ABSTRACT
To better model the contextual information and increase the generalization ability of a voice detection system, this paper leverages a multi-lingual Automatic Speech Recognition (ASR) system to perform Speech Activity Detection (SAD). Sequence-discriminative training of multi-lingual Acoustic Model (AM) using Lattice-Free Maximum Mutual Information (LF-MMI) loss function, effectively extracts the contextual information of the input acoustic frame. The index of maximum output posterior is considered as a frame-level speech/non-speech decision function. Majority voting and logistic regression are applied to fuse the language-dependent decisions. The leveraged multi-lingual ASR is trained on 18 languages of BABEL datasets and the built SAD is evaluated on 3 different languages. In out-of-domain datasets, the proposed SAD model shows significantly better performance w.r.t. baseline models. In the Ester2 dataset, without using any in-domain data, this model outperforms the WebRTC, phoneme recognizer based VAD (Phn_Rec), and Pyannote baselines (respectively 7.1, 1.7, and 2.7% absolutely) in Detection Error Rate (DetER) metrics. Similarly, in the LiveATC dataset, this model outperforms the WebRTC, Phn_Rec, and Pyannote baselines (respectively 6.4, 10.0, and 3.7% absolutely) in DetER metrics.

Index Terms— Speech activity detection, multi-lingual automatic speech recognition, logistic regression, multi-lingual SAD

1. INTRODUCTION
Speech Activity Detection (SAD), a process of identifying the speech segments in an audio utterance [1], is a critical part of Automatic Speech Recognition (ASR), speaker recognition, speaker diarization, and other speech-based applications. Developing an accurate SAD system, operating in the noisy environment is one of the active research fields in speech processing [2][6].

This paper explores SAD built around multi-lingual ASR systems, as we hypothesize it can offer better generalization ability by leveraging the contextual information extracted by ASR [7]. Generally, this paper employs a conventional multi-task network as a multi-lingual Acoustic Model (AM) trained using the Lattice-Free Maximum Mutual Information (LF-MMI) framework, capable to extract the language-dependent contextual information. Using a multi-lingual dataset for the AM training was investigated in [8]. Unlike applying a simple block-softmax loss on stacked input data with added language indicator for phoneme names, we apply LF-MMI loss on multi-task architecture which provides a scalable approach to develop multi-lingual AM. Practically, we use PKWRAP, a PyTorch package for LF-MMI training of acoustic models [9]. The proposed multi-lingual acoustic model is trained on 18 languages of the BABEL datasets. Within each language-dependent part of AM, speech and non-speech acoustic frames are mapped to a different set of output context-dependent phones (i.e. posteriors). For each language, we use index of maximum output posterior as a frame-level speech/non-speech decision function. To fuse the decisions from different languages, conventional logistic regression and majority voting techniques are employed.

To investigate the generalization ability of the proposed SAD, experiments presented in the paper were performed on in-domain and out-of-domain data. For out-of-domain experiments, two specific conditions are considered: (i) an access to small development set is available, or (ii) no in-domain data is available at all. Logistic regression and majority voting fusion are reported for these conditions specifically. Concretely, the development part of the BABEL Kurdish dataset is used as an in-domain evaluation set. Eval parts of Ester2 and LiveATC datasets are used as out-of-domain sets. BABEL Kurdish contains conversational telephony speech (CTS) in the Kurdish language. Ester2 is a broadcast news dataset in French language and LiveATC comprises large number of conversations between Air Traffic Controllers (ATCo) and pilots with a large variety of accents in English language. To investigate the generalizability of our SAD model, we consider different real-life scenarios with high variation in channel, background noise, and language. Having a generalizable and robust SAD is nowadays a must for any production ASR system.

We show that the proposed multi-lingual architecture offers comparable results on in-domain set and significantly outperforms the baselines on out-of-domain Ester2 and LiveATC datasets. For fair comparison with Google WebRTC and popular BUT pre-trained phoneme recognizer based VAD (Phn_Rec) in out-of-domain evaluation, we also assume that no in-domain data is available during training. More specifically, for Ester2 dataset, the proposed SAD method outperforms the WebRTC, Phn_Rec, and Pyannote BLSTM SAD models by absolute 7.1%, 1.7%, and 2.7% in DetER respectively. Similarly, w.r.t. WebRTC, Phn_Rec, and Pyannote BLSTM SAD models, respectively, we obtain an absolute improvement of 6.4%, 10.0%, and 3.7% in DetER on LiveATC dataset. In addition, using a small development set in the logistic regression method further improves the performance of the proposed SAD system.

The rest of this paper is organized as follows: Related works are shown in Section 2. Multi-lingual acoustic model training is briefly explained in Section 3. The proposed multi-lingual ASR-based SAD is described in Section 4. Experiment setup and results are shown in Section 5. Conclusions are discussed in Section 6.

1 http://catalog.elra.info/en-us/repository/browse/ELRA-S0338/
2 https://www.liveatc.net/
3 https://speech.fit.vutbr.cz/software/phoneme-recognizer-based-long-temporal-context
2. RELATED WORKS

Large effort was invested in the past to find the optimal features \cite{10,12}, or classifier \cite{13,15} for the SAD task. We can mention Gaussian Mixture Model (GMM) \cite{13}, Hidden Markov Model (HMM) \cite{14}, or Support Vector Machines (SVM) \cite{15} as the often used classifiers for the SAD task. With the advent of Deep Neural Networks (DNNs), several DNN-based architectures were proposed for the SAD task \cite{16,17} including Convolutional Neural Network (CNN) \cite{18} and Recurrent Neural Network (RNN) \cite{19} architectures. Recently, for training the SAD model in a noisy environment, DNN models with attention mechanism in temporal domain \cite{6} and a combination of temporal and spectral domains \cite{5} were investigated. Contextual Information (CI) is important for training a robust SAD system, especially at low Signal-to-Noise Ratios (SNR) \cite{20}. Several methods for boosting the contextual information have been proposed. In \cite{21}, by boosting CI, Zhang and Wang proposed to generate multiple different predictions from a single DNN and reported significant improvement over the standard DNN in challenging noise scenarios with low SNR levels. In \cite{22}, a boosted DNN (bDNN)-based SAD was proposed. Zhang and Wang exploited the input/output CI by adopting multiple input/output units for the DNN. In addition, to aggregate long-short term CI, they proposed an ensemble model that contains bDNNs of various sizes. However, the computational cost of ensemble method is significantly higher than of a single-bDNN-based SAD.

Capturing sequential contextual information using RNN architecture was investigated in \cite{19}, nevertheless, the improvement in the results were observed when the models were trained as noise-dependent. Using multi-lingual BABEL or Public Safety Communications (PSC) datasets for training the DNN based SAD with simple feed-forward architecture was investigated in \cite{8}. PSC corpus that contains simulated first-responder type background noises and speech affects, was introduced in NIST OpenSAT 2019 challenge \cite{23}. Similar to LiveATC, this dataset is challenging for ASR and SAD tasks.

3. MULTI-LINGUAL ACOUSTIC MODEL TRAINING

Training multi-lingual ASR system is an effective way to compensate data shortage in low-resourced languages. DNN based acoustic models can be considered as a feature extractor to train a monolingual acoustic model for the specific target language. The multi-lingual models can either share the output layer or have separate output layers, which are called single- and multi-task models, respectively. Without any loss in performance, multi-task ASR training provides a much more scalable approach to develop multi-lingual AM \cite{7}. LF-MMI significantly outperformed the conventional cross-entropy (CE) for training the multi-lingual AM \cite{24}. The MMI cost function uses a numerator and a denominator graph to model the observed feature sequence based on the ground truth and compute the probability over all possible sequences, respectively. Sequence-discriminative training of multi-lingual AM using LF-MMI loss function, effectively extracts the contextual information of the input acoustic frame. In this paper, for training the multi-lingual AM, time delayed neural network (TDNN) architecture with LF-MMI loss was applied. In order to obtain alignments to train all the TDNN models, HMM/GMM models were first trained for each language.

In multi-task training of AM, we have \( L \) objective functions where \( L \) is the number of training languages, computed independent of each other based on the language of the input utterance:

\[
F_{\text{MMI}}^{(l)} = \sum_{u=1}^{U_l} \log \frac{p(x(u) | M_{w(u)}^{l}(\theta)) p(w(u))}{p(x(u) | M_{\text{den}}^{l}(\theta))},
\]

where \( U_l \) is the number of utterances in the current minibatch for language \( l \), \( \theta \) contains the shared and language-dependent parameters, \( M_{w(u)}^{l} \) and \( M_{\text{den}}^{l} \) are language-specific numerator and denominator graphs, respectively. The overall cost function is the weighted sum of all language-dependent cost functions:

\[
F_{\text{MMI}} = \sum_{l=1}^{L} \omega_l F_{\text{MMI}}^{(l)},
\]

where \( \omega_l \) is the language-dependent weight for computing the total loss. Gradients for language-dependent layers are computed and updated for each minibatch. Using backpropagation, the shared parameters are then updated.

4. MULTI-LINGUAL ASR BASED SAD

In the trained HMM/GMM model for each language, we can observe the mapping between input phones and the output Probability Density Functions (PDFs). Figure 1 shows the mapping between input phones and output PDFs in the HMM/GMM ASR model of Assamese language. Non-speech phones are mapped to the first five initial PDFs.

![Fig. 1 Mapping between input phones and output PDFs in the HMM/GMM ASR model of Assamese language. Non-speech phones are mapped to the first five initial PDFs.](image-url)
5. EXPERIMENTAL SETUP AND RESULTS

To demonstrate the scalability of the multi-task system, we consider training of the multi-lingual acoustic model with 18 languages from BABEL datasets with approximately 1000 hours of data. All languages are available at Linguistic Data Consortium (LDC). The name of BABEL languages used for training is shown in the Table 1.

| Languages                  |
|----------------------------|
| Assamese, Bengali, Cantonese, Haitian, Kazhakh, Kurmanji-kurdish, Lao, Lithuanian, Pashto, Somali, Swahili, Tagalog, Tamil, Telugu, Tok_pisin, Turkish, Vietnamese, Zulu |

For training the AM model, we used 40-dimensional MFCCs as acoustic features, derived from 25 ms frames with a 10 ms frame shift. In addition, an online i-vector extractor of 100 dimension is trained. For speeding up the training, we used a frame sub-sampling factor of 3. We also augmented the data with 2-fold speed perturbation in all the experiments. The network consists of 8 layers of TDNN with 1024 nodes in each layer. The pre-final layer has only 200 units. For training the AM model, PKWRAP, a PyTorch package for LF-MMI training of acoustic models was used.

For investigating the generalization ability of the proposed SAD, we performed experiments on in-domain and out-of-domain scenarios with high variation in channel, background noise, and language.

![Figure 2](https://github.com/idiap/pkwrap)

**Table 2. Duration and number of segments in the selected datasets.**

| Dataset         | Duration (hour) | # Segments |
|-----------------|-----------------|------------|
| LiveATC_dev     | 2.7             | 1.0k       |
| LiveATC_eval    | 6.8             | 0.9k       |
| Ester2_dev      | 7.4             | 1.2k       |
| Ester2_eval     | 7.2             | 1.7k       |
| BabelKurdish_dev| 20.6            | 11.0k      |
| BabelKurdish_eval| 20.0           | 11.3k      |

In this experiment, False Alarm (FA), Miss detection (Miss), and Detection Error Rate (DetER) were used as performance measures. DetER is defined as:

\[
\text{DetER} = \frac{\text{False alarm} + \text{Miss detection}}{\text{Total duration of speech in the reference file}}.
\]

6https://www.ldc.upenn.edu
7https://github.com/idiap/pkwrap
8https://www.atco2.org/
9https://github.com/wiseman/py-webrtcSAD
10http://www.fee.vutbr.cz/SPEECHDAT-E
11https://dihardchallenge.github.io/dihard2

For all evaluations, we consider the conditions when we have access to the in-domain development set, which is used for training the logistic regression (ASR_Mul_LR) and the condition which we do not have development set, which is the case for majority voting (ASR_Mul_MV) and SP/NSP blocks of single best language. For ASR_Mul_LR models, the threshold for SP/NSP detection was set based on Half Total Error Rate (HTER). The duration and number of segments in the selected datasets are shown in Table 2. For investigating the generalizability of our SAD model, we considered different real life scenarios with high variation in channel, background noise, and language.
Table 3. Comparison of SAD results on in-domain BabelKur-dish_eval set. ASR_SingleBest, ASR_Mul_LR, and ASR_Mul_MV are multi-lingual ASR based SAD systems when single best system, logistic regression based, or majority voting based fusion is considered, respectively.

| SAD Model       | DetER (%) | FA (%) | Miss (%) |
|-----------------|-----------|--------|----------|
| ASR_SingleBest  | 24.4      | 2.7    | 21.7     |
| ASR_Mul_LR      | 23.3      | 5.2    | 18.1     |
| ASR_Mul_MV      | 23.9      | 3.7    | 20.2     |
| Phn_Rec         | 24.3      | 2.9    | 21.4     |
| WebRTC          | 31.7      | 4.1    | 27.6     |
| Pyannote        | **18.1**  | 5.9    | **12.2** |

Comparison of SAD results on out-of-domain LiveATC evaluation set is shown in the Table 4. Here ASR_SingleBest and ASR_Mul_MV models are not using any in-domain data. ASR_Mul_LR model is trained using the in-domain development set. Without considering the ASR_Mul_LR model, ASR_SingleBest and ASR_Mul_MV models, significantly outperformed the baseline models based on DetER performance measure. Training the multi-lingual AM model is one of the reasons for observing good result in the ASR_SingleBest model. The ASR_Mul_LR model outperformed the ASR_SingleBest model with relative improvement of 4.0% on DetER performance measure. Comparison of SAD results on out-of-domain Ester2 evaluation set is shown in the Table 5. In this out-of-domain set we observed the same pattern and based on DetER performance measure, the proposed models significantly outperformed the baselines. The ASR_Mul_LR model outperformed the ASR_SingleBest model with relative improvement of 38.4% on DetER performance measure. Based on the observed results, the proposed multi-lingual ASR based SAD, showed magnificent generalization ability. In addition, having small in-domain dataset improves the performance of the proposed method.

Table 4. Comparison of SAD results on out-of-domain LiveATC evaluation set.

| SAD Model       | DetER (%) | FA (%) | Miss (%) |
|-----------------|-----------|--------|----------|
| ASR_SingleBest  | 10.1      | 4.9    | 5.2      |
| ASR_Mul_LR      | **9.7**   | 6.1    | **3.6**  |
| ASR_Mul_MV      | 11.1      | **4.3**| 6.8      |
| Phn_Rec         | 20.1      | 4.6    | 15.5     |
| WebRTC          | 16.5      | 9.4    | 7.1      |
| Pyannote        | 13.8      | 10.1   | 3.7      |

Table 5. Comparison of SAD results on out-of-domain Ester2 evaluation set.

| SAD Model       | DetER (%) | FA (%) | Miss (%) |
|-----------------|-----------|--------|----------|
| ASR_SingleBest  | 5.2       | 4.7    | 0.5      |
| ASR_Mul_LR      | **3.2**   | 2.3    | 0.9      |
| ASR_Mul_MV      | 4.7       | 4.2    | 0.5      |
| Phn_Rec         | 6.4       | 3.9    | 2.5      |
| WebRTC          | 11.8      | 6.5    | 5.3      |
| Pyannote        | 7.4       | 7.3    | **0.1**  |

6. CONCLUSIONS

Contextual information is important for training a robust SAD system, specially at noisy sets. In this paper, we trained the SAD system using multi-lingual ASR model. This ASR model was trained with LF-MMI loss on multi-task architecture which provides a much more scalable approach to develop AM. Decision for detecting speech/non-speech frames is based on index of maximum output posterior. Majority voting and logistic regression were applied to fuse the language-dependent decisions. We observed the significant improvement w.r.t. baselines on out-of-domain Ester2 and LiveATC evaluation sets. In addition, using small development set in logistic regression method, further improves the performance of the proposed SAD system.

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