INVESTIGATING SELF-SUPERVISED LEARNING FOR LYRICS RECOGNITION

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ABSTRACT

Lyrics recognition is an important task in music processing. Despite the great number of traditional algorithms such as the hybrid HMM-TDNN model achieving good performance, studies on applying end-to-end models and self-supervised learning (SSL) are limited. In this paper, we first establish an end-to-end baseline for lyrics recognition and then explore the performance of SSL models. We evaluate four upstream SSL models based on their training method (masked reconstruction, masked prediction, autoregressive reconstruction, contrastive model). After applying the SSL model, the best performance improved by 5.23\% for the dev set and 2.4\% for the test set compared with the previous state-of-art baseline system even without language model trained by large corpus. Moreover, we study the generalization ability of the SSL features considering that those models were not trained on music datasets.

Index Terms— Lyrics, Singing, Speech Recognition, Lyrics Transcription, Self-Supervised Learning.

1. INTRODUCTION

Lyrics recognition is an important task in music processing. In previous studies, several traditional algorithms such as Hidden Markov Models and TDNN achieved good performance \cite{1}. However, studies on applying end-to-end models to lyrics recognition are limited. Researchers have found that for lyrics recognition, traditional music end-to-end models do not perform well \cite{2,3}. Over the past few years, the new developments in speech recognition using end-to-end models have achieved very low error rates in most benchmarks \cite{4,5}. If there is a such well-performing end-to-end system, we believe that the same approach can be used for lyrics recognition considering lyrics recognition is very similar to automatic speech recognition \cite{2,6}.

Automatic sung speech recognition systems typically use the same acoustic features as spoken speech systems. This is motivated by the fact that spoken and sung speech have the same production system and that semantic information is conveyed in the same way in both speech styles. \cite{7}. However, there are several different acoustic features between sung and spoken speech, such as the pitch ranges, the syllable duration, and the existence of vibrato in singing \cite{7}. These differences make sung speech difficult to recognize. Although handcrafted features such as MFCC or LPCs have been shown to achieve a certain degree of effectiveness, these handcrafted features are also considered to have limitations due to their data-driven nature \cite{8}. For the above reasons, we want to introduce the self-supervised learning model in the lyrics recognition task and use the self-supervised learning model to extract features.

Self-supervised learning models have achieved great success in natural language processing \cite{9}, computer vision \cite{10}, and speech processing \cite{11,12}. In the field of speech processing, self-supervised learning (SSL) models are often used to extract features and apply them to downstream tasks, such as speech recognition, speech enhancement and separation, speaker id, emotion recognition, and other speech tasks \cite{13}. Knowing the success of SSL models for different tasks, this paper explores the integration of SSL models as upstream models (our approach freezes the SSL models and uses them to extract features) with end-to-end downstream models in lyrics recognition. Moreover, we study the generalizability of the SSL features, considering that those models were not trained on music datasets.

In summary, this paper has three contributions

\begin{itemize}
  \item We construct an new baseline for lyrics recognition using the DAMP \cite{14} dataset. The best performance improved by 5.23\% for the dev set and 2.4\% for the test set compared with the previous state-of-art baseline system even without language model trained by large corpus.
  \item We explored the effect of background music on the performance of self-supervised learning models.
  \item We explore the performance of different SSL models and discuss the generalizability of the SSL features, considering that those models were not trained on music datasets.
\end{itemize}

2. METHODOLOGY

In order to investigate the performance of the features extracted by the self-supervised learning model on the song lyrics recognition task, we froze the parameters of the self-supervised learning model, and the specific process is shown in the figure \cite{1}. Moreover, in order to better compare the performance of the features extracted by the self-supervised
learning model on the lyrics recognition task. We also tested the performance of the end-to-end model on the lyrics recognition task without adding the self-supervised learning model.

2.1. Self-supervised pretrained models

In this paper, we evaluate four different types of SSL upstream models for music lyrics recognition. We selected SSL models based on their training method. These upstream SSL models can be categorized into masked reconstruction model (Tera [15] and NPC [16]), masked prediction model (Hubert [12]), auto-regressive reconstruction model (VQ-APC [17]) and contrastive model (wav2Vec2.0 [11]). We freeze these SSL models and use these SSL models to extract speech representations. Following part of SUPERB’s setup [18], we used the weighted-sum representation from all layers as the final representation $F$ instead of using features from the last hidden layers.

$$F = \sum_{i=0}^{K-1} w_i F_i$$  (1)

Where $K$ is the total number of layers, $F_i$ is the representation extracted from the $i$th layer, $w_i$ is the weight for the $i$th layer. The weight $w$ can be updated during the training.

2.2. Downstream models for lyrics recognition

In our experiment, it is found that the optimal downstream models of different self-supervised learning models are not the same in the task of song lyrics recognition. In order to make different self-supervised learning models achieve the optimal performance, we use two different end-to-end downstream models, Conformer [5] and Transformer [19] as downstream model.

Since few people systematically studied the performance of end-to-end models in the task of song lyrics recognition before, in order to better compare the performance of self-supervised learning models, we tested two type of the end-to-end models, Transformer and Conformer in the task of lyrics recognition (we used mel Spectrum as feature input). We select the best performing model as the end-to-end baseline.

3. EXPERIMENTAL SETUP

3.1. Dataset

In this paper, we measure the performance of lyrics recognition on the DAMP dataset [14]. Previous works focus on the DAMP [14] and the DALI [20] dataset because of the large amount of data. However, the audio of the DALI dataset needs to be downloaded from streams like YouTube, which results in inconsistent data due to regional restrictions. To achieve reproducible results, this paper establishes an end-to-end lyric recognition benchmark using the DAMP - Sing! 300x30x2 dataset, following the leading Kaldi-based multi-step approach [6]. DAMP - Sing! 300x30x2 dataset contains 149.1 hours of singing clips with no background music. We used the default split(train/dev/test) for the DAMP dataset. There are roughly 600 utterances were randomly selected from the data assigned to development and test sets. Note that the DAMP dataset is a non-professional recording; most of the singing is mixed with the ambient noise and slightly mismatched with the lyrics.

In order to explore the impact of background music on the performance of self-supervised learning model, we use another dataset, MusDB dataset [21], the professional corpus made by commercial music. This dataset, which has both versions with and without background music, is the most suitable dataset to explore the impact of background music on the performance of self-supervised learning models. The MusDB dataset consists of 150 full-length audios with background music, including 86 music for the train set, 14 for the validation, and 50 for the test set. MusDB is only 10 hours long due to the limited commercial music, and the lyrics are manually aligned using [22].

3.2. Model architecture and finetuning details

3.2.1. End to end baseline model architecture

There are two type of end to end models we test in this paper, transformer [23] and conformer [5]. One of the best performing models is Transformer, which has an encoder with 12 blocks and 4 attention heads, 2048 linear units and 0.1 dropout rate. The decoder is similar to the encoder which has 6 blocks, 2048 linear units and 0.1 dropout rate. We used
3.3. SSL downstream model architecture

In the experiments we found that for different SSL model, its optimal downstream model is not the same. In order to best use features extracted by SSL model, several end-to-end models were tested in our experiment for each SSL model (LSTM, Transformer, Conformer). From our experiments we can see that the best performing downstream model for Tera, VQ-NPC and NPC is Transformer. For Hubert and Hubert Large, the best performing downstream model is Conformer. The parameters of downstream models for conformer and transformer are same as end-to-end baseline model we mentioned in previous section. In stead of training 100 epochs, we only train 50 epochs considering SSL models have good performance on speech task with fewer training epochs. We use Adam optimizer to optimize the model with 0.0025 learning rate and 40000 warm up step.

3.4. Language model data and architecture

There are two type of language we tested in our paper, LSTM and Transformer. For LSTM language model, we use 2 layer with 650 units. For Transformer language model, we use 4 head, 8 layers and 1024 units as parameters. Compared with language model used in this task from the University of Sheffield [6], their language model was trained from a large number of lyrics from LyricsWikia. Because the LyricsWikia data is no longer open source, we can’t use the same language model for comparison. All the data used to train our language model comes from the training set itself. When doing decoding, we use 0.3 as weight of language model.
### 4.2. Ablation studies

In this section, we use the HuBERT model as an example to study the factors that influence the SSL model’s performance on lyrics recognition task.

#### 4.2.1. Effect of Language Model

Compared with the WER results from the University of Sheffield [6][7] (see Table 2), our language model is trained entirely from the training set, which has significantly less data than the data from LyricsWikia they used to train their language model. Since LyricsWikia data is no longer open source, we cannot use this dataset to train and compare, but we can see from the experimental results that the language model has a significant improvement in model performance.

As we can see from Table 3, especially for the test set, the improvement of the language model effect greatly improves the overall effect of the model. We believe that if we use the same language model trained on LyricsWikia data, the overall effect of our model can be further improved.

#### 4.2.2. Effect of Background Music on SSL Models

In order to better explore Effect of Background Music on SSL Models, we use another dataset named MusDB dataset. There are two versions of this dataset, one with background music and one without. Moreover, this dataset is commercially recorded, and the quality of the dataset is relatively high. Because this dataset is small and to avoid the influence of downstream models on the results, we follow the idea of SUPER[18] and only add a simple LSTM model as downstream of the SSL model. The Encoder of LSTM has 4 number of layer with 512 hidden units. The Decoder of LSTM has 1 layer with 512 hidden units. And we train both model for 100 epochs and keep best five models. The final result is shown on Table 4.

Although there are some research shows that the background music help system to achieve better result [2], our result shows that for SSL model, the background music should be like a noisy which will prevent SSL model to extract better features from raw audio. As we can see from attention weight in graph 2. When we have background music in the data, all the output is concentrated on a few inputs, making our results worse compared to the data without background music.

#### 4.3. The generalization ability of the SSL features

As shown in Table 1 combining the performance on both datasets, we observe that Hubert, wav2vec2.0 have the best generalization ability. Previous studies show that the Wav2Vec2.0 and Hubert representations are robust [26]. Our results show that this conclusion still holds even for the music dataset. Comparing the results of Hubert, Hubert Large, wav2vec2 and wav2vec Large, we can found that for the same SSL model, the number of the parameters in the SSL model is not directly related to the generalization ability of the model features.

### 5. CONCLUSION

In this paper, we have three main contributions. We built an end-to-end model baseline for lyrics recognition on Damp datasets, achieving a best WER of 17.2 on the test set and 18.1 on dev set. The best performance improved by 5.23% for the dev set and 2.4% for the test set compared with the previous state-of-art baseline system even without language model trained by large corpus. We further approve that the background music does not help improve the performance of SSL models even it has been approved it helpful in some lyrics recognition model. Finally, we study the generalization ability of the SSL features, our studies verify the conclusion of the previous study that Wav2Vec2.0 and Hubert representations are still robust even in the music dataset. And for the same SSL model, the number of parameters in the SSL model is not directly related to the generalization ability of the model features. In the future, we hope to find better ways to improve the performance of SSL model on music dataset with background music.
6. REFERENCES

[1] Che-Ping Tsai, Yi-Lin Tuan, and Lin-shan Lee, “Transcribing lyrics from commercial song audio: The first step towards singing content processing.” In 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018, pp. 5749–5753.

[2] Chitralekha Gupta, Emre Yulmaz, and Haizhou Li, “Automatic lyrics alignment and transcription in polyphonic music: Does background music help?,” in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 496–500.

[3] Sakya Basak, Shrutina Agarwal, Sriram Ganapathy, and Naoya Takahashi, “End-to-end lyrics recognition with voice to singing style transfer,” in ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2021, pp. 266–270.

[4] Jinyu Li et al., “Recent advances in end-to-end automatic speech recognition,” APSIPA Transactions on Signal and Information Processing, vol. 11, no. 1, 2021.

[5] Anmol Gulati, James Qin, Chung-Cheng Chiu, Niki Parmar, Yu Zhang, Jiahui Yu, Wei Han, Shibo Wang, Zhengdong Zhang, Yonghui Wu, et al., “Conformer: Convolution-augmented transformer for speech recognition,” in Proc. Interspeech 2020, 2020, pp. 5036–5040.

[6] Gerardo Roa Dabike and Jon Barker, “Automatic lyric transcription from karaoke vocal tracks: Resources and a baseline system,” in Interspeech 2019. International Speech Communication Association (ISCA), 2019, pp. 579–583.

[7] Gerardo Roa Dabike and Jon Barker, “The use of voice source features for sung speech recognition,” in ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2021, pp. 6513–6517.

[8] Eric J Humphrey, Sravana Reddy, Prem Seetharaman, Aparna Kumar, Rachel M Bittner, Andrew Demetriou, Sankalp Gulati, Andreas Janson, Tristan Jehan, Bernhard Lehner, et al., “An introduction to signal processing for singing-voice analysis: High notes in the effort to automate the understanding of vocals in music,” IEEE Signal Processing Magazine, vol. 36, no. 1, pp. 82–94, 2018.

[9] Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer, “Deep contextualized word representations,” north american chapter of the association for computational linguistics, 2018.

[10] Ishan Misra and Laurens van der Maaten, “Self-supervised learning of pretext-invariant representations,” computer vision and pattern recognition, 2020.

[11] Alexei Baevski, Yuehua Zhou, Abdelrahman Mohamed, and Michael Auli, “wav2vec 2.0: A framework for self-supervised learning of speech representations,” Advances in Neural Information Processing Systems, vol. 33, pp. 12449–12460, 2020.

[12] Wei-Ning Hsu, Benjamin Bolte, Yao-Hung Hubert Tsai, Kushal Lakhota, Ruslan Salakhutdinov, and Abdelrahman 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.

[13] Zili Huang, Shinji Watanabe, Shu-wen Yang, Paola García, and Sanjeev Khudanpur, “Investigating self-supervised learning for speech enhancement and separation,” in ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2022, pp. 6837–6841.

[14] “Smule sing!300x30x2 dataset,” Dec. 2018.

[15] Andy T Liu, Shang-Wen Li, and Hung-yi Lee, “Tera: Self-supervised learning of transformer encoder representation for speech,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 29, pp. 2351–2366, 2021.