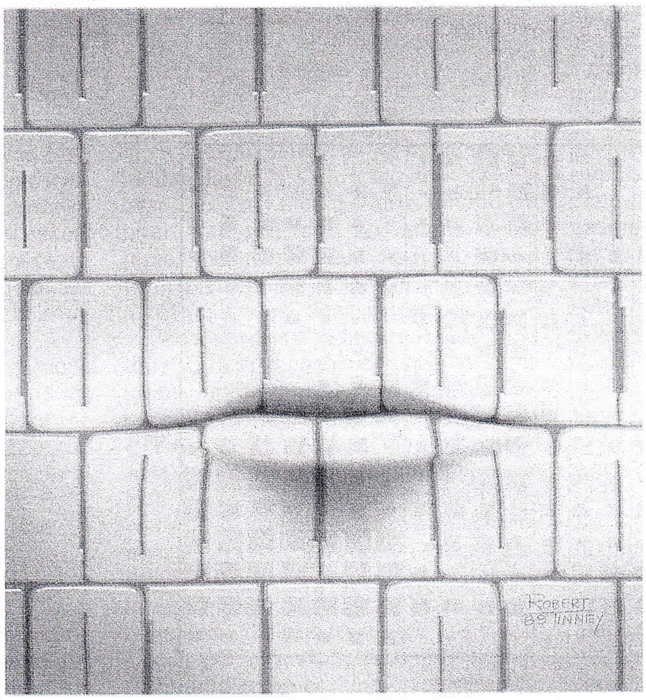
# Building Blocks for Speech

*Modular neural networks are a new approach to high-performance speech recognition*

*Alex Waibel and John Hampshire*



Some speech-recognition abilities that we take for granted—understanding a conversation involving several different speakers over lots of extraneous noise, for instance—are still beyond the reach of even the most powerful supercomputer. This may seem strange, since the human brain can't hope to match the arithmetical performance of a pocket calculator, but it does indicate the complexity of automatic speech recognition. Modular neural networks, however, might hold the key to achieving rapid and more-reliable machine-based speech recognition.

We recognize speech by applying an enormous body of knowledge to rapidly interpret the audio signals from the world around us. This knowledge ranges from low-level acoustic features to high-level facts about the world and the speaker's intent. These features and facts are heavily interrelated. No piece of the speech-recognition puzzle can be considered by itself, nor can pieces be evaluated sequentially. Rather, each provides a constraint that, together with many other facts and constraints, forms a total picture.

## Neural Nets in Speech Recognition

The limited ability of current computer models to absorb and apply a large body of facts restricts efforts to achieve automatic recognition of human speech. Effective models must determine, maintain, and program all necessary facts and rules of speech into a system. They must then integrate the massive number of interrelationships between these facts and rules to rapidly interpret the spoken word. If speech-recognition systems could learn important speech knowledge automatically and represent this knowledge in a parallel distributed fashion for rapid evaluation, they would then be able to overcome the deficiencies of current systems. Such a system would mimic the functions of the human brain, which consists of several billion simple, inaccurate, and slow processors that perform reliable speech recognition.

The development of parallel distributed processing (PDP) or neural-network models and the development of automatic learning algorithms (see reference 1) are two very important steps in the development of reliable speech-recognition systems.

You can implement algorithms that simulate PDP learning models on anything from a microcomputer to a supercomputer (see reference 2). These algorithms are even available commercially.

Two major problems have to be addressed, however, before neural-network models become useful for speech recognition: time and scaling.

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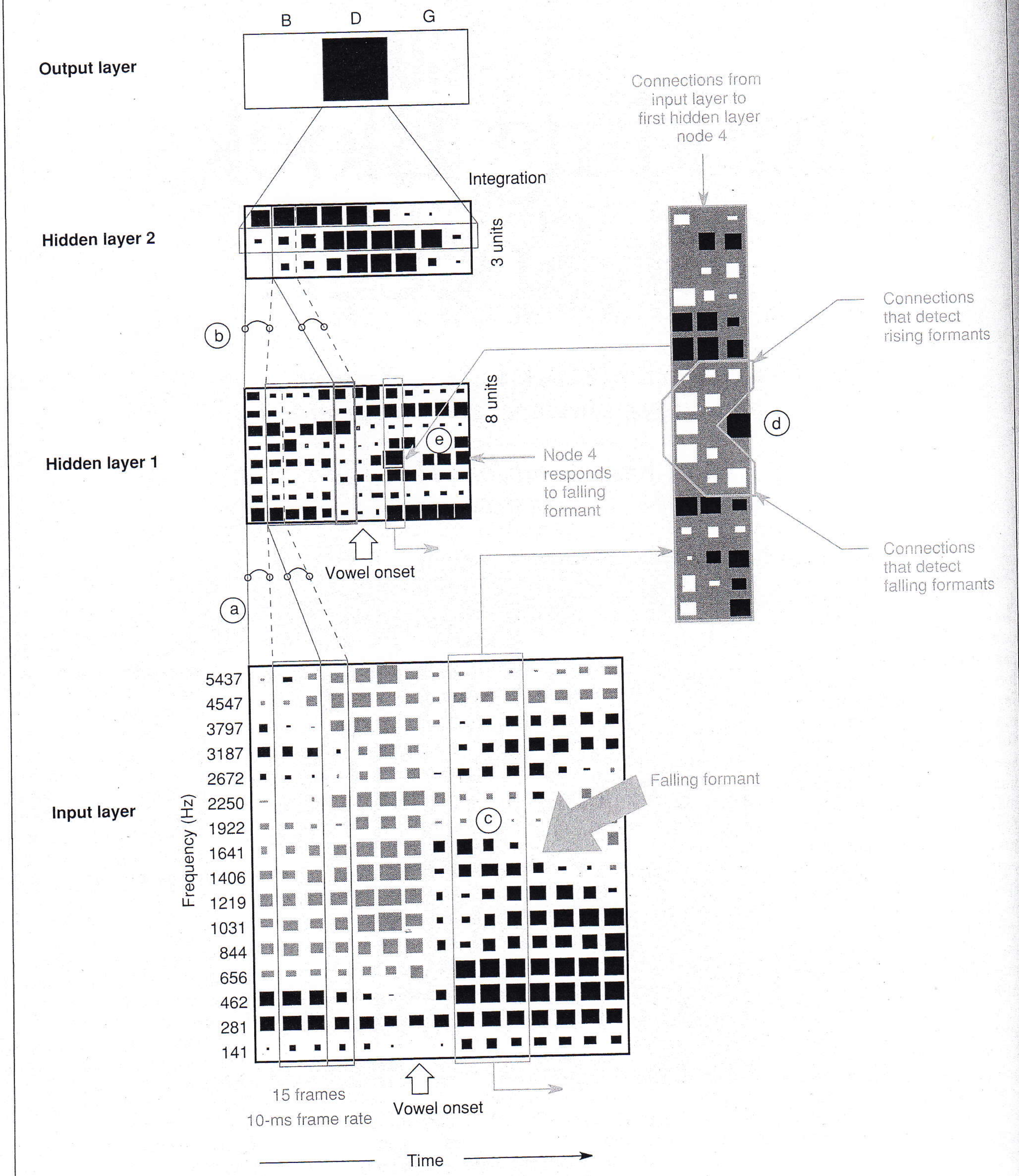


**Figure 1:** *The left side (in red) shows the time-delay feature of the network. Three 10-millisecond input slices are combined to create activations in the first hidden layer* **(a)**. *Activations in the second hidden layer* **(b)** *are created by combining five slices from the first hidden layer. The right side (in blue) shows the connections from the input layer to node 4 of the first hidden layer. When an input* **(c)** *matches the pattern of the connections* **(d)**, *the node is activated strongly* **(e)**.

## Speech and Time

Speech is a dynamic signal, and a speech-recognition system must be able to classify sounds without knowing when a particular sound will occur. It must also be able to capture the time-varying properties—the *signature*—of speech in feature space rather than simply taking static "snapshots" of the signal. These requirements are addressed by the Time-Delay Neural Network (TDNN) (see reference 3).

Rather than trying to decide whether a particular sound is, for example, a letter *b* (the speech signal may not contain useful information at certain points in time), the TDNN scans the input for clues that provide the evidence it needs to construct an overall recognition decision. Using this method, the TDNN has demonstrated performance superior to that of other speech-recognition models in small but difficult recognition tasks.

The TDNN shown in figure 1a is designed to discriminate the voice-stop consonants *b*, *d*, and *g* as they occur in a large database of isolated spoken words. At the output, three units represent each of the three *phoneme* categories. (Phonemes are the unique sounds of a spoken language; they form the acoustic-phonetic building blocks of speech.) The input layer of the network consists of 15 time slices of speech. Each one of these time slices is a frequency spectrum representing 10 milliseconds of the speech waveform—a 10-ms voiceprint of the speaker. Each spectrum, in turn, consists of 16 coefficients representing frequencies ranging from the lower limit of hearing (about 20 Hz) to over 5 kHz.

In many neural networks, each node in a given layer is connected to all the nodes in the next layer. This is not the case, however, for the TDNN. The reasons for this are related to the temporal complexity of human speech.

## Windows to the Spoken Word

Rapid changes in human speech occur over several tens of milliseconds. Therefore, a 30-ms "window" of speech (or an overlapping series of such windows) can capture the local acoustic-phonetic events that act as identifying features of a particular phoneme. The TDNN groups three 10-ms time slices from the input layer into a 30-ms window. Each coefficient in this window connects to eight nodes in the first hidden layer of the TDNN. Each of these nodes forms a condensed feature representing important cues that the network looks for in the input. The network shifts the window one time slice at a time across the input (a range of 150 ms of speech), creating 13 distinct firings at the eight nodes of the first hidden layer.

The grouping scheme in the first hidden layer and its connections to the second hidden layer are analogous to the input layer's groupings and connections to the first hidden layer. The firing patterns of the eight nodes in the first hidden layer over a five-time-slice window form the input to each of three nodes in the second hidden layer. As this window sweeps over the activation patterns in hidden layer 1, it generates activations at the three nodes in hidden layer 2. These form preliminary votes for one of the output's three phoneme categories.

*The TDNN has learned—without any supervision—the importance of rising and falling formant transitions in discriminating between similar sounds.*

Because their weights are fixed across time shifts, the connections between the layers allow the network to find key features of the speech waveform despite the fact that these features may be spread across time or shifted along the time axis. Figure 1a illustrates the activation of a TDNN when given the voiced consonant *d* in the syllable *do*. In this figure, negative node activations in the input layer are gray, and positive node activations throughout the network are black. The degree of node activation is proportional to the size of the rectangle depicting a given node.

In figure 1c, connections from the input-layer window to node 4 of the first hidden-layer time slice are shown to the side of the TDNN. (Unlike activations, positive connections are white and negative connections are black; the background is gray.) The activation level of node 4 in the first hidden layer at a given time slice is obtained by taking the activation of each of the 48 nodes in the input layer window, multiplying this node activation by the strength of its connection to node 4, and adding up these 48 products. This sum forms the input to node 4, which uses a thresholding (or "squashing") function to produce the output activation shown.

Note that the connections from the input layer to node 4 of the first hidden layer are positive for midrange frequencies in the input that rise or fall over time. The positive (white) connections that slope downward over time provide a strong input stimulus to node 4 when they detect a downward-sloping spectrum over time in the input layer. The arrow in figure 3 marks the onset of the *ü* sound in *do*. Beginning at this point, the nodes in the input layer corresponding to frequencies from 800 Hz to 1600 Hz show the downward-sloping activation pattern over time indicative of a *falling formant*. (A formant is a quality of sound representative of vowels.) This results in a strong firing of node 4 in the first hidden layer.

Falling midrange frequencies are characteristic of the utterance *do* shown in figure 1c. There is a great deal of experimental evidence showing that humans rely heavily on the perception of this acoustic event (a *formant transition*) for accurate speech recognition. The positive connections in the figure that slope upward over time detect rising formant transitions, which are also vital to understanding human speech. Clearly, the TDNN has learned—without any explicit supervision—the importance of both rising and falling formant transitions for accurate discrimination of the *b*, *d*, and *g* phonemes.

Because the TDNN scans across the input speech signal, it is relatively insensitive to the timing of vowel onset for the voice stops *b*, *d*, and *g*. A version of the same utterance shown in figure 1c shifted forward in time results in the same strong output activation indicating the detection of the *d* phoneme. The advance of vowel onset merely causes the hidden units to fire earlier, in synchrony with events in the input. The combined accumulated evidence from these firings still allows the network to recognize the utterance as a *d*, as opposed to a *b* or a *g*.

The TDNN has been experimentally evaluated on a number of small phonemic discrimination tasks and has achieved excellent recognition performance. The voiced consonants *b*, *d*, and *g*, for example, can be detected in more than 98 percent of the trials with a TDNN trained on data from a single

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**Accelerated Learning**

Coincident with the development of modular design techniques, recent advances in neural-network learning strategies and hardware and software implementations have led to dramatic improvements in network processing speeds. Learning speeds are also accelerating. These can be increased by improving the metrics that a network uses to measure how well it classifies training data.

> *What seemed impossible a short time ago will soon be done on a personal computer.*

Speed can also be increased significantly by improving the numerical search techniques that form the basis of network learning. Research in this area has resulted in learning procedures that converge to near-optimal results much more rapidly than before (see references 4, 5, and 6). Indeed, improvements in learning algorithms have brought the training time for a typical TDNN task down from three days of run time on a supercomputer to 8 minutes of CPU time on a high-end engineering workstation.

High-speed computing capabilities for neural-network training are becoming more accessible to personal computer and workstation users. Several manufacturers now offer plug-in floating-point accelerator boards for microcomputers that yield speeds of more than one million floating-point operations per second, while workstation manufacturers are producing desktop machines that rival super-minicomputers produced just a few years ago. Massively parallel connectionist hardware designs are also under development in various laboratories (see reference 7).

Speech recognition using modular neural networks is progressing rapidly. What seemed impossible a short time ago will soon be done on a personal computer. Advances in system-design techniques, learning software, and underlying hardware are creating the computing power required for very-large-scale neural-network tasks. All these advances bring connectionist design for speech and signal interpretation within reach of commonly available and affordable technology. ■

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# Neural Networks: Theory and Practice

*For most of their existence, neural networks and neural-network simulations have been solely objects of university-based research. In the last few years, however, researchers and others have founded companies dedicated to producing commercial products based on neural-network technology. To reflect both the academic and commercial aspects of the technology, this resource guide consists of two parts. The In Theory section lists books and articles you can read to learn more about neural networks. The In Practice section lists some of the available neural-network hardware and software products, listed alphabetically by company name.*

## IN THEORY


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