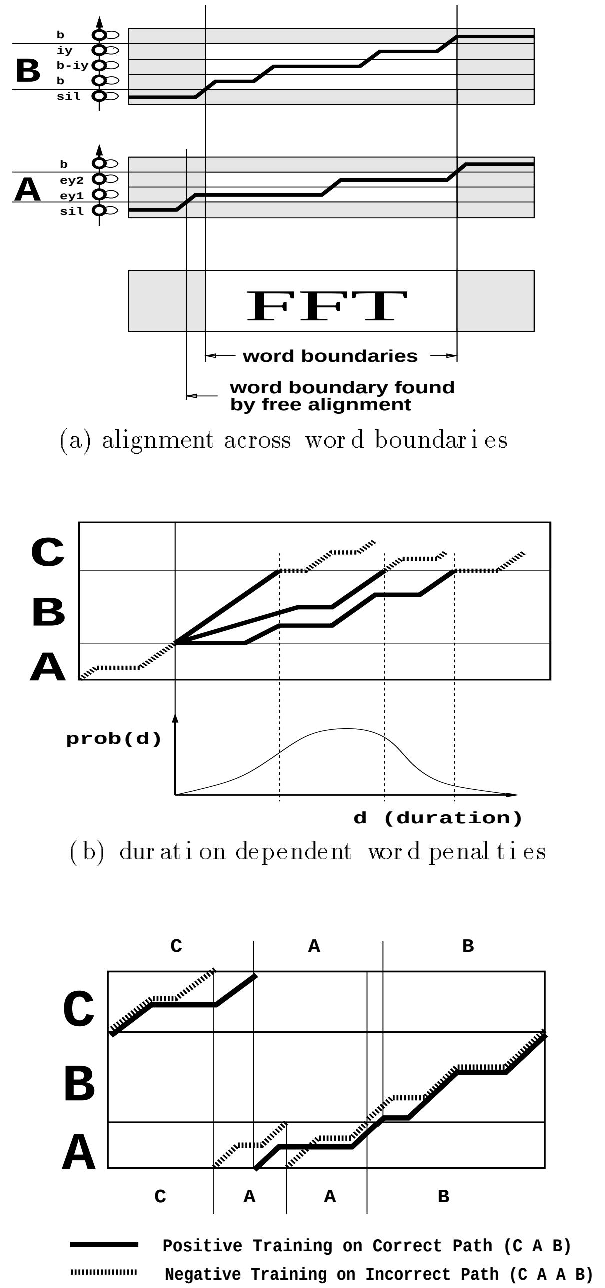

(a) alignment across word boundaries

(b) duration dependent word penalties

(c) training on the sentence level

Figure 2: Various techniques to improve sentence level recognition performance

Speaker Dependent (CMU Alph Data)			
500/2500 train, 100/500 crossvalidation, 400/2000 test sentences/words			
speaker	SPHINX[HFW91]	MS-TDNN[HFW91]	our MS-TDNN
mjmt	96.0	97.5	**98.5**
mdbs	83.9	89.7	**91.1**
maem	–	–	**94.6**
fcaw	–	–	**98.8**
flgt	–	–	**86.9**
fee	–	–	**91.0**
Speaker Independent (Resource Management Spell-Mode)			
109 (ca. 11000) train, 11 (ca. 900) test speaker (words).			
SPHINX[HH92]		our MS-TDNN	
	+ Senone		gender specific
88.7	90.4	**90.8**	**92.0**

Table 1: Word accuracy (in % on the test sets) on speaker dependent and speaker independent connected letter tasks.

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and R. A. Cole. Speaker-independent Phonetic
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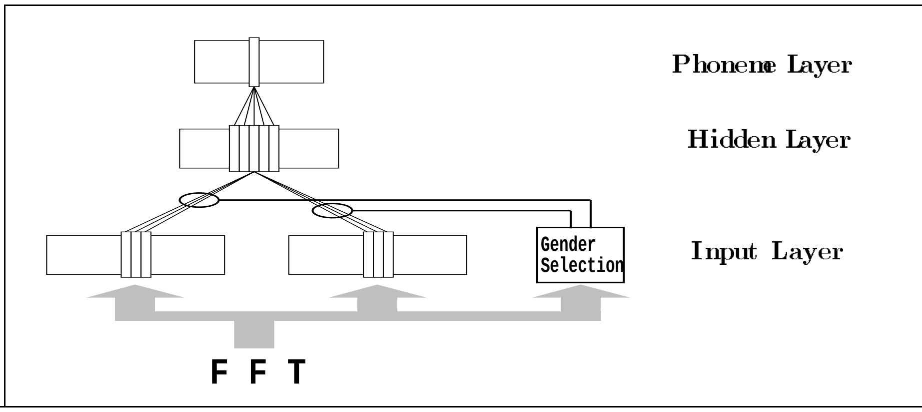

Figure 4: A network architecture with gender-specific and shared connections. Only the front-end TDNN is shown.

ing, cross-validation and test set, respectively. The DARPA Resource Management Spell-Mode Data were used for **speaker independent** testing. This data base contains about 1700 sentences, spelled by 85 male and 35 female speakers. The speech of 7 male and 4 female speakers was set aside for the test set, one sentence from all 109 and all sentences from 6 training speakers were used for crossvali Table 1 summarizes our results. With the help of the training techni above we were able to outperform previously reported [HFW91] s results as well as the HMM-based SPHINX System.

5 SUMMARY AND FUTURE WORK

We have presented a connectionist speech recognition s connected letter recognition. New training techni level recognition enabled our MS-TDNN to out kind as well as a state-of-the art HMM bas specific subnets, we are experimenting "internal speaker models" for a more the future we will also experi

Acknowledgements

The authors gratefully ackn and DARPA. We wish to t McNair for keeping o the ideas presen

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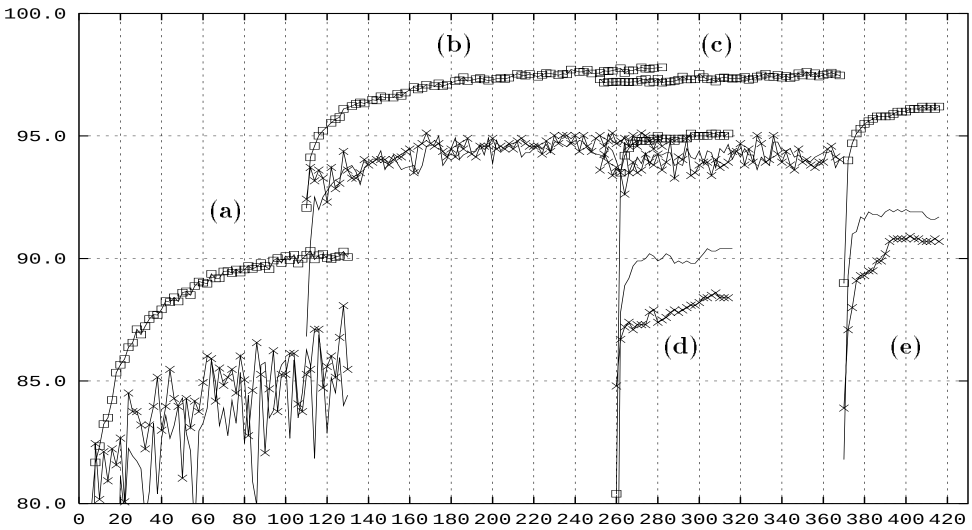

Figure 3: Learning curves (a = bootstrapping, b, c = word level (excerpted words), d, e = sentence level training (continuous speech)) on the training (□), crossvalidation (-) and test set (x) for the speaker-independent RM Spell-Mode data.

3 GENDER SPECIFIC SUBNETS

A straightforward approach to building a more specialized system
two entirely individual networks for male and female speake
the gender of a speaker is known, during testing it
“gender identification network”, which is si
put units representing male and female sp
network classifies the speaker's gen
ularized network improved the
see table 1) to 91.3%. How
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worked even b
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in the same way as the phoneme boundaries within a word. Figure 2(a) shows an example in which the word to recognize is surrounded by a silence and a 'B', thus the left and right context (for all words to be recognized) is the phoneme 'sil' and 'b', respectively. The gray shaded area indicates the extension necessary to the DTW alignment. The diagrams shows how a new boundary for the beginning of the word 'A' is found. As indicated in figure 3, this techniques improves conti recognition significantly, but it doesn't help for excerpted words.

2.2 WORD DURATION DEPENDENT PENALIZING OF INSERTION AND DELETION ERRORS

In "continuous testing mode", instead of looking at word units the well-known "One Stage DTW algorithm[Ney84] is used to find an optimal path through an unspecified sequence of words. The short and confusable English letters cause many word insertion and deletion errors, such as "T E" vs. "T" or "O" vs. "O O", ther proper duration modeling is essential.

As suggested in [HW92], minimum phoneme duration can be enforce duplication". In addition, we are modeling a duration and word de $Pen_w(d) = log(k + prob_w(d))$, where the pdf $prob_w(d)$ is app training data and k is a small constant to avoid zero p added to the accumulated score AS of the search p whenever it crosses the boundary of a word w in rithm, as indicated in figure 2(b). The ratio λ influence of the duration penalty, is ano is no straightforward mathematical of the "weight" λ_w to the inser gradient descent, which c i.e. we are trying to n

2.3 ERROR I

Usually the MS-TDNN is trained to tinuously spoken sentences. training on the sentence "C A B", in whi alignme copied from the Phoneme Layer into the word models of the DTW Layer, where an optimal alignment path is found for each word. The activations along these paths are then collected in the word output units. All units in the DTW and Word Layer are linear and have no biases. 15 (25 to 100) hidden units per frame were used for speaker-dependent (-independent) experiments, the entire 26 letter network has approximately 5200 (8600 to 34500) parameters.

Training starts with "bootstrapping", during which only the front-end TDNN
used with fixed phoneme boundaries as targets. In a second phase, trainin
formed with word level targets. Phoneme boundaries are freely align
word boundaries in the DTW layer. The error derivatives are ba
the word units through the alignment path and the front-en
The choice of sensible objective functions is of gre
$(y_1, \ldots, y_n)$ the output and $T = (t_1, \ldots, t_n)$ th
the phoneme level (bootstrapping), ther
time, representing the correct pho
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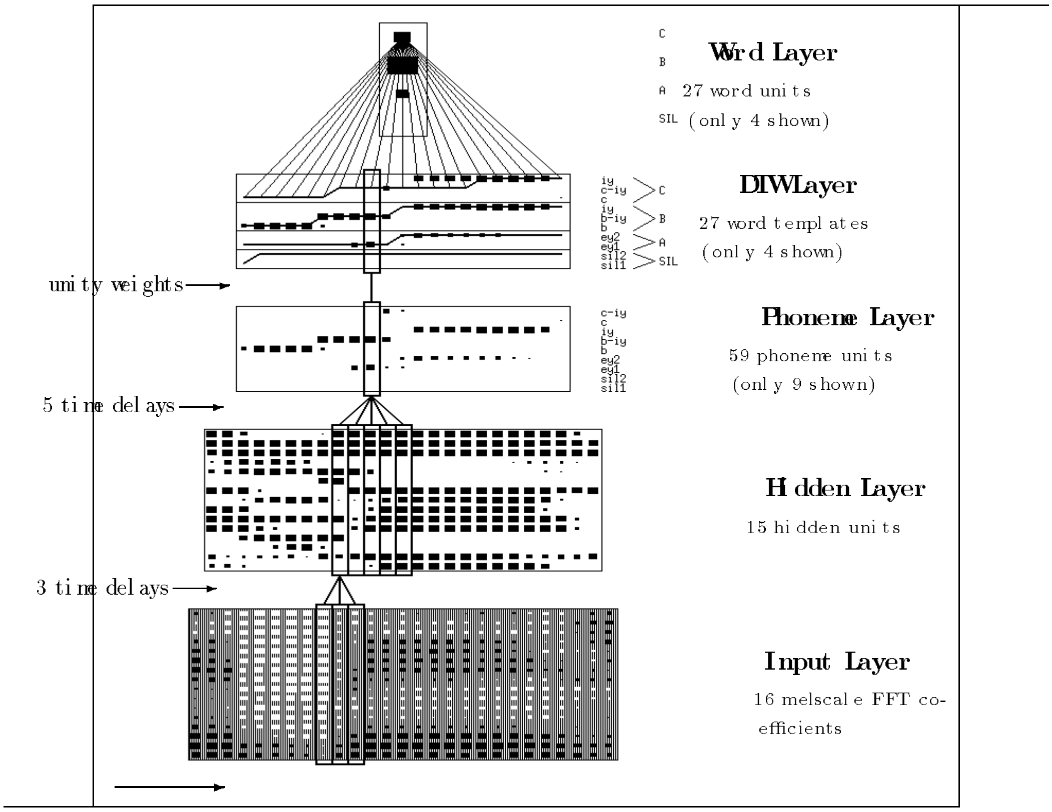

Figure 1: The MS-TDNN recognizing the excerpted word 'B'. Only the activations for the words 'SIL', 'A', 'B', and 'C' are shown.

classified by another network. In this paper, we present the MS-TDNN as a
connectionist speech recognition system for connected letter recognition. After de-
scribing the baseline architecture, training techniques aimed at improving sentence
level performance and architectures with gender-specific subnets are introd

Baseline Architecture. Time Delay Neural Networks (TDNNs) can comb
robustness and discriminative power of Neural Nets with a time-shift
chitecture to form high accuracy phoneme classifiers [WHH+89]
TDNN (MS-TDNN) [HFW91, Haf92, HW92], an extension of the TI
of classifying words (represented as sequences of phonemes) by
ear time alignment procedure (DTW) into the TDNN archi
an MS-TDNN in the process of recognizing the excerpt
16 melscale FFT coefficients at a 10-msec frame ra
tute a standard TDNN, which uses sliding w
to compute a score for each phoneme (st
tions in the "Phoneme Layer". In
is modeled by a sequence of pho

*Advances in Neural Information Processing Systems 5 (NIPS*5).*
San Mateo, CA: Morgan Kaufmann Publishers, 1993

Connected Letter Recognition with a Multi-State Time Delay Neural Network

Hermann Hild and **Alex Waibel**
School of Computer Science
Carnegie Mellon University
Pittsburgh, PA 15213-3891, USA

Abstract

The Multi-State Time Delay Neural Network (MS-TDNN) inte-
grates a nonlinear time alignment procedure (DTW) and the high-
accuracy phoneme spotting capabilities of a TDNN into a connec-
tionist speech recognition system with word-level classification a
error backpropagation. We present an MS-TDNN for recogniz
continuously spelled letters, a task characterized by a
highly confusable vocabulary. Our MS-TDNN achieves
word accuracy on speaker dependent/independent
forming previously reported results on the sar
pose training techniques aimed at improv
mance, including free alignment ac
ration modeling and error back
than the word level. Archi
ized on a subset of

1 INTRODUCT

The recognition of s
proper