Comparison of DCT and Autoencoder-based Features for DNN-HMM Multimodal Silent Speech Recognition

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Motivation

- Mappings between articulatory movements and different units of speech
- DNN-HMMs on ultrasound-based SSR
- Approaches for non-acoustic feature extraction

Significance

- Applications in different areas and situations
- Deep Learning on ultrasound-based SSR as a pioneer

Method

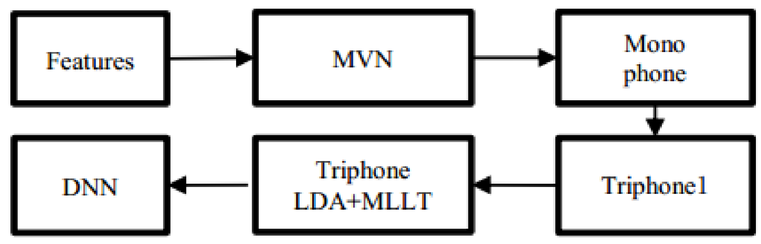
Data Acquisition

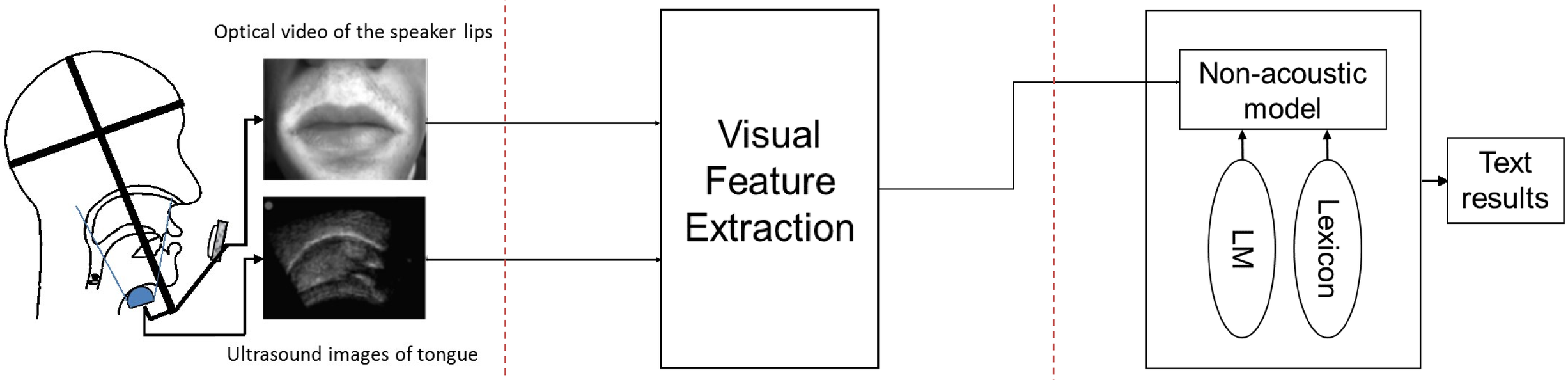
- a 128-element micro convex ultrasound probe
- a CMOS industrial camera
- Ultrasound focal depth: 7cm
- Frame of image streams: 60fps

Non-acoustic feature extraction - Autoencoder

- Pre-train a stack of Restricted Boltzmann Machines (RBMs) to obtain initial weights that are closed to global minima;
- "Unroll" the RBMs to build an encoder and a decoder;
- Perform back-propagation to fine-tune the model.

Silent Speech Recognition





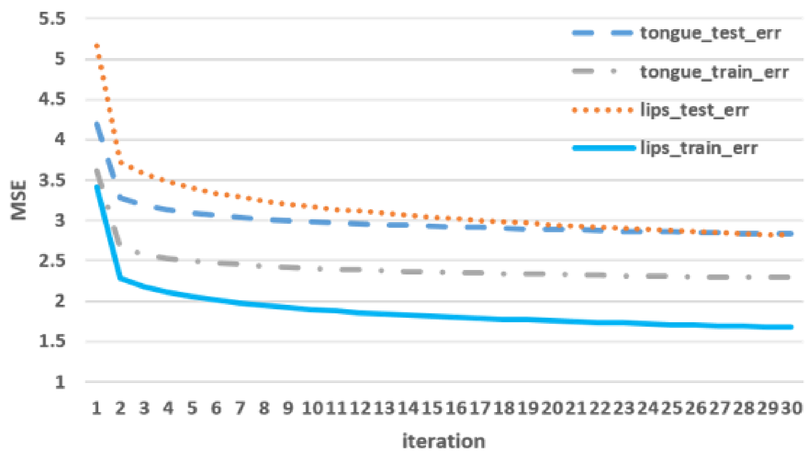
Experiment & Results

Speech corpora - TIMIT text

- 47 lists, each containing 50 sentences
- 5-8s for each utterance and contain 300-500 image frames
- 320*240 for ultrasound and 640*480 for video
- Test set: 100 sentences selected from WSJ0 5000-word

Feature extraction

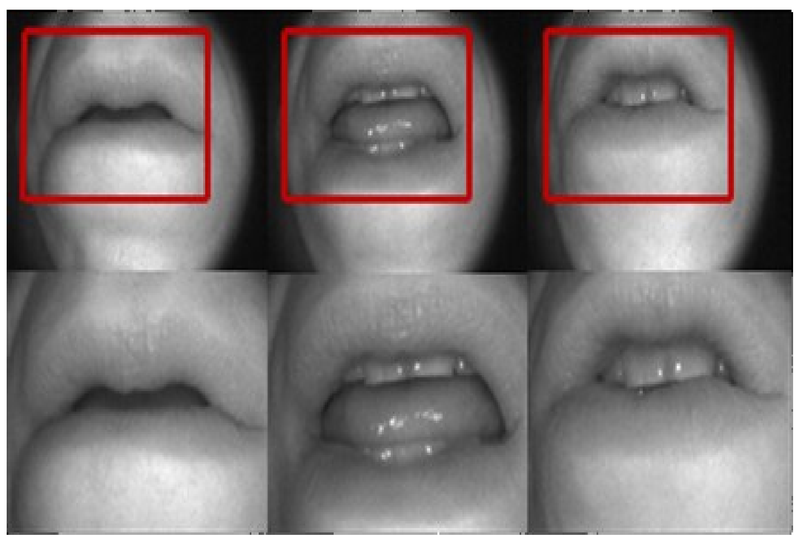
- Region of Interest (ROI) selection
- Bi-cubic interpolation image resizing
- Symmetric 3500(3000)-1000-500-250-30 model training
- Code layer combination of tongue and lip



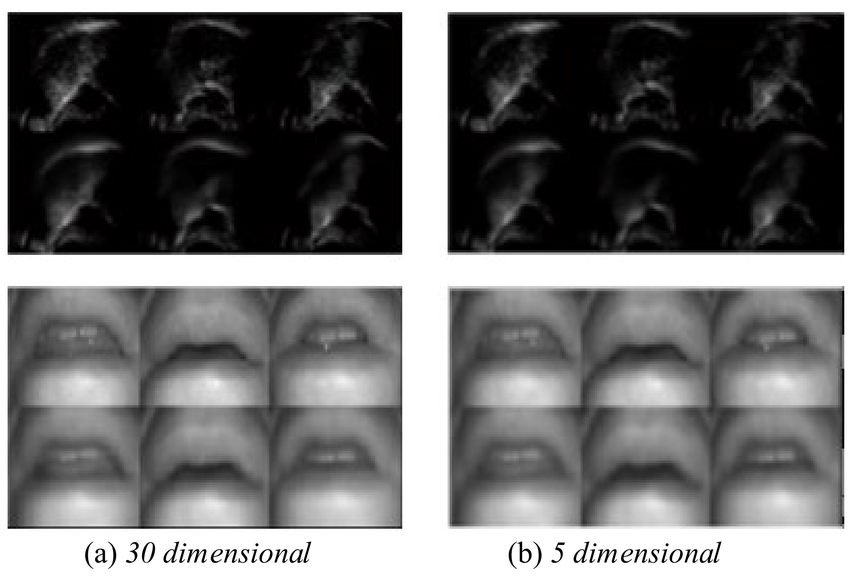
Mean Square Error (MSE) after each iteration of back-propagation.

WER of	DCT (%)			
Dimension	30	20	10	5
monophone	58.94	59.43	60.80	98.14
triphone1	59.24	55.33	55.62	98.44
triphone2b	43.50	44.87	46.73	100
DNN	36.75	37.15	39.49	99.90
WER of	Autoencoder (%)			
Dimension	30	20	10	5
monophone	69.79	65.10	63.44	65.20
triphone1	68.72	59.63	51.81	50.44
triphone2b	46.73	46.33	45.94	48.09
DNN	36.56	37.54	37.54	38.71

Results



ROI selection for raw images.



(a) *30 dimensional* (b) *5 dimensional*

Reconstructed images of tongue and lip

Conclusions

- Two types of features achieve similar WER performances
- Use of DNN-HMM is beneficial for video-based silent speech recognition for the first time
- DAE is able to create compact features that appear to retain saliency even at surprisingly low dimensionality

Acknowledgements

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