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► **To cite this version:**

Victoria Mingote, Pablo Gimeno, Luis Vicente, Sameer Khurana, Antoine Laurent, et al.. Direct Text to Speech Translation System Using Acoustic Units. *IEEE Signal Processing Letters*, 2023, 30, pp.1262-1266. 10.13039/501100011033 . hal-04212239

HAL Id: hal-04212239

<https://univ-lemans.hal.science/hal-04212239v1>

Submitted on 20 Sep 2023

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Direct Text to Speech Translation System using Acoustic Units

Victoria Mingote, Pablo Gimeno, Luis Vicente, Sameer Khurana, Antoine Laurent, Jarod Duret

Abstract—This paper proposes a direct text to speech translation system using discrete acoustic units. This framework employs text in different source languages as input to generate speech in the target language without the need for text transcriptions in this language. Motivated by the success of acoustic units in previous works for direct speech to speech translation systems, we use the same pipeline to extract the acoustic units using a speech encoder combined with a clustering algorithm. Once units are obtained, an encoder-decoder architecture is trained to predict them. Then a vocoder generates speech from units. Our approach for direct text to speech translation was tested on the new CVSS corpus with two different text mBART models employed as initialisation. The systems presented report competitive performance for most of the language pairs evaluated. Besides, results show a remarkable improvement when initialising our proposed architecture with a model pre-trained with more languages.

Index Terms—Acoustic Units, CVSS corpus, Direct Text to Speech Translation, mBART

I. INTRODUCTION

DURING the last years, the huge increase in the available unlabelled data for text and speech in all languages of the world has led to the need to develop powerful new approaches to process this data. Also, recent advances in self-supervised learning have provided the opportunity to benefit from this data and produce general-purpose representations. These representations can be employed for different tasks and languages with impressive results, e.g. for speech processing using XLS-R [1] or for text processing with mBART [2], [3] and mT5 [4]. Moreover, recently many works have focused on the development of multilingual and also multimodal systems, such as mSLAM [5] and SAMU-XLSR [6]. These systems aim to reduce communication problems between people speaking and writing different languages, especially in the case of under-resourced languages.

Previous works have established state-of-the-art performance on a variety of text and speech downstream tasks

This work was performed using HPC resources from GENCI-IDRIS (Grants 2022-AD011012565 and AD011012527). This project has received funding from the European Union’s Horizon 2020 research and innovation program under the Marie Skłodowska-Curie grant agreement No 101007666. This work was also supported by JSALT 2022 at JHU, with gift-funds from Amazon, Microsoft and Google, and by MCIN/AEI/10.13039/501100011033 and European Union “NextGenerationEU”/PRTR Grants PDC2021-120846-C41 & PDI2021-126061OB-C44.

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including machine translation, specifically for the text to text and speech to text translation tasks. However, research interest in speech to speech and text to speech translation tasks is still growing, as these tasks remain a major challenge due to the scarcity of labelled data for fine-tuning the systems. These tasks seek to convert speech and text generated in a source language into speech in another target language. In the case of conventional speech to speech translation, systems rely on a cascade approach that translates speech into text using Automatic Speech Recognition (ASR) followed by text to text machine translation, or a speech to text system. In both cases, after the mentioned steps, a speech synthesis model is applied to generate speech in the target language.

The conventional systems mentioned above achieve high performance, but these systems are text-centric. Thus, having speech in one language as input, an intermediate text representation in the target language has to be obtained as a preliminary step to generate speech. Therefore, the idea of direct speech to speech translation without relying on intermediate text representation has been recently explored in the literature [7], [8]. This approach has shown great computational benefits compared to the cascade approach. Nevertheless, a performance gap can still be observed due to the challenges of simultaneously learning the alignment between two languages and the process of correctly mapping spectrograms from source to target languages. To tackle the existing gap, the research described in [9], [10] has proposed a direct speech to speech translation system which is trained to predict a set of discrete acoustic units extracted from the target speech. In addition to the direct speech to speech system, these works have introduced a text to speech translation part using discrete acoustic units. However, these works apply text to unit translation to the output of an ASR system. Hence, the proposed approach is not considered a direct text to speech system, as it does not take an original text input directly to produce the output speech. Moreover, the performance of this system could be influenced by the use of the output of the ASR module as input, the quality of which may affect the subsequent steps. On the other hand, considering the limitations that still exist in direct translation and the relevance of multimodal and multilingual systems, [11], [12] have developed a system for speech to speech and text to speech translation. In this system, a common fixed representation for speech and text is built to carry out zero-shot cross-modal translation.

Unlike previous works, where text to unit translation systems were used only combined with ASR, this paper describes an implementation of a framework for generating speech in a given language from text input in a different language. The

task can then be formally defined as a direct text to speech translation task. Applying this framework, we use text as source input to obtain discrete acoustic units as intermediate representations to generate speech. Thus, this text framework allows us to generate the same discrete units as using speech as input. The use of this framework could be useful for different real applications. For instance, text to speech translation could be employed as a data augmentation technique for low resource languages or to create audio versions of written content, such as podcasts or story-telling services from texts. Furthermore, in this work, we have also analyzed the effect of using two pre-trained models with a different number of languages as encoder-decoder for the fine-tuning of our direct text to speech system in a new corpus called Common Voice-based Speech-to-Speech (CVSS) translation [13]. This new CVSS dataset has recently been released to address the issues of scarcity in end-to-end labelled data for direct speech to speech and text to speech translation. In addition, the number of languages in similar previous works has also been limited to mostly high-resource languages with 10 different languages. However, with this new dataset, the text to speech translation task has been evaluated on more than 20 input languages.

This paper is laid out as follows. Section II provides a review of the existing approaches which inspire this work, and introduces the proposed direct text to speech framework using acoustic units. The experimental setup is detailed in Section III, focusing on the data and the evaluation protocol. Results and discussions are given in Section IV. Finally, conclusions and future lines are presented in Section V.

II. PROPOSED METHOD

A. Preliminaries: Direct Speech to Speech Translation

Nowadays, there is an expanding line of research in direct speech to speech translation in which the development carried out in [9], [10] has had a great impact. These works have introduced the first systems based on real speech data as target. Thus, instead of predicting continuous spectrograms as in [7], [8], discrete units learned from self-supervised representations of the target speech are predicted. The system proposed is an encoder-decoder based on a sequence-to-sequence transformer model for speech-to-unit translation.

To create the system described in [9], [10], two different blocks are integrated. First, a multilingual Hidden unit BERT (mHuBERT) [14] is employed to extract representations from the target speech that are then discretized using a quantizer model. mHuBERT was chosen as generator due to its superior performance across different speech tasks compared to other unsupervised models. By extracting the discrete units with this approach, the encoder-decoder speech to unit translation model can be trained using the units as target sequence. In a second step, and once this model is trained, the target speech is generated from the discrete units.

B. Direct Text to Speech Translation

Overview.: In view of the success achieved by the use of acoustic units for direct speech to speech translation systems in the preliminary works, this work presents a framework

to apply the same approach for direct text to speech translation. On the other hand, the need for multilingual and multimodal systems has also motivated several state-of-the-art translation systems where speech and text are permitted as input. Therefore, we propose a multilingual framework in which text data is employed as the input source to predict discrete acoustic units as target without the need to know the transcription in the target language. This aspect is especially relevant in low resource languages, where finding text-speech transcription pairs can be difficult. In addition, the application of the approach presented in this section can be seen as a data augmentation strategy to be used in the case of these languages with scarcity of available resources.

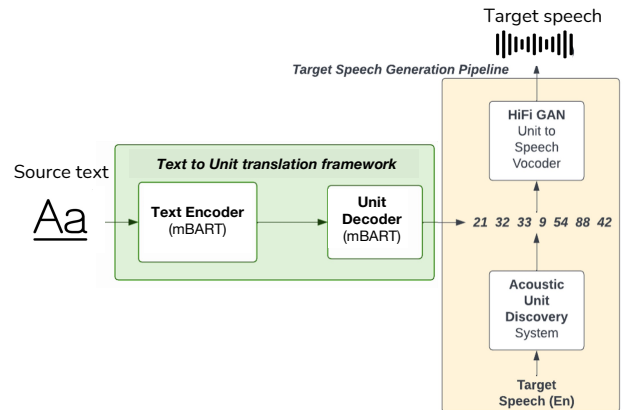


Fig. 1. Direct text to speech translation system, obtaining acoustic units with source text data in any language to generate target speech in English language.

As illustrated in Figure 1, an encoder-decoder architecture is used to perform the direct text to speech translation system. Since the conversion of text inputs into acoustic units can be considered as a machine translation task, we have used a pre-trained text model as initialisation for our encoder-decoder architecture. Namely, we have considered multilingual BART (mBART) model in its two variations, mBART25 and mBART50 [2], [3]. The main difference between both models is the number of languages used in the training process. After initialisation, the full architecture is fine-tuned on the text to acoustic unit translation task. The units employed as targets for this training have previously been extracted with an acoustic unit discovery system. Finally, in inference, the HiFi GAN [15] unit to speech vocoder is applied to generate target speech utterances. This unit-based vocoder is a modified version of the original HiFi-GAN neural vocoder presented in [16]. For this model, we have used the pre-trained English vocoder available at this link¹. This last part corresponds to the orange block in Figure 1 and could be shared with a direct speech to speech system.

Learning.: To train the direct text to speech translation system, pairs of examples (x_S, u_L) are used where x_S is the source text in any of the multiple languages employed, and u_L is set of acoustic units extracted from the target speech. The generation of these units is carried out by a pre-trained

¹https://github.com/facebookresearch/fairseq/blob/main/examples/speech_to_speech/docs/textless_s2st_real_data.md

mHuBERT model [10] and a k-means quantizer¹. Concerning the mHuBERT model, it is based on the HuBERT Base architecture trained using a combination of English, Spanish, and French data from VoxPopuli [17]. Speech representations are learned in a self-supervised way using unlabelled data as explained in [14], [18]. After that, a k-means quantizer is applied to the representations learned in the layer 11th of the mHuBERT model to generate discrete labels or units. This layer is chosen as done in similar direct translation works [10]. Several papers have shown that HuBERT like models provide the most meaningful phonetic and word information towards higher layers of the model [19], [20].

To carry out the k-means quantizer process, the two following steps are applied. First, for training, N centroids are learned using a fraction of the training data. After that, in inference time, the output of the quantizer is chosen as the index of the centroid minimising the euclidean distance between the input embedding and N centroids learned. In this case, the number of k-means clusters employed is 1000 as done in [10]. Moreover, the discrete unit sequences extracted from the k-means algorithm could have consecutive repetitions of the same units. Therefore, to generate the final target units, the original unit sequences are collapsed to convert consecutive equal units into one single unit (e.g., 1 1 2 2 3 3 \rightarrow 1 2 3). This reduction has been applied since the work described in [9] showed that collapsing unit sequences did not lead to a decrease in performance and was more efficient. As these target units are discrete, the text to unit translation system is trained to minimize the cross entropy loss between the predicted and real units using label smoothing with a probability of 0.2.

Hyperparameters.: As optimizer for the fine-tuning process, we have employed the Adam optimizer with $\epsilon = 1e - 6$, $\beta_1 = 0.9$, $\beta_2 = 0.98$, learning rate $3e - 5$, and polynomial learning rate decay scheduling. The model is trained using the fairseq toolkit [21] with a dropout of 0.3 and an attention dropout value of 0.1. The training process was carried out employing 8 V100 (32 GB) NVIDIA GPUs.

III. EXPERIMENTAL SETUP

A. Data

For the direct text to speech translation task, two stages have been carried out. Initially, reference acoustic units are extracted and then text to speech framework is trained using them as targets. To develop both stages, the following data from the new CVSS translation corpus [13] are employed.

Acoustic Units.: For obtaining the acoustic units, the English audios from the CVSS-C (canonical voice) dataset have been used as target speech. These target audios are forwarded through the acoustic unit discovery system based on mHuBERT model and k-means clustering approach to obtain the discrete unit representations.

Direct Text to Speech Translation.: Once the acoustic units are obtained, they are employed as targets to train the direct text to unit translation system. Considering that the CVSS dataset also provides the text transcription for the input audios, we have used this dataset to perform 21 languages to EN text to speech translation tasks.

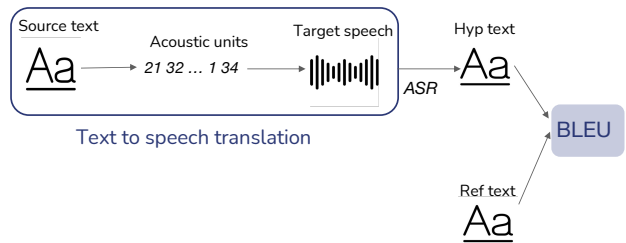


Fig. 2. Text to speech evaluation pipeline, using an ASR model to generate hypothesis text and compare with reference text to obtain BLEU scores.

B. Evaluation

Aiming to evaluate the text to speech translation task, and considering that it is not feasible to directly compare two audio signals, we adopt a similar framework as the one described in [8] to evaluate the translation quality of the generated speech. This setup is described in Figure 2.

As it can be seen, an ASR system is used to generate transcriptions for the target speech. The ASR system used² is an open-source English model based on wav2vec 2.0 features trained through a self-training objective [22]. The evaluation metric shown in our results is then computed as the BLEU score between the obtained transcriptions and the reference text which is normalized in CVSS to perform this standard evaluation. This metric provides an objective measure of speech intelligibility and translation quality.

IV. RESULTS AND DISCUSSION

As mentioned above, to build the direct text to speech translation system, we have explored different models as initialisation for the encoder-decoder architecture. Therefore, we have conducted experiments to evaluate the proposed approach using pre-trained mBART25 and mBART50 models. In addition, we also developed a cascade system in order to have a reference system for comparison. This system is composed of a machine translation module based on the mBART50 model followed by a speech synthesis module implemented using tacotron2 [23].

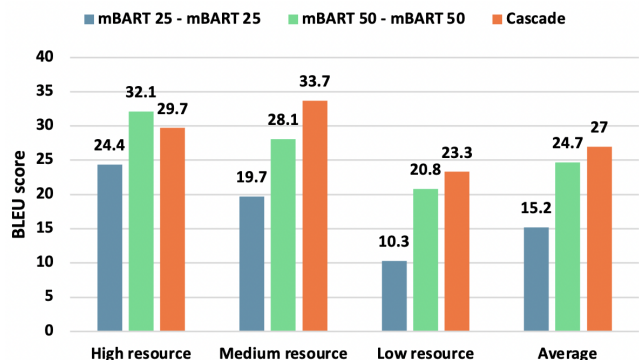


Fig. 3. BLEU results on CVSS test set, comparing the cascade and two mBART models used as encoder-decoder initialisation and divided into groups of languages according to the number of resources available for each of them.

²<https://huggingface.co/facebook/wav2vec2-large-960h-1v60-self>

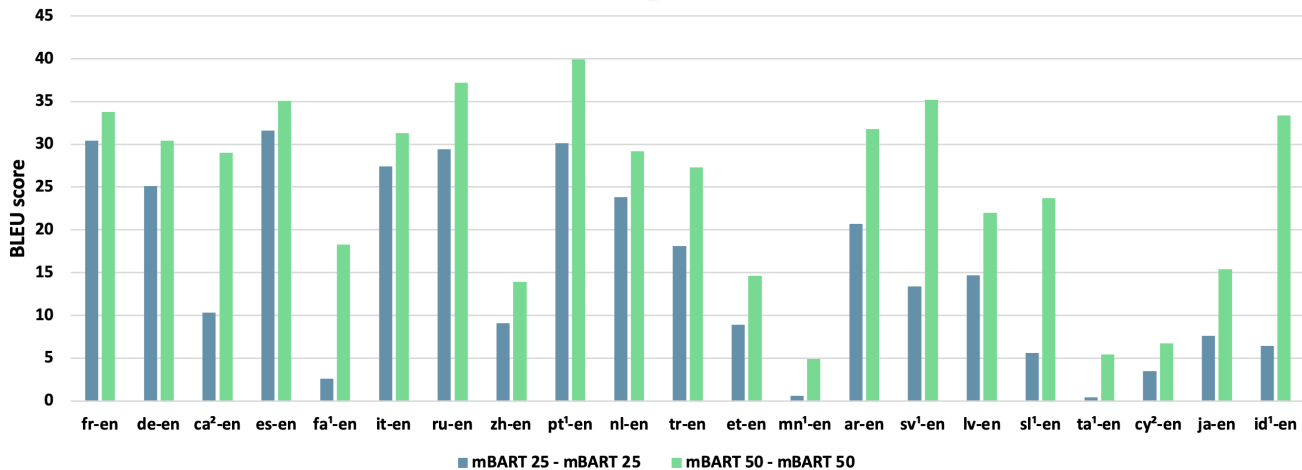


Fig. 4. BLEU results on CVSS data test partition for each language available. ¹ Languages not present in mBART-25, but present in mBART-50. ² Languages not present in mBART-25 or mBART-50.

Figure 3 presents the BLEU scores in the test partition of the CVSS dataset for our proposed direct text-to-speech system and cascade approach. In this figure, the performance is shown separately for high, medium and low resource languages. We have considered high resource languages as those with more than 100h, and low resource languages as those with less than 10h of training data. Moreover, the average of the results is also presented. These results show that the best proposed approach achieves performance close to the cascade system. Furthermore, our direct text to speech system has the advantage that it does not need to know the transcription in the target language, while the cascade system needs it to perform the whole translation process. Note that, if we focus on the two alternatives for the direct text to speech system, a large performance improvement in all splits is observed when the mBART50 model is used as a pre-training model to initialize our encoder-decoder pipeline.

For a more in-depth analysis of the differences found between the two types of mBART models employed, we can see the results for each language of the 21 languages available in the CVSS dataset in Figure 4. This figure shows that the performance of all the languages improves using mBART50. In addition, the improvement achieved is particularly remarkable in the following translation pairs of languages: fa-en, pt-en, mn-en, sv-en, sl-en, ta-en, id-en, marked with 1 in the figure. The relevant performance improvement is motivated by the fact that these languages are not included in mBART25 but are part of the training languages in mBART50. Note that even languages, such as Catalan (ca) and Welsh (cy) marked with 2, that are not included in either mBART25 or mBART50, benefit from the influence of having more languages in the second model and improve their results. To highlight these graphical results, we have calculated the improvement achieved in the three language sets. We can observe that an average relative improvement of 40% is achieved in terms of BLEU score in the languages employed for the pre-training of both mBART models. In the case of the languages included in mBART50, an average relative improvement of 501% is obtained, while

for the languages not present in either of the two, mBART50 achieves an average improvement of 136%. These improved results remark the fact that the use of a pre-trained multilingual model in more languages, mBART50, shows a great impact on the results obtained for the new languages included, and also, this increased multilingualism helps to improve the results in languages not presented during the pre-training process.

V. CONCLUSIONS AND FUTURE WORKS

In this paper, we have presented a new approach to carry out direct text to speech translation. This approach is based on an encoder-decoder framework using text as input and discrete acoustic units as the target sequence. Hence, multilingual text to speech translation can be performed without explicit knowledge of the text transcription in the target language. The system presented in this paper could be used for different applications such as generating audio books from texts in different languages. Moreover, the proposed framework could be applied to get augmented data in order to expand datasets from low resource languages. The evaluation of this proposal was carried out on the new CVSS dataset to confirm the great performance achieved with this approach to generate speech. In these experiments, we have also shown an improvement in performance when the model used as initialisation for the encoder-decoder architecture has been pre-trained by including more languages of the translation pairs from the CVSS dataset. This fact suggests that cross language learning might benefit low resource languages to a significant amount in the text to speech translation task.

The promising results achieved with the proposed system have opened an interesting line of research, so future work will focus on extending our direct text to speech framework to join with a direct speech to speech framework. In this way, a multimodal system could be built in which source input could be speech or text since both modalities are compatible to produce the same discrete acoustic units and thus generate the target speech. Considering that only speech in the target language is needed, further work could also explore the use of languages different from English as target.

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