Direct Punjabi to English speech translation using discrete units

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Abstract. Speech-to-speech translation is yet to reach the same level of coverage as text-to-text translation systems. The current speech technology is highly limited in its coverage of over 7000 languages spoken worldwide, leaving more than half of the population deprived of such technology and shared experiences. With voice-assisted technology (such as social robots and speech-to-text apps) and auditory content (such as podcasts and lectures) on the rise, ensuring that the technology is available for all is more important than ever. Speech translation can play a vital role in mitigating technological disparity and creating a more inclusive society. With a motive to contribute towards speech translation research for low-resource languages, our work presents a direct speech-to-speech translation model for one of the Indic languages called Punjabi to English. Additionally, we explore the performance of using a discrete representation of speech called discrete acoustic units as input to the Transformer-based translation model. The model, abbreviated as Unit-to-Unit Translation (U2UT), takes a sequence of discrete units of the source language (the language being translated from) and outputs a sequence of discrete units of the target language (the language being translated to). Our results show that the U2UT model performs better than the Speech-to-Unit Translation (S2UT) model by a 3.69 BLEU score.

Keywords: Direct speech-to-speech translation; Natural Language Processing (NLP), Deep Learning, Transformer.

1 Introduction

Speech technology can play a vital role in bridging the gap between cultures of the world, fostering the exchange of ideas, and enabling more shared experiences. However, the current state of the speech technology is far from being inclusive to over 7000 languages worldwide[1] [1], [2], [3]. Several automated services offer speech translation, including industry leaders like Google Translate, DeepL, and Bing Microsoft Translator. However, most of these systems rely on a 2-stage or 3-stage cascaded approach to speech translation. For example, a 3-stage cascaded approach involves integrating Automatic Speech Recognition (ASR), Machine Translation (MT), and Text-to-Speech (TTS) at its core. This design limits the availability of these text-based speech translation services to languages for which these three underlying subsystems are available, resulting in a notable absence of support for low-resource languages and those that are without a written form[2] [4], [5]. Additionally, languages with accent types, tonal languages, and those with special sounds pose challenges to text-based translations. Therefore, the direct Speech-to-Speech Translation (S2ST) approach is a more practical and inclusive alternative to traditional cascade approaches. Though direct S2ST methods are still in their infancy and currently lag in performance compared to their cascaded counterparts, they promise the benefit of lower computational cost and inference latency. They are inherently less prone to error propagation[6], [5] and have other benefits, such as preserving prosodic features, thus generating a more natural translation [7].

[1] `https://www.ethnologue.com/insights/how-many-languages/`
[2] `https://speechbot.github.io/`

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The direct S2ST is an end-to-end approach that "directly" converts speech in the source language to speech in the target language without going through a pipeline of ASR, MT, and TTS models. In contrast, the traditional cascade approach relies on intermediate text translation as it goes through a sequence of steps; namely, the speech in the source language is first converted to text in the source language by an ASR model, followed by source text to target text translation using the MT model. Finally, the translated text is processed through a TTS model that synthesizes target speech from the target text. Such a cascaded approach suffers from error propagation and accumulation from downstream ASR, MT, and TTS models, in addition to other limitations mentioned earlier. Our paper presents a method for direct S2ST called Unit-to-Unit Translation (U2UT). We demonstrate the approach through a Punjabi to English language pair, though the method works for any other pair of languages. Punjabi is the world's 36th most-spoken language, with over 51.7 million speakers.[3] The limited research in NLP for the Punjabi language can be attributed to limited data availability in the digital form to train NLP models for various tasks [8], [9], [10] and lack of global benchmarks [11]. Researchers often collect and use their own data in such cases, making it challenging to compare results [10], [12].

1.1 Motivation

Our research specifically sought to i) explore the performance of discretized speech representation approaches and ii) develop speech translation for low resource languages. The raw/continuous speech signals are typically sampled between 16kHz - 44kHz for downstream speech processing tasks. The sampled signals are then either used as such [13] or are converted to a frequency representation of a signal (spectrogram, MFCC) [14], [6] for feeding as input to the machine learning models. The sampled speech and its frequency representation are high dimensional and have redundancies [15]. A recent development in speech processing is the use of discrete representations of speech called acoustic discrete units (also referred to as discrete speech units or simply as discrete units). These speech units are learned from a large speech corpus in a self-supervised learning fashion [16], [17]. The benefit of using a discrete representation of speech is that it significantly reduces the dimension of the speech signal while still preserving the original speech content. [6] was the first work to utilize acoustic discrete units for speech-to-speech translation tasks. However, it utilizes discrete units only for the target speech, while the source speech still uses frequency representation. Motivated by the recent performance gains of using acoustic discrete units in various speech processing tasks [18], [15], our goal is to study the impacts of using acoustic discrete units for both source and target speech in the speech to speech translation task.

1.2 Contribution

The contribution of our work is as follows. Firstly, we introduce a Transformer-based, Unit-to-Unit Translation (U2UT) model for direct speech translation. Unlike prior approaches that rely on spectrograms or raw audio as input, our model leverages discrete acoustic units to represent source speech. Since speech is represented in a lower dimension compared to the raw audio or spectrograms, discrete unit representation has the advantage of lower memory footprint and computational cost. The exploration of discrete acoustic units to represent input speech is one of the contributions of our work. Our findings demonstrate that the U2UT model achieves a BLEU score that is 3.69 points higher than a prior

[3] https://www.ethnologue.com/insights/ethnologue200/

state-of-the-art method which uses a spectrogram to represent input speech. It leads us to conclude that acoustic discrete units are sufficient to represent speech and offer a superior representation compared to spectrograms. The second contribution of our research is to advance the speech translation research by focusing on low-resource languages. Through our work, we release a direct speech-to-speech translation model for Punjabi to English.

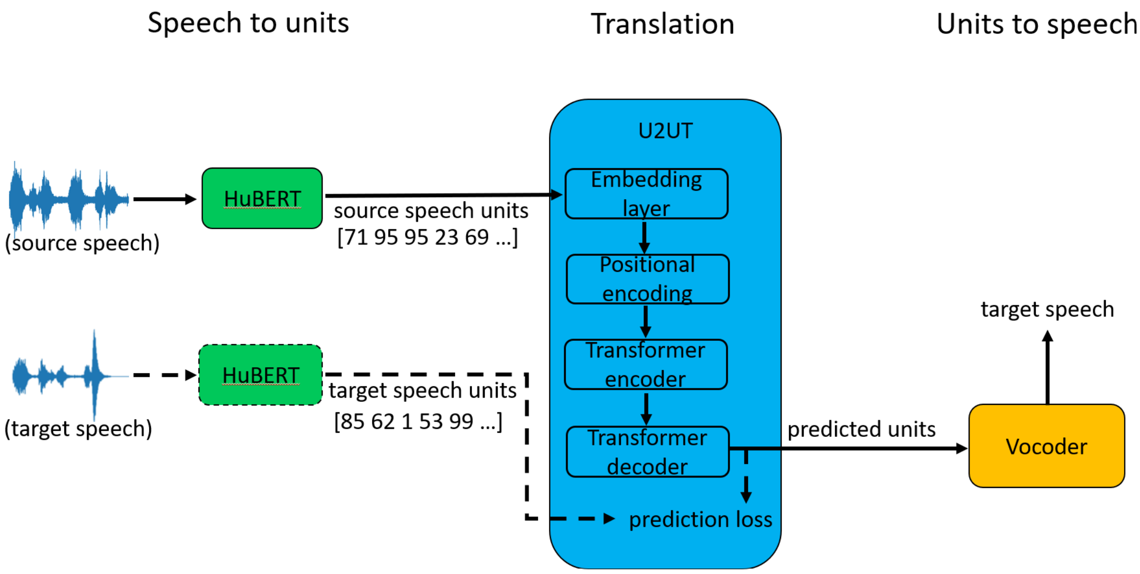


Fig. 1: The overall framework of direct speech-to-speech translation using acoustic discrete units: It consists of (1) a Pre-processing step that converts speech to units, (2) a Transformer based Unit to Unit Translation (U2UT) model, (3) a Post-processing step that converts predicted target units to target speech. The dotted lines represent part of the framework that runs only during model training.

The rest of the paper is organized as follows. Section 2 reviews existing direct S2ST models and parallel speech corpora, followed by Section 3, which describes the dataset used in our work and the model framework in detail. Section 4 discusses the results and experiments conducted. Section 5 highlights the limitations of our approach and future directions, followed by a conclusion in Section 6.

2 Related Work

2.1 Direct Speech-to-Speech Translation (S2ST) models

Direct S2ST is a recent development in speech translation research. Within the domain, there are two approaches to translation when given the source speech. Both approaches output speech representations. In the first approach, the translation model is trained to predict the spectrogram for the target speech. In the second and newer approach, the translation model predicts discrete acoustic units [17] for target speech. These speech representations from the translation model are converted to a raw audio waveform using a vocoder as the final output. [6] demonstrates that the second approach yields better results.

Translatotron [14] is the first direct S2ST model. The model consists of an attention-based encoder-decoder architecture that converts a spectrogram for a speech in the source language to a spectrogram for a speech in the target language, a vocoder that converts the generated spectrogram to a waveform, and finally, a speaker encoder that allows the model to preserve the voice of the source speaker throughout the translation process. The encoder and decoder both use layers of LSTMs. Additionally, the authors emphasize that multitask training is essential, which in this case is integrated by including decoders for the auxiliary tasks of predicting the phonemes of source and target languages. The model is tested on two different datasets for English and Spanish. The results show that the performance of Translatotron is comparable to the conventional cascade approaches, with Translatotron slightly underperforming the conventional approaches. Further, [19] improves upon the results of the Translatotron model and presents a Translatotron 2 model. The architecture consists of an encoder, a decoder, and a synthesizer. All these components are connected through a single attention module. Translatotron 2 uses conformer [20] as an encoder, LSTMs as a decoder, and multi-head attention for attention. The paper states that the overall architecture leads to a performance boost in the model rather than the individual sub-components. Both Translatotron 1 and 2 predict the spectrogram of the target speech given the source speech.

Next, [6] presents a first Speech-to-Unit Translation (S2UT) model, which predicts discrete units for the target speech instead of predicting the spectrograms. It is a Transformer[21] based model. It takes the Mel-Frequency Cepstral Coefficient (MFCC) features derived from the source language speech as input to the encoder layer, followed by multi-head attention. The decoder then predicts a sequence of discrete units for the target language from the encoded input. It is important to note that the overall model is trained using discrete units obtained from a pre-trained HuBERT model [17]. Finally, a separately trained vocoder converts the discrete units to a raw audio waveform (speech). The model exploits multitask learning and pre-training. For multitask learning, the model uses auxiliary tasks such as predicting the phonemes, characters, and text of the target or the source language. The model is tested on the Fisher dataset for Spanish to English translation tasks. Further, [22] extends the S2UT model in [6] to training and testing with the real-world S2ST data in multiple languages. Specifically, the authors propose a novel speech normalization technique that minimizes the variation in speech from multiple speakers and recording environments. The speech normalizer is created by fine-tuning the HuBERT [17] model with a speech from a reference speaker. This speech normalizer is then used to create targets (labels) for training the S2UT model [6]. The experiments on the VoxPopuli dataset show that speech normalization is essential in increasing the effectiveness of the S2UT model. [23] provide further improvements to S2UT model by incorporating pre-training. [24] extends S2UT [6] to from bilingual to multilingual. It supports S2ST from English to sixteen other target languages. Finally, SeamlessM4T [5] is the latest model in the S2ST domain. It is a multitask, multimodal, and multilingual model that supports speech-to-speech translation and other tasks such as speech-to-text translation and text-to-speech translation. The language coverage for SeamlessM4T is available here[4]. It uses UnitY model [25] at its core and predicts target discrete units. Other notable works in this area include Transformer based direct speech-to-speech translation with transcoder [26], AudioPaLM [27], direct translation between Hokkien and English language pairs [4].

It is important to note that S2ST (either using a direct or cascade approach) for Indian languages is still an under-explored area [28]. It is especially true for the Punjabi language. [29] and [28] are the only pieces of work we have found that develop English-to-Punjabi speech translation pipelines. Both of these works use a cascade approach. As

[4] `https://github.com/facebookresearch/seamless_communication/blob/main/docs/m4t/README.md`

highlighted earlier, building a pipeline for English to Punjabi speech translation using the cascade approach is limited by the unavailability of state-of-the-art ASR [30], [9], MT [31], and S2T models for Punjabi. Specifically, there is no S2T model available for Punjabi [29]. Luckily, there is a growing interest from the research community to develop speech technologies for all languages worldwide. Some of the works include [32], [11], No Language Left Behind [33], and Massively Multilingual Speech [3]. These models are incrementally supporting additional languages. For example, the recent release of the seamlessM4T model [5] supports direct S2ST for Punjabi to English direction. However, it does not support English to Punjabi speech translation. Therefore, more work is needed to develop speech translation technologies for lower-resource languages like Punjabi.

2.2 S2ST dataset

The direct S2ST models require parallel speech data in source and target languages for training. The scarcity of parallel speech data, especially for Punjabi and English pairs, is critical. Table 1 provides a comprehensive overview of the currently available multilingual datasets. The table further highlights the datasets that include parallel speech data for Punjabi and English (the last column), accentuating our focus's urgency and significance.

It is important to note that there are other multilingual speech datasets available publicly not included in Table 1, such as Multilinguagl LibriSpeech dataset [34] supporting 8 languages and Common Voice [35] containing over 70 languages, and CoVOST 2 [36] derived from the Common Voice corpus (Check again if CoVOST 2 contains parallel speech to speech dataset), BABEL speech corpus[37], Voxlingua107 [38], Indian languages datasets from AI4Bharat[5]. However, these datasets do not provide parallel speech in a given pair of languages; hence, they are not included in the table.

Dataset	**Description**	**Parallel text**	**Parallel speech**	**Parallel speech for English and Punjabi**
CVSS [39]	sentence level speech to speech translation pairs from 21 other languages to English, derived from Common Voice and CoVoST2	Yes	Yes	No
VoxPopuli [40]	spontaneous speech, parallel speech to speech translation dataset for 15 languages	Yes	Yes	No
CMU Wilderness [1]	read speech, parallel speech to speech translation dataset for 700 languages	Yes	Yes	No
MaSS [41]	read speech, derived from CMU Wilderness dataset [1], sentence level speech to speech parallel dataset for 8 language pairs	Yes	Yes	No
MuST-C [42]	spontaneous speech, English to 8 other languages translation of the TED talks	Yes	No	No
SpeechMatrix [43]	spontaneous speech, 136 language pairs translated from European Parliament recordings	Yes	Yes	No
Fleurs [44]	read speech, parallel speech data for 102 languages	Yes	Yes	**Yes**

Table 1: Summary of public multilingual datasets.

[5] https://ai4bharat.iitm.ac.in/.

3 Methodology

As mentioned in Section 2, the current S2ST models predict either the spectrogram (as in Translatotron[14]) or the discrete units (as in S2UT[6]) of the target language. However, both model types use spectrogram or its derivative, such as MFCC of the source speech as an input. Our model takes discrete units of the source language as an input and predicts discrete units of the target language as an output, thus the name U2UT. Section 3.1 explains the dataset used for training and testing the model, followed by Section 3.2, which provides model details, training, and evaluation framework.

3.1 Data

FLEURS dataset [44] is the only publicly available data with parallel speech for English and Punjabi. However, with only 1625 Punjabi and English pairs in the training set, it is too small to train an S2ST model from scratch. Therefore, we first prepare a parallel speech dataset for English and Punjabi using a large-scale ASR dataset called Kathbath [45].

Kathbath[6] is an ASR dataset that contains read speech and transcript pairs for 12 Indian languages, including Punjabi. It contains around 136 hours of Punjabi speech from several native speakers. The average sentence length of samples in the dataset is between 5-10 words. The dataset has train, dev, and test subsets containing 83578 samples, 3270 samples, and 3202 samples. Since we need parallel speech data for training a direct S2ST model for English and Punjabi, we first create a parallel English speech and text from the Punjabi subset of the Kathbath dataset. We accomplish this using the SeamlessM4T[7] model. The translated English speech and text generated by SeamlessM4T are manually verified for quality by a proficient speaker in Punjabi and English. It is important to note that while Punjabi speech is natural, English speech is all synthetic generated by the SeamlessM4T model. Finally, both English and Punjabi audios have a 16kHz sampling rate.

3.2 Model framework and training

We implement the Transformer [21] model and train it to predict the target language's discrete units. The discrete units of the source language are given as input to the Transformer encoder. The Transformer decoder takes the encoded representation of the discrete units of the source language to produce a sequence of discrete units of the target language. The training is done in a teacher-forcing manner, using discrete units of the actual/true output sequence to learn to generate the next actual unit. Therefore, we must first create discrete units for both source and target languages to train the model.

Convert speech to units The discrete units for both target and source languages are derived using a pre-trained HuBERT Base model[8] [17], trained on 960 hours of Librispeech [46] corpus. Similar to [6], we use the 6th layer of the HuBERT model and derive the discrete units using 100 clusters. The discrete units are created from raw English and Punjabi audio. The average number of discrete units in a given sentence is about 300, as shown in Figure 2. Finally, we create pairs of sequences of discrete units for the source and the target languages to train the model. Further, since the original audio samples are

[6] https://github.com/AI4Bharat/indicSUPERB.

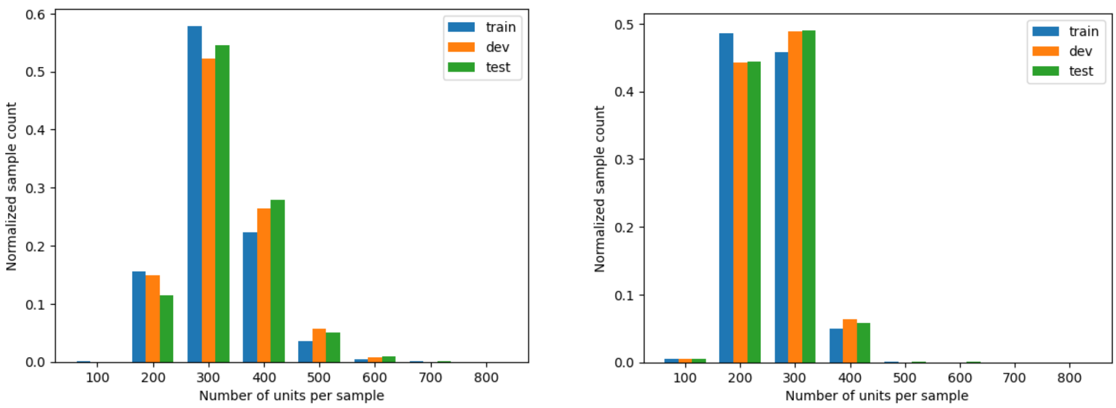
[7] https://github.com/facebookresearch/seamless_communication.

[8] https://github.com/facebookresearch/fairseq/blob/main/examples/hubert/README.md

of different lengths, the resulting sequence of discrete units is also of varying lengths for different samples in the dataset. We pad the shorter sequences with 0s and trim the longer sequences to ensure that all of them are of sequence length of 300 before they are fed into the model for training.

Unit-to-Unit Translation (U2UT) Next, we build a sequence-to-sequence model based on the Transformer architecture that learns to translate the source language's discrete units to the target language's discrete units. The best model contains three encoder layers, three decoder layers, and one head, and the embedding size (d_model) is set to 512. The model is trained with a learning rate of 0.0001, Adam optimizer, 0.1 dropout rate, 25 batch size, and cross-entropy loss. After training for 80 epochs, we save the model for evaluation and inference.

Convert predicted units to target speech Since the end goal is to obtain the audio in the target language, an additional step is required to convert this predicted sequence of discrete units to a waveform. A Vocoder does the speech synthesis. We use a pre-trained Vocoder called unit-based HiFi-GAN[9] from [6] for this step. The overall framework of our approach consisting of all three steps mentioned above is shown in Figure 1.



(a) Punjabi subset (b) English subset

Fig. 2: Sample count vs number of discrete units per sample in English and Punjabi subsets of Kathbath dataset

3.3 Model evaluation

We evaluate the trained model on the test set consisting of 3202 samples. First, we derive discrete units of the source language using the HuBERT model as described in Section 3.2. The source discrete units are fed to the model to predict target discrete units in a greedy fashion. The target discrete units are then converted to raw speech using the Vocoder as a post-processing step. Eventually, we have a target speech. To quantify how much the predicted target speech matches the ground truth, we convert the translated audio to text using an ASR model (specifically the Whisper large-v3[10] [47]) and compare the Whisper

[9] `https://github.com/facebookresearch/fairseq/blob/main/examples/speech_to_speech/docs/direct_s2st_discrete_units.md`
[10] `https://huggingface.co/openai/whisper-large-v3`

generated transcripts to ground truth text for the target language. The Whisper model is chosen during evaluation as it is the state-of-the-art model for ASR. It is a multitask speech recognition model trained on 680,000 hours of multilingual speech. We report the final result of our method as a BiLingual Evaluation Understudy (BLEU) score [48]. We use the SacreBLEU [49] method.

4 Results and discussion

To compare the results of our method with previous work published in speech translation research, we compare the results with both cascaded and direct speech-to-speech translation approaches. For the direct approach, we compare with the S2UT model [6] as it also involves predicting discrete units of the target language. We begin with training the original S2UT model available in the fairseq[11] library on the same dataset as was used to train our U2UT model. The S2UT model takes the spectrograms of the source speech as an input and is trained to predict the sequence of discrete units of the target speech. Similar to our work, the S2UT model also involves a data pre-processing step to create discrete units of target language using the HuBERT model for training. However, it needs the discrete units only for the target speech. We trained with multitasking (joint text and speech) and without multitasking and noticed no significant difference in the performance. The model is trained for 50 epochs. The model architecture contains six encoder layers, six decoder layers, four heads, 256 dimensions of the encoder embedding, and 2048 dimensions for the feed-forward. The sequence of target discrete units predicted by the trained model is converted to speech using the Vocoder. Finally, we use the Whisper ASR model to transcribe the predicted speech and report the BLEU score.

Next, to compare our results with a traditional cascaded approach, we choose Whisper. It uses a 2-stage approach (ASR followed by MT) for speech-to-text translation. The Whisper ASR first converts Punjabi speech input to Punjabi text, and then the Whisper MT translates Punjabi text to English text. The generated English text is compared with the ground truth transcripts. The results of our method, S2UT, and Whisper are shown in Table 2. We also show samples of generated translations by all three models in Table 3. Our model attempts to reproduce the sounds in the original speech but does not quite output the original word. Our method outperforms the S2UT model. We conclude that using acoustic discrete units are sufficient to represent input speech compared to the spectrogram representation. We would like to emphasize that the S2UT model used for comparing our results was used as a black-box model, meaning we used the default model parameters for training. Further, both approaches lag in performance compared to the cascaded approach. We believe that the significant difference in the performance is due to the sample size used for training. U2UT and S2UT models were trained with 83578 samples, whereas the Whisper model was trained on a much larger dataset. Access to large-scale parallel speech data is challenging for building direct speech-to-speech translation systems that outperform cascaded approaches.

5 Limitations and future directions

The limitations of our study were the dataset size and available computing. We had 83578 samples for training, which is much smaller than the dataset used in the state-of-the-art models in speech processing, such as Whisper and SeamlessM4T. Further, the limitation of using acoustic discrete units for source speech as input to the machine learning model

[11] https://github.com/facebookresearch/fairseq/tree/main/examples/speech_to_speech

Method	**Description**	**BLEU** (↑)
U2UT (**Ours**)	source discrete in and target discrete out	3.9829
S2UT [6]	source spectrogram in and target discrete out	0.2954
2-stage cascade approach (Whisper) [47]	ASR followed by MT	18.1136

Table 2: Results for Punjabi to English translation using Kathbath test set.

Audio sample ID (Kathbath test set)	**Actual transcript**	**Prediction (U2UT)**	**Prediction (Whisper)**	**Prediction (S2UT)**
844424933626045-586-m.wav	doctor gurbaksh singh frank explains the culture in this way	actor gerbache saying fraud	doctor gurubaksh singh frank describes the practice in this way	this is necessary to talk about the process of the country
844424933639213-32-m.wav	he also wrote sketches memoirs biographies travelogues and translated some works	he is wrecked at measure the post of the resident of the cagular and some novel	he also translated the book of kujra chanaama in rekha chitra yadda jeevaniyaan falsafah safar naam	the ceremony was given by the punjab government by the chief minister of punjab
844424933647726-601-m.wav	the greed of the ministers to come home with money is turned upside down	determined by finnish minister is provided by the people	minister says that he will give money to the greedy people	it is very difficult to imagination and investigation of the country
844424931569220-989-f.wav	congress workers started distributing cheap grain at dharmakot bagga	the congress said the pack and congress was began to started	the term court has declared that the	it is very difficult to imagination in the country
844424933162326-703-f.wav	n r i ravindra kakku inaugurated the school s kitchens	dees views officers of the schools of faith prona cases officerer	i am ravindra kakku from the school of dehep kaaleya uttakadam	it is very difficult to imagination in the country

Table 3: Sample output (Transcripts corresponding to the audio translated from Punjabi to English by various models).

Expt. No.	**Sequence length**	**Heads**	**Encoder-Decoder layers**	**Feedforward dimension**	**Learning rate**	**Epochs**	**Val loss**	**BLEU** (↑)	**WER** (↓)
1	300	1	3	2048	0.0001	80	0.006462	3.9829	99.62
2	300	1	3	2048	0.00001	100	0.02434	1.0601	101.52
3	300	1	3	1024	0.0001	100	0.01	3.4736	99.66
4	300	1	6	1024	0.0001	80	0.004758	3.3838	100.50
5	200	1	3	1024	0.0001	80	0.010644	2.4202	99.77
6	300	4	6	1024	0.0001	100	0.001998	1.3939	107.02
7	300	1	3	2048	0.001	100	0.021073	0.1922	103.83

Table 4: Ablation study: Results for various model parameters.

is that it introduces an additional pre-processing step of obtaining the discrete units. A possible future direction could be to leverage transfer learning rather than training the model from scratch to mitigate data scarcity issues. There is also a need for more parallel speech datasets for Punjabi and English pairs.

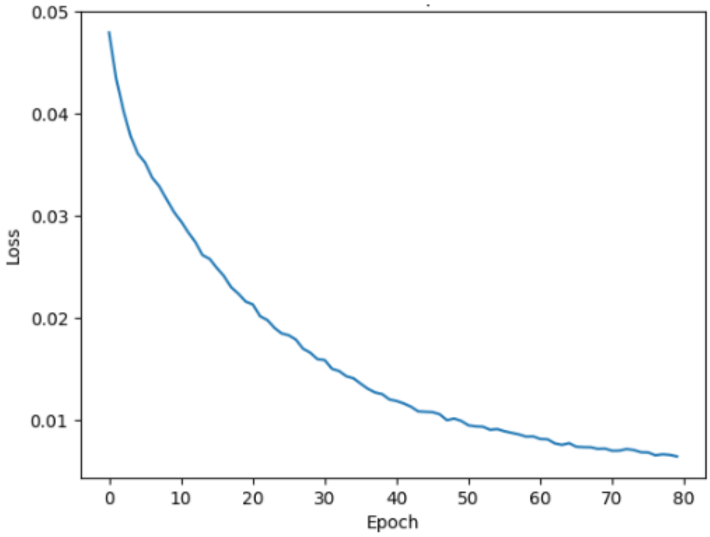


Fig. 3: Validation loss for Exp1. 1 in Table 4.

6 Conclusion

We have created a direct speech-to-speech translation model called U2UT. Specifically, we investigated using discrete representations of speech, called acoustic discrete units, to represent input speech in the direct speech-to-speech translation model. Previous work in direct speech translation research uses frequency representations such as spectrograms and MFCC to represent input speech. Spectrograms are high-dimensional and consume more memory for storage and processing. Discrete unit representation offers an alternative that is much lower in dimension. Our results show that using discrete units to represent input speech is a promising future direction for direct speech-to-speech translation. We achieved a BLEU score of 3.9829, which is 3.69 points higher than the BLEU score achieved by an S2UT model that uses spectrograms to represent input speech. We demonstrated the performance of the U2UT model for Punjabi to English translation, although the method can be applied to any two pairs of languages. Additionally, the choice of the Punjabi language is deliberate, as it is one of the low-resource languages. We need to focus research efforts on such languages, as this is a step to ensure that speech technology is available to people who speak languages other than English. Lastly, as a future direction toward improving the performance of our translation system, we will focus on transfer learning and collecting more parallel speech data.

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