.

¹²https://github.com/hlt-mt/FBK-fairseq/blob/master/fbk_works/BUGFREE_CONFORMER.md

<i>NAST-S2T on En→De</i>					
$T_s(ms)$	AP	AL	DAL	LAAL	BLEU
160	0.58	1082	1359	1191	19.51
320	0.65	1234	1546	1346	21.56
640	0.73	1582	1969	1692	22.85
1280	0.81	2338	2812	2423	23.30
∞	-	-	-	-	24.54

Table 5: Numerical results of NAST-S2T on MuST-C English to German speech-to-text translation dataset.

<i>NAST-S2T on En→Es</i>					
$T_s(ms)$	AP	AL	DAL	LAAL	BLEU
160	0.62	1023	1541	1242	23.81
320	0.71	1114	1692	1377	26.48
640	0.79	1396	2030	1648	27.02
1280	0.86	2180	2843	2364	28.05
∞	-	-	-	-	28.21

Table 6: Numerical results of NAST-S2T on MuST-C English to Spanish speech-to-text translation dataset.

<i>EDAtt on En→De</i>					
α	AP	AL	DAL	LAAL	BLEU
0.8	0.80	705	1973	1289	14.43
0.7	0.82	1287	2430	1765	15.93
0.6	0.86	1996	3009	2362	17.57
0.5	0.89	2897	3736	3152	19.87
0.4	0.93	4045	4562	4149	22.53
0.3	0.97	4947	5198	4971	23.97
0.2	0.99	5460	5540	5463	24.54
0.1	0.99	5636	5643	5636	24.77
0	-	-	-	-	25.39

Table 7: Numerical results of EDAtt on MuST-C English to German speech-to-text translation dataset.

<i>EDAtt on En→Es</i>					
α	AP	AL	DAL	LAAL	BLEU
0.8	0.81	715	1939	1184	22.93
0.7	0.82	900	2119	1319	24.19
0.6	0.84	1104	2314	1491	25.15
0.5	0.85	1321	2489	1661	26.31
0.4	0.87	1547	2688	1855	27.02
0.3	0.89	1822	2939	2089	27.81
0.2	0.92	2328	3454	2554	28.42
0.1	1.00	3853	4770	3984	29.11
0	-	-	-	-	31.20

Table 8: Numerical results of EDAtt on MuST-C English to Spanish speech-to-text translation dataset.

<i>NAST-S2S on CVSS-C Fr→En</i>						
$T_s + T_a(ms)$	AL	AL_EOW	AL_BOW	StartOffset	EndOffset	ASR-BLEU
320 + 320	-393	1405	1085	655	562	19.67
640 + 640	1533	1802	1455	1295	863	19.15
1280 + 1280	3330	2961	2601	2566	1648	20.20
1920 + 1280	3975	3390	3046	3179	1920	21.77
1920 + 1920	4335	4021	3689	3753	2292	22.70
2560 + 1280	4408	3785	3448	3753	2175	23.58
2560 + 2560	4976	4886	4573	4697	2753	24.88
∞	-	-	-	-	-	25.82

Table 9: Numerical results of NAST-S2S on CVSS-C French to English speech-to-speech translation dataset.

<i>NAST-S2S on CVSS-C Fr→En</i>						
$T_s + T_a(ms)$	AL	AL_CA	StartOffset	StartOffset_CA	EndOffset	EndOffset_CA
320 + 320	-393	347	655	713	562	1550
640 + 640	1533	1824	1295	1351	863	1344
1280 + 1280	3330	3501	2566	2642	1648	1901
1920 + 1280	3975	4103	3179	3245	1920	2088
1920 + 1920	4335	4482	3753	3844	2291	2465
2560 + 1280	4408	4527	3753	3823	2175	2312
2560 + 2560	4976	5098	4697	4781	2753	2879

Table 10: Comparison of non-computation-aware and computation-aware metrics results for NAST-S2S on CVSS-C French to English speech-to-speech translation dataset.

<i>NAST-S2S on CVSS-C Fr→En</i>			
$T_s + T_a(ms)$	ASR-BLEU	ASR-BLEU (Silence Removed)	AL
320+320	19.67	24.90	-393
640+640	19.15	25.67	1533
1280+1280	20.20	25.71	3330
2560+2560	24.88	26.14	4976

Table 11: Comparison between ASR-BLEU and ASR-BLEU (Silence Removed) of NAST-S2S on CVSS-C French to English speech-to-speech translation dataset.

<i>NAST-S2S on CVSS-C Fr→En</i>			
$T_s + T_a(ms)$	ASR-BLEU	BLASER 2.0	AL
320+320	19.67	3.022	-393
640+640	19.15	3.017	1533
1280+1280	20.20	3.066	3330
1920+1280	21.77	3.103	3975
1920+1920	22.70	3.113	4335
2560+1280	23.58	3.123	4408
2560+2560	24.88	3.136	4976
∞	25.82	3.144	-
<i>Offline Models</i>			
S2UT	23.39	3.062	-
UnitY	27.80	3.178	-

Table 12: BLASER 2.0 scores of NAST-S2S on CVSS-C French to English speech-to-speech translation dataset.

<i>Wait-k-Stride-n on CVSS-C Fr→En</i>								
$T_s(ms)$	n	5	AL	StartOffset	EndOffset	DCNum	DCAve	ASR-BLEU
320	5	5	-164	1934	1503	11.7	161	8.41
320	5	10	2154	3472	2172	6.9	136	13.30
320	5	15	4023	4697	2766	3.1	83	17.06
640	10	1	1188	1295	1242	6.9	318	7.34
640	10	3	2449	2566	1731	4.9	294	11.61
640	10	5	3627	3753	2312	3.0	235	14.55
1280	20	1	3302	2566	1693	2.5	541	14.06
1280	20	2	4159	3753	2248	1.5	404	16.18
1280	20	3	4859	4697	2732	0.8	233	17.91

Table 13: Numerical results of Wait- k -Stride- n on CVSS-C French to English speech-to-speech translation dataset.

<i>EDAtt + Tacotron2 on CVSS-C Fr→En</i>						
α	AL	StartOffset	EndOffset	DCNum	DCAve	ASR-BLEU
0.8	2850	2131	5846	0.8	360	11.90
0.6	3136	2383	5451	0.8	442	13.69
0.4	3585	2859	4848	0.7	472	15.93
0.2	4431	3922	3887	0.4	358	19.76

Table 14: Numerical results of EDAtt + Tacotron2 on CVSS-C French to English speech-to-speech translation dataset.

r_{down}	1	2	4
$L_{\text{decoder}}/L_{\text{target}}$	9.3	4.6	2.3
BLEU	24.52	24.54	22.05

Table 15: Performance of offline NAST-S2T with varying hyperparameter r_{down} on MuST-C English to German speech-to-text translation dataset. L_{decoder} and L_{target} represent the length of linguistic decoder and text target, respectively. The average ratio of these lengths is calculated using the training dataset.

r_{up}	4	6	8
$L_{\text{decoder}}/L_{\text{target}}$	2.4	3.6	4.8
ASR-BLEU	25.06	25.82	26.16

Table 16: Performance of offline NAST-S2S with varying hyperparameter r_{up} when r_{down} is fixed to 2 on CVSS-C French to English speech-to-speech translation dataset. L_{decoder} and L_{target} represent the length of acoustic decoder and unit target, respectively. The average ratio of these lengths is calculated using the training dataset.