IMPROVING SPEECH-TO-SPEECH TRANSLATION THROUGH UNLABELED TEXT

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ABSTRACT

Direct speech-to-speech translation (S2ST) is among the most challenging problems in the translation paradigm due to the significant scarcity of S2ST data. While effort has been made to increase the data size from unlabeled speech by cascading pretrained speech recognition (ASR), machine translation (MT) and text-to-speech (TTS) models; unlabeled speech text has remained relatively under-utilized to improve S2ST. We propose an effective way to utilize the massive existing unlabeled text from different languages to create a large amount of S2ST data to improve S2ST performance by applying various acoustic effects to the generated synthetic data. Empirically our method outperforms the state of the art in Spanish-English translation by up to 2 BLEU. Significant gains by the proposed method are demonstrated in extremely low-resource settings for both Spanish-English and Russian-English translations.

Index Terms— Speech-to-speech translation, augmentation, unlabeled text

1. INTRODUCTION

Translating speech of a language to speech of another can be done by trivially cascading an automatic speech recognition (ASR) [1], machine translation (MT) [2, 3, 4], or combinatory speech-to-text translation (S2T) [5] and finally a text-to-speech (TTS) systems [6, 7, 8, 9]. But such process suffers from significant inference latency and is prone to error propagation through each stage. Alternatively, there is a growing interest in developing direct speech-to-speech translation systems (S2ST) [10, 11, 12]. Not only do these systems have faster inference but also allow translations between unwritten languages and dialects [13]. Recent speech-to-speech model [12] employs a self-supervised pretrained speech encoder [14] and a discrete unit mBART model to train a speech-to-unit translation (S2UT), where the target speech is converted into discrete units [15]. Such units are trained with self-supervision to group speech frames based on their linguistic and prosodic information using k-means clustering [16].

Despite promising capability, direct speech-to-speech (S2ST) models suffer from significant data scarcity due to the challenge of collecting human annotated parallel speech. To improve S2ST performance, apart from self-supervised pretraining on unlabeled speech [10, 14, 17], [12] also tried to generate extra synthetic S2ST data from speech recognition (ASR) data by converting its texts to speech in the target language using a cascaded MT-TTS system [18]. Nonetheless, such work only makes use of the available audio data, while not utilizing the existing unlabeled text data from numerous languages, sources and domains [19, 17, 20]. Text data is known to be much more massive and diverse than the current speech data. However, such textual data may be difficult to deal with in the speech paradigm as they lack crucial information about speakers, speed, pitch and emotions.

In this work, we present an effective strategy to generate synthetic speech-to-speech training data from the abundant unlabeled text data so that the resulting speech data is not only diverse in terms of semantic content, but also randomly varying in acoustic features such as speaker tones. Our approach consists of two processes: (i) “Text-aug” data generation, which is the synthetic S2ST data created from unlabeled text; and (ii) “Effects-aug” process, which is an on-the-fly speech augmentation process that transforms toneless Text-aug speech into a varying-tone and noisy version that tries to mimic the distribution of real speech data. Our approach does not introduce any extra model or data supervision besides those used in the recent S2UT baseline [12], which use supervised MT and TTS models. Instead, we utilize an unsupervised MT model [3] to generate data. In the experiments, our method achieves up to 35.2 BLEU on the CoVoST-2 Es-En task and 35.1 BLEU on Europarl-ST En-En task, surpassing the state-of-the-art approach [12] by up to 2 BLEU. Further analysis shows that Effects-aug is a crucial step for the extra data to improve the performance. We also demonstrate that our method achieves significant performance gain of up to 28 BLEU in low-resource speech-to-speech setups with only 10 hours (hr) S2ST data.

*Work done during an internship at Meta AI.
2. BACKGROUND

Success in self-supervised training of speech encoder [14] enables significant advancements in various speech processing tasks, ranging from ASR [1, 21], speech-to-text translation (S2T) [5, 22], which are critical components in building speech-to-speech translation systems [11, 12]. Such pretrained encoder produces speech hidden representations that can be discretized into units that condense semantic and prosodic information [21]. Specifically, the self-supervised HuBERT model [21] is trained to encode input speech into discrete units by performing $k$-means clustering over the hidden vectors by a pretrained $k$-means model.

Recent S2ST models [10, 13, 12] make use of such $k$-means units that, instead of directly generating an audio signal, which is considerably slow, they generate shorter unit sequences with a heavy speech-to-unit translation (S2UT) model and use a lightweight vocoder [23] to convert units to output audios. Specifically, the S2UT model is an attention-based Seq2Seq model [2]. Its encoder is a Wav2vec 2.0 [14] model that is pretrained to encode speech representations from unlabeled audios. It consists of a multi-layer convolutional network to encode raw audio signal, followed by a Transformer [2] (or Conformer [24]) encoder to produce contextual representations for the audio. Meanwhile, the decoder is a unit-mBART [17], which is pretrained with masked language modeling on the unsupervised reduced discrete unit data derived from unlabeled speech via the HuBERT-$k$-means model [21]. During S2S training, the S2UT model is initialized with the pretrained models [14, 17] and then finetuned with speech-to-unit data, which is in fact the S2S data where the target speech is converted to discrete units. During finetuning, Popuri et al [12] suggest that it is most beneficial to freeze the decoder parameters, except its layer-norm layers [25] in the attention modules. Figure 1 depicts the architecture of the direct speech-to-speech translation system. More importantly, Popuri et al [12] also make use of intensive data augmentation, where extra supervised speech recognition (ASR) data is used with pretrained MT [2] and TTS [7] models to synthetically generate more speech-to-speech data for training, which profoundly improves the performance. Our approach is built on top of this work in that, in addition to speech-based data augmentation, we introduce an effective way to convert the existing massive unlabeled text data into prosodically diverse speech-to-speech data to add into the training data pool.

3. METHOD

This section describes our strategy in building extra training data from unlabeled text (§3.1) and the training process that augments such synthetic data to be acoustically diverse (§3.2).

3.1. Text-Aug Data Creation

Text-aug data is the extra synthetic S2ST dataset that is created from unlabeled text. Figure 2 illustrates how it is generated and trained. Specifically, given an unlabeled text corpus $Y$ of the target language, we first clean them and remove non-conversational sentences, such as those that contain URLs, special characters, words in brackets, etc, to obtain a cleaner unlabeled text corpus $Y_t$. We then use an unsupervised MT model, namely CRISS [3], to translate $Y_t$ into a text corpus $X_t$ of the source language. Then, we use an unsupervised MT model, namely CRISS [3], to translate $Y_t$ into a text corpus $X_t$ of the source language. The resulting data will undergo further filtering to remove pairs with excessive length difference or repetitions. Then, the source $(X_t)$ and target $(Y_t)$ texts are converted into speech $X_s$ and $Y_s$ using existing text-to-speech (TTS) models [6]. The target speech $Y_s$ is then transformed into reduced units $U_s$ to form the speech-to-unit training data.

3.2. Effects-Aug Data Augmentation

As the Text-aug speech is generated by a single TTS model, which was trained from single-speaker data, its speech prosody
is largely monotonic, single-style, unnatural. Training the S2UT model with a large amount of such data will overwhelm the existing real speech data and cause a shift in the real data distribution at convergence, thus leading to failure in generalization in test sets. Therefore, during training, we apply a series of random acoustic effects and background noise impositions, which we collectively call Effects-aug, to each Text-aug speech utterance of the source language. Specifically, for each input utterance \( X \), we augment \( X \) into \( \tilde{X} \) as follows:

\[
\tilde{X} = f_1(f_2(\ldots f_n(X)\ldots))
\]

where each function \( f_i \) will, at \( p\% \) chance, either apply augmentation \( h_i \) to input \( x \) with a random configuration or do nothing and return \( x \). Each \( h_i \in \{h_1, \ldots, h_n\} \) represents a distinct type of audio perturbation effects, which include SoX effects like speed, pitch and frequency variations, low-pass filter; as well as random mixing with real environmental noise or music segments [26] at different positions and signal-to-noise (SNR) ratio [27]. We argue that applying multiple random Effects-aug augmentations on the unnatural Text-aug data may, to a certain degree, help them mimic the realistic conditions, where there can be multiple speakers with different tones, pitches and emotions recording their speech in various environments such as coffee shops or construction sites. Our analysis experiments show that without such augmentation processes, the Text-aug data actually cause performance decline instead, as they may be unrealistic that they potentially cause a shift in the convergence point of the model.

4. EXPERIMENTS

4.1. Spanish-English Speech-to-Speech Translation

Regarding training data, we reuse the same S2ST dataset as used by Popuri et al [12]. Specifically, we use single-speaker TTS models to convert the target text of S2T data from various sources, namely CoVoST-2 [29], Europarl-ST [30], mTEDx [31]. These data is joint with VoxPopuli [13] S2ST data. In addition, we also include the extra ASR augmentation data introduced in Popuri et al [12], which originates from MLS [32], CommonVoice [33], Librispeech [34] and TEDLIUM [35]. These sources result in the total original dataset sizes of 1800 and 2880 hours (hr) for Es→En and En→Es respectively.

In terms of model setup, similar to [12], we use the multilingual HuBERT and k-means model [13], which was pretrained from unlabeled VoxPopuli speech data [36]. The S2U model’s encoder is a large Conformer Wav2Vec 2.0 [14, 24] pretrained with Libri-light [34] for En and VoxPopuli [36] for Es. The decoder is the unit mBART [17] that was pretrained from reduced units derived from the aforementioned unlabeled speech with the HuBERT-k-means models.

Regarding setups relating to our method, to produce the Text-aug dataset, we use the pretrained unsupervised MT model CRISS [3] to translate \( \sim 12M \) En and 12M Es monolingual sentences, which are randomly sampled from the CC25 [19] corpora, into Es and En for respectively. After further filtering and TTS speech conversion [6], we obtain \( \sim 14K \) and 21K hours of audio Text-aug data for Es→En and En→Es tasks, which are almost 10x the original data [12]. Despite its much larger size, during S2U finetuning, we sample the original and Text-aug data at a 50:50 sampling ratio to ensure that the model has sufficient exposure to real audios to avoid further distribution shift. We compare our method with the state of the art [12], along with related baselines such as the cascaded S2T+TTS and ASR+MT+TTS systems or [12] with back-translation data from unlabeled speech [28]. In terms of Effects-aug settings, we randomly select at \( p = 50\% \) chance: (i) speed variations by 0.95-1.05 ratio, (ii) pitch variations by 0.95-1.05 ratio, (iii) low-pass filter with cut-off frequency in 300-1000Hz, (iv) up to 4 noise utterances chosen in the Musan corpus [26] at SNR ratio between 25-35. To stabilize the model, we average the best 10 checkpoints after training for 50K updates.

Table 1 compares the ASR-BLEU [12] scores of our method against related baselines on the CoVoST-2, Europarl-ST and mTEDx Es→En S2ST task; as well as the Europarl-ST and MuST-C En→Es task. Specifically, on average across multiple test sets, our method surpasses [12] by up to 2 BLEU for Es→En and 1 BLEU for En→Es tasks. In addition, despite achieving improvements with extra back-translation data [28] generated from unlabeled speech [36], [12] still lags behind our method by 1 BLEU score on average.

4.2. Low-resource and Unsupervised Translation

To demonstrate the effectiveness of the Text-aug data, we evaluate our method in extremely low-resource conditions, where we use only 10hr, 50hr and 100hr of S2ST data randomly sampled from the original training data [11]. Table 2 compare the averaged test scores for Es→En and En→Es between each low-resource performance of S2UT models [12] trained with different original S2ST data (e.g., 10hr) and those trained with both S2ST and our synthetic Text-aug (e.g., 10hr+Text-Effects-aug). The results indicate that our method offers significant performance boost for extremely low-resource conditions (10hr), while diminishing return is observed as the amount of S2ST data with natural speech input increase to 100hr. Furthermore, in the unsupervised setup without any natural-speech S2ST data, our method is able to achieve 17.1 and 18.1 BLEU for Es→En and En→Es respectively.

4.3. Russian-to-English Translation

We also evaluate our method on Russian-English S2ST task. Specifically, we apply the same S2UT setup as [12] to train the model on a 10hr sub-sample and the full 25hr natural S2ST dataset for Ru-En task, which is produced from a combination of CoVoST-2 [29] and mTEDx [31] speech corpora. As it can be seen in Table 3, our method achieves up to 34 BLEU
Table 1: ASR-BLEU scores for Spanish (Es) - English (En) speech-to-speech translation tasks.

| Method | CoVoST-2 | Europarl-ST | mTEDx | Avg | Europarl-ST | MuST-C | Avg |
|--------|----------|-------------|-------|-----|-------------|--------|-----|
| S2T (w2v2-L) + TTS | 28.4 | 23.6 | 21.5 | 24.5 | 32.6 | 30.1 | 31.4 |
| ASR + MT + TTS | 33.8 | 29.1 | 32.4 | 31.8 | 28.8 | 34.2 | 31.5 |
| S2UT [11] | 22.7 | 18.0 | 16.9 | 19.2 | 25.8 | 24.3 | 25.1 |
| S2UT + ASR aug [12] | 33.5 | 28.6 | 29.1 | 30.4 | 33.6 | 33.7 | 33.7 |
| [12] + Back-translation [28] | 34.3 | 30.3 | 30.1 | 31.6 | 33.9 | 33.7 | 33.8 |
| [12] + Text-aug + Effects-aug | 35.1 | 31.1 | 31.0 | 32.4 | 35.1 | 34.1 | 34.6 |

Table 2: Averaged test scores for low-resource and unsupervised Es→En and En→Es S2ST tasks.

| Low-resource S2T data | Es-En (Avg) | En-En (Avg) |
|-----------------------|-------------|-------------|
| 10hr / 10hr+Text-Effects-aug | 1.7 / 27.3 | 0.3 / 28.4 |
| 50hr / 50hr+Text-Effects-aug | 21.4 / 29.2 | 18.9 / 30.3 |
| 100hr / 100hr+Text-Effects-aug | 26.2 / 29.7 | 26.1 / 30.4 |

Table 3: Scores on the CoVoST-2 Russian-English S2T task.

| CoVoST-2 Ru-En | 10hr / 10hr+Text-Effects-aug | 25hr / 25hr+Text-Effects-aug |
|----------------|-------------------------------|-------------------------------|
| 0.1 / 28.1     | 0.2 / 34.9                   |

gain compared to the standard S2ST setup, which is mostly attributed to the fact that Ru-En dataset is inherently extremely low-resource. The observation for Ru-En is thus consistent with that for low-resource Es-En explained in §4.2.

4.4. Ablation Studies

We conduct ablation study experiments to gain more insights into the method, which are presented in Table 4. Specifically, we empirically answer the following questions by comparing the averaged test ASR-BLEU scores for Es→En task.

**Which is the best audio augmentation?** It is shown that applying either SoX effects or background noises on the Text-aug data brings in decent gain, while applying both yields the best results. However, skipping the Effects-aug suite causes a dramatic performance degradation due to the monotonicity and unnaturalness of these text-based synthetic data.

**On which data should Effects-aug be applied?** Applying Effects-aug on the Text-aug data is shown to be critical, while augmenting the S2ST data as well gives a slight improvement.

**Should we apply Effects-aug on target audio too?** Meanwhile, applying augmentation on the target side audios is unnecessary as it is shown to make little difference.

**Should we omit Text-aug entirely and use Effects-aug only?** Without the synthetic Text-aug data, applying Effects-aug augmentation on the original S2ST data only yields up to 1 BLEU gain over the baseline [12]. However, adding the Text-aug data offers an extra 1 BLEU improvement.

5. CONCLUSION

We presented an effective method to generate a large amount of synthetic S2ST data from unlabeled text corpora, as well as an online audio augmentation process that can transform them into more prosodically diverse, which is shown to outperform the state of the art in the speech-to-speech Es-En translation tasks by up to 2 ASR-BLEU. In our analysis, we also demonstrate that the method is also more beneficial for low-resource and unsupervised setups.

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