Abstract

In this paper, we introduce a new and simple method for comparing speech utterances without relying on text transcripts. Our speech-to-speech comparison metric utilizes state-of-the-art speech2unit encoders like HuBERT to convert speech utterances into discrete acoustic units. We then propose a simple and easily replicable neural architecture that learns a speech-based metric that closely corresponds to its text-based counterpart. This textless metric has numerous potential applications, including evaluating speech-to-speech translation for oral languages, languages without dependable ASR systems, or to avoid the need for ASR transcription altogether.

Index Terms: evaluation metric, speech-to-speech translation, speech-to-speech comparison, COMET, BLEU, ChrF.

1. Introduction

In natural language processing (NLP), matching a text hypothesis with a text reference is a common practice to evaluate systems such as natural language generation, machine translation, etc. With the rise of speech generation and end-to-end speech-to-speech (S2S) translation systems [1, 2], there is a growing need for speech-to-speech comparison directly in the signal domain [3]. This paper proposes a simple and efficient implementation of such “textless” metric. More specifically, we want to develop a metric in order to compare a speech hypothesis (H) with a speech reference (R) along several axes. In this work, our main axis is meaning, i.e., similarity score should be high if both utterances convey the same message. But other axes could be interesting in the future: eg. high similarity if H and R voices are similar (similar speaker, gender, etc.). We want our textless metric to have a strong correlation with its text-based counterpart that would be applied to the transcripts of H and R (see figure 1). We believe such metric could be interesting for following use cases: (a) evaluating a S2S translation system w/o falling back to a transcription of H and R (unlike sentence-level ASR-BLEU [1] does); (b) evaluating target languages for which we cannot fall back to a transcription such as Tamasheq [4] (>50% of languages are oral; even more are not equipped with good ASR) and (c) defining training objective for end-to-end S2S model optimization.

This paper is structured as follows: section 2 positions our contribution in respect to previous works. Section 3 describes a naive approach that fails and supports our proposal of a learnt metric. Section 4 presents our textless metric while section 5 illustrates its use through speech comparison experiments with synthetic and natural speech. Finally section 6 concludes this work and gives some perspectives.
spotting applications, it is ill-equipped to reach our goal of measuring subtle differences in meaning between long speech hypothesi and reference. These limitations of signal-based comparison metrics such as DTW lead us to get interested by the textless NLP area. One building block of this emerging domain is the use of Speech-to-Units (S2U) encoders that automatically discover discrete acoustic units and decode speech into a pseudo-text. Examples of such encoders are HuBERT [13] or Wav2Vec2.0 [14] followed by a quantization function (using k-means algorithm for instance). Such representations were successfully used for automatic speech recognition (ASR) tasks which shows that, whether discretized or not, they convey information related to text message hidden in speech signal.

Contemporaneous to this work, [15] propose a text-free metric for S2S evaluation but they train it on human annotations (to correlate with human judgements) whereas we will train our S2S evaluation metric to correlate with its text-based counterpart (which will allow us to take advantage of much more data as no human evaluation data is needed in our case).

3. A (Too) Naïve Approach

Our first attempt was to apply text-based translation metrics to our pseudo-transcribed (S2U) speech signals. Discrete acoustic units were generated after clustering audio features; standard machine translation metrics such as BLEU were then applied to the unit sequences obtained. We then verified if speech-BLEU would correlate with text-BLEU when applied to multiple pairs $(H, R)$ of utterances. We applied the following experimental setup: (a) build a dictionary of $k$ centroids from large speech data using k-means algorithm applied to cepstral features; (b) pseudo-transcribe the pairs of speech utterances by mapping each feature vector to the nearest centroid (using l2 or cosine distance); (c) reduce consecutive repetitions of the same discrete symbol into one instance (de-duplication).

We computed speech-based metrics (and their text-based counterpart) on a subset of commonvoice4.0 english dataset. More precisely, we selected 20M pairs of utterances with at least one 4-gram in common (in order to have non-zero BLEU scores in our collection). Figure 2 presents a scatterplot of the text-based metric (on X axis) and speech-based metric (on Y axis) for a subset of those pairs when a vocabulary of k=50 acoustic units is used (we experimented with different values of k and a cosine metric instead of l2 with similar results).

Initially, we noted that our selection procedure, which involves choosing pairs of natural speech utterances that share at least one 4-gram, enables the collection of pairs with a wide range of BLEU scores between 0 and 1, reflecting their varying degrees of closeness. However, naive speech-BLEU does not correlate well with text-BLEU which shows that text-based metrics simply applied to discrete speech units fail. This leads us to propose a new approach that differs in two main points:

- instead of local acoustic (cepstral) quantized units, we use HuBERT [13] units that have been shown to convey more contextualized and semantic speech information,
- simple unsupervised (such as BLEU) metrics used are replaced by learnt metrics.

4. A Learnt Metric for Speech-to-Speech Comparison

As it has been observed that text-based metrics applied to discretized acoustic speech units are unreliable, we believe that the best approach is to develop a metric that learns the semantic similarity between a speech hypothesis and a speech reference. To experiment with this idea, we re-use COMET [10] framework widely adopted in machine translation evaluation where it is trained to correlate with human judgements. We adapt it to our need as illustrated in figure 3: both audio $H$ and $R$ are pseudo-transcribed in a sequence of de-duplicated speech units (with HuBERT [13]). Both sequences of discrete units are mapped to a sequence of characters and encoded with a neural text encoder. Obtained $\hat{H}$ and $\hat{R}$ vectors are pooled and a regression layer predicts the score we want to approximate.

In the follow-up experiments we use ChrF or BLEU text-based metrics as a target. Mean Square Error (MSE) loss is used to train model parameters. As done in initial COMET framework, not only regression layer parameters will be learnt during training but also parameters of the “text” encoder (after 30% of the first epoch and for the rest of the training steps). We highlight below main differences between initial COMET and its adaptation to speech-to-speech comparison:

- COMET uses source $S$, hypothesis $H$ and reference $R$ utterances to predict MT quality, whereas we only use $H$ and $R$ in this work ($S$ is ignored during pooling operation),
- COMET predicts human judgement of MT quality whereas our learnt metric predicts a text-based score (no human judgements are needed to train our metric),
- COMET proposes two different training objectives: regression to predict a score or ranking using a triplet loss; we use only regression here,
- COMET comes with several text encoders (XLM-Roberta [16], BERT [17]); we use XLM-Roberta (277M param.) to encode our sequence of discrete acoustic units as we believe it should be able to capture sequential patterns; XLM-Roberta parameters are fine-tuned after 30% of first epoch.\(^5\)

5. Experiments

In order to show that our approach can learn several metrics, we first experiment on English synthetic speech and train a metric to predict speech-ChrF. In a second step we predict speech-BLEU using English natural (human) speech.

\(^5\)Each discrete unit is mapped to a rare character in the Unicode set
\(^6\)Using a true speech encoder such as XLSR [18] to replace the stacking of HuBERT and XLM-Roberta is an option left for future work as it would require major modification of COMET codebase.
5.1. ChrF prediction on synthetic speech

We start from synthetic CVSS speech corpus [19] (English target part), a massively multilingual-to-English S2S corpus. To obtain dissimilar audios with different voices, we enrich CVSS using the following process applied to each English speech utterance:

(a) ASR transcription;
(b) BART [20] encoding and decoding to further add noise to the already noisy ASR transcript; and
(c) TTS from the noisy transcript (with a different speaker voice).

We end-up with a corpus of 256,882 pairs \((H, R)\) of speech utterances (similar, slightly dissimilar or very dissimilar) with associated transcripts splitted into train (207,364 pairs), dev (14,759 pairs) and test (14,759 pairs). True text-ChrF distribution (on our test set) is displayed in figure 4 (left). We learn several metrics using COMET and display correlations (Pearson and Spearman) between true ChrF and learnt ChrF for different setups (table 1):

- different input (text or speech),
- different amount of training data (for learnt metrics): dev set (14.7k utterances) or train set (207.4k utterances),
- different number of HuBERT acoustic units: 50 or 200,
- different number of training epochs: 5 or 10.

First row in table 1 is a topline were ChrF was learnt (using our dev set) with initial COMET framework and text inputs. As expected, neural architecture can learn to approximate a sequence based metric such as ChrF easily (high correlation between true and predicted ChrF scores). Remaining rows use speech \(H\) and \(R\) inputs: second row is the naive baseline presented in section 3 with poor correlation scores. Rows 3-6 display results obtained with our learnt textless metric (speech-ChrF). We observe that more acoustic units (200 instead of 50), adding training data (207k utterances instead of 14.7k utterances) and training longer (10 epochs instead of 5) improves correlation. To illustrate better what 0.779 Pearson correlation score means, figure 4 (right) displays distribution of our speech-ChrF scores (with best configuration of last row in table 1). We observe that left (text-ChrF) and right (speech-ChrF) distributions are very similar. Our modified COMET has learnt to replicate the text-ChrF distribution using speech input only.

5.2. BLEU prediction on natural speech

5.2.1. Setup

We now evaluate on natural speech. We use 1M pairs obtained with methodology described in section 3 (commonvoice corpus) where \(H\) and \(R\) are natural speech utterances most of the time from different speakers. Target score is now BLEU metric obtained from text. Our corpus is splitted into train (990k pairs), dev (5k pairs) and test (5k pairs). Figure 5 (left) displays BLEU distribution of our test set (train/dev distributions are similar): distribution is bimodal with many unmatched pairs in range \([0;0.4]\) and even more matched pairs in range \([0.8;1.0]\).

After extracting HuBERT-200 acoustic units for the full speech collection, we learn our speech-BLEU on the train set of 990,000 pairs of speech utterances (for 5 epochs) and evaluate on our dev and test (5k pairs each). Overall our model has 279M trainable parameters (among them 277M for XLM-R) and was learnt in 60h on a single GPU-V100. Training loss is displayed on figure 6: we clearly see when parameters of the XLM-R encoder (after 20k steps corresponding to 30% of the first epoch) start to be adapted in addition to the regression layer parameters. At this moment XLM-R specializes itself at encoding acoustic HuBERT units and loss significantly decreases.

We obtain very good correlations on the test set (see table...
Table 1: Correlations between text-ChrF and speech-ChrF (on synthetic speech, test set) for different experimental setups.

| Input              | Train Data | Encoder     | Epochs | Metric       | $\rho$ (Pearson) | $\rho$ (Spearman) |
|--------------------|------------|-------------|--------|--------------|------------------|-------------------|
| Text (topline)     | 14.7k utt. | XLM-R       | 5      | learnt chrF  | 0.902            | 0.922             |
| Speech (baseline)  | None       | Hubert-50   |        | naive chrF  | 0.431            | 0.386             |
| Speech             | dev (14.7k)| Hubert-50 + XLM-R | 5 | learnt chrF  | 0.542            | 0.480             |
| Speech             | dev (14.7k)| Hubert-200 + XLM-R | 5 | learnt chrF  | 0.595            | 0.567             |
| Speech             | train (207.4k) | Hubert-200 + XLM-R | 5 | learnt chrF  | 0.755            | 0.700             |
| Speech             | train (207.4k) | Hubert-200 + XLM-R | 10 | learnt chrF  | 0.779            | 0.733             |

Table 2: Correlations between (a) text-BLEU and speech-BLEU (b) text-BLEU and sentence-level ASR-BLEU (natural speech)

| metric           | speech-BLEU (ours) | ASR-BLEU [1] (whisper tiny 28.8% WER) | ASR-BLEU [1] (whisper large 10.1% WER) |
|------------------|---------------------|---------------------------------------|----------------------------------------|
|                  | $\rho$ (Pearson)    | $\rho$ (Spearman)                     | $\rho$ (Pearson)                       |
| dev              | 0.838               | 0.988                                 | 0.531                                  |
| test             | 0.881               | 0.976                                 | 0.579                                  |

Figure 6: Loss (MSE) during 5 epochs of training speech-BLEU on 990,000 pairs of natural speech utterances.

2): $\rho$(Pearson) = 0.976 and $\rho$(Spearman) = 0.881. This demonstrates that our approach, when learnt on enough pairs of natural speech, can be used to train a similarity metric (such as BLEU) between two audio speech samples. The high correlation coefficients (actually higher than the ones obtained on synthetic speech) can be explained by the fact that our training data is bigger for natural speech (1M pairs) than for synthetic speech (207k pairs) and also by the BLEU distribution of our dataset (figure 5) which is bimodal with large majority of high scores ([0.8, 1.0]) making score prediction task probably easier.

5.2.2. Comparison with sentence-level ASR-BLEU

We compare our approach with sentence-level ASR-BLEU [1] which consists in automatically transcribing both speech hypothesis and reference and compute sentence-level BLEU between transcripts.\(^7\) We used two multilingual ASR [21] models with different performance (whisper-tiny/39M parameters and whisper-large/1550M parameters) to decode signals of dev and test sets (we keep punctuation and case for ASR-BLEU computation). Right part of table 2 shows that sentence-level ASR-BLEU is a poor proxy to real-text-BLEU even when ASR system is strong (whisper-large obtains 10.1% WER on common voice data according to [21]). When ASR system is weaker (whisper-tiny obtains 28.8% WER on common voice data according to [21]) correlation scores are even worse. This indicates that in situations where the target language lacks a robust ASR system, relying solely on ASR-BLEU could be misleading. Conversely, our trained speech-BLEU metric exhibits the strongest correlation with the original text-BLEU.

5.2.3. Qualitative analysis

Figure 5 (right) displays speech-BLEU distribution of our test set which is similar to the original text-BLEU distribution which confirms, for natural speech, results of figure 4 already found for synthetic speech.\(^8\) As supplementary multimedia material, we offer audio pairs with their text-BLEU, speech-BLEU, and ASR-BLEU scores for randomly selected utterances from the test set. Through our observations, we found that our speech-BLEU metric is capable of predicting low scores for poorly related utterances, while also indicating a score close to 1 for similar utterances spoken by different speakers.

6. Conclusion and Future Work

We have introduced our architecture for developing a text-free metric for speech-to-speech comparison. Our initial findings indicate that a sequence of discrete HuBERT units contains enough information to measure semantic similarity between an audio hypothesis and reference, even when the speakers are different. However, proper training of the metric is necessary to improve its correlation with text-based scores. Moving forward, we aim to determine if the metric can be trained on multilingual data and applied to unseen languages, similar to COMET in machine translation evaluation. Another objective is to use the text-free metric to evaluate speech-to-speech translation into oral languages (for the low-resource speech translation shared task at IWSLT2022\(^7\)). Additionally, our metric can be applied to other evaluation tasks, such as the MOS prediction task in TTS, which was recently presented as a challenge at Interspeech 2022.\(^8\) We could also adapt our architecture to ASR confidence measures by replacing the reference $R$ with the source $S$.

\(^7\)Supplementary material provides distrib of ASR-BLEU scores and show those are different from text-BLEU and speech-BLEU ones.

\(^8\)https://iwslt.org/2022/low-resource

\(^8\)https://voicemoa-challenge-2022.github.io
7. References

[1] Y. Jia, R. J. Weiss, F. Biadsy, W. Macherey, M. Johnson, Z. Chen, and Y. Wu, “Direct speech-to-speech translation with a sequence-to-sequence model,” CoRR, vol. abs/1904.06037, 2019. [Online]. Available: http://arxiv.org/abs/1904.06037

[2] A. Lee, P.-J. Chen, C. Wang, J. Gu, S. Popuri, X. Ma, A. Polyak, Y. Adi, Q. He, Y. Tang, J. Pino, and W.-N. Hsu, “Direct speech-to-speech translation with discrete units,” in Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). Dublin, Ireland: Association for Computational Linguistics, May 2022, pp. 3327–3339. [Online]. Available: https://aclanthology.org/2022.acl-long.235

[3] E. Salesky, J. Mäder, and S. Klinger, “Assessing evaluation metrics for speech-to-speech translation,” CoRR, vol. abs/2110.13877, 2021. [Online]. Available: https://arxiv.org/abs/2110.13877

[4] M. Z. Boito, F. Bougares, F. Barbier, S. Gabhi, L. Barrault, M. Rouver, and Y. Estèves, “Speech resources in the tamahq language,” CoRR, vol. abs/2201.05051, 2022. [Online]. Available: https://arxiv.org/abs/2201.05051

[5] K. Papineni, S. Roukos, T. Ward, and W.-J. Zhu, “Bleu: a method for automated machine translation evaluation,” in Proceedings of the 40th annual meeting of the Association for Computational Linguistics, 2002, pp. 311–318.

[6] M. Snover, B. Dorf, R. Schwartz, L. Micciulla, and J. Makhoul, “A study of translation edit rate with targeted human annotation,” in Proceedings of the 7th Conference of the Association for Machine Translation in the Americas: Technical Papers. Cambridge, Massachusetts, USA: Association for Machine Translation in the Americas, Aug. 8-12 2006, pp. 223–231. [Online]. Available: https://aclanthology.org/2006.amta-papers.25

[7] M. Popović, “chrF: character n-gram F-score for automatic MT evaluation,” in Proceedings of the Tenth Workshop on Statistical Machine Translation. Lisbon, Portugal: Association for Computational Linguistics, Sep. 2015, pp. 392–395. [Online]. Available: https://aclanthology.org/W15-3049

[8] T. Zhang, V. Kishore, F. Wu, K. Q. Weinberger, and Y. Artzi, “Bertscore: Evaluating text generation with BERT,” in 8th International Conference on Learning Representations, ICLR 2020. Addis Ababa, Ethiopia, April 26–30, 2020. OpenReview.net, 2020. [Online]. Available: https://openreview.net/forum?id=SkeHuCVFDr

[9] M. Stanoević and K. Sima’an, “Fitting sentence level translation evaluation with many dense features,” in Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP). Doha, Qatar: Association for Computational Linguistics, Oct. 2014, pp. 202–206. [Online]. Available: https://aclanthology.org/D14-1025

[10] R. Rei, C. Stewart, A. A. Farinha, and A. Lavie, “COMET: A neural framework for MT evaluation,” in Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP). Online: Association for Computational Linguistics, Nov. 2020, pp. 2685–2702. [Online]. Available: https://aclanthology.org/2020.emnlp-main.213

[11] H. Sakoe and S. Chiba, “Dynamic programming algorithm optimization for spoken word recognition,” IEEE transactions on acoustics, speech, and signal processing, vol. 26, no. 1, pp. 43–49, 1978.

[12] E. Kharitonov, J. Copet, K. Lakhotia, T. A. Nguyen, P. Tomassello, A. Lee, A. Elkahky, W.-N. Hsu, A. Mohamed, E. Dupoux, and Y. Adi, “textless-lib: a library for textless spoken language processing,” in Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies: System Demonstrations. Hybrid: Seattle, Washington + Online: Association for Computational Linguistics, Jul. 2022, pp. 1–9. [Online]. Available: https://aclanthology.org/2022.naacl-demo.1

[13] W.-N. Hsu, B. Bolte, Y.-H. H. Tsai, K. Lakhota, R. Salakhutdinov, and A. Mohamed, “Hubert: Self-supervised speech representation learning by masked prediction of hidden units,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 29, pp. 3451–3460, 2021.

[14] A. Baevski, H. Zhou, A. Mohamed, and M. Auli, “Wav2vec 2.0: A framework for self-supervised learning of speech representations,” in Proceedings of the 36th International Conference on Neural Information Processing Systems, ser. NIPS ’20. Red Hook, NY, USA: Curran Associates Inc., 2020.

[15] M. Chen, P.-A. Duqueenne, P. Andrews, J. Kao, A. Mourachko, H. Schwenk, and M. R. Costa-jussà, “Blaser: A text-free speech-to-speech translation evaluation metric,” 2022. [Online]. Available: https://arxiv.org/abs/2212.08486

[16] A. Conneau, K. Khandelwal, N. Goyal, V. Chaudhary, G. Weniez, F. Guzmán, E. Grave, M. Ott, L. Zettlemoyer, and V. Stoyanov, “Unsupervised cross-lingual representation learning at scale,” CoRR, vol. abs/1911.02116, 2019. [Online]. Available: http://arxiv.org/abs/1911.02116

[17] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “BERT: Pre-training of deep bidirectional transformers for language understanding,” in Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers). Minneapolis, Minnesota: Association for Computational Linguistics, Jun. 2019, pp. 4171–4186. [Online]. Available: https://aclanthology.org/N19-1423

[18] A. Babu, C. Wang, A. Tjandra, K. Lakhotia, Q. Xu, N. Goyal, K. Singh, P. von Platen, Y. Saraf, J. Pino, A. Baevski, A. Conneau, and M. Auli, “XL-S-R: self-supervised cross-lingual speech representation learning at scale,” CoRR, vol. abs/2111.09296, 2021. [Online]. Available: https://arxiv.org/abs/2111.09296

[19] Y. Jia, M. T. Ramanovich, Q. Wang, and H. Zen, “CVSS corpus and massively multilingual speech-to-speech translation,” CoRR, vol. abs/2201.03713, 2022. [Online]. Available: https://arxiv.org/abs/2201.03713

[20] M. Lewis, Y. Liu, N. Goyal, M. Ghazvininejad, A. Mohamed, O. Levy, V. Stoyanov, and L. Zettlemoyer, “BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension,” in Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. Online: Association for Computational Linguistics, Jul. 2020, pp. 7871–7880. [Online]. Available: https://aclanthology.org/2020.acl-main.703

[21] A. Radford, J. W. Kim, T. Xu, G. Brockman, C. McLeavay, and I. Sutskever, “Robust speech recognition via large-scale weak supervision,” 2022. [Online]. Available: https://arxiv.org/abs/2212.04356