



# Oriental Language Recognition (OLR) 2020: Summary and Analysis

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## Abstract

The fifth Oriental Language Recognition (OLR) Challenge focuses on language recognition in a variety of complex environments to promote its development. The OLR 2020 Challenge includes three tasks: (1) cross-channel language identification, (2) dialect identification, and (3) noisy language identification. We choose  $C_{avg}$  as the principle evaluation metric, and the Equal Error Rate (EER) as the secondary metric. There were 58 teams participating in this challenge and one third of the teams submitted valid results. Compared with the best baseline, the  $C_{avg}$  values of Top 1 system for the three tasks were relatively reduced by 82%, 62% and 48%, respectively. This paper describes the three tasks, the database profile, and the final results. We also outline the novel approaches that improve the performance of language recognition systems most significantly, such as the utilization of auxiliary information.

**Index Terms:** language recognition, language identification, oriental language, OLR 2020 Challenge

## 1. Introduction

The Oriental Language Recognition (OLR) Challenge [1–4] is an annual competition, which aims to improve the research on multilingual phenomena and develop language recognition technologies. OLR 2020 challenge [5] is the fifth edition of the OLR challenge, with some extensions in the competition methodology based on the experience of the past four challenges. The OLR 2020 challenge includes more languages, dialects and real-life data, and focuses on more practical and challenging tasks: (1) cross-channel language identification (LID), inherited from OLR 2019 challenge, (2) dialect identification, introduced to OLR challenge for the first time, and (3) noisy LID, also newly introduced this year, considering the general importance of noisy speech processing.

Cross-channel LID is a close-set identification task, which means the language of each utterance is among the known 6 target languages (Cantonese, Indonesian, Japanese, Russian, Korean and Vietnamese), but utterances were recorded with different channels. In real-world applications, channel differences always severely deteriorate the language identification performance. Channel compensation algorithms, such as Linear Discriminant Analysis (LDA) [6] and Probabilistic Linear Discriminant Analysis (PLDA) [7], are the most commonly used approaches to address the channel variance, but might be not sufficient. This challenge aims to explore more possibilities in solving the cross-channel issue.

Open-set dialect identification is an open-set identification task, in which three non-target languages (Mandarin, Malay and Thai) and three target dialects (Hokkien, Sichuanese, Shanghaiese) in China are merged to form the test set. This combined dialect identification, with the open-set LID issue, which

encourages exploring algorithms that improves open-set LID performance.

Noisy LID is the third task, where the test set involves noisy utterances of 5 languages (Cantonese, Japanese, Russian, Korean and Mandarin). This challenge was settled for an important real-life issue of speech technology, i.e., dealing with the low SNR condition.

The remainder of this paper is organized as follows. Section 2 presents the data profile. Section 3 gives an introduction to the evaluation metrics, as well as the baselines. Section 4 analyses the results in detail and summarizes the methodologies involved in the competition. Section 5 discusses some novel approaches. In section 6, we make a conclusion on OLR 2020 Challenge.

## 2. Database profile

The OLR 2020 Challenge involved 16 languages and 3 Chinese dialects, provided by SpeechOcean and the NSFC M2ASR project [8], and all the data is free for participants. The datasets of OLR 2020 Challenge include the data from the past four OLR challenges and two newly provided datasets. All the data that could be used for submission systems construction are listed below.

- AP16-OL7: The standard database for AP16-OLR, including AP16-OL7-train, AP16-OL7-dev and AP16-OL7-test.
- AP17-OL3: A dataset provided by the M2ASR project, involving three additional languages. It contains AP17-OL3-train and AP17-OL3-dev.
- AP17-OLR-test: The standard test set for AP17-OLR. It contains AP17-OL7-test and AP17-OL3-test.
- AP18-OLR-test: The standard test set for AP18-OLR. It contains AP18-OL7-test and AP18-OL3-test.
- AP19-OLR-dev: The development set for AP19-OLR. It contains AP19-OLR-dev-task2 and AP19-OLR-dev-task3.
- AP19-OLR-test: The standard test set for AP19-OLR. It contains AP19-OL7-test and AP19-OL3-test.
- AP20-OLR-dialect: The newly provided training set, including three kinds of Chinese dialects.
- THCHS30: The THCHS30 database (plus the accompanied resources) published by CSLT, Tsinghua University [9].

The test dataset AP20-OLR-test includes three parts, corresponding to the three LID tasks, respectively. The labelled test set was provided to participants after the submission deadline. More informations about these datasets can be found in [5].

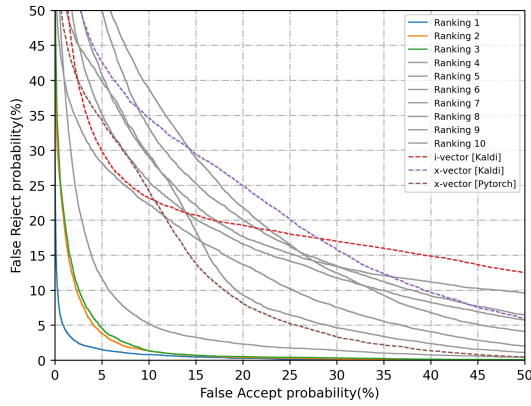


Figure 1: DET curves for Cross-channel LID.

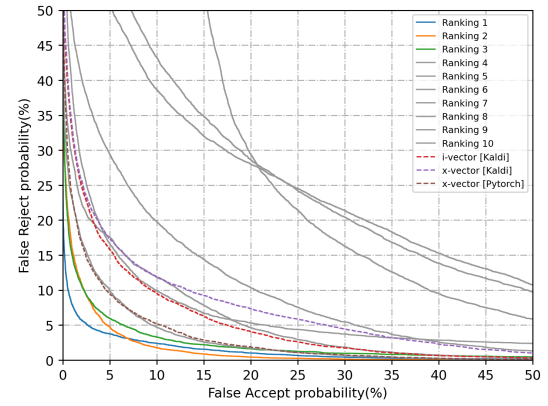


Figure 3: DET curves for Noisy LID.

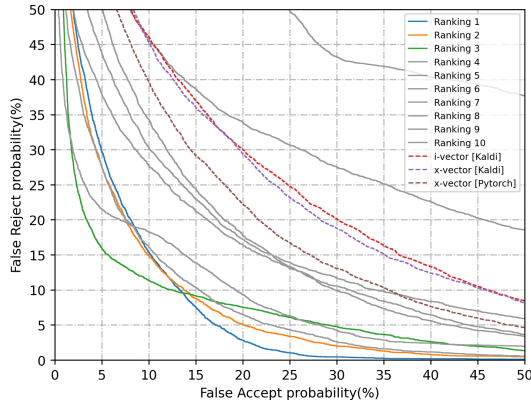


Figure 2: DET curves for Open-set dialect identification.

### 3. Evaluation metrics and baselines

As in NIST LRE15 [10], the OLR 2020 Challenge chooses  $C_{avg}$  as the principle evaluation metric, and the Equal Error Rate (EER) as the secondary metric. First define the pair-wise loss that composes the missing and false alarm probabilities for a particular target/non-target language pair:

$$C(L_t, L_n) = P_{Target} P_{Miss}(L_t) + (1 - P_{Target}) P_{FA}(L_t, L_n) \quad (1)$$

where  $L_t$  and  $L_n$  are the target and non-target languages, respectively;  $P_{Miss}$  and  $P_{FA}$  are the missing and false alarm probabilities, respectively.  $P_{Target}$  is the prior probability for the target language, which is set to 0.5 in the evaluation. Then the principle metric  $C_{avg}$  is defined as the average of the above pair-wise performance:

$$C_{avg} = \frac{1}{N} \sum_{L_t} \left\{ \frac{P_{Target} \cdot P_{Miss}(L_t)}{1 - P_{Target}} + \sum_{L_n} P_{Non-Target} \cdot P_{FA}(L_t, L_n) \right\} \quad (2)$$

where  $N$  is the number of languages, and  $P_{Non-Target} = (1 - P_{Target}) / (N - 1)$ . For the open-set testing condition,

all of the interfering languages are treated as a single unknown language in the computation of  $C_{avg}$ . We have provided the evaluation scripts for system development.

Two kinds of baseline LID systems were constructed in this challenge: the i-vector model baseline and the extended TDNN (E-TDNN) [11] x-vector model baseline, respectively. The feature extracting and back-end were all conducted with Kaldi. We built the x-vector model baselines with Kaldi [12] and Pytorch [13, 30], respectively. To provide more options, we also built the i-vector model baseline with Kaldi. The recipes of these baselines can be downloaded from the project web site<sup>1</sup>.

## 4. Challenge results

### 4.1. System descriptions

Figure 1, 2, and 3 illustrate the Detection Error Tradeoff (DET) curves for the top 10 systems and 3 baselines on three tasks, where the colored solid line, gray solid line, and colored dotted line represent the top 3 systems, other systems, and baseline systems on Kaldi or Pytorch, respectively.

For the three tasks, the optimal baseline is the x-vector system built with Pytorch, and all the top 3 systems outperform the optimal baseline system with a large margin. For Task 1, the top 3 systems deliver EERs below 5%. Most of the systems deliver EERs between 15% and 20%. The top 3 systems of Task 2 deliver EERs between 10% and 15%, with a small number of systems outside of 25%. The EERs of the top 3 systems in Task 3 were around 5%, and the other systems were below 25%. It can be seen that the EERs of the top 3 systems for both Task 1 and Task 3 are already at a lower level, while for the open-set testing condition, the EERs of the top 3 systems are relatively higher, indicating that the open-set testing is still a difficult task for language recognition. Descriptions of the top 3 systems for each task can be downloaded from the challenge web site<sup>2</sup>.

#### 4.1.1. Cross-channel LID

$C_{avg}$  and EERs for the top 10 teams on the cross-channel LID task are shown in Table 1. For this task, 17 teams in total submitted valid scores, with 4 teams outperforming the Pytorch

<sup>1</sup> <https://github.com/Snowdar/asv-subtools#2-ap-olr-challenge-2020-baseline-recipe-language-identification>

<sup>2</sup> [http://csit.rtiit.tsinghua.edu.cn/mediawiki/index.php?title=OLR\\_Challenge\\_2020](http://csit.rtiit.tsinghua.edu.cn/mediawiki/index.php?title=OLR_Challenge_2020)

Table 1: Cross-channel LID Top 10. # indicates baselines on Kaldi and Pytorch, respectively.

Ranking	Team Name	$C_{avg}$	EER (%)
1	LORIA-Inria-Multispeech	0.0239	2.47
2	NTU-XJU	0.0421	4.51
3	Malaxiaolongxia	0.0477	4.82
4	IBG_AI	0.0760	7.51
#	x-vector [Pytorch]	0.1321	15.48
5	youdao	0.1377	15.99
6	RoyalFlush	0.1483	16.37
#	i-vector [Kaldi]	0.1542	19.40
7	gz	0.1669	18.00
8	Phonexia	0.1694	18.70
9	BJFU	0.2037	20.86
10	Anonymous	0.2088	20.03
#	x-vector [Kaldi]	0.2098	22.49

Table 2: Open-set dialect identification Top 10. # indicates baselines on Kaldi and Pytorch, respectively.

Ranking	Team Name	$C_{avg}$	EER (%)
1	Phonexia	0.0738	11.97
2	Royal-Flush	0.0871	11.97
3	IBG_AI	0.1096	10.84
4	youdao	0.1116	14.42
5	Anonymous	0.1312	12.67
6	NTU-XJU	0.1546	18.02
7	BJFU	0.1808	18.60
#	x-vector [Pytorch]	0.1938	19.74
8	gz	0.2084	19.08
#	x-vector [Kaldi]	0.2370	22.25
#	i-vector [Kaldi]	0.2439	23.94
9	Anonymous	0.2614	28.40
10	ABSPlab_IIT_KGP	0.3848	40.32

baseline. The champion system, LORIA-Inria-Multispeech, achieved a  $C_{avg}$  of 0.0239 and an EER of 2.47%. They used embeddings extracted from an intermediate bottleneck layer of a multilingual Deep Neural Network (DNN), trained with the Connectionist Temporal Classification (CTC) loss [14]. These bottleneck embeddings were used as input features to train a DNN LID system. They tried different loss functions such as Additive Angular Margin softmax (AAM-softmax) [15], Maximum Mean Discrepancy (MMD) [16] and n-pair loss function [17]. They chose Stochastic Gradient Descent (SGD) [18] to optimize the LID model, and average the parameters of candidate models by Stochastic Weight Average (SWA) [19]. Finally, they fused their subsystems by the Focal toolkit<sup>3</sup>. The team at the second place used semi-supervised training and the model was based on x-vector, while the third place team chose to use Residual Network (ResNet) [20] with a deformation structure of the Gated Recurrent Unit (GRU).

#### 4.1.2. Open-set dialect identification

Table 2 shows the  $C_{avg}$  and EERs for the top 10 systems and the baselines. For this task, among the 13 participating teams, 7 teams had better results than the best baseline. The top-

Table 3: Noisy LID Top 10. # indicates baselines on Kaldi and Pytorch, respectively.

Ranking	Team Name	$C_{avg}$	EER (%)
1	LORIA-Inria-Multispeech	0.0374	4.07
2	NTU-XJU	0.0476	4.87
3	Malaxiaolongxia	0.0538	5.60
4	RoyalFlush	0.0722	7.12
#	x-vector [Pytorch]	0.0715	7.14
#	i-vector [Kaldi]	0.0967	9.77
5	Phonexia	0.0986	9.96
6	youdao	0.1057	11.10
#	x-vector [Kaldi]	0.1079	11.12
7	gz	0.1467	14.70
8	BJFU	0.2261	23.40
9	Anonymous	0.2326	24.69
10	Anonymous	0.2444	24.62

performing system, Phonexia, achieved a  $C_{avg}$  of 0.0738 and an EER of 11.97%. They trained ResNet18 by Pytorch with SGD optimizer. The model was trained with the Cross Entropy (CE) loss. The input to the ResNet18 was on raw features (i.e. no VAD, no mean-variance normalization). The third-place team also chose the ResNet architecture, including 5 ResNet subsystems. Among them, the optimal single system on the development set is ResNet18 plus Squeeze and Excitation (SE) block [21], which is the same as ResNet18 selected by the Top 1 system, corroborating that ResNet18 has a certain advantage in open-set dialect identification. Too deep or too shallow network structures are all suboptimal. To reduce the impact of open-set testing condition, the second place system first trained a transformer-based CTC loss or attention end-to-end Automatic Speech Recognition (ASR) model based on the ESPNet platform [22]. Then, they trained a 6-layer transformer as the LID model to classify the three dialects. The training of transformer uses knowledge transfer learning by using the 12-layer encoder of the transformer-based CTC or attention ASR model. Because of the materialization of the phonetic information, the recognition accuracy of the open-set testing is improved.

#### 4.1.3. Noisy LID

The  $C_{avg}$  and EERs of the top 10 teams and baselines are presented in Table 3. Four out of fourteen submitted scores outperformed the Pytorch x-vector baseline. The top 1 system, LORIA-Inria-Multispeech, achieved a  $C_{avg}$  of 0.0374 and an EER of 4.07%. Their submitted system is the same as the one for Task 1, with data augmentation to attenuate the effect of noise, e.g., adding white noise and babble noise (generated by mixing other files from the training set) and convolving with random artificial band-pass filters. The second-place team also submitted the same system as in Task 1, and on top of that, the enrollment set of Task 3 was augmented with background noise to reduce the effect of noise. They extracted noise and all data of randomly chosen 4 speakers for each target languages (Cantonese, Japanese, and Mandarin) from AP16-OL7, and merged noisy part of Korean and Russian data into them. Finally, they combined those merged noisy data with noisy part of Korean and Russian data as enrollment set of Task 3.

<sup>3</sup> <https://sites.google.com/site/nikobrummer/focalmulticlass>

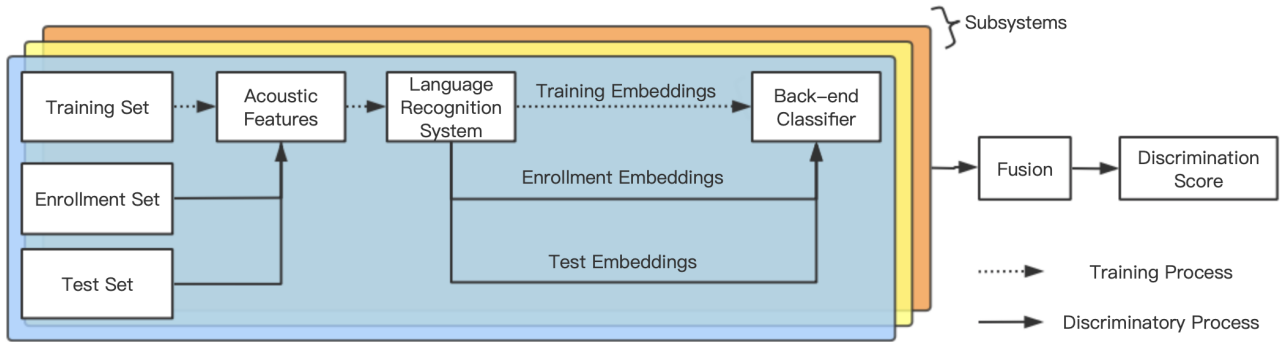


Figure 4: The flow chart of language recognition.

#### 4.2. Technology summary

Figure 4 shows the flow of language recognition. We will summarize the acoustic features, language recognition models, back-end classifiers and score fusion strategies that OLR 2020 teams have used in their submissions, as described below.

- **Input features:** Augmentation (e.g., velocity, volume perturbations) was widely used. Some systems used background noise extracted from the training data, white noise and random artificial band-pass filters. Most systems applied the SpecAugment strategy [23] during training. Mel-filterbank (FBank) and Mel Frequency Cepstral Coefficients (MFCCs) were two most frequently used acoustic features. A few systems used Perceptual Linear Predictive (PLP) [24] and spectrum as acoustic features.
- **Structure and Optimization:** The standard TDNN and ResNet architecture were two mostly used model structures. Some of them used other network structures, such as Convolutional Neural Networks (CNN), incorporating the SE blocks in the deep Residual Networks (ResNet-SE), Polar Transformer Network (PTN) [25], GRU, BLSTM [26], attention structure, attentive pooling, Global Context Network (GC-Net) [27], NetVLAD [28] or inspired Vector of Locally Aggregated Descriptors (VLAD) [29].
- **Auxiliary information:** The introduction of ASR to help language recognition was investigated by top teams (two out of five top teams used E2E ASR technologies). The phonetic information based on spectral features and Bottleneck Features (BNFs) or multi-task learning can be further investigated to improve the performance of LID.
- **Loss:** CE and Additive Margin softmax (AM-softmax) were two mostly used loss functions. AAM-softmax, MMD and n-pair loss were also experimented with.
- **Scoring backend:** After the LDA projection and centering, the Logistic Regression (LR) was used to compute the score; one team used Gaussian Mixture Model (GMM) to enhance the performance. Cosine, Support Vector Machines (SVM) and PLDA were also chosen.
- **Model fusion:** Most of submitted systems were the fusion of many subsystems. The fusion was mostly based on the score, and the fusion methods included average fusion, greedy fusion and the fusion approach implemented in the FoCal toolkit.
- **Platform:** Most teams chose to use ASV-Subtools (Pytorch) [30], Kaldi, Pytorch; a few teams chose ESPNet, TensorFlow, Matlab or Web Real-Time Communication (WebRTC).

#### 5. Discussion

In this challenge, most teams used the x-vector system with the E-TDNN structure as the baseline and used LR as the back-end. One interesting finding was that multiple teams submitted the same system on Task 1 and Task 3, and the same system received good performance in both tasks, e.g., the top 1 system on Task 1 had a  $C_{avg}$  of 0.0239 and an EER of 2.47%, and the same system obtained a  $C_{avg}$  of 0.0374 and an EER of 4.07% on Task 3. Because cross-channel and noise can be regarded as two kinds of distortion in the background environment, many systems cast them into one problem, i.e cross-domain. To counteract this distortion, some systems added background noise extracted from other datasets to the training set and enrollment set and obtained phonetic information from the speech recognition system. For the open-set testing condition, many teams chose the ResNet network structure coupled with SGD optimizer, which allows to use very deep networks with residual connections. In summary, it can be seen that the utilization of phonetic information and the ResNet structure contribute the most to language recognition in OLR 2020 challenge. In the future, involving more auxiliary or multimodal information and investigating more suitable network structures may be the most promising directions for language recognition.

#### 6. Conclusions

In this paper, we presented the database profile, evaluation metrics, task definitions and their baselines of OLR 2020 Challenge. We also summarized the ranking results of the participating teams and analyzed the technologies that the participants used, as well as language recognition. This competition was designed based on realistic scenarios with three tasks: (1) cross-channel LID, (2) open-set dialect identification, and (3) noisy LID. Due to public availability of the script for the baseline systems, more people participate in this competition. The participants used a wide variety of approaches to improve the performance on the three tasks, especially by obtaining additional information through ASR model to reduce the impact of noise, unknown channels, and unknown test sets.

#### 7. Acknowledgements

This work was supported by the National Natural Science Foundation of China No.61876160, No.61633013 and No.62001405.

We would like to thank Ming Li at Duke Kunshan University, Xiaolei Zhang at Northwestern Polytechnical University for their help in organizing this OLR 2020 challenge.

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