Pairwise Learning using Multi-lingual Bottleneck Features for Low-resource Query-by-example Spoken Term Detection

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Outline

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   - Background
   - Motivation and contribution
2. Methods
   - Multi-lingual bottleneck features (BNFs)
   - Pairwise learning
   - Query-by-example spoken term detection (QbE-STD)
3. Experiments
   - Data and evaluation
   - Results and analysis
4. Conclusions

Problem description of low-resource query-by-example spoken term detection (QbE-STD)

- A search problem for the occurrence of a spoken query in audio archives.
- Limited training data in low-resource scenarios.
- Difficult to give utterances with labels if no prior linguistic knowledge in the language.

Previous work

- Extract unsupervised acoustic features directly in low-resource target languages [1, 2, 3, 4].
- Extract posterior or bottleneck features (BNFs) from neural networks (NNs) trained using high-resource non-target languages [5, 6, 7, 8, 9].

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Motivation

- Pairwise learning
  - Training NNs with paired examples.
  - Successful for various tasks, including face verification [10], sentence similarity [12], phone discrimination [11], and our previous study [13] on a word discrimination task.
- Multi-lingual BNFs
  - A kind of compact representations.
  - More language-independent and more flexible for rapid language adaptation; especially in low-resource languages.

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Contribution

- The first attempt to use pairwise learning based on multi-lingual BNFs.
- The first attempt to use pairwise learning for QbE-STD.

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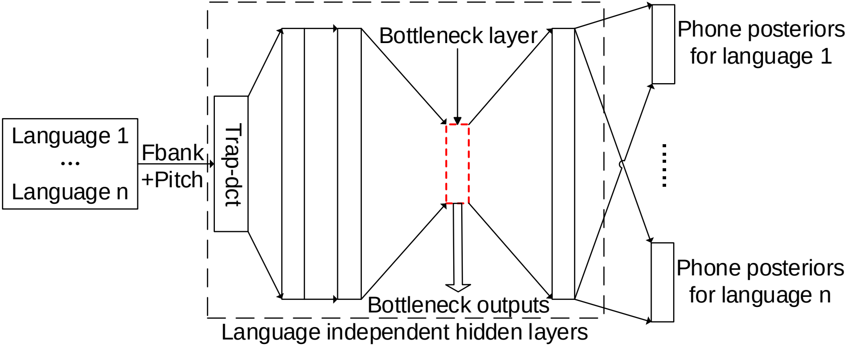
Multi-lingual BNF extraction

- Train a multi-lingual bottle-type NN from non-target languages.



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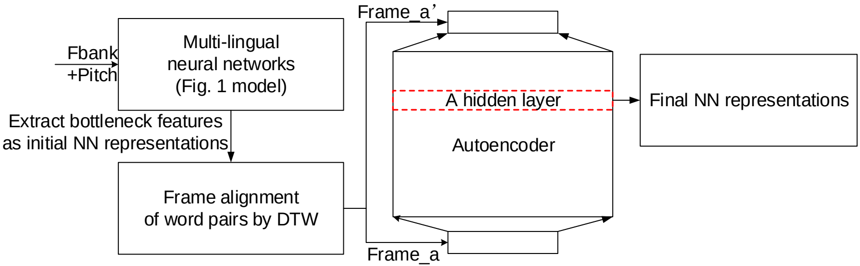
Pairwise learning with an autoencoder

- Align two sequences of multi-lingual BNFs with DTW.
- Train a pre-trained AE with Mean Squared Error (MSE) using aligned frame pairs.
- Extract newly learned feature representation from an internal hidden layer of trained NN.



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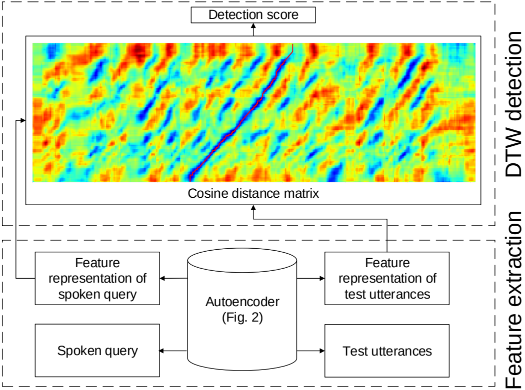
NN-based template matching method for QbE-STD



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Data

- Target language (for QbE-STD)

Corpus	Training set (No. of word pairs)	Keyword set (No. of examples)	Test set (No. of utterances)
TIMIT [3, 4]	10,000	346	944
Switchboard	100,000	346	100

- Non-target languages (for multi-lingual BNFs extractor)
  - HKUST Mandarin Chinese (LDC2005S15; 170hr)
  - Fisher Spanish (LDC2001S01; 152hr)

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Metrics of evaluation

MAP : the mean average precision of each query in the test set.

P@N : the average precision of the top N utterances where N is the number of the correct hit utterances in test set.

P@5/P@10 : the average precision of the first five or ten ranked utterances.

Outline

QbE-STD on TIMIT and Switchboard

Corpus	Representation	No pairwise training (MAP/P@N/P@10)	Pairwise training (MAP/P@N/P@10)
TIMIT	MFCCs	0.285/0.289/0.247	0.297/0.293/0.257
	BNFs (Mandarin)	0.494/0.459/0.413	0.571/0.538/0.467
	BNFs (Spanish)	0.540/0.512/0.446	**0.594/0.561**/0.484
	BNFs (Multi-lingual)	**0.552/0.524/0.461**	**0.594/0.561/0.490**
Switchboard	MFCCs	0.232/0.200/0.232	0.258/0.236/0.260
	BNFs (Mandarin)	0.370/0.338/0.446	0.417/0.382/0.451
	BNFs (Spanish)	0.388/0.358/0.475	0.430/0.398/**0.484**
	BNFs (Multi-lingual)	**0.400/0.365/0.485**	**0.435/0.404**/0.473

Analysis

- Multi-lingual BNFs
  - Are much better than MFCCs.
  - Usually outperform the cross-lingual BNFs.
- Pairwise learning
  - Provides a more efficient feature representation for QbE-STD.
  - Usually hold the best performance with multi-lingual BNFs in the QbE-STD tasks.

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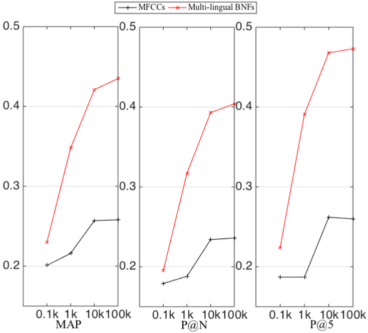
Dependence on the amount of word-pair supervision

- With more word pairs, pairwise learned NN feature representation gives a better performance.
- With 10,000 word pairs, pairwise learned features give comparable performance to those using all word pairs.



Effect of input features and frame alignment

- Regardless of either MFCCs or multi-lingual BNFs are used for frame-level DTW alignment, multi-lingual BNFs consistently provide much better QbE-STD results than MFCCs as input features.

Corpus	Input features of AE	Features for alignment	
		MFCCs	BNFs (Multi-lingual)
TIMIT	MFCCs	0.285/0.289/0.247	0.320/0.314/0.274
	BNFs (Multi-lingual)	0.587/0.556/0.486	**0.594**/**0.561**/**0.490**
Switchboard	MFCCs	0.258/0.236/0.260	0.273/0.248/0.286
	BNFs (Multi-lingual)	0.432/0.395/**0.483**	**0.435**/**0.404**/0.473

Conclusions and future work

- We have proposed to perform pairwise learning using multilingual BNFs of word pairs for QbE-STD.
- Pairwise learning makes the resulted features more capable in phonetic discrimination for a new target language.
  - Brings further performance improvement on low-resource QbE-STD tasks.
- In future work, we will investigate methods of word-level pairwise learning for this task, which avoids frame-level alignment of word pairs.

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