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13. ABSTRACT *(Maximum 200 words)*

Neural adaptive beamformers (NABFs) utilize neural paradigms to accomplish desired adaptions that are associated with sensory-field-responsive partitioning and selection processes. Kohonen-type organization and Hopfield-type optimization have been formulated as NABF mechanisms and have been applied to test data. Formulations and results are included. NABF's are also used in conjunction with a learning network for interpretation of weight sets as population codings of direction. An example is included. Finally, desirable qualities of human auditory response are being interpreted in the context of neural adaptive beamforming for the purpose of creating an integrated processing structure that incorporates NABF's, a cochlear model, and an associative memory as part of a total spatio-temporal processing scheme for selective attention.

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Neural Adaptive Sensory Processing for Undersea Sonar

Steven L. Speidel

Abstract—**Neural adaptive beamformers (NABF's) utilize neural paradigms to accomplish desired adaptions that are associated with sensory-field-responsive partitioning and selection processes. Kohonen-type organization and Hopfield-type optimization have been formulated as NABF mechanisms and have been applied to test data. Formulations and results are included. NABF's are also used in conjunction with a learning network for interpretation of weight sets as population codings of direction. An example is included. Finally, desirable qualities of human auditory response are being interpreted in the context of neural adaptive beamforming for the purpose of creating an integrated processing structure that incorporates NABF's, a cochlear model, and an associative memory as part of a total spatio-temporal processing scheme for selective attention.**

I. Background

During the course of this work on sensory processing, information from the studies of biological systems, including psychosensory experiments on humans [1], [2] detailed physiological studies [3], and detailed neurological studies of animal sonar systems [4], has guided the philosophical and architectural orientation of the developing computational system. In this respect, studies of vertibrate auditory systems are germane to our work with regard to ocean sonar systems, both passive and active. For example, it is important to acknowledge that a desirable object orientation is supported, in the neurobiological context, by the integration of the computation products of different nuclei of the brain through their interaction along afferent and efferent propagation channels. This often includes the integration of different sensory modalities, but even within a single modality there is considerable interactive integration. For example, cognitive auditory function encompasses the simultaneous acts of 1) attending memory according to stimuli, 2) attending stimuli according to memory, and 3) attending stimuli and memory according to an ongoing thought process.

What does an auditory system do? One answer is that the auditory system creates the perception of individuated, recognizable sounds out of the ongoing composite excitation received at the two ears. To perform this function upon the excitation of man-made sensor arrays using a man-made computer is the goal of the work being reported here.

It has long been known that beamforming is useful for aiding the interpretation of composite excitations in sonar applications where multiple sounds are simultaneously incident upon sensory arrays. What do beamformers do? Beamformers are devices that exhibit nonuniform response across ranges of dimensions of the stimulus field. It is suggested that this is an important function of the neurons of our brains and of cognitive sensory processors in general, including those that are man-made. In these devices, the focussing of the beamformers is to be directed by providing exemplary excitations of interest (as from memory). Hence these devices are to perform *adaptive* beamforming and adjust their ranges of maximum response according to the content of the sensory field.

Augmented Kohonen-style organization and Hopfield-style optimization processes have been used to perform "neural" adaptive beamforming [5–8], where "neural" is being used in the sense of the popular metaphor. The NABF paradigms easily integrate the qualities of attentiveness and binding when they are applied to partitioned/segmented sensory excitation. A brief overview of these two principal neural beamforming schemes is given here.

1) The *crossbar beamformer* is based on the Hopfield crossbar circuit. In its simplest form the crossbar adaptive beamformer (CABF) can be described as an adaptive combiner or mixer [9] with an augmented crossbar network of graded response and associated regulator embedded as processing kernel elements [10]. A method for controlling a crossbar circuit is derived from Wiener optimal least-squares filtering principles. The regulator, crossbar network, and adaptive combiner arrangement function to selectively attend task-relevant sensory excitation from within a total excitation which includes nonrelevant components. Adaption of the network response occurs without explicit computation of the error between the output and the exemplar. This is possible because hypothesis/memory-driven exemplars are supplied at the input. The CABF circuit form allows an organized implementation in dedicated VLSI hardware. Simulations suggest convergence in merely a few time constants of the hardware devices.

2) The *multivector adaptive beamformer* (MABF) is related to Kohonen feature map learning. It does a statistical segmentation of the stimulus field, independent of any exemplars, and it can serve as an element of continually

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modifiable associative memory or a classifier; it is formulated in terms of multidimensional geometrical calculus [11].

II. NABF Mechanisms

A. Crossbar Beamformer

Key elements of the beamforming structure (Fig. 1) are: 1) activity representing propagation of time and/or phase lagged excitation to the adaptive synapses, 2) a model that relates conductivity and current flow at the synapses to measures of time averaged coexcitation of afferent activities with each other and measures of correlation of afferent activity with exemplars/memories, 3) the crossbar kernel, and 4) multiplicative connections from the crossbar kernel outputs (ν_i) onto the combiner portion of the CABF.

The CABF minimizes the mean square error (ξ) between the real part of the beamformer output (y) and the exemplar (h)[1]

$$\xi = E\left\{\left[\sum_{i\ \mathrm{odd}} (\nu_i x_i - \nu_{i+1} x_{i+1}) - h\right]^2\right\} \tag{1}$$

where E denotes the expectation. Let the beamformer weights, (w_i), be related to the Hopfield circuit output voltages according to

$$w_i = \nu_i, \qquad w_{i+1} = -\nu_{i+1}; \qquad i\ \mathrm{odd} \tag{2}$$

resulting in the simplified expressions

$$\mathrm{Re}\{y\} = \sum_i w_i x_i \tag{3}$$

$$\xi = E\left\{\left[\left(\sum_i w_i x_i\right) - h\right]^2\right\}. \tag{4}$$

A direct relationship is established between the magnitude of ξ and the value of the Hopfield energy function, H (a Lyapunov function associated with the crossbar circuit). This relationship is established, in practice, by applying a controller (the black box labeled "membrane model" in Fig. 1) to the crossbar arrangement. The required behavior of the controller can be derived analytically by equating ξ and H and solving for the currents and connectivities of the crossbar as functions of the excitations (x_i).

The crossbar circuit which is illustrated in Fig. 1 is shown in more detail in Fig. 2. The circuit is simply a number (N) of charge flow control devices, each connected with variable efficacy to each of the others. Hopfield has shown that if the connections are symmetric ($T_{ij} = T_{ji}$) and direct feedback is zero ($T_{ii} = 0$) then the circuit will converge to stable states representing the local minima. These conditions on the connectivity are sufficient but not always necessary, dependent on the application. It is convenient to choose the simplified form of the

[1] For simplicity it is assumed here that the quadrature input is available. Other cases have been considered elsewhere (Speidel, 1990).

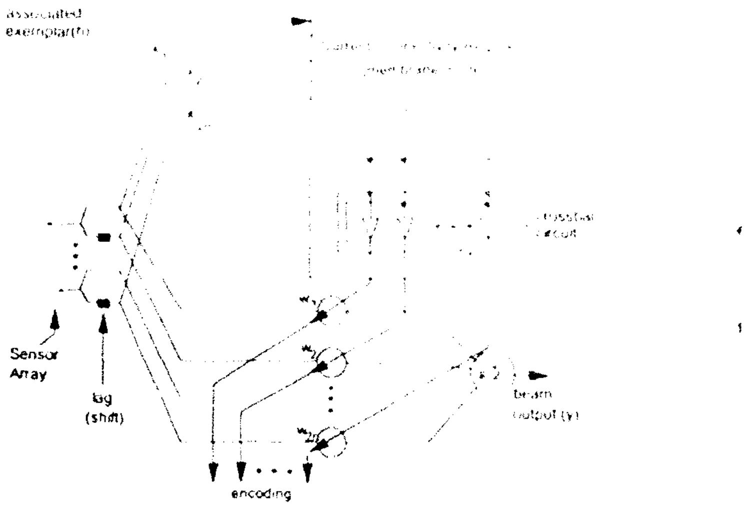

Fig. 1. The crossbar adaptive beamformer.

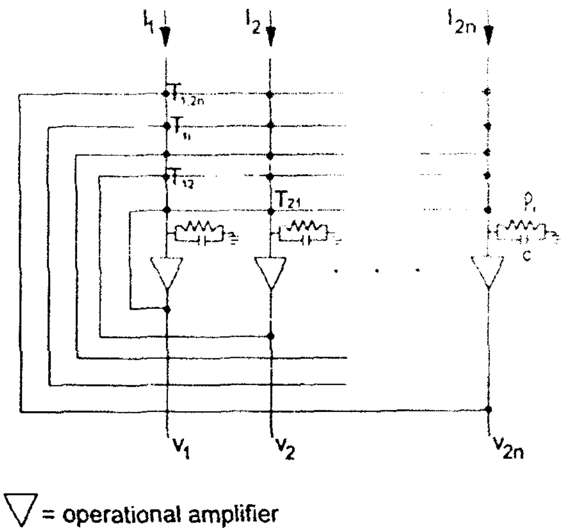

Fig. 2. Hopfield crossbar arrangement.

Lyapunov function

$$\varphi = -\frac{1}{2}\sum_i \sum_j T_{ij}\nu_i\nu_j - \sum_i I_i\nu_i. \tag{5}$$

Hopfield and Tank (1985) use this form when they operate at the high-gain limit. However, here the primary motive is to simplify the expression for φ. The behavior of the neglected term of φ (as a function of the gain) is examined elsewhere [8]. The term can be neglected without much sensitivity to the gain (g) in this application.

It is convenient to set the doubled modified Lyapunov function equal to the mean square error (ξ) minus the mean square exemplar (h). The quantities to be equated are

$$2\varphi = -\sum\sum_{i\neq j} T_{ij}\nu_i\nu_j - 2\sum_i \nu_i I_i \tag{6}$$

$$\xi - E[h^2] = \sum\sum_{i\neq j} E[x_i x_j]\nu_i\nu_j + \sum_i \nu_i^2 E[x_i]^2$$

$$2 \sum v_i E[\dot{x}_i] \tag{7}$$

The resulting expressions for the connectivities and currents are

$$\text{connectivity } T_{ij}(t) = \frac{1}{\tau} \int_{t-\tau}^{t} x_i(\eta) x_j(\eta)\, d\eta, \qquad T_{ii} = 0 \tag{8}$$

$$\begin{aligned}\text{ion flow } I_i = {} & \frac{1}{\tau} \int_{t-\tau}^{t} x_i(\eta) h(\eta + \tau - t)\, d\eta \\ & - \frac{1}{2} \nu_i(t - \tau) \int_{t-\tau}^{t} x_i(\eta) x_i(\eta)\, d\eta \end{aligned} \tag{9}$$

where τ is a response latency period, and $\nu_i(t - \tau)$ is the output amplitude at the end of the previous epoch from the ith element. In the case of discrete time-step simulations, the expectation value is usually evaluated by summing.

The voltage controlled feedback to the input current, (9), is equivalent to a direct negative feedback connection, $T_{ii} \neq 0$, if the value of the voltage feedback term of the current is allowed to vary during equilibration of the crossbar circuit. However, in the present implementation, the current is fixed, i.e., the controller (membrane model) clamps the current during equilibration. Thus, there are in effect two time-scales: the epoch scale and the scale of dynamic equilibration of the crossbar arrangement (membrane dynamics) in which the time increment is chosen to be a fraction of the device (cell) time-constant.

Fast and compact analog electronic implementations of (8) and (9) may be used to compose the controller and crossbar circuit. The specific circuits would be the "leaky integrators," differentiators, and hardware convolvers that have been pivotal advancements in the area of neural hardware [12], [13].

B. Multivector Beamformer

The action of the MABF is pictorially represented in Fig. 3. During learning, memory formation is accomplished according to

$$W_i^{\text{new}} = W_i^{\text{old}} + \alpha\left(\vec{x}_i - \vec{c}_i\right) \Lambda \vec{d}_i \tag{10}$$

where W is the "weight plane," expressed as a bivector, of the ith processing element (PE) of a layer of PE's that receives a fanout of the inputs, α is the learning rate, $\vec{d}_{ik} = \vec{x}_k \cdot \overline{W_i^{\text{old}}}$ (the bar denotes normalization), $\vec{c}_{ik}$ is the projection of $\vec{x}_k$ onto W_i, normalized to unit length, and the symbol Λ denotes the wedge product [11]. For the case of temporal learning, the input vectors are formed from a tapped delay line.

III. NABF Application

A. Sonobuoy Deployment Test Case

The performance of the CABF was validated against composite sounds of a real sonar scene impinging upon a spatially complex array. The data were obtained from the Sonar Thinned Random Array Program (STRAP). Fig. 4 depicts the spatial arrangement of 11 sonobuoys that were dropped in the Atlantic Ocean. A known source was active at a distance of approximately 10 mi. It consisted of two frequencies, seven and eleven Hertz. Figs. 5 and 6 show spectral densities from various channels. Notice the inconsistency across the channels.

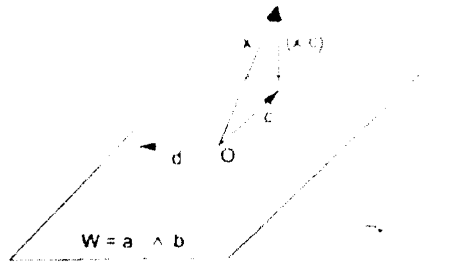

Fig. 3. Geometric representation of multivector beamformer

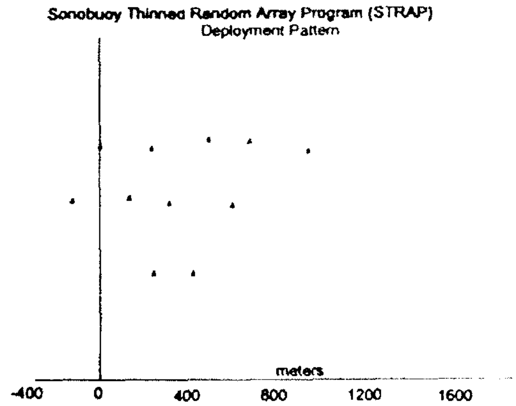

Fig. 4. The deployment pattern for the sonobuoys.

The temporal recordings made at these buoys were played into the beamformer. Fig. 7 shows the adapted sensitivity of the CABF as a function of time. The CABF is correctly attending the desired signal at approximately 41°. Though the beamformer's attention is occasionally distracted, these results are very good when you consider that no spectral preprocessing was performed, i.e., the desired signal was still mixed with the other interfering components at a level of approximately −20 dB with respect to some higher frequency components (Fig. 5).

Currently, more tests are being performed with interfering signals arriving at other directions. Fig. 8 shows what happens when an identical signal is simultaneously coming in at zero degrees and at approximately the same sound level. Notice how the attention of the beamformer flips alternately back and forth between 41° and 0° azimuth. This is not always undesirable but in some contexts it makes the simultaneous tracking of multiple sources of the same kind difficult.

B. Fast Computation via Digital Hardware

Two digital signal processing boards are currently being utilized to achieve real-time performance for combined wavelet processing (as in Aussel, 1989) and adaptive beamforming. These boards include analog input/output

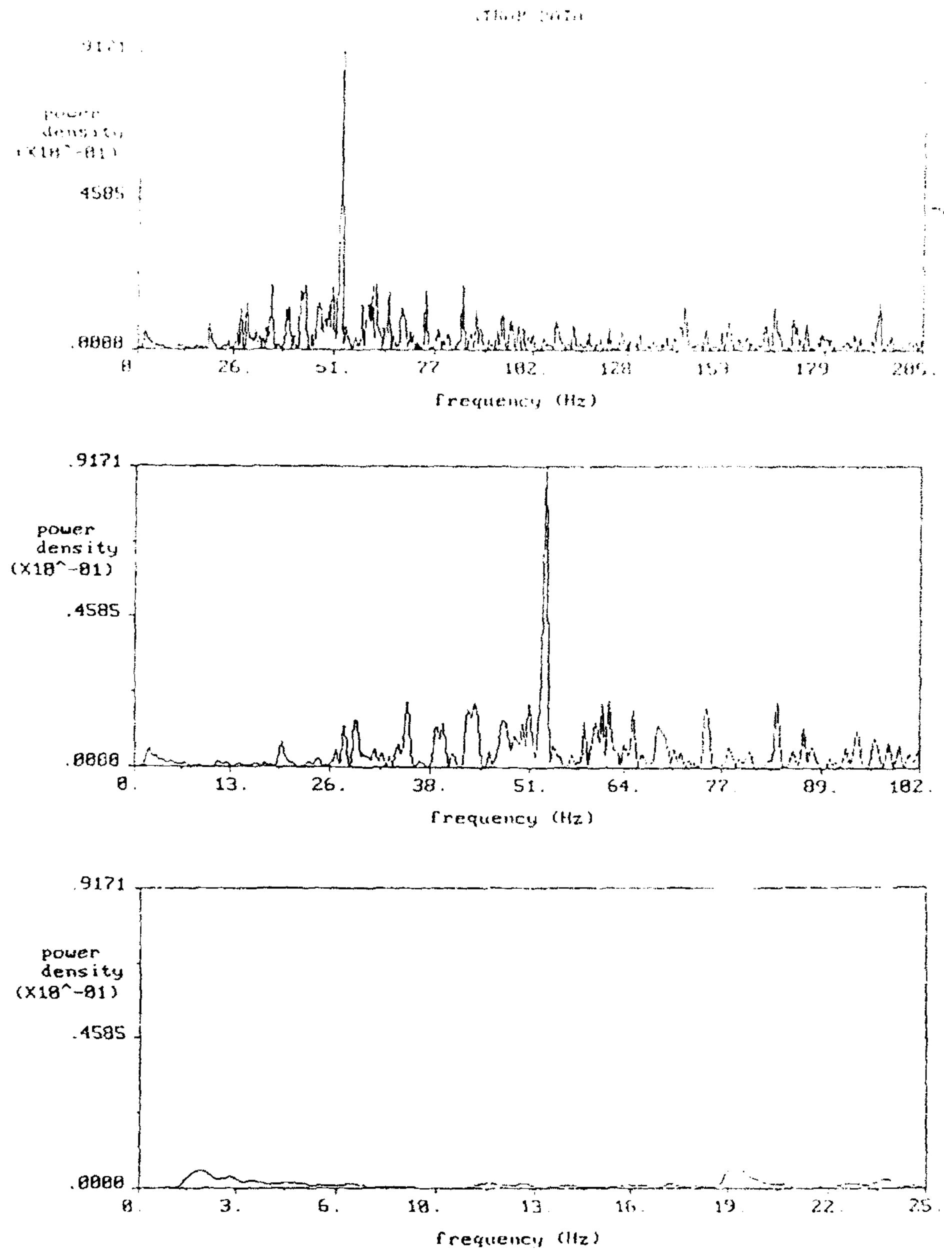

Fig. 5. Spectral density for the STRAP data set, channel 1. It is plotted on three different frequency scales.

daughter boards with built-in active filters. Each board gives two input channels with simultaneous sampling to 400 kHz at 12 bits resolution which is sufficient for sonar processing, and a floating point DSP with performance at 50 million floating-point operations per second (MFLOPS). With the two boards (100 MFLOPS performance) the processor operates in real time. The clocks of multiple boards are slaved together to give simultaneous sampling on all channels and communication busses between the boards allow true parallel processing.

In experiments using an array of microphones operated in a laboratory room, the CABF was able to locate a sound source while rejecting other interfering sounds in the laboratory. For these experiments, notes were played on musical instruments in a high noise background. Recognition in this case was pitch dependent. Future experiments will explore pitch-independent recognition of musical instruments.

IV. Population Coding and Decoding of Direction

In the case where a set of sensors have been deployed in a manner that results in unknown or inaccurately known positions, or when environmental conditions produce multiple propagation paths, special techniques are required for associating directions with array phase patterns. As a concept demonstration, a neural network was trained to associate direction sines with patterns of the phase of sensory excitation. Its performance was tested with both regularly spaced and randomly dithered arrays.

One advantage of using this technique is that when training a network the output direction values can be

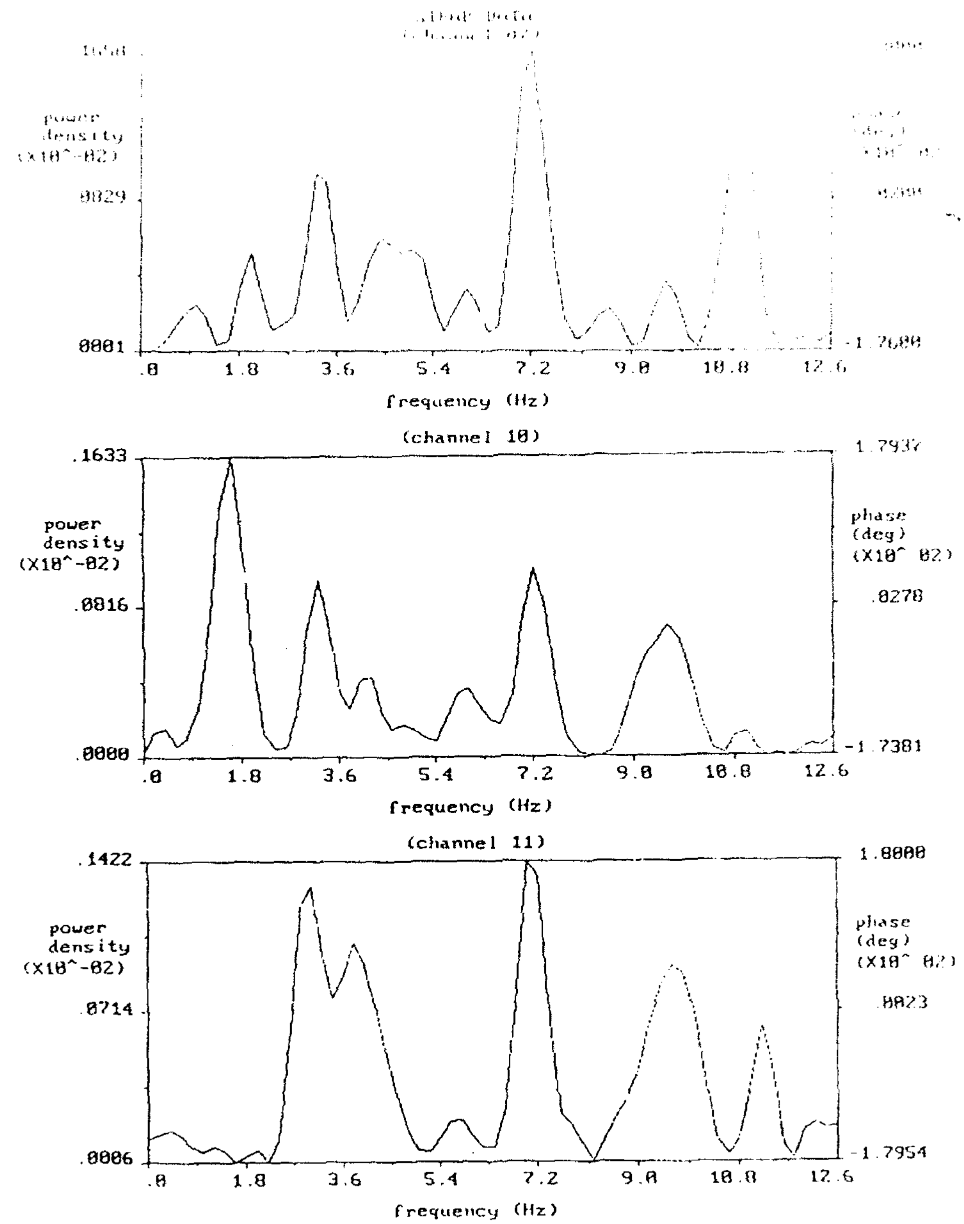

Fig. 6. Spectral densities for three different channels. Scale was expanded to accentuate the frequency region of interest.

referenced to a landmark or platform frame not necessarily associated with or related to the array geometry (although the array geometry will certainly affect the network's performance). Also, if direction to target is used for training, rather than direction of incidence, then the direction association network (DAN) forms a propagation model as it learns its associations. Compensation for near-field effects (non-planar wavefronts across the aperture of the array) can also be attained.

The patterns to be input to the DAN can be generated by an NABF weight generation process such as the CABF which, in this case, functions as an encoder of features of incoming signals. A useful neural computing cluster can thus be formed out of the CABF and a DAN. The cluster integrates the direction finding and adaptive beamforming functions (see Fig. 9). The azimuth and elevation may be output as direction sines/cosines. In the autonomous vehicles application, the output can be a control vector instead of the azimuth and elevation outputs shown.

A DAN that uses the backpropagation algorithm to learn to associate directions with beamformer weight patterns has been implemented and tested on a digital computer. It was found that a subnet can be trained to perform well at associating beam weights with directions even though the sensor positions are randomized and not known to the subnet.

The network consists of three layers. There are 18 processing elements in the first layer, four elements in the second layer, and one element in the output layer. The choice of the number of hidden units was made by doing exploratory runs with fewer and more units, compromising between performance gain and the computation load. The minimum number of hidden units was used, which was sufficient to give good performance on the training set.

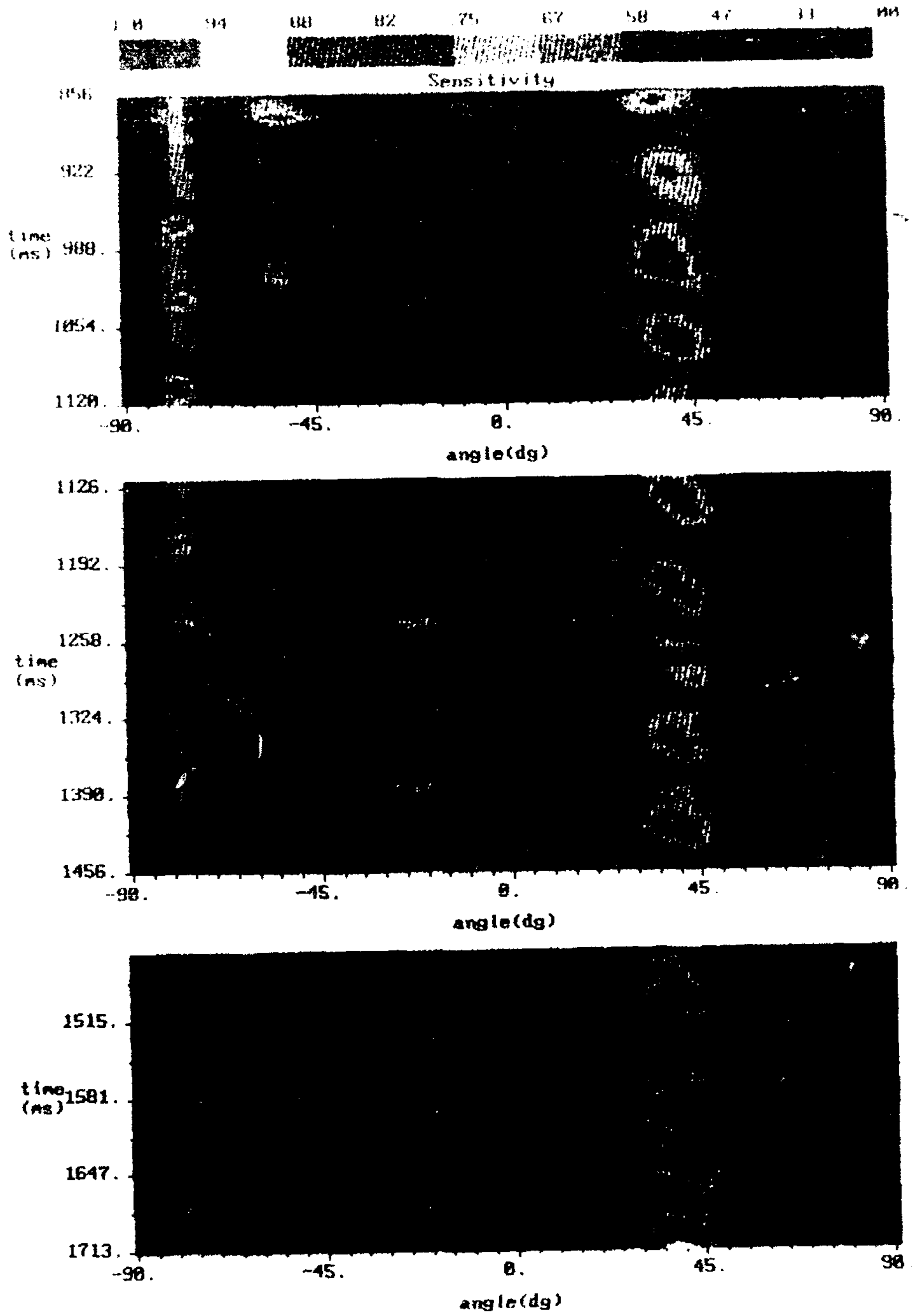

Fig. 7. Mapping of beamformer sensitivity as a function of time and angle for the STRAP data set. The desired signal is coming in at approximately 40° azimuth.

The network is given full layer to layer connectivity, i.e., every layer-2 element is connected to every layer-1 element and the single layer-3 element is connected to every layer-2 element.

Training inputs to the first layer are generated by simply computing beamforming weights (similar to what would be output by an RCN) for each angle of a set of test angles that span −90 to +90°. Resulting patterns are stored in a file, then they are fed to the network repeatedly during training with appropriate sines of the training angles presented simultaneously as output values for the network. The backpropagation training algorithm that was used closely follows the derivation by Rumelhart *et al.* [14].

Training and test data were synthesized for the following array geometries: 1) the training set is generated as if the sensor array is a regular-spaced, linear array with half wavelength spacing between the sensors, and 2) the training set was generated with the sensor positions dithered by amounts determined by a pseudorandom number generator and within a wavelength of nominal regular spacing as in case 1) (see Fig. 10). In both cases the training sets have entries every 5.0° while the test set used to generate the error plots has entries every 1.0°.

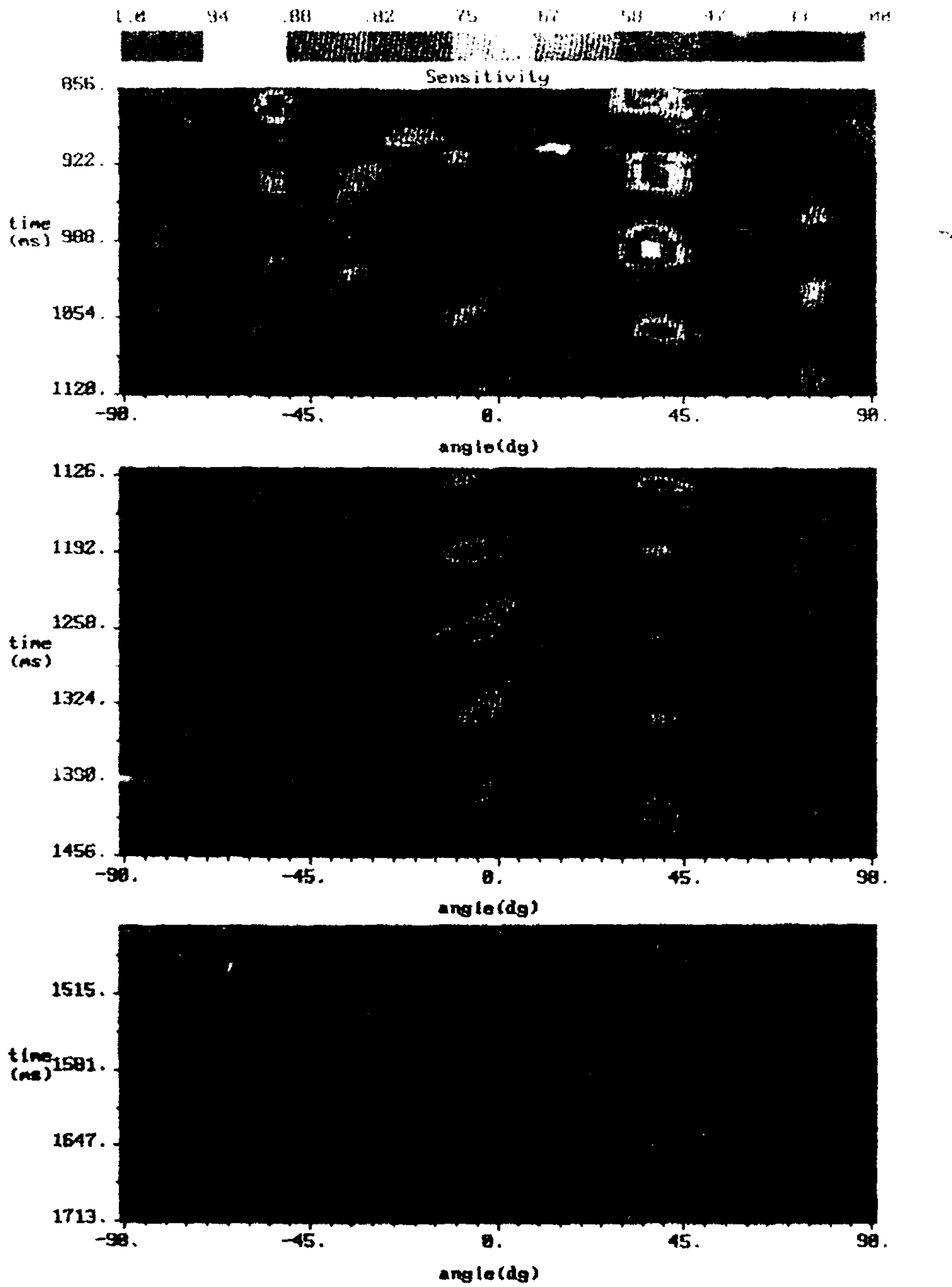

Fig. 8. Mapping of beamformer sensitivity for the STRAP data set with an interfering 7-Hz signal inserted at 0° incidence.

Fig. 11(a) and (b) show error summaries for the regular-spaced array and with 100 and 1000 training passes, respectively. Note that in the training beyond 100 passes the network continues to improve performance at the near end-on incidence angles to the detriment of performance at the array broadside angles. One way to alleviate this problem would be to leave the data for end-on angles out of the training for linear array geometries.

Fig. 12(a) and (b) are similar to Fig. 11(a) and (b) except that the training and test data are relevant to the randomly dithered array. The same overtraining effect is evident here as was discussed relative to the regular spaced array case. The array is a nearly linear array since the sensor locations were only dithered by plus or minus one half wavelength.

V. Cognitive Sensory Processing

A. Architectural Overview

A conceptual overview and some key elements of a comprehensive processing scheme are depicted in Figs. 13 and 14, respectively. The conceptual overview is a simplified representation that includes four principal functions: 1) the partitioning function, such as the partitioning done by the cochlea or retina or computational correlates of these, 2) the selection function, such as the adaptive

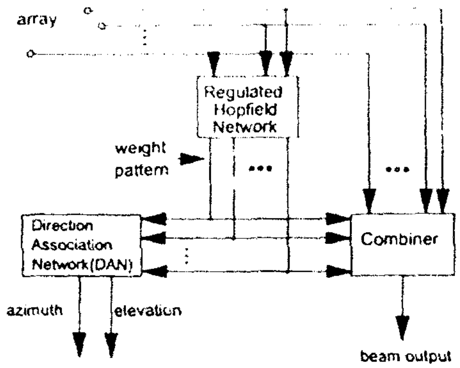

Fig. 9. Structure for simultaneous beamforming and interpretation of weights as a population coding of direction.

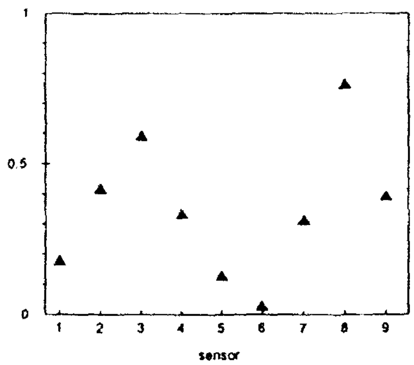

Fig. 10. Sensor positions for the dithered array (distances represented as fractions of a wavelength from nominal linear configuration).

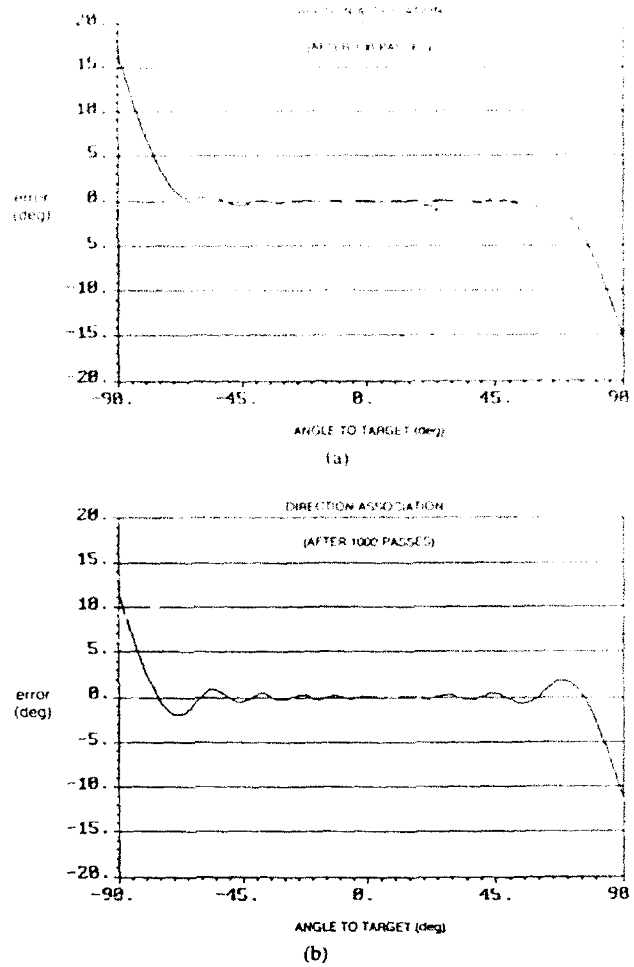

Fig. 11. The results of processing test data with the DAN after it has been trained. (a) The DAN was trained with 100 passes through the training set, and (b) the DAN was trained with 1000 passes. The DAN has four hidden units; the array is regularly spaced.

focussing provided by adaptive beamforming or filtering, 3) position and motion determination, and 4) recognition. In reality, these functions are not performed separately. They are provided by the interacting elements of the processing scheme.

The key elements of the processing scheme are: 1) multiple band filtering, 2) binaural correlation, 3) spatial attentional focussing, and 4) temporal attentional focussing/recognition. In practice, multiple-band filtering corresponding to the cochlear filtering indicated in Fig. 14 is performed using a scaled-wavelet formulation, providing a spread of bandwidths associated with the various best-frequencies [15]. It is recognized that this model cannot account for the sharpness of the cochlear response function near the best frequency [16].

Spatial mappings have been observed in the colliculus in some vertebrates [17], [18] and in cortical field AI of the cat. Intermediate between the cochlear processing and the bandwise spatial mapping (Fig. 14) is an adaptive spatial process (not depicted) provided by the NABF. The darkened areas represent those attended (emphasized) by the NABF. Thus the spatial layer acts as a sieve, passing attended stimulus partials.

The spatial mappings can be related to the beamformer sensitivity maps of Figs. 7 and 8 where a single row of the spatial map as a function of time is plotted contiguously down the page. These maps represent the activity of a layer of beamformers with relatively fixed directional preferences. What is the purpose of forming a topological organization of the beamformers? The topological mapping creates an organization by which the cells for the various auditory bands which respond to a given object in space are close together. This simplifies the projection of the output of the spatial neurons to the cortical area where recognition is accomplished. This organization is also beneficial in the digital signal processing application, though the units are not actually arranged spatially but are arranged by ordinal number instead.

Notice that a loop has been formed, because the output of the spatial map projects as input to the recognition area, the output of which was utilized in the formation of the spatial map. In the biological case, it is not clear whether this system constantly feeds back on itself or if there is an afferent wave of activity followed by an efferent wave or vice versa. In the case of the computational model, it can be done either way and perhaps an investigation of this will lead to some conclusions. It could be that the loop leads to oscillations in some circumstances. If it does, the relationship of the oscillations may be studied in light of recent observations [19].

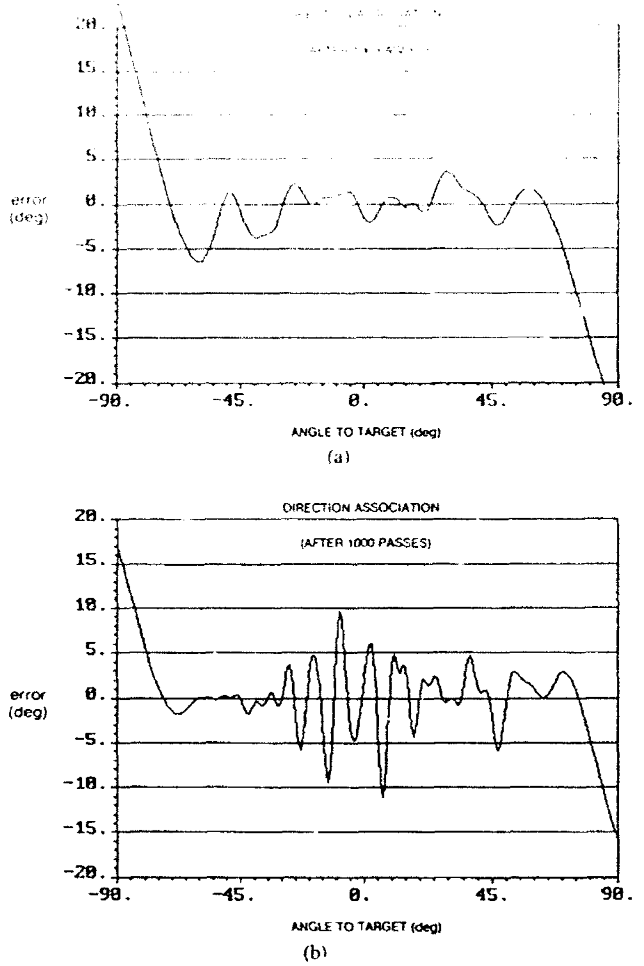

Fig. 12. Results of processing test data with the DAN after it has been trained. (a) The DAN was trained with 100 passes through the training set, and (b) the DAN was trained with 1000 passes. The DAN has four hidden units, and the array is randomly spaced.

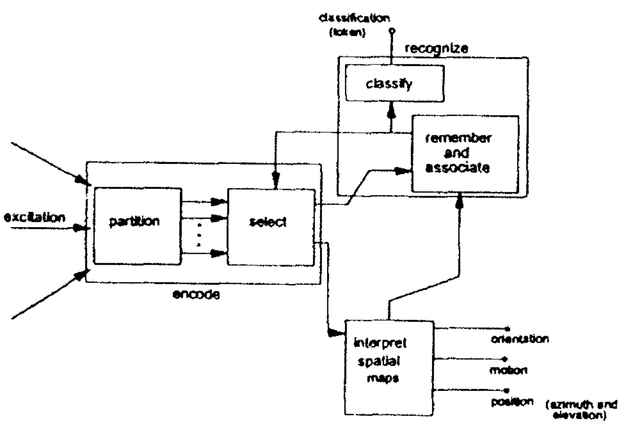

Fig. 13. Conceptual overview of the model for cognitive sensory processing.

In the computational model, the projections from the spatial map are input to a MABF process. The overall action of the recognition MABF is to segment and identify patterns of temporal activity across the auditory bands which are established in the cochlea. Each spatial stimulus segment is again segmented temporally according to memory by creating a time dependent sensitivity. The MABF attempts to create a stimulus partial which matches the temporal characteristics of each band, the total effect being to match the spectral content as a function of time, including relative phase variations, of an elicited memory using the spatially oriented spectral-band inputs as a basis. Recognition depends upon a combination of responses across the bands, i.e., the temporal qualities of all the individual frequency bands is being assessed simultaneously. Frequency modulation in the stimulus will appear as recognizable temporal variation in the bands. In the training mode, memories are established as a set of weightings.

The main function of the recognizer is to attend memory according to the stimulus. Only the temporally varying activities of the *attended* spatial segments elicit memories, because they are stronger. Initially, however, the system may not be attentionally focussed and the performance of the NABF on composite waveforms becomes important. In some cases, individual sounds may not be discerned without intervention of a thought process.

When a memory is elicited, a partial of the stimulus is produced through the action of the temporal beamformer, i.e., when a beamformer wins then the temporal vector associated with that memory is considered a partial of the stimulus (a significant one). This partial is fed back to the spatial mapping process, resulting in attention to or a focussing upon the spatial sector from where the partial came.

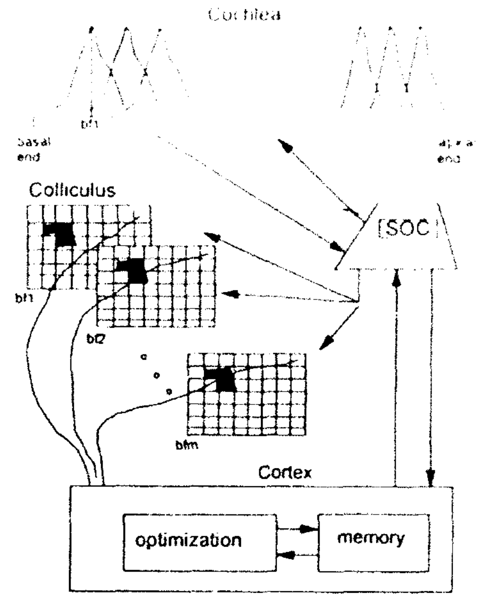

Fig. 14. Depiction of a comprehensive processor that includes cochlear partitioning, spatial maps, and associative memory.

B. Example

This comprehensive processing scheme is being built into the fast digital implementation that was discussed above. The needed capacity will soon be supplied by five central processing units (CPU's) operating simultaneously.

Currently, three CPU's are producing a wavelet filter bank as a simple cochlea model and are also producing the spatial maps for a small number of bands when running with two microphones. In real-time demonstrations single-band spatial maps are displayed as a function of time.

The final operation of this system will proceed as follows: the analog input boards sample the sensor excitations simultaneously and pass the data to the DSP boards where delays, Hilbert transforms, and wavelet bandpass filters are applied by use of digital filtering techniques. Initially, the adaptive selection processes are in a state as if no stimulus of interest is present, therefore there is no focussing. When a stimulus of interest appears, it will ellicit the generation of a nearest match exemplar from associative memory, the exemplar will be fed to the adaptive process and focussing will occur. The exemplar may change during the course of focussing. Of course, the associative memory will continually be providing exemplars even when no stimulus of interest is present, but there will be no significant focussing.

In the first implementation of this simulated auditory process, there was no associative memory of exemplars. Task relevant exemplars were made available in a sequential manner from a stored set of digitized exemplars. This may be appropriate for a device which performs a single task (like tracking any object that is a member of a set of task-relevant objects that are relatively distinct from one another).

References

[1] S. A. Hillyard, G. R. Mangun, S. J. Luck, and H. Heinze, "Electrophysiology of visual attention," *ONR Rep.*, program element 61153N 42, project RR04209, 1989.

[2] A. S. Bregman, *Auditory Scene Analysis*. London, England: MIT Press, 1990.

[3] J. O. Pickles, *An Introduction to the Physiology of Hearing*. New York: Academic Press, 2nd ed., 1988.

[4] N. Suga, "Cortical computational maps for auditory imaging," *Neural Networks*, vol. 3, pp. 3–21, 1990.

[5] S. L. Speidel, "Neurobeamformer," *JUA*, vol. 39, pp. 127–155, Apr. 1989.

[6] ——, "Neurobeamformer II: Further exploration of adaptive beamforming via neural networks," Naval Ocean Systems Center, *Tech. Document 1606*, 1989.

[7] ——, "Neural target locator," Naval Ocean Systems Center, *Tech. Document TD1914*, 1990.

[8] ——, "Sonar scene analysis using neurobionic sound segregation," in *Proc. IEEE Conf. Neural Networks for Ocean Engineering*, 1991.

[9] B. Widrow and S. Stearns, *Adaptive Signal Processing*. Englewood Cliffs, NJ: Prentice Hall, 1985.

[10] J. J. Hopfield and D. W. Tank, "'Neural' computation of decisions in optimization problems," *Biol. Cybern.*, vol. 52, pp. 141–152, 1985.

[11] D. Hestenes and G. Sobczyk, *Clifford Algebra to Geometric Calculus: a Unified Language for Mathematics and Physics*. Boston, MA: Dordrecht, 1984.

[12] C. Mead, *Analog VLSI and Neural Systems*. Reading, MA: Addison-Wesley, ch. 9 and 10, 1989.

[13] J. L. Wyatt and D. L. Standley, "Criterea for robust stability in a class of lateral inhibition networks coupled through resistive grids," *Neural Computation*, vol. 1, pp. 58–67, 1989.

[14] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning internal representations by error propagation," in *Parallel Distributed Processing*, vol. 1, D. E. Rumelhart, J. L. McClelland, and the PDP Res. Group, Eds., ch. 8, pp. 322–328, 1986.

[15] J. D. Aussel, "Split spectrum processing with finite impulse response filters of constant frequency-to-bandwidth ratio," *Ultrasonics*, vol. 28, pp. 229–240, 1989.

[16] E. Zwicker and W. Peisl, "Cochlear preprocessing in analog models, in digital models and in human inner ear," *Hear Res.*, vol. 44, pp. 209–216, 1990.

[17] A. R. Palmer and A. J. King, "The representation of auditory space in the mammalian superior colliculus," *Nature*, vol. 299, pp. 248–249, 1982.

[18] R. B. Masterton and T. J. Imig, "Neural mechanisms for sound localization," *Ann. Rev. Physiol.*, vol. 46, pp. 275–287, 1984.

[19] C. M. Gray and W. Singer, "Stimulus-specific neuronal oscillations in orientation columns of cat visual cortex," *Proc. Nat. Acad. Sci. USA*, vol. 86, pp. 1698–1702, 1989.

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