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Joint Optimisation of Tandem Systems using Gaussian Mixture Density Neural Network Discriminative Sequence Training

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Introduction

Tandem Systems as Mixture Density Neural Networks (MDNNs)

- Tandem systems model features produced by DNN using GMMs
- A bottleneck (BN) DNN and GMMs combine to form an MDNN

Importance of Tandem Systems

- A general framework for modelling non-Gaussian distributions
- Can apply GMM techniques (e.g., adaptation) to improve MDNNs
- Tandem and hybrid systems produce complementary errors

Weakness of Conventional Tandem Systems

- GMMs and DNN are independently estimated$\rightarrow$suboptimal

Introduction

Can Tandem and Hybrid Systems Have Comparable WERs?

Improved Training of Tandem Systems

- Jointly optimise tandem system with MPE or other discriminative sequence criteria
- Can be viewed as MDNN hybrid system MPE training

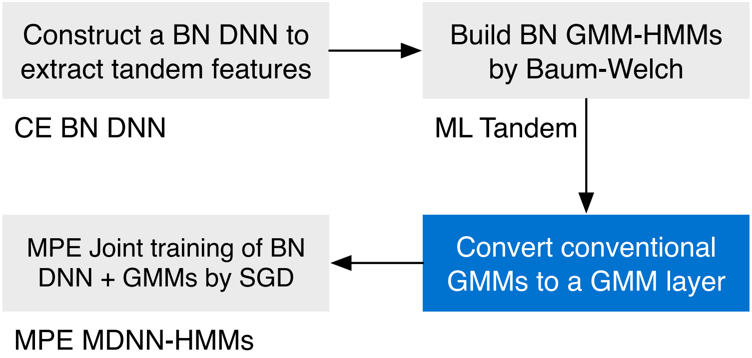
Proposed Methods

- Adapt extended Baum-Welch (EBW) based GMM MPE training to use stochastic gradient descent (SGD)
- Propose a set of methods to improve joint optimisation stability

Methodology

System Construction Procedure

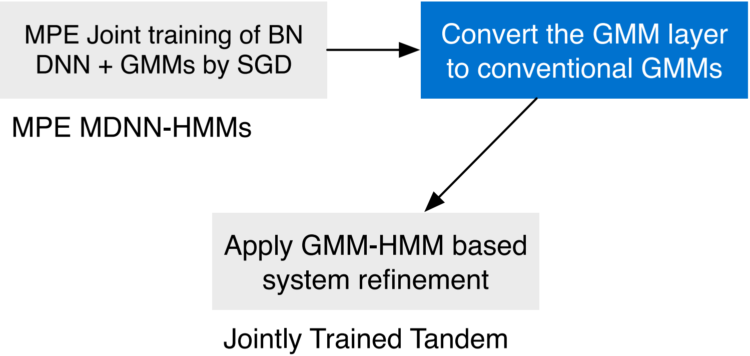
- Convert GMMs to an MDNN GMM output layer for joint training



Methodology

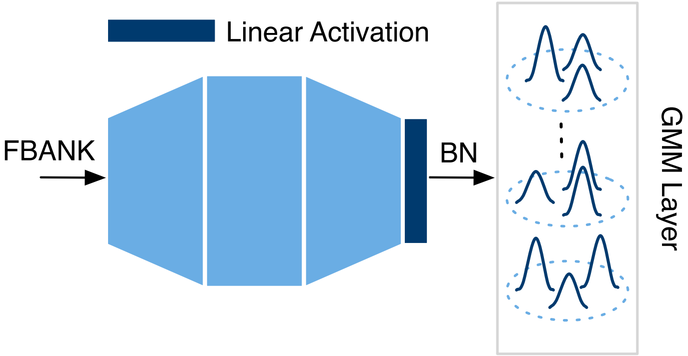
System Refinement and Decoding

- GMM layer is converted back to GMMs to reuse existing facilities



ML Tandem System Construction

- monophone BN GMM-HMMs → initial triphone BN GMM-HMMs → HMM state clustering → final triphone BN GMM-HMMs



SGD based GMM-HMM Training

GMM Parameter Update Values

- Calculate the partial derivatives of $\mathcal{F}$ w.r.t. each GMM parameter and input value
- For SGD, Gaussian component weight and std. dev. values are transformed so constraints satisfied

Speed Up

- Rearrange mean and std. dev. from of Gaussians as matrices
- Speed up GMM calculations by highly optimised general matrix multiplication (GEMM) functions in the BLAS library

MPE Training for GMM-HMMs using SGD

Regularisation

- Parameter smoothing
  - I-smoothing with $\mathcal{F}^{\text{ML}}$: data dependent coeff. $\tau^{\text{ML}}(s, g)$
  - H-criterion with $\mathcal{F}^{\text{MMI}}$: fixed coeff. τ^{MMI} (H-criterion)
- L2 regularisation: $\lambda \cdot \theta^2/2$
- Composite objective function

$$\mathcal{F}^{\text{MPE}} + \tau^{\text{MMI}}(\mathcal{F}^{\text{MMI}} + \tau^{\text{ML}}(s, g)\mathcal{F}^{\text{ML}}) + \lambda\,\theta^2/2$$

Percentile based Variance Floor

- Modified to find the flooring threshold more efficiently to apply frequently in SGD

Tandem System Joint Optimisation

Linear to ReLU Activation Function Conversion

- Observe instability issue when averaged partial derivatives w.r.t. linear BN features shifting from positive to negative
- To avoid negative values, modify BN layer bias to equivalently use ReLU by

$$b^{\text{bn}} - \mu^{\text{bn}} + 6\,\sigma^{\text{bn}}$$

Amplified GMM Learning

- GMMs have a rather different functional form than DNN layers
- Learning rates and L2 reg. coeff. are amplified for GMMs by α

Tandem System Joint Optimisation

Relative Update Value Clipping

- To avoid setting a specific threshold for each type of parameter
- Assuming values are Gaussian distributed, compute thresholds of Θ based on stats. in nth mini-batch by

$$\mu_{\Theta}[n] + m\,\sigma_{\Theta}[n]$$

Parameter Update Schemes

- Update GMMs and hidden layers in an interleaved manner
- Update all parameters concurrently without any restriction
- Update all parameters concurrently, then update the GMMs only

Experimental Setup

Data

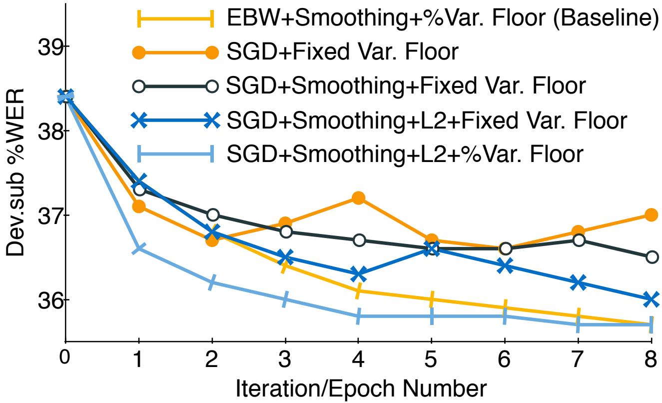
- 50h and 200h data from ASRU 2015 MGB challenge
- A trigram word level LM with a 160k word dictionary
- **dev.sub** test set contains 5.5h data with reference segmentation and 285 automatic speaker clusters

Systems

- All experiments were conducted with HTK 3.5
- 40-dim log-Mel filter bank features with their Δ coefficients
- DNN structure $720 \times 1000^5 \times \{4000, 6000\}$
  BN DNN structure $720 \times 1000^4 \times 39 \times 1000 \times \{4000, 6000\}$
- Each GMM has 16 Gaussians (`sil`/`sp` has 32 Gaussians)

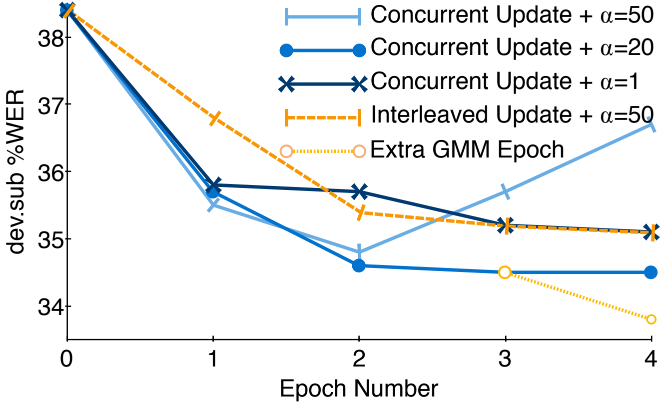
Experimental Results

Comparison of EBW and SGD GMM Training (50h)



Experimental Results

Joint Training Experiments with Different α (50h)



Experimental Results

Comparisons Among Various 50h Systems

- T_2^{50h} is comparable to hybrid MPE systems (H_1^{50h}&H_2^{50h}) in both WER and #parameters, and is useful for hybrid system (H_4^{50h})

ID	System	WER%
T_0^{50h}	ML BN-GMM-HMMs	38.4
T_1^{50h}	MPE BN-GMM-HMMs	36.1
T_2^{50h}	MPE MDNN-HMMs	33.8
H_0^{50h}	CE DNN-HMMs	36.9
H_1^{50h}	MPE DNN-HMMs	34.2
H_2^{50h}	MPE DNN-HMMs+H_1^{50h} align.	33.7
H_3^{50h}	MPE DNN-HMMs+T_2^{50h} align.	33.6
H_4^{50h}	MPE DNN-HMMs+T_2^{50h} align. & tree	33.2

Experimental Results

Comparisons Among Various 200h Systems

- MLLR and joint decoding still improve system performance

ID	System	WER%
T_0^{200h}	ML BN-GMM-HMMs	33.7
T_1^{200h}	MPE MDNN-HMMs	29.8
T_2^{200h}	MPE MDNN-HMMs+MLLR	28.6
H_0^{200h}	CE DNN-HMMs	31.9
H_1^{200h}	MPE DNN-HMMs	29.6
H_2^{200h}	MPE DNN-HMMs+T_1^{200h} align. & tree	29.0
J_1^{200h}	$T_1^{200h} \otimes H_2^{200h}$ joint decoding	28.3
J_2^{200h}	$T_2^{200h} \otimes H_2^{200h}$ joint decoding	27.4

Conclusions

Main Contributions Include

- EBW based GMM-HMM MPE training is extended to SGD
- MDNN discriminative sequence training is studied as tandem system joint optimisation
- A set of methods are modified/proposed to improve training that result in an 6.4% rel. WER reduction over MPE tandem systems

The Jointly Trained Tandem System

- is comparable to MPE hybrid systems in WER and #parameters
- is useful for hybrid system construction and system combination
- can also benefit from existing GMM approaches (e.g., MLLR)

Thanks for listening!