SINGING LANGUAGE IDENTIFICATION USING A DEEP PHONOTACTIC APPROACH

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ABSTRACT

Extensive works have tackled Language Identification (LID) in the speech domain, however their application to the singing voice trails and performances on Singing Language Identification (SLID) can be improved leveraging recent progresses made in other singing related tasks. This work presents a modernized phonotactic system for SLID on polyphonic music: phoneme recognition is performed with a Connectionist Temporal Classification (CTC)-based acoustic model trained with multilingual data, before language classification with a recurrent model based on the phonemes estimation. The full pipeline is trained and evaluated with a large and publicly available dataset, with unprecedented performances. First results of SLID with out-of-set languages are also presented.

Index Terms— Singing language identification, CTC training, phonotactic approach, music information retrieval

1. INTRODUCTION

Having semantically meaningful and accurate descriptions of songs is crucial for organizing and retrieving relevant tracks in a large musical catalog. Language tags are of particular interest for characterizing vocal music. This information can easily be extracted using the song lyrics with a text-based language identifier. However, lyrics are not ubiquitously available for consequent musical collections. One then may want to estimate the song language from the frequently accessible metadata (e.g., song title, artist name). Yet, this method is limited as the metadata language can differ from the song language, and metadata may not contain enough information for retrieving the language. A more robust approach would be to extract the language information from the audio content. Such data is indeed always available, but the task is arguably more challenging.

The speech community has long tackled language recognition from audio data, notably with the Language Recognition Evaluation (LRE) series. However, the task was scarcely transposed in the music domain and most of the techniques used for spoken LID have yet to be adapted for SLID. The latter task is more difficult, as the prosodic specificities of languages are disturbed by the greater variabilities of the singing voice, in terms of pitch, pronunciation and vowels duration. The musical accompaniment can be framed as noise and assumed to be loud and highly correlated with the signal of interest, being the voice.

Previous works on SLID include acoustic-phonetic systems which characterize language-specific acoustic events and their distribution with carefully chosen acoustic features, such as Mel Frequency Cepstral Coefficients (MFCC), Stabilized Auditory Images (SAI) and Temporal Patterns (TRAP). Statistical modeling and supervised classification are then applied to identify the language. In particular, Kruspe’s system using the i-vector extraction technique obtains the current best performances on SLID, with 78% accuracy on a capella performances in 3 languages.

Phonotactic approaches, on the other hand, try to identify phonemes from the audio and examine their combinations and sequences, which are distinctive from one language to another. These approaches are more resource-demanding as phoneme recognizers, or acoustic models, have to be trained. Mehrabani et al. use multiple language-specific phoneme recognizers trained on speech data, to then compute language likelihoods with n-gram models for each target language. While the performances are on par with Kruspe’s i-vector-based approach, it is more complex to train and is hardly scalable to a large set of languages. In the author simplifies the approach by using a unique Deep Neural Network (DNN)-based English phoneme recognizer and identifies the language from phoneme statistics. While singing data are included in the acoustic model training, the frame-wise phoneme annotations are obtained by a forced-alignment step, which leads to poorly annotated data. Also, this statistics-based language modeling overlooks the information contained in the phoneme transitions.

Recent works have trained new acoustic models with singing data and show great results in lyrics transcription, lyrics-to-audio alignment and explicit content detection, using more recent DNN techniques. In this work, we propose to apply these advances to a phonotactic SLID system: in particular, the usage of the CTC algorithm allows the acoustic model to be trained with DALL, a large multilingual singing dataset, while alleviating the need for frame-level aligned lyrics. For language modeling, we use a recurrent architecture that can capture temporal information...
in phoneme estimation sequences. We show that our system outperforms the previous state-of-the-art in a standard closed-set scenario, obtaining a 91.7% balanced accuracy score on polyphonic songs in 5 languages. We also investigate a harder setup with out-of-set languages where we can acknowledge the limits of our model. In Section 2, we describe the key aspects of our deep phonotactic SLID approach. The dataset, baselines and implementation details are given in Section 3. Results are presented in Section 4 providing a first reproducible benchmark on the public DALI dataset.

2. PROPOSED SYSTEM

As in previous SLID works, we frame the problem as a multiclass classification task. The system takes as input audio features of a musical excerpt $X \in \mathbb{R}^{N \times F}$, with $N$ the number of time frames and $F$ the feature dimensionality. The system should then estimate the language $l$ used in the musical excerpt, among a set of $L$ languages $\{l_1, l_2, \ldots, l_L\}$.

Our deep phonotactic system, as illustrated by Figure 1 is composed of two main models: an acoustic model $F$ for phoneme estimation, followed by a language classifier $G$. The acoustic model estimates the occurring phonemes in the input audio $X$ by producing a $|C|$-dimensional vector of probabilities at each time frame, with $C$ the set of characters supported by $F$. Here, $C$ encompasses the International Phonetic Alphabet (IPA) symbols appearing in the training excerpts, a word-boundary “space” token, an instrumental “I” token and the blank token $\epsilon$ introduced by the CTC algorithm in Section 2.1. The sequence of phoneme probability vectors is referred as the posteriorgram $R := F(X) \in [0, 1]^{N \times |C|}$.

The language classifier $G$ then produces a language probability vector score $G(R) \in [0, 1]^L$ from the posteriorgram $R$. The language decision is finally taken from this vector score:

$$\hat{l} = \arg \max_{l \in \{l_1, l_2, \ldots, l_L\}} [G(F(X))]_l.$$  

Previous phonotactic approaches on SLID made distinct training of the two models, with different training sets $\{11, 12\}$. $F$ needs the phonetic transcription $y$ of each training excerpt $X$, whereas $G$ needs the posteriorgram representation $R$ and the language label $l$ of its training excerpts. We use the same dataset of musical excerpts for both model training. Following the works on joint Automatic Speech Recognition (ASR) and LID $\{18\}$, we train both models simultaneously. The joint loss function can be expressed as:

$$\mathcal{L}_{\text{Joint}}(R, \hat{l}, y, l) = \mathcal{L}_{\text{CTC}}(R, y) + \lambda \mathcal{L}_{\text{LID}}(\hat{l}, l),$$

2.1. Phoneme recognition

For the acoustic model $F$, we rely on a Convolutional Reurrent Neural Network (CRNN) trained with the CTC algorithm, as in $\{10\}$. CTC-based acoustic models were successfully implemented for singing-related tasks, such as lyrics-to-audio alignment [13, 15] and keyword spotting [16]. Following their works, we also employ a singing voice separation preprocessing step during training and inference, which improves performance over using polyphonic data in [13]. For the recurrent layers, we choose bidirectional Long Short-Term Memory (LSTM) cells to take the full sequence into account when predicting characters at each time frame.

The CTC algorithm enables to train a Recurrent Neural Network (RNN) with weakly aligned data, e.g. at word or line level, by introducing a blank token $\epsilon$ in the set $C$ of characters supported by the model. The associated loss function computes the probability of an output sequence by marginalizing over all possible alignments with the input. Following the work in [15], the output sequences are composed of multilingual phonemes according to the IPA. As the CTC loss function is differentiable, network training can be done with any gradient descent algorithm, by providing the phonetic transcription $y$ of the segment lyrics. Further details on the CTC algorithm can be found in [19].

2.2. Language Classifier

The language classifier $G$ is built upon a RNN. The usage of recurrent architectures has been successful for end-to-end spoken LID $\{20, 21\}$. Here, the phoneme posteriorgram representation is given as input, instead of the raw acoustic features extracted from the audio excerpt. Bidirectional LSTM layers are chosen with the last layer only outputting a single probability vector for the whole input segment. This architecture takes the combination of phonemes into account, as in n-gram modeling [11], but with confidence scores on the phoneme predictions by using the full probability vectors, as in statistical modeling [12]. To avoid vanishing gradient on very long input sequence [22], we choose to perform SLID on fixed-length segments for a given song. Song language is then inferred from the mean of language scores output by the system on all segments.
3. EXPERIMENTAL SETUP

3.1. Dataset
All versions of our system are trained and tested on tracks from the DALI dataset [17]. This dataset contains 5358 songs of various western genres with the lyrics annotations at word-level and song-level language labels. All tracks are downsampled to 16kHz and converted to mono. Musical accompaniments are removed by vocal extraction with Spleeter [23].

We design two language sets from this dataset: a closed-set scenario and an open-set scenario. The closed-set retains languages with more than 10 hours of data each: English, French, German, Italian and Spanish. The open-set also adds a sixth label “Others” regrouping low-resource languages (Dutch, Finnish, Portuguese, Polish). Train, validation and test sets are obtained with a 80%-10%-10% language-wise and artist-aware split [24]. Songs in neither target nor low-resource languages are also labelled as “Others” and added to the open-set test set only. These out-of-domain samples help monitoring the generalization of out-of-set modeling learned from the subset of in-domain “Others” languages. As English is over-represented in the dataset, all systems and baselines are trained with a class-weighted LID objective function.

Our system performs SLID at segment-level. Each song is split into 20s segments with a 0.5 overlapping factor between two consecutive segments. Segment lyrics are retrieved using the word-level annotations from DALI and decomposed into IPA symbols using Phonemizer [25]. Collecting all phonemes occurring in the training segments and adding the space, instrumental and blank tokens, the total number of characters obtained is $|C| = 66$ in the closed-set scenario and $|C| = 71$ in the open-set scenario. For the segment language label, the FastText language identifier [26] is used on the segment lyrics. A segment is labeled instrumental when it has less than 3 words, or ambiguous when the lyrics repetitiveness or the FastText non-confidence score is above an empirically found threshold. During inference, ambiguous and instrumental scores are not taken into account when estimating the song language from segment language scores.

3.2. Baseline systems
Two baseline systems are implemented for comparison with our system. The Metadata baseline is a text-based language identifier using the artist name and song title metadata provided with the DALI dataset. The language is extracted using the FastText language identifier [26].

The i-vector baseline is an acoustic-phonetic i-vector-based system, as in [9]. Implemented with the Kaldi LRE receipt [27], this system computes 600-dimensional i-vector per vocal-isolated song. Sequences of 20 MFCC feature vectors are extracted then modeled by a Gaussian Model Mixtures (GMM)-based Universal Background Model (UBM). Supervised language classification is performed from the i-vector representation of the song using Support Vector Machines (SVM) with a cosine kernel, as in [9] [28].

3.3. Acoustic model architecture
40 Mel-scale log filterbanks coefficients and energy features, plus deltas and double-deltas are computed from the extracted vocals using a 32ms Hann window with 0.5 overlap. The input feature sequences are downsampled by two sub-modules each composed of a 2D-convolutional layer (32 filters with kernel size $3 \times 3$), a ReLU activation function and a $2 \times 3$ max-pooling layer: sequence length is thus divided by 4.

The recurrent part of the acoustic model is composed of 3 bidirectional LSTM layers with 256-dimensional hidden states. Dropout and recurrent dropout of 0.1 each is applied. Finally a time-distributed dense layer and a softmax activation function are applied for obtaining per-frame character probability vectors from $C$. The CTC layer and objective function implementations are taken from [29].

3.4. Language classifier
Inputted posteriorgrams are pre-processed by a deterministic cleaning module: frames with $\epsilon$-emission probability $p(\epsilon) > 95\%$ are removed, to account only for frames with actual phoneme predictions.

The language classifier model is composed of 2 bidirectional LSTM layers with 64-dimensional hidden states each. The second layer outputs a single vector per segment, which is processed by a dense layer with a softmax activation function to produce one language probability vector. Recurrent layers have a 0.1 recurrent dropout factor and 0.2 dropout is applied between each layer. A class-weighted categorical cross-entropy loss function is used for training the model given the one-hot encoded language labels.

3.5. Training strategies for our approach
We test two strategies for training our system, implemented in Tensorflow. Each training variant relies on the ADAM optimization algorithm [30] with a learning rate of $10^{-3}$, a batching size of 32 and validation-based early stopping.

The 2-step variant first trains the acoustic model $F$ alone. The language classifier $G$ is then trained for SLID from the posteriorgrams of the training segments computed by $F$. The Joint variant trains both models at the same time from scratch. With hyper-parameter tuning, we found that training the system with a loss balance $\lambda = 0.1$, then fine-tuning it with $\lambda = 100$ yields the best performances on the validation set.

3.6. Ablation study
We evaluate the relevance of our system parts by designing two simplified systems for comparison. The E2E system is an end-to-end approach to SLID with the same architecture.
as the Joint variant, except for the CTC component which is removed from the loss function. The phoneme recognition task is ignored as the model is solely trained to identify the language in song segments.

The Statistics system is a modified 2-step variant. Instead of the recurrent layers, the language classifier is a pooling step of the mean and variance statistics of each phoneme class over the full song length. Song language is directly predicted from these statistic vectors using SVM. This system is analogous to a modernized version of [12], with a CTC-based acoustic model instead of the DNN-based one.

### 4. RESULTS

#### 4.1. Performances in the closed-set scenario

The results of the evaluation of our systems on the test songs in a closed-set scenario are reported Table 1.

| System  | bAccuracy (%) | F1-score (%) |
|---------|---------------|--------------|
| Metadata| 76.48 (3.98)  | 76.71 (3.45) |
| i-vector| 77.26 (3.88)  | 67.78 (3.57) |
| E2E    | 59.90 (4.33)  | 65.43 (4.47) |
| Statistics | 88.46 (3.04) | 89.00 (2.95) |
| 2-step  | 88.62 (3.03)  | 90.75 (2.62) |
| Joint   | **91.74 (2.70)** | **92.39 (2.31)** |

**Table 1.** Systems evaluation in the closed-set scenario. Measured by balanced accuracy (bAccuracy) and macro-averaged F1-score (with standard errors in parenthesis).

All phonotactic approaches (Statistics, 2-step and Joint) outperform the Metadata baseline, on the contrary of the E2E system. The phonetic information contained in the audio data is thus better suited for estimating the language than common metadata. Reliable estimations from the raw audio cannot be achieved with a naive end-to-end approach and seems to require more refined techniques. Our deep phonotactic system also significantly outperforms the re-implemented state-of-the-art i-vector system. In particular, joint training of the acoustic model and language classifier further improves the system performance, as the Joint variant yields the best overall scores, with 91.7% of balanced accuracy.

Regarding the efficiency of each system part, the Statistics system has better performances that the i-vector baseline, which was not the case between the two analog approaches from Kruspe [9] [12]. Hence, our CTC-based acoustic model seems to offer better modeling capability than the DNN-based model from [12]. The 2-step variant does not significantly outperform the Statistics system, which implies that the language classifier can be improved. Finally, even though the side phoneme recognition task requires more detailed information for training, it proves to be profitable for SLID since the 2-step and Joint systems outperform the E2E baseline.

#### 4.2. Performances in the open-set scenario

The results of the evaluation of our systems on the test songs in the open-set scenario are reported Table 2. All phonotactic systems still outperform the Metadata, E2E and i-vector approaches. However, both variants of our deep phonotactic system are less robust to the introduction of the “Others” class than the simpler Statistics system. Indeed, they seem to overfit on the “Others” training data. It can be explained as this class has a greater linguistic variability than other classes, but has the same amount of data as a low-resource target language. This effect is further demonstrated in Table 2 as only the Statistics system can generalize the out-of-set modeling to out-of-domain languages unseen during training.

| System  | In-domain “Others” (%) | Out-of-domain “Others” (%) |
|---------|------------------------|-----------------------------|
| i-vector| 50.00 (10.66)          | 20.00 (4.46)                |
| E2E    | 0.00 (0.00)            | 0.00 (0.00)                 |
| Statistics | **86.36 (7.29)** | **56.25 (5.58)** |
| 2-step  | 63.64 (10.28)          | 21.25 (4.61)                |
| Joint   | 31.82 (9.87)           | 11.25 (3.56)                |

**Table 3.** Performances comparison on “Others” labelled test songs in in-domain and out-of-domain languages cases. Measured by accuracy (with standard errors in parenthesis).

### 5. CONCLUSION

We investigate modernized phonotactic systems for SLID on polyphonic music, using recurrent models for both phoneme recognition and language classification. Trained on a publicly available multilingual dataset, the proposed system outperforms metadata-based and the previous state-of-the-art SLID approaches. The CTC-based acoustic model greatly contributes to the performance increase, both in closed-set and open-set scenarios. However, the proposed language classifier hardly exceeds statistical modeling in a closed-set scenario, and deteriorates with out-of-set languages. Future works would focus on exploring hierarchical language modeling techniques for SLID with out-of-set languages, taking inspiration from the speech literature [31].
6. REFERENCES

[1] Douglas Turnbull, Luke Barrington, David Torres, and Gert Lanckriet, “Semantic annotation and retrieval of music and sound effects,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 16, no. 2, pp. 467–476, 2008.

[2] Jose P. G. Mahedero, Álvaro Martínez, Pedro Cano, Markus Koppenberger, and Fabien Gouyon, “Natural language processing of lyrics,” in Proc. of the Annual ACM International Conference on Multimedia, 2005, pp. 475–478.

[3] Wei-Ho Tsai and Hsin-Min Wang, “Towards Automatic Identification of Singing Language In Popular Music Recordings,” in Proc. of the International Conference on Music Information Retrieval (ISMIR), 2004, pp. 568–576.

[4] Alvin F. Martin, Craig S. Greenberg, John M. Howard, George R. Doddington, and John J. Godfrey, “Nist language recognition evaluation - past and future,” in Proc. of the Odyssey The Speaker and Language Recognition Workshop, 2014, pp. 145–151.

[5] Annamaria Mesaros and Tuomas Virtanen, “Automatic recognition of lyrics in singing,” EURASIP Journal on Audio, Speech, and Music Processing, 2010.

[6] Jochen Schwenninger, Raymond Brueckner, Daniel Willett, and Marcus Hennecke, “Language identification in vocal music,” in Proc. of the International Conference on Music Information Retrieval (ISMIR), 2006, pp. 377–379.

[7] Vijay Chandrasekhar, Mehmet Emre Sargin, and David A. Ross, “Automatic language identification in music videos with low level audio and visual features,” in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2011, pp. 5724–5727.

[8] Anna M. Kruspe, Jakob Abesser, and Christian Dittmar, “A GMM approach to singing language identification,” Journal of the Audio Engineering Society, pp. 140–148, 2014.

[9] Anna M. Kruspe, “Improving singing language identification through I-vector extraction,” in Proc. of the International Conference on Digital Audio Effects (DAFx), 2014.

[10] Haizhou Li, Bin Ma, and Kong A. Lee, “Spoken language recognition: From fundamentals to practice,” Proc. of the IEEE, vol. 101, no. 5, pp. 1136–1159, 2013.

[11] Mahnoosh Mehrabani and John H. L. Hansen, “Language identification for singing,” in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2011, pp. 4408–4411.

[12] Anna M. Kruspe, “Phonotactic language identification for singing,” in Proc. Annual Conference of the International Speech Communication Association (INTERSPEECH), 2016, pp. 3319–3323.

[13] Daniel Stoller, Simon Durand, and Sebastian Ewert, “End-to-end lyrics alignment for polyphonic music using an audio-to-character recognition model,” in Proc. of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2019, pp. 181–185.

[14] Chitralekha Gupta, Emre Yılmaz, and Haizhou Li, “Acoustic modeling for automatic lyrics-to-audio alignment,” in Proc. Annual Conference of the International Speech Communication Association (INTERSPEECH), 2019, pp. 2040–2044.

[15] Andrea Vaglio, Romain Hennequin, Manuel Moussallam, Gaël Richard, and Florence d’Alché-Buc, “Multilingual lyrics-to-audio alignment,” in Proc. of the International Conference on Music Information Retrieval (ISMIR), 2020.

[16] Andrea Vaglio, Romain Hennequin, Manuel Moussallam, Gaël Richard, and Florence d’Alché-Buc, “Audio-based detection of explicit content in music,” in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2020, pp. 526–530.

[17] Gabriel Meseguer-Brocá, Alice Cohen-Hadria, and Geoffroy Peeters, “DALI: A Large Dataset of Synchronized Audio, Lyrics and notes, Automatically Created using Teacher-student Machine Learning Paradigm,” in Proc. of the International Society for Music Information Retrieval (ISMIR), 2018, pp. 431–437.

[18] Shinji Watanabe, Takaaki Horii, and John R. Hershey, “Language independent end-to-end architecture for joint language identification and speech recognition,” in Proc. IEEE Automatic Speech Recognition and Understanding Workshop (ASRU), 2017, pp. 263–271.

[19] Alex Graves, Santiago Fernández, Faustino Gomez, and Jürgen Schmidhuber, “Connectionist temporal classification: Labelling unsegmented sequence data with recurrent neural networks,” in Proc. of the International Conference on Machine Learning (ICML), 2006, pp. 369–376.

[20] Trung Ngo Trong, Ville Hautamäki, and Kong Aik Lee, “Deep language: a comprehensive deep learning approach to end-to-end language recognition,” in Proc. of the Odyssey The Speaker and Language Recognition Workshop, 2016, pp. 109–116.

[21] Weicheng Cai, Danwei Cai, Sheng Huang, and Ming Li, “Uterance-level end-to-end language identification using attention-based enn-bilstm,” in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2019, pp. 5991–5995.

[22] Sepp Hochreiter, Yoshua Bengio, Paolo Frasconi, Jürgen Schmidhuber, et al., “Gradient flow in recurrent nets: the difficulty of learning long-term dependencies,” A field guide to dynamical recurrent neural networks, 2001.

[23] Romain Hennesqun, Anis Khilf, Félix Voituret, and Manuel Moussalam, “Spleeter: a fast and efficient music source separation tool with pre-trained models,” Journal of Open Source Software, vol. 5, no. 50, pp. 2154, 2020.

[24] Arthur Flexer, “A closer look on artist filters for musical genre classification,” in Proc. of the International Conference on Music Information Retrieval (ISMIR), 2007, pp. 341–344.

[25] M. Bernard, “Phonemizer (version 2.2.1),” https://github.com/bootphon/phonemizer, 2015, [Online; accessed 15-October-2020].

[26] Armand Joulin, Edouard Grave, Piotr Bojanowski, Matthijs Douze, Hérve Jégou, and Tomas Mikolov, “Fasttext.zip: Compressing text classification models,” arXiv preprint arXiv:1612.03651, 2016.

[27] Daniel Povey, Arnab Ghoshal, Gilles Boulianne, Lukas Burget, Ondrej Glembek, Nagendra Goel, Mirko Hannemann, Petr Motlicek, Yannin Qian, Petr Schwarz, Jan Silovsky, Georg Stemmer, and Karel Vesely, “The kaldi speech recognition toolkit,” in Proc. IEEE Automatic Speech Recognition and Understanding (ASRU), 2011.

[28] Najim Dehak, Pedro A. Torres-Carrasquillo, Douglas Reynolds, and Reda Dehak, “Language recognition via i-vectors and dimensionality reduction,” in Proc. of the Annual Conference of the International Speech Communication Association (INTERSPEECH), 2011, pp. 857–860.

[29] Yann Soullard, Cyprien Ruffino, and Thierry Paquet, “CTCModel: Connectionist Temporal Classification in Keras,” 2018.

[30] Diederik P. Kingma and Jimmy Ba, “Adam: A method for stochastic optimization,” International Conference for Learning Representations (ICLR), 2015.

[31] Trung Ngo Trong, Ville Hautamaki, and Kristina Jokinen, “Staircase network: structural language identification via hierarchical attentive units,” in Proc. of the Odyssey The Speaker and Language Recognition Workshop, 2018, pp. 60–67.