

was no way to use (say) the vowels of one ISM and the
consonants of another ISM. In a more flexible tuning-in
scheme, an individual speaker-mixture can be selected
for each phoneme independently, conceptually
to the speaker-adaptive
this approach

4. EXPERIMENTAL RESULTS

4.1 CMU Alph Data

Mul t i-S p e a k e r. The 3 male and 3 female speakers listed in Table 1 were used to train and test the four different architectures. The results (% correct, ex words, averaged over all 6 sp table 2. In

2. IMPROVED CONTINUOUS RESULTS

Speaker Dependent (CMU Alph Data)			
600/3000 train, 400/2000 test sentences/words			
speaker	SPHINX[2]	MS-TDNN[2]	our MS-TDNN
mjnt	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 (Res. Manag. Sp			
109/11000 train, 11/900			
SPHINX[6]		+ Sen	
88.7		9	

Table 1

MULTI-SPEAKER/SPEAKER- INDEPENDENT ARCHITECTURES FOR THE MULTI - STATE TIME DELAY NEURAL NETWORK

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ABSTRACT

In this paper we present an improved Multi-State
Time Delay Neural Network (MS-TDNN) for speaker-
independent, connected letter recognition which out-
performs an HMM based system (SPH) and other
previous MS-TDNNs [2], and presents new archi-
tectures