An Experiment on Speech-to-Text Translation Systems for Manipuri to English on Low Resource Setting

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Abstract

In this paper, we report the experimental findings of building Speech-to-Text translation systems for Manipuri→English on low resource setting which is first of its kind in this language pair. For this purpose, a new dataset consisting of a Manipuri-English parallel corpus along with the corresponding audio version of the Manipuri text is built. Based on this dataset, a benchmark evaluation is reported for the Manipuri→English Speech-to-Text translation using two approaches: 1) a pipeline model consisting of ASR (Automatic Speech Recognition) and Machine translation, and 2) an end-to-end Speech-to-Text translation. Gaussian Mixture Model-Hidden Markov Model (GMM-HMM) and Time delay neural network (TDNN) Acoustic models are used to build two different pipeline systems using a shared MT system. Experimental result shows that the TDNN model outperforms GMM-HMM model significantly by a margin of 2.53% WER. However, their evaluation of Speech-to-Text translation differs by a small margin of 0.1 BLEU. Both the pipeline translation models outperform the end-to-end translation model by a margin of 2.6 BLEU score.

1 Introduction

In recent times, the advance in machine translation (MT) systems research jumped from textual modality to multi modality. The success of the several machine translation system for major languages based on statistical and neural approaches shed light towards building better translations systems for low resource languages as well. Of these, the statistical machine translation (SMT) (Koehn et al., 2003) and neural machine translation (NMT) models (Cho et al., 2014) started its journey from the traditional text-to-text translation which further expanded to the use of multiple modalities (Huang et al., 2016; Caglayan et al., 2016; Meetei et al., 2019; Gain et al., 2021) in the translation task. The usage of multiple modalities in MT uncovers new avenues for MT researchers. MT tasks where multiple modalities are utilized include using multiple-input modalities, for example, incorporating visual and text modalities (Meetei et al., 2021; Singh et al., 2021), translation between different input and output modalities such as Speech-to-Text translation (Ney, 1999; Weiss et al., 2017), etc. With these various methodologies of MT, the main goal is to obtain the most key information in a modality in generating the optimal sentence translation.

The Speech-to-Text (S2T) translation is the translation of a speech in a source language to a target language text. The Speech-to-Text translation task can be broadly addressed using two approaches: 1) with a pipeline strategy, which separates the different modalities into modality conversion, i.e., ASR, followed by text-to-text MT. 2) end-to-end (E2E) translation where the target text is directly generated from the speech in the source language. The Speech-to-Text (S2T) can find its application in our daily life by creating an ease form of communication for individuals with physical disabilities. It can also be used in reducing the turnaround of quick documentation, generating subtitles, etc.

Despite the fact that researchers are pushing the frontiers in machine translation and improving their capabilities, most of the work is focused on well-studied languages while work on low resource languages such as Manipuri is falling behind. Manipuri (also known as Meiteilon) is the official language of Manipur, a northeastern state of India. Manipuri is an extremely low resource language with a limited dataset available for the NLP (Natural Language Processing) tasks which is one of the primary reasons that hindered the development of NLP systems for the language.
This work aims to promote Speech-to-Text translation of an extremely low resource language by presenting a benchmark evaluation on a manually collected speech dataset. This work makes the following contributions:

- We build the first Manipuri→English S2T translation dataset.

- Comparison between a pipeline and end-to-end S2T translation model on the collected corpus is reported as the benchmark evaluation.

The rest of this paper is presented as follows: The prior relevant research is discussed in Section 2, followed by the framework of our model in Section 3. Section 4 and Section 5 explain the setup of our system and analysis of our results. The conclusion and future work are summarized in Section 6.

2 Related Works

Early attempts to address S2T translation follows a pipeline approach of two independent models: ASR and MT systems (Ney, 1999; Matusov et al., 2005). The approach utilized the hypothesis of ASR as an input to the MT model to generate the target-language text. Initial work on direct Speech-to-Text translation includes (Bérard et al., 2016; Duong et al., 2016; Bansal et al., 2017). Using a small French-English synthetic dataset from 7 speakers, Bérard et al. (2016) carried out an end-to-end S2T translation. The author reported that their system to be capable of generalizing to a new speaker effectively. Bansal et al. (2018) carried out an end-to-end S2T translation in low resource settings by training with smaller subsets of 160 hours labeled data. The author reported a BLEU score of 5.3 and 29.4 when trained with 20 hours and 160 hours, respectively.

Some of the work in the development of speech technology for the Manipuri language includes Rahul et al. (2013); Patel et al. (2018); Devi et al. (2021). Patel et al. (2018) reported a WER of 19.28% on a GMM-HMM and WER of 13.57% on a Deep Neural Network-HMM (DNN-HMM) acoustic model systems. The speech corpus used in the experiment comprised around 61 hours. Works on MT for Manipuri-English language pair are reported using various techniques such as Example-based MT (Singh and Bandyopadhyay, 2010a), SMT (Singh and Bandyopadhyay, 2010b; Singh, 2013), and unsupervised NMT (Singh and Singh, 2020). In a comparative study of SMT and NMT systems on the Manipuri-English language pair, the authors (Rahul et al., 2021; Singh and Singh, 2021) reported NMT system to perform better than the SMT system. To date, there is no work in S2T translation for Manipuri-English language pair. In order to fill this gap, a Manipuri-English S2T translation is developed using a small dataset in our work.

3 Methodologies

Figure 1 illustrates the methodology of our work. As the initial step of our work, English text dataset is collected from news articles, which is translated to Manipuri language. In the next step, speech is
recorded for the Manipuri text. The overall collected dataset is then used to train the pipeline and End-to-End S2T translation models.

### 3.1 Language Resources

To build the dataset for our experiment, we collected news articles reported in English from a local daily newspaper\(^1\). The collected English text is machine translated to Manipuri followed by manual post-editing of the MT output and training the MT system with the incremental approach (Meetei et al., 2020). Following the development of the parallel dataset, speech is recorded for each of the Manipuri sentences by the native speakers of Manipur. The total number of participants for speech records is five: one male speaker and four female speakers. There is no overlapping of utterances among the participants. The recorded speech is post-processed, where the quality of speech records are verified manually. Any invalid speech found is rerecorded to collect quality speech records for the experiment. The overall collected dataset comprises of:

- 3500 Manipuri-English parallel text datasets, and
- around 5 hrs 30 minutes of speech record of the Manipuri text.

### 3.2 Speech Feature Extraction

For any Speech-to-Text system, extracting the audio signal components that can be used to determine linguistic content is important. Mel-frequency cepstral coefficients (MFCCs), the most popular, extensively utilized cepstral feature for ASR, is used as the audio feature for the ASR system and the E2E Speech-to-Text translation system.

### 3.3 Pipeline translation model: ASR and MT

Our pipeline S2T translation model consists of two independent models:

- Automatic Speech Recognition, and
- Neural Machine Translation (NMT)

In our work, we built two separate pipeline systems using GMM-HMM and TDNN Acoustic models, which is followed by a shared NMT system. The ASR output is fed to the NMT system to generate the target language.

### 3.3.1 Automatic Speech Recognition (ASR)

The objective of an automatic speech recognition system is to predict the most likely discrete symbol sequence from a given input acoustic speech vector \(O\), out of all valid sequences in a target language \(T\). Taking input speech sequence as a set of observation \(O= (o_1, o_2, ...o_n)\) and the symbol to be predicted represented by \(S= (s_1, s_2, ...s_m)\), the aim of the ASR model is:

\[
\hat{S} = \arg\max P(O|S)P(S). \tag{1}
\]

where \(P(S)\) is the prior probability for the sequence \(S\), and the observation likelihood, \(P(O|S)\) is the likelihood of the acoustic input sequence \(O\) given the sequence \(S\), computed using HMM.

The acoustic model based on deep neural networks is trained with time delay neural network, TDNN (Peddinti et al., 2015).

### 3.3.2 Neural Machine Translation (NMT)

A Neural Machine Translation (NMT) is built for the MT system in the pipeline model. For a source sentence, \(S = \{s_1, ..., s_n\}\), NMT, an encoder-decoder sequence-to-sequence technique, jointly models the conditional probability \(p(T|S)\) to translate a target sequence, \(T = \{t_1, ..., t_m\}\).

Following the attention mechanism (Bahdanau et al., 2014; Luong et al., 2015), a bi-LSTM (Sutskever et al., 2014) is used as an encoder. At time step \(t\), the encoder state is represented by the concatenation of the forward hidden state, \(\vec{h}_t\), and backward hidden state, \(\vec{h}_t\). As each word in the output sequence is decoded, the attention mechanism learns where to focus attention on the input sequence.

### 3.4 End-to-End S2T translation model

Our end-to-end S2T translation model follows Bérard et al. (2018) architecture, an attentive encoder-decoder model. The speech encoder takes audio features, \(X = (x_1, x_2, ..., x_T) \in \mathbb{R}^{T_x \times N}\) as an input sequence. The audio features are fed into two non-linear (\(\tanh\)) layers, which generate \(N\) size features. The new feature sequence length is reduced by a factor of 4 using two 2D convolutional layers with stride (2; 2), which is then passed to a three stacked bidirectional LSTMs (Schuster and Paliwal, 1997). The decoder generates target-language sequences at the character level. The character-level decoder is composed of a conditional LSTM with the global attention mechanism (Bahdanau et al., 2014).

\(^1\)Imphal Free Press [https://www.ifp.co.in/](https://www.ifp.co.in/)
|        | sentences | duration (in min) |
|--------|-----------|------------------|
| train  | 3300      | ~314             |
| dev    | 100       | ~9               |
| test   | 100       | ~8               |

Table 1: Manipuri→English Speech-to-Text translation dataset setup

4 Experimental Setup

In this section, we present the different Speech-to-Text translation experiments conducted, including the dataset and experimental setup.

The training, development, and test data sets for Manipuri→English S2T translation models are summarized in Table 1.

4.1 Pipeline S2T Translation Models

The system set up of independent ASR and MT systems of pipeline S2T translation model are as follows:

4.1.1 ASR systems

The transcript of the Manipuri text is written in Bengali script. Words in Manipuri have exact grapheme-to-phoneme mapping. A grapheme-to-phoneme list for the Manipuri ASR system is prepared by using the Bengali to Roman script transliteration module of (Meetei et al., 2021). The acoustic features fed to the GMM-HMM model consists of 13-dimensional MFCC, and 3-dimensional pitch features for speaker adaptation, namely Probability of Voicing (POV)-weighted mean subtraction over 1.5 second windows, Normalized Cross Correlation Function (NCCF)-derived POV feature, and delta pitch calculated on raw log pitch. While TDNN acoustic models are trained using 40-dimensional MFCC with 100-dimensional i-vectors and 3-dimensional pitch features. We utilized a 3-gram model trained with SRILM (Stolcke, 2002) for decoding. The ASR systems are built using the Kaldi toolkit (Povey et al., 2011).

4.1.2 NMT systems

Two NMT systems are trained using different dataset set up:

- \( NMT_{in} \): NMT model trained with the in-domain dataset (Table 1).
- \( NMT_{g} \): NMT model trained by combining the in-domain and additional parallel Manipuri-English text dataset. The additional dataset is acquired from TDIL\(^2\), data scrapped from vikaspedia \(^3\) which are then manually aligned and the work from (Meetei et al., 2020). Overall, the domain of the dataset is from tourism, agriculture, medical and news articles. The total training dataset size is 23126 (3300 in-domain and 19823 additional parallel sentences).

As an encoder, a two-layer bi-LSTM with 512 hidden units is used, and the batch size is set to 32. With a learning rate of 0.001 and Adam optimizer (Kingma and Ba, 2014), we train the system utilizing early stopping, where training is halted if a model does not progress on the validation set for more than 15 epochs.

4.2 End-to-End S2T Translation Model

End-to-End S2T translation models are implemented in PyTorch (Paszke et al., 2019) with fairseq toolkit\(^4\). We utilize “T-Sm” architecture (Wang et al., 2020) with default hyper-parameters and train with Adam optimizer and a learning rate of 0.002. Early stopping is used to halt the training when the system does not improve for 15 epochs on the development set.

4.3 Evaluation Metrics

The word error rate (WER), which is the ratio of word insertion, deletion, and substitution errors in a transcript to the total number of uttered words, is used to evaluate our ASR systems. The final hypothesis of S2T are evaluated with BLEU (Papineni et al., 2002). BLEU is a precision-based automatic metric used to evaluate the quality of machine-translated text.

5 Results and Analysis

In this section, we illustrate the results of our Manipuri→English pipeline and end-to-end S2T translation models. Along with the automatic metric evaluation, we carried out an in-depth qualitative analysis and human evaluation of our translation systems.

5.1 Automatic Metrics based Evaluation

The ASR systems are evaluated in terms of word error rate (WER), and the final hypothesis of translation from the pipeline and end-
Table 2: Manipuri-English Speech-to-Text translation results

| Acoustic Model | WER  | MT    | BLEU | Translation Model |
|----------------|------|-------|------|-------------------|
| Pipeline       | 27.69| NMT,  | 6.1  | PipeHmmIN         |
|                |      | NMT,  | 4.6  | PipeHmmG          |
| TDNN           | 25.16| NMT,  | 6.2  | PipeTdnmIN        |
|                |      | NMT,  | 4.1  | PipeTdnmG         |
| E2E            | -    | -     | 3.6  | E2E               |

Table 3: Sample input-output of Manipuri Automatic Speech Recognition systems

| transcript1  | অহুমশ‌ুবা কার্যা কৃহিম হৌরযেকেঝে | Third Kwatha Festival inaugurated |
| GMM-HMM       | ৩ শ‌ুবা কার্যা কৃহিম হৌরযেকেঝে | Drivers union suspends bandh |
| TDNN          | অহুমশ‌ুবা কার্যা কৃহিম হৌরযেকেঝে | Drivers union suspends bandh |
| transcript2  | প্রাইডারনিংগী মুখিননা বশ থৈয়েকেঝে | All Jiribam Road Transport Drivers Union suspends bandh |
| GMM-HMM       | প্রাইডারনিংগী মুখিননা বশ থৈয়েকেঝে | All Jiribam Road Transport Drivers Union suspends bandh |
| TDNN          | প্রাইডারনিংগী মুখিননা বশ থৈয়েকেঝে | All Jiribam Road Transport Drivers Union suspends bandh |
| transcript3  | সি তিরিয়াম রেড প্রাফলেট প্রাইডার মুখিননা বশ থৈয়েকেঝে | All Jiribam Road Transport Drivers Union suspends bandh |
| GMM-HMM       | সি তিরিয়াম রেড প্রাফলেট প্রাইডার মুখিননা বশ থৈয়েকেঝে | All Jiribam Road Transport Drivers Union suspends bandh |
| TDNN          | সি তিরিয়াম রেড প্রাফলেট প্রাইডার মুখিননা বশ থৈয়েকেঝে | All Jiribam Road Transport Drivers Union suspends bandh |
| transcript4  | ইঞ্জিন ৩১ লানলবা মতুংদা ইিধয়ান বাইকরিশং ইমফাল মৌরকেঝে | Indian bikers reach Imphal after crossing 31 countries |
| GMM-HMM       | ইঞ্জিন ৩১ লানলবা মতুংদা ইিধয়ান বাইকরিশং ইমফাল মৌরকেঝে | Indian bikers reach Imphal after crossing 31 countries |
| TDNN          | ইঞ্জিন ৩১ লানলবা মতুংদা ইিধয়ান বাইকরিশং ইমফাল মৌরকেঝে | Indian bikers reach Imphal after crossing 31 countries |

to-end systems is measured in terms of BLEU score using SacreBLEU (Post, 2018). Table 2 shows the automatic evaluation score of the ASR (GMM-HMM and TDNN) output and the translation output. The signature of the SacreBLEU is: \( \text{BLEU} + \text{case.mixed} + \text{numrefs.1} + \text{smooth.exp} + \text{tok.13a} + \text{version.1.5.1} \).

- **ASR**: TDNN model outperforms the GMM-HMM model significantly by achieving an improvement of 2.53% WER.

- **Translation**: The pipeline model with TDNN ASR and \( NMT_n \) achieve the highest BLEU score.

From the results in Table 2, it is observed that the evaluation of the target language translations from the output of the ASR systems using a shared NMT system differ by a small margin. The TDNN pipeline model achieve a 0.1 to 0.5 BLEU score more than the GMM-HMM pipeline model.

Comparing the evaluation scores of the translation hypothesis from the pipeline and End-to-End models, it is clear that the pipeline models outperforms the End-to-End model significantly by a margin of 2.6 BLEU score. The result also shows that the usage of additional out of domain data where the size of the dataset is substantially larger than the in-domain dataset size has negative effect on the BLEU score. A likely cause is the use of development and test dataset from the in-domain dataset.

### 5.2 Qualitative Analysis of Manipuri ASR Systems

Table 3 shows some sample input-output of Manipuri ASR systems where we analyse the robustness of the systems on selected words in the reference transcript highlighted in green.

In **transcript1**, “অহুমশ‌ুবা” (~ “ahumsuba” meaning *third*) is generated in its numerical format “৩ শ‌ুবা” (~ “3 suba” meaning 3rd) by GMM-HMM ASR system while the TDNN ASR system generate it in its actual format. Though, both the format has same speech feature, TDNN ASR system performs better in n-gram match.
The samples transcript2 to transcript4 shows some of the examples where ASR systems generates incorrect transcript words (highlighted in “red”) of reference words (highlighted in “green”). From the sample results, it is observed that the ASR systems suffer when the word contains the phoneme “b” ( “বন্ধ” - “bandh”, “ভাবন” - “bhan”, “বাল” - “bal”).

A single phoneme in Manipuri could be represented by different graphemes in the Bengali script. One such case is shown in transcript3 where the ASR systems generate the word “ক্রাসপোট” (¬ “transport”) as “ক্রাসপোট” (¬ “transport”). In transcript4, the word “ইমফাল” (¬ “imphal”) is a correct representation of the word “ইমফাল” (¬ “imphal”) where the joined characters are written separately.

As the automatic evaluation metrics are computed at the word level, the cases highlighted in transcript3 and transcript4 often led to low evaluation score.

5.3 Sentence Level Evaluation

An analysis of the Manipuri→English S2T translation system is carried out by computing the BLEU score at the sentence level. Figure 2 shows the analysis based on the number of sentences with respect to the BLEU score. While the analysis in Figure 3 shows the performance of the systems with shorter and longer sentences based on the length of the reference sentence.

In Figure 2, the majority of the translations from the E2E model are observed to score a BLEU score of less than 10, while less than half of the translations from the pipeline model scored less than 10. It is interesting to note that the highest sentence level BLEU is achieved by the E2E model even though the overall performance of the pipeline model outperforms the E2E model significantly. A likely cause of the poor performance of end-to-end S2T translation system is the small size of the dataset. The result in Figure 3 shows that the systems perform well with longer sentences [20,30)
while the sentences with length below 20 score a BLEU score less than 10.

With only very few samples achieving a BLEU score above 50, it is clear that a massive effort is required for the development of Manipuri→English Speech-to-Text translation systems.

### 5.4 Qualitative Analysis of Manipuri→English S2T Systems

Sample input and output from the pipeline models and E2E Speech-to-Text translation model are shown in Table 4. The grammatical error or incorrect word(s) in the output from our systems are highlighted in "blue".

In the first sample, despite preserving the information moderately, the fluency scale of translation output with the Pipeline-GMM-HMM is worse compared to the other systems. One of the main reason is error propagation from the ASR model where word “এককী” (~ “act-ki”) is incorrectly generated as “ঈ কী” (~ “e-ki”). Furthermore, E2E translation model generate additional non-relevant information even though the output sentence is fluent. In the second sample, the named entity word “Wareppa Naba” (a name of a person) is incorrectly generated and is replaced by another name of a person (i.e., Ng Ibobi, Ibobi and Ng . Uttam). In different languages, there are cases where multiple words in one language is represented by a single word in another language. One such case is highlighted in the second sample where both the words meet and conference which are synonyms is represented by a single word in Manipuri “মীফম” (~ “mifam”). This often results to low BLEU score as the evaluation metric is computed at the word level n-gram matching and doesn’t consider synonyms. The third sample shows the handling of long Manipuri multi-word named entity “অপুনবা ইরেইপাক্কি মাহেরী সিঙ্গলুপুকী” (~ “Apunba Ireipakki Mheiroi Sinpanglup-ki”), where the suffix “-ki” is used to denote the possessive noun. It is observed that the multi-word named entity is translated correctly despite the slight variation in the output of

| source1 | reference1 | আর. তি. আই. এককী মতাঙ্গনা সহমিতিকী যৌরম্য পার্থোক্ষে | Awareness programme on RTI Act held |
| GMM-HMM ASR | আর. তি. আই. এককী মতাঙ্গনা সহমিতিকী যৌরম্য পার্থোক্ষে | Awareness programme on RTI Act held |
| PipeHmmlIN | Awareness programme on Mudra Dayal held |
| PipeHmmlG | Awareness programme on foot held |
| TDNN ASR | আর. তি. আই. এককী মতাঙ্গনা সহমিতিকী যৌরম্য পার্থোক্ষে | Awareness programme on tobacco Dayal control held |
| PipeTdhnnIN | Awareness programme on Act held at Moreh |
| PipeTdhnnG | |
| E2E | Awareness programme on RTI Act held at Manipur Press Club, Majorkhul |

| source2 | reference2 | পাওমীিশংগী মীফম মনুংদা ৱােরķা নাবানা েমিডয়াগী মীওইিশংদা ৱা ঙাংিখ | WareppaNaba speaks to media persons during press meet |
| GMM-HMM ASR | পাওমীিশংগী মীফম মনুংদা ৱােরķা নাবানা েমিডয়াগী মীওইিশংদা ৱা ঙাংিখ | Ng Ibobi speaks to media persons during press conference |
| PipeHmmlN | Ng Ibobi speaks during media persons during press conference |
| PipeHmmlG | Ibobi speaks during media persons during press conference |
| TDNN ASR | পাওমীিশংগী মীফম মনুংদা ৱােরķা নাবানা েমিডয়াগী মীওইিশংদা ৱা ঙাংিখ | Ng Ibobi speaks to media persons during press conference |
| PipeTdhnnIN | Ng Ibobi speaks during media persons during press conference |
| PipeTdhnnG | Ibobi speaks during media persons during press conference |
| E2E | Ng . Uttam speaks to media persons during press conference |

| source3 | reference3 | অপুনবা ইরেইপাক্কি মাহেরী সিঙ্গলুপুকী মীহুৎিশংনা েমিডয়াদা ৱা ঙাংিল | Representatives of Apunba Ireipakki Maheiroi Sinpanglup speaking to the media |
| GMM-HMM ASR | অপুনবা ইরেইপাক্কি মাহেরী সিঙ্গলুপুকী মীহুৎিশংনা েমিডয়াদা ৱা ঙাংিল | Representatives of Apunba Ireipakki Maheiroi Sinpanglup speaking to media |
| PipeHmmlIN | Representatives of Apunba Ireipakki Maheiroi Sinpanglup speaking to media |
| PipeHmmlG | Representatives of Ukhrul woman speaking during the inaugural ceremony |
| TDNN ASR | অপুনবা ইরেইপাক্কি মাহেরী সিঙ্গলুপুকী মীহুৎিশংনা েমিডয়াদা ৱা ঙাংিল | Representatives of Apunba Ireipakki Maheiroi Sinpanglup speaking to media |
| PipeTdhnnIN | Representatives of Apunba Ireipakki Maheiroi Sinpanglup speaking to media |
| PipeTdhnnG | Representatives of Ukhrul woman speaking during the inaugural ceremony |
| E2E | Representatives of Apunba Ireipakki Maheiroi Sinpanglup speaking to the media |

Table 4: Manipuri→English Speech-to-Text translation sample input-output
the ASR system (GMM-HMM). This is the impact of the system trained on in-domain training dataset. However, the translation is not in the line with the NMT system trained on mixed domain training dataset ($NMT_g$) as the probability distribution got skewed towards the add-on dataset.

5.5 Adequacy and Fluency Analysis of Translation Outputs

Fluency analysis provide evaluation based mainly on grammatical rules. Adequacy indicates information preserved. Adequacy and fluency are measured on a scale of 1 to 4 and the meaning of the various scales are summarized in Table 5. To measure adequacy and fluency, human evaluation on the test dataset from each S2T translation system is carried out. The adequacy and fluency ratings reported by our human evaluators are shown in Table 6.

- Among our translation systems, the pipeline model (PipeTdnnIN) achieves the highest adequacy score. The adequacy score of all the systems are observed to be in correlation with our automatic evaluation.
- The fluency score is observed to be non-correlated with the automatic evaluation scores. In terms of fluency, the end-to-end model achieved the highest score. This indicates that despite not preserving the information of the source language, the system is able to generate a fluent text.

6 Conclusion and Future work

In this work, a comparative study of the conventional pipeline model and end-to-end model of S2T translation on an extremely low-resource Manipuri-English language pair is presented. We also made a comparison of two acoustic models: GMM-HMM and TDNN, for the ASR module. An improvement of 2.53% WER is observed in the ASR model with TDNN compared to GMM-HMM. The TDNN ASR model is observed to be more robust than the GMM-HMM model in terms of n-gram match. The ASR output is fed to a shared NMT system (trained with the in-domain or the additional out of domain dataset) in our pipeline model. In comparison, the translation hypothesis of the pipeline models are comparable in terms of the BLEU score. However, using an NMT system trained with a dataset from mixed domain results to the decrease in the automatic evaluation score. Though the end-to-end S2T translation has various advantages over traditional pipeline models, the limited size of our dataset led to the end-to-end S2T model’s low performance compared to the pipeline model. An extensive collection of parallel S2T translation training data is generally required to train such an end-to-end S2T translation model.

In future, we plan to increase the size of the dataset along with the collection of other forms of modalities such as images. We also plan to explore various Speech-to-Text machine translation models to enhance the performance.
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