# Can We Achieve High-quality Direct Speech-to-Speech Translation without Parallel Speech Data?

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### **Abstract**

Recently proposed two-pass direct speech-tospeech translation (S2ST) models decompose the task into speech-to-text translation (S2TT) and text-to-speech (TTS) within an end-to-end model, yielding promising results. However, the training of these models still relies on parallel speech data, which is extremely challenging to collect. In contrast, S2TT and TTS have accumulated a large amount of data and pretrained models, which have not been fully utilized in the development of S2ST models. Inspired by this, in this paper, we first introduce a composite S2ST model named Com-Speech, which can seamlessly integrate any pretrained S2TT and TTS models into a direct S2ST model. Furthermore, to eliminate the reliance on parallel speech data, we propose a novel training method ComSpeech-ZS that solely utilizes S2TT and TTS data. It aligns representations in the latent space through contrastive learning, enabling the speech synthesis capability learned from the TTS data to generalize to S2ST in a zero-shot manner. Experimental results on the CVSS dataset show that when the parallel speech data is available, ComSpeech surpasses previous two-pass models like UnitY and Translatotron 2 in both translation quality and decoding speed. When there is no parallel speech data, ComSpeech-ZS lags behind ComSpeech by only 0.7 ASR-BLEU and outperforms the cascaded models.<sup>1</sup>

### 1 Introduction

Direct speech-to-speech translation (S2ST) refers to the process of translating source language speech directly into target language speech using an end-to-end model (Jia et al., 2019). In contrast to traditional cascaded S2ST (Wahlster, 2000; Nakamura et al., 2006), which comprises a pipeline of automatic speech recognition (ASR), machine translation (MT), and text-to-speech (TTS), direct S2ST

has the advantage of reducing errors accumulation between modules and being easier to deploy (Lee et al., 2022a). Therefore, it has attracted considerable interest from researchers in recent years (Chen et al., 2022; Huang et al., 2023; Fang et al., 2023).

S2ST needs to learn the mapping between speech in different languages. However, due to the complex distribution of speech data, learning such mapping presents significant challenges. To address this, Jia et al. (2022b) introduces the two-pass direct S2ST model, which decomposes S2ST into the subtasks of speech-to-text translation (S2TT) and TTS within an end-to-end model. It begins by generating the target text using one decoder, followed by generating the target speech using another decoder. This modeling approach reduces learning complexity while retaining the benefits of end-to-end modeling, surpassing the performance of cascaded S2ST (Inaguma et al., 2023).

Despite the success of two-pass S2ST models, they still face a significant challenge: the training of these models still relies on parallel speech data, which is extremely difficult to collect. In fact, current S2ST datasets are mostly derived from existing S2TT datasets by converting the target text into speech using TTS models, which is very timeconsuming and becomes impractical when dealing with large-scale S2TT datasets. In contrast, S2TT and TTS have accumulated numerous datasets and pretrained models through past developments. A natural question is how to utilize those pretrained models when constructing an S2ST model, thereby maximizing the utilization of existing resources. Intuitively, we can feed the representations output by the S2TT model into the TTS encoder, thereby combining the pretrained S2TT and TTS models into a two-pass S2ST model. However, one major challenge is that S2TT and TTS models typically use different vocabularies for the target language. For example, S2TT models often use subword vocabularies, while TTS models often use phoneme or

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character vocabularies. Inconsistent vocabularies lead to different segmentations of the same target text. Consequently, directly combining them into an S2ST model results in the TTS model being unable to process the representations output by the S2TT model. Even if we can utilize S2TT and TTS models with the same vocabulary, it is still necessary to finetune the overall model with parallel speech data to adapt it to the S2ST task.

To address the aforementioned challenges, in this paper, we first propose a composite speech-tospeech translation model, named ComSpeech. By introducing a vocabulary adaptor based on connectionist temporal classification (CTC; Graves et al., 2006), it facilitates the conversion of representation sequences between any vocabularies, thus enabling the integration of any pretrained S2TT and TTS models into an S2ST model. Furthermore, to eliminate the dependence on parallel speech data during training, we propose a novel training strategy ComSpeech-ZS that uses only S2TT and TTS data. It employs contrastive learning to align representations in the latent space, allowing the speech synthesis capabilities acquired from the TTS data to generalize to S2ST. Experimental results on the CVSS dataset demonstrate that ComSpeech surpasses previous two-pass models in both translation quality and decoding speed. In the zero-shot learning scenario, the translation quality of ComSpeech-ZS is only 0.7 ASR-BLEU lower than ComSpeech and surpasses cascaded systems.

### 2 Background: Two-pass S2ST

The S2ST dataset usually contains three-way parallel data  $\mathcal{D}_{\text{S2ST}} = \{(S,Y,T)\}$ , where S denotes the source speech, Y is the target text, and T is the target speech. Due to the challenges of directly generating target speech, recent developments have introduced two-pass S2ST models, which enhance translation quality by incorporating the target text into the generation process (Jia et al., 2022b; Inaguma et al., 2023). Formally, a two-pass model typically consists of four sub-modules: the source speech encoder  $\mathcal{F}_{\text{enc}}$ , the target text decoder  $\mathcal{F}_{\text{dec}}$ , the text-to-speech encoder  $\mathcal{G}_{\text{enc}}$ , and the target speech decoder  $\mathcal{G}_{\text{dec}}$ . Firstly,  $\mathcal{F}_{\text{enc}}$  and  $\mathcal{F}_{\text{dec}}$  perform the S2TT task, trained with the cross-entropy loss:

$$\mathcal{L}_{S2TT} = -\sum_{i=1}^{|Y|} \log P(y_i | \mathcal{F}_{dec}(\mathcal{F}_{enc}(S), Y_{< i})).$$
(1)

Subsequently,  $\mathcal{G}_{enc}$  takes the representation from the last layer of  $\mathcal{F}_{dec}$  as its input, and then  $\mathcal{G}_{dec}$  predicts the target speech. The training objective is to minimize the distance between the predicted speech and the ground truth speech:

$$\mathcal{L}_{\text{S2ST}} = d(T, \mathcal{G}_{\text{dec}} \circ \mathcal{G}_{\text{enc}} \circ \mathcal{F}_{\text{dec}}(\mathcal{F}_{\text{enc}}(S), Y_{< i})), \tag{2}$$

where  $d(\cdot,\cdot)$  denotes the distance function, with its specific form determined by the representation type of the target speech (e.g., discrete units or melspectrograms). In summary, the two-pass S2ST model is trained on the parallel speech dataset  $\mathcal{D}_{\text{S2ST}}$  with the following objective:

$$\mathcal{L}_{\text{Two-Pass}} = \mathcal{L}_{\text{S2TT}} + \gamma \cdot \mathcal{L}_{\text{S2ST}}, \tag{3}$$

where  $\gamma$  denotes the weight of the second term. However, **current two-pass S2ST models still** have two main issues: (1) First, they implicitly assumes that  $\mathcal{F}_{dec}$  and  $\mathcal{G}_{enc}$  share the same target text vocabulary, making it challenging to simultaneously employ an existing S2TT model  $\mathcal{F}$  as  $\mathcal{F}_{enc}$  and  $\mathcal{F}_{dec}$ , while utilizing an existing TTS model  $\mathcal{G}$  as  $\mathcal{G}_{enc}$  and  $\mathcal{G}_{dec}$ . (2) Second, their training requires parallel speech data, which is extremely difficult to collect. To address these issues, we first propose a composite S2ST model built upon existing S2TT and TTS models (Section 3). Next, to eliminate the reliance on parallel speech data, we introduce a novel training method that uses only S2TT and TTS data to achieve zero-shot S2ST (Section 4).

# 3 Proposed Model: ComSpeech

In this section, we introduce a more general two-pass S2ST model architecture: Composite Speech-to-Speech Translation (ComSpeech) model. ComSpeech comprises three modules:  $\mathcal{F}$ ,  $\mathcal{A}$ , and  $\mathcal{G}$ , where  $\mathcal{F}$  denotes arbitrary S2TT model,  $\mathcal{G}$  denotes arbitrary TTS model for the target language, and  $\mathcal{A}$  represents the *vocabulary adaptor* inserted between  $\mathcal{F}$  and  $\mathcal{G}$ . The inclusion of the vocabulary adaptor  $\mathcal{A}$  is necessitated by the fact that S2TT and TTS models typically employ different vocabularies for the target language. It can facilitate the conversion of target text representation sequences between different vocabularies. Figure 1 illustrates the model architecture of ComSpeech.

Specifically, we use  $\mathbb{W}$  and  $\mathbb{V}$  to denote the vocabularies of the S2TT model and the TTS model, respectively. The tokenized sequences of the target text Y under these two vocabularies are represented

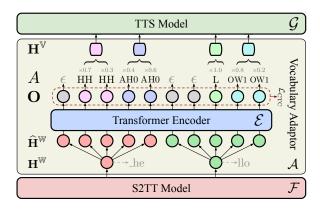


Figure 1: Model architecture of our proposed Com-Speech. It includes an S2TT model  $\mathcal{F}$ , a TTS model  $\mathcal{G}$ , and a vocabulary adaptor  $\mathcal{A}$  to connect F and G.

as  $Y^{\mathbb{W}}=(y_1^{\mathbb{W}},...,y_N^{\mathbb{W}})$  and  $Y^{\mathbb{V}}=(y_1^{\mathbb{V}},...,y_M^{\mathbb{V}})$ , respectively. Next, we will introduce the detailed implementations of each module in ComSpeech.

**S2TT Model** We use the s2t\_conformer model in *fairseq S2T*<sup>2</sup> (Wang et al., 2020) as the S2TT model  $\mathcal{F}$ . Specifically, it comprises a Conformer-based speech encoder (Gulati et al., 2020) and a Transformer-based text decoder (Vaswani et al., 2017). The decoder adopts a subword vocabulary  $\mathbb{W}$  for the target language. Formally, the decoder output hidden states of the S2TT model can be represented as  $\mathbf{H}^{\mathbb{W}} = (\mathbf{h}_1^{\mathbb{W}}, ..., \mathbf{h}_N^{\mathbb{W}})$ , where  $\mathbf{h}_i^{\mathbb{W}} = \mathcal{F}(S, Y_{< i}^{\mathbb{W}})$ . The S2TT model is trained by minimizing the cross-entropy loss:

$$\mathcal{L}_{\text{S2TT}} = -\sum_{i=1}^{N} \log P(y_i^{\mathbb{W}} | \mathcal{F}(S, Y_{< i}^{\mathbb{W}})). \quad (4)$$

**TTS Model** We use FastSpeech 2 (Ren et al., 2021) as the TTS model  $\mathcal{G}$ . Specifically, it consists of an encoder, a variance adapter, and a decoder. FastSpeech 2 adopts a phoneme vocabulary  $\mathbb{V}$  for the target language. For the independent TTS model, the encoder takes the target text embedding EMB( $Y^{\mathbb{V}}$ ) as input, where EMB(·) denotes the phoneme embedding layer. The variance adaptor and decoder predict variance information and target mel-spectrogram, respectively. The training objective of FastSpeech 2 can be written as follows:

$$\mathcal{L}_{TTS} = \mathcal{L}_{L1} + \mathcal{L}_{dur} + \mathcal{L}_{pitch} + \mathcal{L}_{energy}, \quad (5)$$

where  $\mathcal{L}_{L1}$  calculates the L1 distance between the predicted and ground truth mel-spectrograms,  $\mathcal{L}_{dur}$ ,

 $\mathcal{L}_{pitch}$ , and  $\mathcal{L}_{energy}$  denote the mean square error (MSE) loss between ground truth and predictions for duration, pitch, and energy, respectively.

When we combine  $\mathcal{F}$  and  $\mathcal{G}$  into a two-pass S2ST model, the TTS encoder  $\mathcal{G}_{enc}$  no longer takes EMB $(Y^{\mathbb{V}})$  as input but instead accepts the representations  $\mathbf{H}^{\mathbb{W}}$  from the S2TT model. However,  $\mathbf{H}^{\mathbb{W}}$  corresponds to  $Y^{\mathbb{W}}$  and cannot be directly understood by the TTS encoder due to the vocabulary mismatch. Therefore, we introduce a vocabulary adaptor to convert the representation sequence corresponding to  $Y^{\mathbb{W}}$  into that corresponding to  $Y^{\mathbb{V}}$ .

**Vocabulary Adaptor** To facilitate variable-length sequence conversion between different vocabularies ( $\mathbb{W} \to \mathbb{V}$ ), we introduce a vocabulary adaptor  $\mathcal{A}$  based on connectionist temporal classification (CTC; Graves et al., 2006). Specifically, we first upsample each hidden state in  $\mathbf{H}^{\mathbb{W}}$  by a factor of  $\lambda$ , resulting in an upsampled hidden state sequence  $\widehat{\mathbf{H}}^{\mathbb{W}} = (\widehat{\mathbf{h}}_{1}^{\mathbb{W}}, ..., \widehat{\mathbf{h}}_{\lambda \cdot N}^{\mathbb{W}})$ , where  $\widehat{\mathbf{h}}_{i}^{\mathbb{W}} = \mathbf{h}_{[i/\lambda]}^{\mathbb{W}}$ . Next, we add positional encoding to  $\widehat{\mathbf{H}}^{\mathbb{W}}$  and then use an L-layer Transformer encoder  $\mathcal{E}$  for encoding, obtaining the output hidden state sequence  $\mathbf{O} = (\mathbf{o}_{1}, \ldots, \mathbf{o}_{\lambda \cdot N})$ :

$$\mathbf{O} = \mathcal{E}(\widehat{\mathbf{H}}^{\mathbb{W}} + \operatorname{Pos}(\widehat{\mathbf{H}}^{\mathbb{W}})), \tag{6}$$

where  $\operatorname{Pos}(\cdot)$  denotes the sinusoid positional encoding (Vaswani et al., 2017). To achieve cross-vocabulary conversion, we aim to align  $\mathbf O$  with the target text  $Y^{\mathbb V}$  tokenized by the TTS vocabulary  $\mathbb V$ . Thus, we use CTC to model the alignment between the two sequences. Specifically, CTC extends the output space  $\mathbb V$  with a special blank token  $\epsilon$ , and maps each element in  $\mathbf O$  into the output space:

$$P(a_i|\mathbf{O}) = \operatorname{softmax}(\mathbf{Wo}_i + \mathbf{b})[a_i] \ \forall a_i \in \mathbb{V} \cup \{\epsilon\},$$
 (7) where  $\mathbf{W} \in \mathbb{R}^{(|\mathbb{V}|+1)\times d}$  and  $\mathbf{b} \in \mathbb{R}^{|\mathbb{V}|+1}$  are the weights and biases of the linear layer, and  $A = (a_1, ..., a_{\lambda \cdot N})$  is referred to as the *alignment*. CTC introduces a collapsing function  $\beta(A)$  that initially merges all consecutively repeated tokens in  $A$  and then removes all blank tokens  $\epsilon$ . For example:  $\beta(\mathsf{aab}\epsilon \epsilon \mathsf{bbc}) = \mathsf{abbc}$ . During training, CTC marginalizes out all possible alignments as follows:

$$\mathcal{L}_{\text{CTC}} = -\log P(Y^{\mathbb{V}}|\mathbf{O})$$

$$= -\log \sum_{A \in \beta^{-1}(Y^{\mathbb{V}})} P(A|\mathbf{O})$$

$$= -\log \sum_{A \in \beta^{-1}(Y^{\mathbb{V}})} \prod_{i=1}^{\lambda \cdot N} P(a_i|\mathbf{O}),$$
(8)

<sup>2</sup>https://github.com/facebookresearch/fairseq/ tree/main/examples/speech\_to\_text

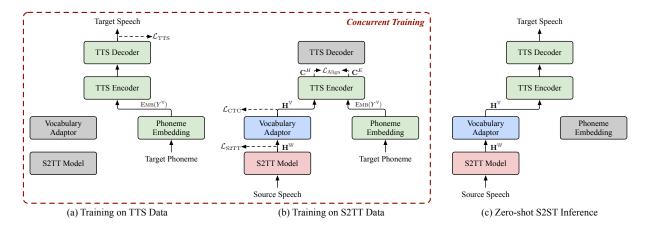


Figure 2: Illustration of training and inference process in the zero-shot learning scenario. Solid lines represent data flow, while dashed lines represent loss calculation. The gray modules do not participate in the computation.

where  $\beta^{-1}(Y^{\mathbb{V}})$  denotes all possible alignments of length  $\lambda \cdot N$  that can be collapsed to  $Y^{\mathbb{V}}$ .

Through CTC, we can learn the alignment between the output representation sequence O and the target text sequence  $Y^{\mathbb{V}}$ . However, the length of **O** is greater than or equal to  $Y^{\mathbb{V}}$   $(\lambda \cdot N > M)$ due to the presence of repeated and blank tokens in the alignment A. During training, it is essential to obtain the representation sequence exactly corresponding to the ground truth target  $Y^{\mathbb{V}}$ , which enables joint training with the subsequent TTS model. Therefore, we compress  $\mathbf{O}$  to length M following these steps: (1) Firstly, we find the most probable alignment  $A^* = \arg \max_A P(A|\mathbf{O}, Y^{\mathbb{V}})$  via Viterbi algorithm (Viterbi, 1967), which is often referred to as forced alignment. (2) Secondly, each continuous repetition of non-blank tokens in  $A^*$  is divided into a segment. In this way, each token  $y_i^{\mathbb{V}}$ in  $Y^{\mathbb{V}}$  corresponds to a segment  $[a_{l_i}^*,...,a_{r_i}^*]$ , where  $a_i^* = y_i^{\mathbb{V}}, \forall l_i \leq j \leq r_i$ . (3) Finally, the representations within each segment are merged into a vector according to the prediction confidence (Liu et al., 2020; Gaido et al., 2021):

$$\mathbf{h}_{i}^{\mathbb{V}} = \sum_{j=l_{i}}^{r_{i}} p_{j} \cdot \mathbf{o}_{j}, \tag{9}$$

$$p_j = \frac{\exp(P(a_j^*|\mathbf{O}))}{\sum_{k=l_i}^{r_i} \exp(P(a_k^*|\mathbf{O}))}.$$
 (10)

The representations corresponding to blank tokens are discarded. Finally, we obtain the representation sequence  $\mathbf{H}^{\mathbb{V}} = (\mathbf{h}_1^{\mathbb{V}},...,\mathbf{h}_M^{\mathbb{V}})$  corresponding to  $Y^{\mathbb{V}}$ , which is fed into the TTS encoder for subsequent speech synthesis. During inference, we select the most probable path  $A^* = (a_1^*,...,a_{\lambda \cdot N}^*)$  with argmax decoding:  $a_i^* = \arg\max_{a_i} P(a_i|\mathbf{O})$ ,

and then merge representations in the same manner as during training.

**Training** ComSpeech can be trained using S2TT, TTS, and S2ST data. Specifically, we can utilize S2TT data to pretrain the S2TT model  $\mathcal{F}$  and TTS data to pretrain the TTS model  $\mathcal{G}$ . Subsequently, the entire model is finetuned using S2ST data. The training objective during finetuning is as follows:

$$\mathcal{L}_{ComSpeech} = \mathcal{L}_{S2TT} + \mathcal{L}_{CTC} + \mathcal{L}_{TTS}. \tag{11}$$

Moreover, as the vocabulary adaptor can establish connections between arbitrary S2TT and TTS models, theoretically, we can leverage any pretrained S2TT and TTS models for S2ST finetuning.

# 4 ComSpeech-ZS: Training ComSpeech without Parallel Speech Data

As mentioned earlier, collecting S2ST data is extremely challenging. In this section, we explore the possibility of training ComSpeech exclusively on S2TT and TTS data, achieving *zero-shot* S2ST without the need for parallel speech data. The idea is to train distinct modules using S2TT and TTS data concurrently, while achieving representation alignment in the output space of the TTS encoder. This enables the speech synthesis capabilities learned from the TTS data to generalize to S2ST during inference. Figure 2 illustrates the process of training and inference.

Specifically, we use  $\mathcal{D}_{S2TT} = \{(S,Y)\}$  and  $\mathcal{D}_{TTS} = \{(Y,T)\}$  to denote the S2TT and TTS datasets, respectively, and train the model concurrently using both datasets. For TTS data batches, we train the TTS model  $\mathcal{G}$  with  $\mathcal{L}_{TTS}$ , as illustrated in Figure 2(a). For S2TT data batches, firstly, we

train the S2TT model  $\mathcal{F}$  and vocabulary adaptor  $\mathcal{A}$  with  $\mathcal{L}_{S2TT}$  and  $\mathcal{L}_{CTC}$ . Secondly, since the TTS encoder receives the target text embedding EMB( $Y^{\mathbb{V}}$ ) during TTS training but vocabulary adaptor's output  $\mathbf{H}^{\mathbb{V}}$  during inference, we aim for the output representations of the TTS encoder with these two inputs to be identical, thereby achieving zero-shot generalization. Therefore, we introduce a representation alignment loss after the TTS encoder during S2TT training, as illustrated in Figure 2(b).

**Representation Alignment** Formally, we use  $\mathbf{C}^H = (\mathbf{c}_1^H, ..., \mathbf{c}_M^H)$  and  $\mathbf{C}^E = (\mathbf{c}_1^E, ..., \mathbf{c}_M^E)$  to denote the output representations of TTS encoder with these two types of input:

$$\mathbf{C}^H = \mathcal{G}_{\text{enc}}(\mathbf{H}^{\mathbb{V}}), \ \mathbf{C}^E = \mathcal{G}_{\text{enc}}(\text{EMB}(Y^{\mathbb{V}})).$$
 (12)

Firstly, we align representations with the MSE loss:

$$\mathcal{L}_{MSE} = \sum_{i=1}^{M} \|\mathbf{c}_{i}^{H} - \mathbf{c}_{i}^{E}\|_{2}^{2}.$$
 (13)

Additionally, we incorporate a contrastive learning objective to align representations. This objective maximizes the similarity between representations from the same input pairs and minimizes the similarity between representations from different input pairs. The contrastive loss is formulated as:

$$\mathcal{L}_{\text{CTR}} = -\frac{1}{2} \sum_{i=1}^{M} \log \frac{\exp(s(\mathbf{c}_{i}^{H}, \mathbf{c}_{i}^{E})/\tau)}{\sum_{j=1}^{M} \exp(s(\mathbf{c}_{i}^{H}, \mathbf{c}_{j}^{E})/\tau)}$$
$$-\frac{1}{2} \sum_{i=1}^{M} \log \frac{\exp(s(\mathbf{c}_{i}^{H}, \mathbf{c}_{i}^{E})/\tau)}{\sum_{j=1}^{M} \exp(s(\mathbf{c}_{j}^{H}, \mathbf{c}_{i}^{E})/\tau)},$$
(14)

where we use a similarity function based on L1 distance:  $s(\mathbf{x}, \mathbf{y}) = -\|\mathbf{x} - \mathbf{y}\|_1$ , and  $\tau$  denotes the temperature hyperparameter. The final training objective for representation alignment is as follows:

$$\mathcal{L}_{Align} = \mathcal{L}_{MSE} + \mathcal{L}_{CTR}.$$
 (15)

**Two-stage Finetuning** In the zero-shot learning scenario, we adopt a two-stage finetuning strategy to facilitate the learning process. In the first stage, we only utilize the S2TT dataset  $\mathcal{D}_{S2TT}$  to train the S2TT Model  $\mathcal{F}$  and vocabulary adaptor  $\mathcal{A}$  through the objectives  $\mathcal{L}_{S2TT}$  and  $\mathcal{L}_{CTC}$ . In the second stage, we conduct training using both the S2TT and TTS datasets, with the following training objectives:

$$\begin{aligned} \mathcal{L}_{\text{ComSpeech-ZS}} &= \mathbb{E}_{\mathcal{D}_{\text{TTS}}} \left[ \mathcal{L}_{\text{TTS}} \right] \\ &+ \mathbb{E}_{\mathcal{D}_{\text{S2TT}}} \left[ \mathcal{L}_{\text{S2TT}} + \mathcal{L}_{\text{CTC}} + \mathcal{L}_{\text{Align}} \right]. \end{aligned} \tag{16}$$

Direction	S2ST (src / tgt)	S2TT (src)	TTS (tgt)	
Fr→En	264h / 174h	264h		
De→En	184h / 112h	184h	191h	
$Es{\rightarrow}En$	113h / 70h	113h		

Table 1: The speech hour statistics of all datasets. src: source speech; tgt: target speech.

Throughout the entire training process, the S2ST data is not used. During inference, we can achieve zero-shot S2ST as illustrated in Figure 2(c).

# 5 Experiments

## 5.1 Datasets

The S2ST, S2TT, and TTS datasets utilized in our experiments are all sourced from the CVSS dataset (Jia et al., 2022c). CVSS is a large-scale S2ST dataset containing <source speech, target text, target speech> triples across 21 source languages to English. We conduct experiments on three language pairs: French $\rightarrow$ English (Fr $\rightarrow$ En), German $\rightarrow$ English (De $\rightarrow$ En), and Spanish $\rightarrow$ English (Es $\rightarrow$ En). Our experiments consist of two scenarios: *supervised learning* and *zero-shot learning* scenarios. The former involves training using S2ST data, while the latter involves training using only S2TT and TTS data.

**S2ST Dataset** In the supervised learning scenario, we utilize triplet data from the CVSS Fr/De/Es→En datasets to train the model.

**S2TT Dataset** In the zero-shot learning scenario, we employ <source speech, target text> pairs from the CVSS Fr/De/Es→En datasets as the S2TT data, with the target speech being discarded.

**TTS Dataset** In the zero-shot learning scenario, we combine all <target text, target speech> pairs from CVSS  $X\rightarrow En$  ( $X\notin \{Fr, De, Es\}$ ) datasets as the TTS data. We exclude the target speech-text pairs from CVSS  $Fr/De/Es\rightarrow En$  datasets, ensuring that there is no overlap in the target text between S2TT and TTS datasets. This guarantees that in the zero-shot learning scenario, the model has not implicitly utilized parallel <source speech, target speech> pairs for training. The statistical information for all datasets are presented in Table 1.

### 5.2 Experimental Setup

**Data Processing** For the source speech, we convert it to 16000Hz and compute 80-dimensional

ID	Model	Training Data		ASR-BLEU				Speedup	
	Widdel	S2ST	S2TT	TTS	Fr→En	De→En	Es→En	Avg.	Specuap
-	- Ground Truth		/	/	84.52	75.53	88.54	82.86	/
		,	Supervise	ed Lear	ning				
A1	Translatotron 2 (Jia et al., 2022b)	<b> √</b>	×	×	26.12	16.92	22.98	22.01	1.00×
A2	UnitY (Inaguma et al., 2023)	✓	×	×	26.90	16.36	24.06	22.44	0.98×
A3	3 S2UT (Lee et al., 2022a)		×	×	22.23	2.99	18.53	14.58	0.62×
A4	DASpeech (Fang et al., 2023)	✓	$\checkmark$	$\checkmark^{\dagger}$	25.03	/	/	/	10.05×
Α5	ComSpeech w/o pretrain	✓	×	$\times$	27.58**	17.35**	24.29**	23.07	3.40×
A6	ComSpeech w/ pretrain	✓	$\checkmark$	$\checkmark^{\dagger}$	28.15**	18.16**	24.80**	23.70	3.40×
	Zero-shot Learning								
B1	S2TT + G2P + TTS	×	✓	<b>√</b>	27.04	16.97	23.26	22.42	3.49×
B2	ComSpeech-ZS	×	$\checkmark$	$\checkmark$	27.55**	17.67**	23.80**	23.01	3.40×

Table 2: ASR-BLEU scores on CVSS Fr/De/Es $\rightarrow$ En test set. †: The TTS data used in the supervised learning scenario is different from that used in the zero-shot learning scenario as described in footnote 3. \*\* means the improvements over the baseline system (A1 in the supervised learning scenario and B1 in the zero-shot learning scenario) are statistically significant (p < 0.01).

mel-filterbank features. For the target speech, we convert it to 22050Hz and transform the waveform into mel-spectrograms. Utterance-level and global-level cepstral mean-variance normalization are applied to the source speech and target speech, respectively. For the target text, the S2TT model employs a subword vocabulary of size 6k which is learned on the target text of CVSS. The TTS model employs a phoneme vocabulary of size 70. We follow Ren et al. (2021) to extract the duration, pitch, and energy information of the target speech.

**Model Configuration** The S2TT model comprises 12 Conformer encoder layers and 4 Transformer decoder layers. The TTS model follows the standard configuration of FastSpeech 2. The vocabulary adaptor contains 4 Transformer encoder layers and the upsample factor  $\lambda$  is set to 5. The detailed hyperparameters can be found in Appendix B. The dropout is set to 0.3. The label smoothing of the S2TT model is set to 0.1. The HiFi-GAN (Kong et al., 2020) vocoder pretrained on the VCTK dataset (Veaux et al., 2017) is used to generate waveform from the mel-spectrogram.

**Training** During the training process, the batch size for S2TT and S2ST data is set to 320k source audio frames, while the batch size for TTS data is set to 512. In the supervised learning scenario, the model is first pretrained on S2TT and TTS data<sup>3</sup>,

followed by finetuning using S2ST data. In the zero-shot learning scenario, a two-stage finetuning approach is employed as stated in Section 4. During each training stage, the learning rate warms up to 1e-3 within 4k steps, and the training is halted if the validation loss does not decrease for 10 consecutive validations. We use Adam optimizer (Kingma and Ba, 2015) in all training stages. The temperature  $\tau$  in contrastive learning is set to 0.1. All models are trained on 4 RTX 3090 GPUs.

**Evaluation** We average the best 5 checkpoints based on validation loss for evaluation, and employ two evaluation metrics: ASR-BLEU and BLASER 2.0 (Communication et al., 2023). For ASR-BLEU, we first transcribes the translated speech into text using a pretrained ASR model<sup>4</sup>, and then calculates the BLEU score (Papineni et al., 2002) and the statistical significance of translation results using the SacreBLEU toolkit<sup>5</sup> (Post, 2018). For BLASER 2.0, we use the blaser-2.0-ref model<sup>6</sup> to evaluate the cross-lingual semantic similarity. The decoding speed is measured on the CVSS-C Fr→En test set with a batch size of 1.

**Baseline Systems** We primarily compare Com-Speech with two state-of-the-art two-pass S2ST models: Translatotron 2 (Jia et al., 2022b) and UnitY (Inaguma et al., 2023). Their S2TT compo-

<sup>&</sup>lt;sup>3</sup>It should be noted that in the supervised learning scenario, the TTS pretraining data are <target text, target speech> pairs sourced from S2ST data, distinct from the TTS data utilized in the zero-shot learning scenario.

<sup>4</sup>https://dl.fbaipublicfiles.com/fairseq/ wav2vec/wav2vec\_vox\_960h\_pl.pt

<sup>5</sup>https://github.com/mjpost/sacrebleu

<sup>6</sup>https://huggingface.co/facebook/blaser-2. 0-ref

Madal	Fr→En		De→En		<b>Es</b> → <b>En</b>				
Model	S2TT	S2ST	$\Delta$	S2TT	S2ST	$\Delta$	S2TT	S2ST	$\Delta$
S2TT	30.49	/	/	18.54	/	/	25.39	/	/
Translatotron 2 (Jia et al., 2022b)	28.82	26.12	2.70	18.66	16.92	1.74	25.82	22.98	2.84
UnitY (Inaguma et al., 2023)	30.37	26.90	3.47	17.95	16.36	1.59	26.59	24.06	2.53
ComSpeech w/o pretrain	29.98	<u>27.58</u>	2.40	18.44	<u>17.35</u>	1.09	25.73	<u>24.29</u>	1.44
ComSpeech w/ pretrain	30.72	28.15	<u>2.57</u>	19.41	18.16	<u>1.25</u>	<u>26.51</u>	24.80	<u>1.71</u>

Table 3: BLEU scores of the S2TT results and ASR-BLEU scores of the S2ST results. The S2TT results come from the first pass of decoding. The best and second-best results are indicated by **bold** and <u>underline</u>, respectively.

Model	BLASER 2.0				
Wiodei	Fr→En	$De{\rightarrow}En$	De→En Es→En		
Supervised	Learning				
Translatotron 2 (Jia et al., 2022b)	3.1801	2.9034	3.2592		
UnitY (Inaguma et al., 2023)	3.1749	2.8278	3.2310		
ComSpeech w/ pretrain	3.1890	2.9281	3.2785		
Zero-shot i					
S2TT + G2P + TTS	3.1716	2.8680	3.2172		
ComSpeech-ZS	3.1681	2.9242	3.2555		

Table 4: BLASER 2.0 scores on CVSS Fr/De/Es $\rightarrow$ En test set.

nent is identical to the S2TT part of ComSpeech. Upon the S2TT model, a 2-layer Transformer encoder is employed to encode the S2TT decoder hidden states. Finally, UnitY utilizes a 2-layer decoder to generate the target units, while Translatotron 2 employs a 6-layer decoder to generate the target mel-spectrograms. Besides, we include the results of the single-pass model S2UT (Lee et al., 2022a) and the non-autoregressive two-pass model DASpeech (Fang et al., 2023) for comparison. We implement all above models with the open-source fairseq<sup>7</sup> (Ott et al., 2019) library.

In the zero-shot learning scenario, we compare our proposed ComSpeech-ZS with a cascaded system: S2TT + G2P + TTS. Here, the S2TT and TTS models correspond to those used for initializing the ComSpeech-ZS model. The G2P is a model that converts English graphemes to phonemes. We achieve this conversion using the g2p\_en<sup>8</sup> library.

### 5.3 Main Results

Results in the Supervised Learning Scenario Table 2 presents the ASR-BLEU scores on the CVSS test set. In the supervised learning scenario, it can be observed that: (1) ComSpeech outperforms Translatotron 2 and UnitY in translation

quality across all three language pairs (A1-A2 vs. A5-A6). Since the S2TT parts of these three models are the same, the performance improvement in S2ST is mainly attributed to the adoption of a more powerful TTS model for speech synthesis in Com-Speech. We also report the performance of S2TT and S2ST, along with their gap in Table 3. We observe that ComSpeech narrows the performance gap between S2TT and S2ST compared to previous models, further demonstrating the importance of incorporating a more powerful TTS for speech synthesis. (2) Benefiting from the parallel decoding capability of FastSpeech 2, ComSpeech achieves a 3.40× decoding speedup compared with Translatotron 2. (3) Compared to S2UT, ComSpeech shows significant improvements in translation quality (A3 vs. A5), demonstrating the effectiveness of two-pass modeling in S2ST. (4) Compared to DASpeech, which also employs FastSpeech 2 as the TTS module, ComSpeech shows a 3.1 ASR-BLEU improvement in translation quality (A4 vs. A6). We believe the main reason is that DASpeech uses a phoneme vocabulary for the S2TT model to be compatible with FastSpeech 2's vocabulary, which may lead to a decrease in translation quality. Despite ComSpeech's slower decoding speed compared to DASpeech, we consider this is not the focus of our work. Theoretically, our proposed vocabulary adaptor can be also used to connect a more powerful non-autoregressive S2TT model with a TTS model. We leave this for future research.

# Results in the Zero-shot Learning Scenario In the zero-shot learning scenario, we find that: (1) Despite not using any S2ST data, the translation quality of ComSpeech-ZS is comparable to that of ComSpeech in the supervised learning scenario, with only a 0.7 ASR-BLEU difference (A6 vs. B2). (2) ComSpeech-ZS also surpasses the performance of Translatotron 2, UnitY, S2UT, and DASpeech (A1-A4 vs. B2), further demonstrating the effec-

<sup>&</sup>lt;sup>7</sup>https://github.com/facebookresearch/fairseq

<sup>8</sup>https://github.com/Kyubyong/g2p

MSE	CTR $(s(\mathbf{x}, \mathbf{y}))$	ASR-BLEU↑	Alignment↓	$Uniformity \downarrow$
×	×	0.01	101.55	-56.75
$\checkmark$	×	13.33	1.05	-2.01
×	$-\ \mathbf{x} - \mathbf{y}\ _1$	25.14	4.29	-14.19
×	$-\ \mathbf{x} - \mathbf{y}\ _{2}^{2}$	25.40	10.14	-23.38
×	$\mathbf{x} \cdot \mathbf{y}$	24.35	18.56	-32.87
$\checkmark$	$-\ {\bf x} - {\bf y}\ _1$	27.55	0.85	-3.97
$\checkmark$	$-\ \mathbf{x} - \mathbf{y}\ _{2}^{2}$	27.11	0.98	-8.22
$\checkmark$	$\mathbf{x} \cdot \mathbf{y}$	27.13	0.92	-9.30

Table 5: Results on CVSS Fr→En test set with different alignment training objectives.

tiveness of our proposed model architecture and training approach. (3) The translation quality of ComSpeech-ZS surpasses that of the cascaded system, possibly due to avoiding error accumulation. Meanwhile, ComSpeech-ZS is easier to deploy compared to the cascaded system, requiring only the deployment of a single model without the need to store intermediate results.

Results of BLASER 2.0 Scores Table 4 shows the BLASER 2.0 scores on the CVSS test set. We observe that our ComSpeech and ComSpeech-ZS consistently outperform other baseline systems in most cases. Since BLASER 2.0 evaluates directly based on speech rather than the transcribed text, this further validates that the speech generated by our model not only exhibits accurate translation but also reliable speech quality.

# 5.4 Ablation Studies

**Training Objectives** In the zero-shot learning scenario, achieving representation alignment is crucial for the final translation quality. In Table 5, we explore different alignment training objectives. In addition to ASR-BLEU, we follow Wang and Isola (2020) to measure the alignment and uniformity of the representation space, defined as follows:

Alignment = 
$$\mathbb{E}_{(\mathbf{c}_i^H, \mathbf{c}_i^E)} \left[ \| \mathbf{c}_i^H - \mathbf{c}_i^E \|_1 \right]$$
 (17)

Uniformity = 
$$\log \mathbb{E}_{(\mathbf{c}_i^H, \mathbf{c}_i^E)} \left[ e^{-\|\mathbf{c}_i^H - \mathbf{c}_j^E\|_1} \right]$$
 (18)

From the results in Table 5, it can be observed that using only MSE loss results in a relatively low ASR-BLEU. Using only contrastive learning also leads to a performance drop of around 2 ASR-BLEU, as the alignment score is high in this case. Hence, both contrastive learning and MSE loss are indispensable. Specifically, our experiments reveal that using L1 distance as the similarity function yields better results than L2 distance and dot product. In this case, even though the uniformity score

Pretrain Two		Two-stage	ASR-BLEU			
S2TT	TTS	Finetune	ComSpeech	ComSpeech-ZS		
×	×	×	27.58	23.43		
×	$\checkmark$	×	27.43	0.19		
$\checkmark$	×	×	28.03	25.67		
$\checkmark$	$\checkmark$	×	28.15	27.10		
$\checkmark$	$\checkmark$	✓	/	27.55		

Table 6: ASR-BLEU scores on CVSS Fr→En test set with different pretraining and finetuning strategies.

is higher, the alignment score is the lowest. We speculate that the alignment of representation space plays a more crucial role in the ultimate zero-shot transfer performance.

Pretraining and Finetuning Strategies Com-Speech supports S2TT and TTS pretraining. We explore the impact of pretraining in both supervised and zero-shot learning scenarios. As shown in Table 6, using only TTS pretraining often has a negative effect, especially in the zero-shot learning scenario. On the other hand, S2TT pretraining brings a significant performance improvement, and combining both S2TT and TTS pretraining results in additional performance gains. Overall, pretraining has a greater impact on performance in the zero-shot learning scenario. Additionally, our proposed two-stage fine-tuning strategy leads to a performance improvement of 0.45 ASR-BLEU in the zero-shot learning scenario.

# 5.5 Effects of the Size of S2TT and TTS Data

In this section, we explore the effects of the size of S2TT and TTS data on ComSpeech-ZS and the cascaded system (S2TT + G2P + TTS).

**S2TT Data Size** As shown in Figure 3, the size of S2TT data significantly impacts the performance of both the cascaded system and ComSpeech-ZS. With only 10 hours of S2TT data, both systems have poor translation quality. However, as the amount of S2TT data increases, ComSpeech-ZS consistently achieves higher translation quality than the cascaded system, demonstrating the advantages of end-to-end modeling.

TTS Data Size As shown in Figure 4, the performance of the cascaded system remains relatively stable with the expansion of TTS data size, while ComSpeech-ZS gradually improves with the increase in TTS data. When TTS data is limited, ComSpeech-ZS performs worse than the cascaded system, and we speculate this may be due to the

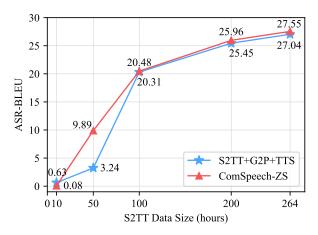


Figure 3: ASR-BLEU scores on CVSS Fr→En test set with different amounts of S2TT data.

imbalance in the S2TT and TTS data scales during finetuning. As the TTS data exceeds 50 hours, ComSpeech-ZS outperforms the cascaded system, and the gap between them grows as the TTS data size increases. This indicates that ComSpeech-ZS has a higher upper limit than the cascaded system.

## 6 Related Work

**Speech-to-Speech Translation** S2ST extends S2TT (Fang et al., 2022; Fang and Feng, 2023a,b; Zhou et al., 2023) which further generates the target speech. Jia et al. (2019) first proposes direct S2ST with a sequence-to-sequence model. Zhang et al. (2021); Lee et al. (2022a,b) propose using the discrete representation of speech as the prediction target and achieve better performance. Huang et al. (2023); Zhu et al. (2023); Wu (2023); Fang et al. (2023, 2024) adopt non-autoregressive models or diffusion models to generate the target speech for faster decoding speed. To make training easier, Jia et al. (2022b); Inaguma et al. (2023) introduce twopass S2ST models that generate target text and target speech successively. To further enhance S2ST, researchers introduce techniques like pretraining (Wei et al., 2023; Zhang et al., 2023; Dong et al., 2024) and data augmentation (Popuri et al., 2022; Jia et al., 2022a; Dong et al., 2022; Nguyen et al., 2022; Communication et al., 2023) to alleviate the data scarcity. Zhang et al. (2024); Ma et al. (2024) achieve simultaneous speech-to-speech translation with multi-task learning and non-autoregressive streaming Transformer, respectively. Our work extends the research on two-pass S2ST, introducing a more general model architecture and a novel training method that achieves zero-shot S2ST without parallel speech data.

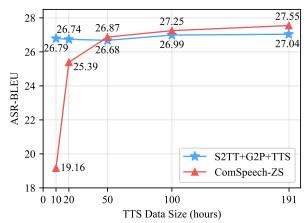


Figure 4: ASR-BLEU scores on CVSS Fr→En test set with different amounts of TTS data.

Zero-shot Speech Translation Dinh (2021); Wang et al. (2022); Duquenne et al. (2022, 2023) explore cross-modal alignment between speech and text, achieving zero-shot S2TT using only ASR and MT data. For S2ST, Diwan et al. (2023); Nachmani et al. (2024) focus on achieving zero-shot S2ST using only monolingual speech data in both source and target languages. To the best of our knowledge, we are the first to study achieving zero-shot S2ST using only S2TT and TTS data.

## 7 Conclusion

In this paper, we first introduce a novel S2ST model architecture, named ComSpeech, which incorporates a CTC-based vocabulary adaptor capable of connecting arbitrary S2TT and TTS models to obtain an S2ST model. Furthermore, we propose a training method using only S2TT and TTS data. By aligning in the TTS encoder's representation space using contrastive learning, we achieve zeroshot S2ST without relying on parallel speech data. Experimental results on the CVSS dataset demonstrate that ComSpeech surpasses previous S2ST models in both translation quality and decoding efficiency. Moreover, in the zero-shot learning scenario, our model achieves performance close to the supervised learning scenario and surpasses the cascaded system. In summary, we hope that our method can inspire future work in direct S2ST in terms of model architecture and training approach, making more comprehensive use of existing S2TT and TTS pretrained models and training data to improve S2ST. In the future, we will explore building direct S2ST models based on more powerful S2TT and TTS models.

### Limitations

Although our model achieves satisfactory performance in both supervised learning and zero-shot learning scenarios, there are still some limitations: (1) In cases where TTS data is limited, the performance of ComSpeech-ZS still lags behind the cascaded system. In the future, we will explore how to improve performance by balancing the S2TT and TTS training data. (2) Currently, our method cannot preserve the speaker characteristics of the source speech. We will explore this in the future.

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# References

- Peng-Jen Chen, Kevin Tran, Yilin Yang, Jingfei Du, Justine Kao, Yu-An Chung, Paden Tomasello, Paul-Ambroise Duquenne, Holger Schwenk, Hongyu Gong, Hirofumi Inaguma, Sravya Popuri, Changhan Wang, Juan Miguel Pino, Wei-Ning Hsu, and Ann Lee. 2022. Speech-to-speech translation for A real-world unwritten language. *CoRR*, abs/2211.06474.
- Seamless Communication, Loïc Barrault, Yu-An Chung, Mariano Cora Meglioli, David Dale, Ning Dong, Paul-Ambroise Duquenne, Hady Elsahar, Hongyu Gong, Kevin Heffernan, John Hoffman, Christopher Klaiber, Pengwei Li, Daniel Licht, Jean Maillard, Alice Rakotoarison, Kaushik Ram Sadagopan, Guillaume Wenzek, Ethan Ye, Bapi Akula, Peng-Jen Chen, Naji El Hachem, Brian Ellis, Gabriel Mejia Gonzalez, Justin Haaheim, Prangthip Hansanti, Russ Howes, Bernie Huang, Min-Jae Hwang, Hirofumi Inaguma, Somya Jain, Elahe Kalbassi, Amanda Kallet, Ilia Kulikov, Janice Lam, Daniel Li, Xutai Ma, Ruslan Mavlyutov, Benjamin Peloquin, Mohamed Ramadan, Abinesh Ramakrishnan, Anna Sun, Kevin Tran, Tuan Tran, Igor Tufanov, Vish Vogeti, Carleigh Wood, Yilin Yang, Bokai Yu, Pierre Andrews, Can Balioglu, Marta R. Costa-jussà, Onur Celebi, Maha Elbayad, Cynthia Gao, Francisco Guzmán, Justine Kao, Ann Lee, Alexandre Mourachko, Juan Pino, Sravya Popuri, Christophe Ropers, Safiyyah Saleem, Holger Schwenk, Paden Tomasello, Changhan Wang, Jeff Wang, and Skyler Wang. 2023. Seamlessm4t: Massively multilingual & multimodal machine translation.
- Tu Anh Dinh. 2021. Zero-shot speech translation. *CoRR*, abs/2107.06010.
- Anuj Diwan, Anirudh Srinivasan, David Harwath, and Eunsol Choi. 2023. Unit-based speech-to-speech translation without parallel data.

- Qianqian Dong, Zhiying Huang, Qiao Tian, Chen Xu, Tom Ko, Yunlong Zhao, Siyuan Feng, Tang Li, Kexin Wang, Xuxin Cheng, Fengpeng Yue, Ye Bai, Xi Chen, Lu Lu, Zejun Ma, Yuping Wang, Mingxuan Wang, and Yuxuan Wang. 2024. Polyvoice: Language models for speech to speech translation. In *The Twelfth International Conference on Learning Representations*
- Qianqian Dong, Fengpeng Yue, Tom Ko, Mingxuan Wang, Qibing Bai, and Yu Zhang. 2022. Leveraging pseudo-labeled data to improve direct speech-to-speech translation. In *Interspeech* 2022, 23rd Annual Conference of the International Speech Communication Association, Incheon, Korea, 18-22 September 2022, pages 1781–1785. ISCA.
- Paul-Ambroise Duquenne, Hongyu Gong, Benoît Sagot, and Holger Schwenk. 2022. T-modules: Translation modules for zero-shot cross-modal machine translation. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 5794–5806, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Paul-Ambroise Duquenne, Holger Schwenk, and Benoît Sagot. 2023. Modular speech-to-text translation for zero-shot cross-modal transfer. *CoRR*, abs/2310.03724.
- Qingkai Fang and Yang Feng. 2023a. Back translation for speech-to-text translation without transcripts. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics*.
- Qingkai Fang and Yang Feng. 2023b. Understanding and bridging the modality gap for speech translation. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics*.
- Qingkai Fang, Zhengrui Ma, Yan Zhou, Min Zhang, and Yang Feng. 2024. CTC-based non-autoregressive textless speech-to-speech translation. In *Findings of the Association for Computational Linguistics: ACL* 2024.
- Qingkai Fang, Rong Ye, Lei Li, Yang Feng, and Mingxuan Wang. 2022. Stemm: Self-learning with speechtext manifold mixup for speech translation. In *Pro*ceedings of the 60th Annual Meeting of the Association for Computational Linguistics.
- Qingkai Fang, Yan Zhou, and Yang Feng. 2023. DASpeech: Directed acyclic transformer for fast and high-quality speech-to-speech translation. In *Advances in Neural Information Processing Systems*.
- Marco Gaido, Mauro Cettolo, Matteo Negri, and Marco Turchi. 2021. CTC-based compression for direct speech translation. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 690–696, Online. Association for Computational Linguistics.

- Alex Graves, Santiago Fernández, Faustino Gomez, and Jürgen Schmidhuber. 2006. Connectionist temporal classification: Labelling unsegmented sequence data with recurrent neural networks. In *Proceedings of the 23rd International Conference on Machine Learning*, ICML '06, page 369–376, New York, NY, USA. Association for Computing Machinery.
- Anmol Gulati, James Qin, Chung-Cheng Chiu, Niki Parmar, Yu Zhang, Jiahui Yu, Wei Han, Shibo Wang, Zhengdong Zhang, Yonghui Wu, and Ruoming Pang. 2020. Conformer: Convolution-augmented Transformer for Speech Recognition. In *Proc. Interspeech* 2020, pages 5036–5040.
- Rongjie Huang, Jinglin Liu, Huadai Liu, Yi Ren, Lichao Zhang, Jinzheng He, and Zhou Zhao. 2023. Transpeech: Speech-to-speech translation with bilateral perturbation. In *The Eleventh International Conference on Learning Representations*.
- Hirofumi Inaguma, Sravya Popuri, Ilia Kulikov, Peng-Jen Chen, Changhan Wang, Yu-An Chung, Yun Tang, Ann Lee, Shinji Watanabe, and Juan Pino. 2023. UnitY: Two-pass direct speech-to-speech translation with discrete units. In *Proceedings of the 61st An*nual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 15655– 15680, Toronto, Canada. Association for Computational Linguistics.
- Ye Jia, Yifan Ding, Ankur Bapna, Colin Cherry, Yu Zhang, Alexis Conneau, and Nobu Morioka. 2022a. Leveraging unsupervised and weakly-supervised data to improve direct speech-to-speech translation. In *Interspeech 2022, 23rd Annual Conference of the International Speech Communication Association, Incheon, Korea, 18-22 September 2022*, pages 1721–1725. ISCA.
- Ye Jia, Michelle Tadmor Ramanovich, Tal Remez, and Roi Pomerantz. 2022b. Translatotron 2: High-quality direct speech-to-speech translation with voice preservation. In *Proceedings of the 39th International Conference on Machine Learning*, volume 162 of *Proceedings of Machine Learning Research*, pages 10120–10134. PMLR.
- Ye Jia, Michelle Tadmor Ramanovich, Quan Wang, and Heiga Zen. 2022c. CVSS corpus and massively multilingual speech-to-speech translation. In *Proceedings of Language Resources and Evaluation Conference (LREC)*, pages 6691–6703.
- 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. In *Interspeech 2019*, 20th Annual Conference of the International Speech Communication Association, Graz, Austria, 15-19 September 2019, pages 1123–1127. ISCA.
- Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In *3rd International Conference on Learning Representations*,

- ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings.
- Jungil Kong, Jaehyeon Kim, and Jaekyoung Bae. 2020. Hifi-gan: Generative adversarial networks for efficient and high fidelity speech synthesis. In *Proceedings of the 34th International Conference on Neural Information Processing Systems*, NIPS'20, Red Hook, NY, USA. Curran Associates Inc.
- Ann Lee, Peng-Jen Chen, Changhan Wang, Jiatao Gu, Sravya Popuri, Xutai Ma, Adam Polyak, Yossi Adi, Qing He, Yun Tang, Juan Pino, and Wei-Ning Hsu. 2022a. Direct speech-to-speech translation with discrete units. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics* (Volume 1: Long Papers), pages 3327–3339, Dublin, Ireland. Association for Computational Linguistics.
- Ann Lee, Hongyu Gong, Paul-Ambroise Duquenne, Holger Schwenk, Peng-Jen Chen, Changhan Wang, Sravya Popuri, Yossi Adi, Juan Pino, Jiatao Gu, and Wei-Ning Hsu. 2022b. Textless speech-to-speech translation on real data. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 860–872, Seattle, United States. Association for Computational Linguistics.
- Yuchen Liu, Junnan Zhu, Jiajun Zhang, and Chengqing Zong. 2020. Bridging the modality gap for speech-to-text translation. *CoRR*, abs/2010.14920.
- Zhengrui Ma, Qingkai Fang, Shaolei Zhang, Shoutao Guo, Yang Feng, and Min Zhang. 2024. A non-autoregressive generation framework for end-to-end simultaneous speech-to-any translation. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics*.
- Eliya Nachmani, Alon Levkovitch, Yifan Ding, Chulayuth Asawaroengchai, Heiga Zen, and Michelle Tadmor Ramanovich. 2024. Translatotron 3: Speech to speech translation with monolingual data.
- S. Nakamura, K. Markov, H. Nakaiwa, G. Kikui, H. Kawai, T. Jitsuhiro, J.-S. Zhang, H. Yamamoto, E. Sumita, and S. Yamamoto. 2006. The atr multilingual speech-to-speech translation system. *IEEE Transactions on Audio, Speech, and Language Processing*, 14(2):365–376.
- Xuan-Phi Nguyen, Sravya Popuri, Changhan Wang, Yun Tang, Ilia Kulikov, and Hongyu Gong. 2022. Improving speech-to-speech translation through unlabeled text. *arXiv preprint arXiv:2210.14514*.
- Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli. 2019. fairseq: A fast, extensible toolkit for sequence modeling. In *Proceedings of NAACL-HLT 2019: Demonstrations*.

- Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the* 40th Annual Meeting of the Association for Computational Linguistics, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.
- Sravya Popuri, Peng-Jen Chen, Changhan Wang, Juan Pino, Yossi Adi, Jiatao Gu, Wei-Ning Hsu, and Ann Lee. 2022. Enhanced direct speech-to-speech translation using self-supervised pre-training and data augmentation. In *Interspeech 2022, 23rd Annual Conference of the International Speech Communication Association, Incheon, Korea, 18-22 September 2022*, pages 5195–5199. ISCA.
- Matt Post. 2018. A call for clarity in reporting BLEU scores. In *Proceedings of the Third Conference on Machine Translation: Research Papers*, pages 186–191, Brussels, Belgium. Association for Computational Linguistics.
- 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 International Conference on Learning Representations.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc.
- Christophe Veaux, Junichi Yamagishi, and Kirsten Mac-Donald. 2017. Cstr vctk corpus: English multispeaker corpus for cstr voice cloning toolkit.
- A. Viterbi. 1967. Error bounds for convolutional codes and an asymptotically optimum decoding algorithm. *IEEE Transactions on Information Theory*, 13(2):260–269.
- Wolfgang Wahlster, editor. 2000. Verbmobil: Foundations of Speech-to-Speech Translation. Springer, Berlin.
- 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 2020 Conference of the Asian Chapter of the Association for Computational Linguistics (AACL): System Demonstrations.*
- Chen Wang, Yuchen Liu, Boxing Chen, Jiajun Zhang, Wei Luo, Zhongqiang Huang, and Chengqing Zong. 2022. Discrete cross-modal alignment enables zero-shot speech translation. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 5291–5302, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Tongzhou Wang and Phillip Isola. 2020. Understanding contrastive representation learning through alignment

- and uniformity on the hypersphere. In *Proceedings* of the 37th International Conference on Machine Learning, volume 119 of *Proceedings of Machine Learning Research*, pages 9929–9939. PMLR.
- Kun Wei, Long Zhou, Ziqiang Zhang, Liping Chen,
  Shujie Liu, Lei He, Jinyu Li, and Furu Wei. 2023.
  Joint pre-training with speech and bilingual text for direct speech to speech translation. In ICASSP 2023 2023 IEEE International Conference on Acoustics,
  Speech and Signal Processing (ICASSP), pages 1–5.
- Xianchao Wu. 2023. Duplex diffusion models improve speech-to-speech translation. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 8035–8047, Toronto, Canada. Association for Computational Linguistics.
- Chen Zhang, Xu Tan, Yi Ren, Tao Qin, Kejun Zhang, and Tie-Yan Liu. 2021. Uwspeech: Speech to speech translation for unwritten languages. *Proceedings of the AAAI Conference on Artificial Intelligence*, 35(16):14319–14327.
- Shaolei Zhang, Qingkai Fang, Shoutao Guo, Zhengrui Ma, Min Zhang, and Yang Feng. 2024. Stream-Speech: Simultaneous speech-to-speech translation with multi-task learning. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics*.
- Ziqiang Zhang, Long Zhou, Chengyi Wang, Sanyuan Chen, Yu Wu, Shujie Liu, Zhuo Chen, Yanqing Liu, Huaming Wang, Jinyu Li, Lei He, Sheng Zhao, and Furu Wei. 2023. Speak foreign languages with your own voice: Cross-lingual neural codec language modeling. *CoRR*, abs/2303.03926.
- Yan Zhou, Qingkai Fang, and Yang Feng. 2023. CMOT: Cross-modal mixup via optimal transport for speech translation. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7873–7887, Toronto, Canada. Association for Computational Linguistics.
- Yongxin Zhu, Zhujin Gao, Xinyuan Zhou, Ye Zhongyi, and Linli Xu. 2023. DiffS2UT: A semantic preserving diffusion model for textless direct speech-to-speech translation. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 11573–11583, Singapore. Association for Computational Linguistics.

# A Effects of the Hyperparameters of Vocabulary Adaptor

The vocabulary adaptor has two important hyperparameters: the number of Transformer encoder layers L and the upsampling factor  $\lambda$  for the input sequence. We investigate the influence of these hyperparameters in the supervised learning scenario without S2TT and TTS pretraining. According to the performance on the CVSS Fr $\rightarrow$ En dev set as shown in Table 7, we choose L=4 and  $\lambda=5$  in our expriments.

$\overline{L}$	ASR-BLEU	λ	ASR-BLEU
2	27.58	2	11.94
4	28.04	5	28.04
6	28.02	8	27.75

Table 7: Results on CVSS Fr→En dev set with different hyperparameters of the vocabulary adaptor.

# **B** Hyperparameters

We list the hyperparameters of ComSpeech and other baseline models in Table 8.

Нуре	erparameters	S2UT	UnitY	Translatotron 2	DASpeech	ComSpeech
	conv_kernel_sizes	(5, 5)	(5, 5)	(5, 5)	(5, 5)	(5, 5)
	encoder_type	conformer	conformer	conformer	conformer	conformer
	encoder_layers	12	12	12	12	12
S2TT Encoder	encoder_embed_dim	256	256	256	256	256
S211 Elicouei	encoder_ffn_embed_dim	2048	2048	2048	2048	2048
	encoder_attention_heads	4	4	4	4	4
	encoder_pos_enc_type	relative	relative	relative	relative	relative
	depthwise_conv_kernel_size	31	31	31	31	31
	decoder_layers	4	4	4	4	4
	decoder_embed_dim	512	512	512	512	512
S2TT Decoder	decoder_ffn_embed_dim	2048	2048	2048	2048	2048
3211 Decodel	decoder_attention_heads	8	8	8	8	8
	label_smoothing	0.1	0.1	0.1	0.0	0.1
	s2t_loss_weight	8.0	8.0	0.1	1.0	1.0
	encoder_layers	-	-	-	-	4
Vasahulami Adamtan	encoder_embed_dim	-	-	-	-	512
Vocabulary Adaptor	encoder_ffn_embed_dim	-	-	-	-	2048
	encoder_attention_heads	-	-	-	-	8
	encoder_layers	-	2	2	4	4
TTS Encoder	encoder_embed_dim	-	512	512	256	256
113 Elicodei	encoder_ffn_embed_dim	-	2048	2048	1024	1024
	encoder_attention_heads	-	8	8	4	4
	decoder_layers	6	2	6	4	4
	decoder_embed_dim	512	512	512	256	256
	decoder_ffn_embed_dim	2048	2048	2048	1024	1024
	decoder_attention_heads	8	8	8	4	4
	label_smoothing	0.1	0.1	-	-	-
TTS Decoder	n_frames_per_step	1	1	5	1	1
	unit_dictionary_size	1000	1000	-	-	-
	var_pred_hidden_dim	-	-	-	256	256
	var_pred_kernel_size	-	-	-	3	3
	var_pred_dropout	-	-	-	0.5	0.5
	s2s_loss_weight	1.0	1.0	1.0	5.0	1.0

Table 8: Hyperparameters of ComSpeech and baseline models.