SEE ME, HEAR ME: INTEGRATI NG AUTOMATI C SPEECH RECOGNI TI ON AND LI P-READI NG

 $Paul \ Duchnowski^1$

 $Uwe Meier^1$

 $Al \ ex \ Wai \ bel^{1,2}$

¹University of Karlsruhe, Karlsruhe, Germany ²Carnegie Mellon University, Pittsburgh PA, USA

ABSTRACT

t recent work on integration of visual informaaccustic speech for bet-



Figure 1. Original recognition network architecture (Net-P).

data, respectively. Wighted sums of the phone and cor-responding viseme activations are entered in the combined

layer and a one stage DIWal gorithmfinds the optimal path

through the phone states that decodes the recognized letter

sequence. The weights in the parallel networks are trained by backpropagation. There are 15 hidden units in both sub-

nets. The combination weights are computed dynamically

during recognition to reflect the estimated reliability of each modality. These "entropy weights" [2], λ_A for the acoustic

side and λ_V for the visual are given by:

$$\lambda_{A} = b + \frac{S_{V} - S_{A}}{\Delta S_{max-over-data}}$$
(1)
$$\lambda_{V} = 1 - \lambda_{A}$$

The entropy quantities S_A and S_V are computed for the

acoustic and visual phone/viseme activations by normaliz-

ing these to sum to one and treating themas probability

mass functions. Hgh entropy is found when activations are

evenly spread over the units which indicates high anhi gui ty

of the decision from that particular modality. The bias b

pre-skews the weights to favor one of the modalities.

2.2. Visual Data Representation

Unlike for acoustic speech data, there are no generally agreed-upon parameterization strategies for the visual lip images. Since we are using a connectionist algorithm for recognition we have followed the philosophy of avoiding exfeature extraction and segmentation of the image. Inon the network to devel op appropriate inter-higher level features. Whave been e visual data representations ixel vector is quite i nput vec-

ю



y recognition rates for different data repre-

ents the recognizer from taking advantage of ons between acoustic and visual events ationships. There is evidence

nputs to take advan-



Net H

ic and visual combi-

rated i n Figure 2. v be con-



Figure 4. Combination results for Net-I and Net-H.

Comparison of different net structures yields more equiv-ocal conclusions. All three are clearly capable of improving recognition with the addition of visual information. How Net-P combination of the modalities al ways yields a than either modality alone which is not true of res. On the other hand, neither Net-I at this time (for instance, rited from Net-P). lently for