BINGHAMTON UNIVERSITY
STATE UNIVERSITY OF NEW YORK

A Neural Network Based Nonlinear Feature Transformation for Speech Recognition

Hongbing Hu, Stephen A. Zahorian

Department of Electrical and Computer Engineering, Binghamton University, Binghamton, NY 13902, USA

hongbing.hu@binghamton.edu, zahorian@binghamton.edu

Introduction

- Accurate Automatic Speech Recognition (ASR)
  - Highly discriminative features
    - Incorporate nonlinear frequency scales and time dependency
    - Low dimensionality of feature space
  - Efficient recognition models
    - HMMs: good time alignment capability and convenient mechanisms for incorporating language models
    - Neural Networks: good discriminative power
- Nonlinear Feature Transformation for Speech Recognition
  - Combination of Neural Networks and HMMs
  - A neural network based Nonlinear Principal Component Analysis (NLPCA) is used as a dimensionality reduction approach for speech features

NLPCA for HMM Recognition

- Nonlinear Principal Components Analysis (NLPCA)
  - Based on a bottleneck neural network
  - Activations from the middle hidden layer are used as the reduced dimensionality data

$$x \rightarrow \phi(x)$$

$\phi(x)$: Transformed feature of the data point x for machine learning

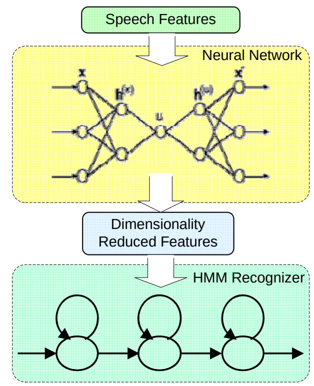
$$\phi(.): R^D \rightarrow R^M$$

R^M: M dimension feature space

$\phi(.)$: A neural network mapping to obtain dimensionality reduced data more suitable for speech representation

- Phoneme HMMs for Phonetic Recognition
  - Dimensionality reduced features are recognized as phonemes using HMMs with Gaussian Mixture Model
  - Parameters of the HMMs are trained by the Baum-Welch algorithm, independent of the NLPCA training

- Architecture of HMM recognition with NLPCA



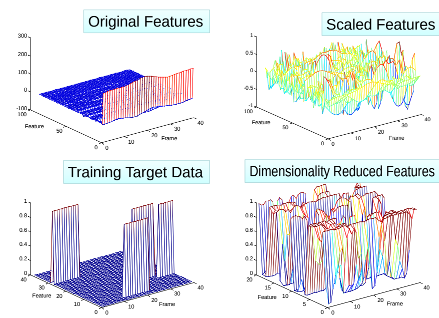
NLPCA Training

- Neural Network in NLPCA is trained as a Classifier
- Feature Scaling
  - A input feature vector **x** at time *i* is scaled using

$$\mathbf{o}_i = \frac{\mathbf{x}_i - \boldsymbol{\mu}}{5\boldsymbol{\sigma}}$$

μ: mean vector
σ: standard deviation vector of input features

- Training Target Data
  - A number of output nodes equal to the number of phone categories with a value of 1 for the target category and 0 for the non-target categories
- Weights estimation of the neural network
  - Back-propagation algorithm to minimize the distance between the input features and target data is used
- Illustrations of features



Experimental Evaluation

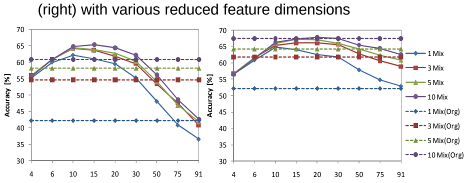
- Database

TIMIT database	
Target	Reduced 39 phone set mapped down from the TIMIT 62 phone set
Training data	4620 sentences (460 speakers)
Testing data	1680 sentences (168 speakers)

- Speech Features
  - A modified Discrete Cosine Transformation Coefficients (DCTC) for representing speech spectra
  - Discrete Cosine Series Coefficients (DCSC) for representing speech trajectories
  - A total of 91 features (13 DCTCs x 7 DCSCs) are computed using 20 ms frames with 10 ms frame spacing
  - Block lengths are fixed (10 frames in Exp. 1) and varied (Exp. 2 and 3)
- HMM
  - Left-to-right Markov models with no skip
  - 39 monophone HMMs are created using the HTK toolbox
  - Bigram phone information is used as the language model
- Neural network in NLPCA
  - 3 hidden-layers with 500 nodes in the first and third hidden layers and varied nodes in the second layer
  - Input layer with 91 nodes and output layer with 39 nodes

Experiment 1

- NLPCA was evaluated with various dimensions in the reduced feature space
- HMMs were trained with 1, 3 and 5 states, and with 1, 2, 5 and 10 mixtures per state
- Experiment 1 Results
  - Recognition accuracies of 1-state (left) and 3-state HMMs (right) with various reduced feature dimensions

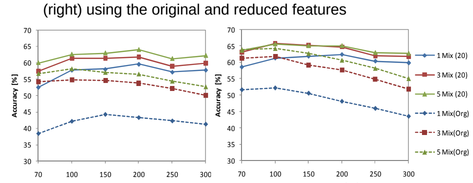


  - For both the 1-state and 3-state HMMs, best accuracy was obtained with feature dimensionality between 10 and 30

> NLPCA is able to represent the complexity of original feature in a reduced dimensionality space
>
> The reduced features result in high accuracy using a small number of mixtures and states in HMMs

Experiment 2

- Various block lengths in DCTC-DCSC feature calculation were evaluated for optimal block length
- 20-dimensional NLPCA features were used to compare with the original 91-dimensional features
- Experiment 2 Results
  - Recognition accuracies of 1-state (left) and 3-state HMMs (right) using the original and reduced features

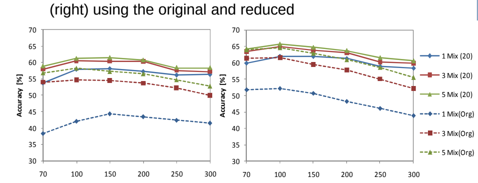


  - NLPCA features are better able to represent speech information over longer segment

> NLPCA can account for some of the temporal information accounted with HMMS, thus potentially simplifying the HMM configuration

Experiment 3

- 50% of the training data was used for the NLPCA training and the other 50% of the data for HMMs
- 20-dimensional NLPCA features were compared with the original features with varying block length
- Experiment 3 Results
  - Recognition accuracies of 1-state (left) and 3-state HMMs (right) using the original and reduced



  - Comparing results with full training data, the best 1 state HMMs results are 2% lower and the best 3 state results are slightly lower using the partitioned training data

> Only a small degradation due to reduced size of the training data

Conclusions

- A neural network based nonlinear feature transformation (NLPCA) is incorporated with an HMM recognition model for continuous speech phonetic recognition
- Recognition accuracies with NLPCA reduced dimensionality features are higher than that with original features, especially for a small number of states and mixtures
- NLPCA features are able to well represent spectral-temporal information in segments as long as 200ms, thus potentially reducing HMM model complexity
- The entire recognition system could benefit from low dimensional features in terms of processing time and recognition accuracy