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Sensory Discrimination in a Short-Term Trace Memory

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Abstract

We propose a fully recurrent neural network to model low-level auditory memory in a task to discriminate intensities of sequentially presented tones across a range of varying interstimulus intervals. In this model, memory represents a *sensory-trace* of the stimulus and takes the form of slow relaxation of a number of units to a globally attractive equilibrium value near zero. The same-different judgment is based on a derivative of the output of the dynamic memory. Gaussian noise added to unit activations was found to improve the resilience of stored information although at the cost of decreased sensitivity. The model exhibits many qualitative properties of human performance on a roving-standard intensity discrimination task.

Introduction: Memory and Comparison

A critical step in the development of a model of auditory processing is the ability to discriminate input stimuli: the capacity to make same-different judgments about simple properties of a pair of stimuli. Since sequential presentation is unavoidable for auditory processing models, some form of memory for the first stimulus is required while the second is presented and a comparison made. If this task is approached from an engineering perspective, the problem is easily solved with a buffer which stores the first item perfectly (for all practical purposes) until the second item is available (Port, 1990). However, as we will show below, there is evidence against storage of the raw stimulus.

The process of serial comparison in relation to the underlying memory mechanism is an important issue. In traditional discrimination procedures, where the intensity level of the standard (or reference) stimulus, I, is held constant across trials and only the ΔI component of the comparison stimulus, $(I + \Delta I)$, changes from trial to trial, the duration of the interstimulus interval is found to have little or no effect. For example, in a single block of trials, a subject might be asked to discriminate between 50 dB and 50 $+\Delta I$ dB. Only a small increase in the Weber ratio is found when the two stimuli are separated by as much as 24 hours (Pollack, 1955). However, if a between-trial roving discrimination task is used, it is found that increasing ISI *does* reduce performance (Berliner & Durlach, 1973) [1].

To explain why roving the level of the standard between trials has such an effect, Durlach and Braida (1969) proposed two modes of memory processing for intensity discrimination: *sensory-trace coding* and *context-coding*. When using *context* mode, subjects are believed to base discrimination on some form of categorical description of the standard stimulus level. Such categorical descriptions are known to be very resistant to changes in ISI. Most studies of same-different comparison in cognitive science are implicitly models of *context-coded*, or categorical, representations—codes that are well-learned and highly resistant to temporal decay (e.g., Liberman et al., 1967; Gasser and Smith, 1991). Since in a roving-level discrimination task, intensity varies randomly, subjects cannot learn to use a categorical representation and must instead rely upon an ephemeral *sensory trace* of the stimulus. Thus, their performance deteriorates with increasing ISI.

The research reported here is an attempt to model the *sensory-trace* processing mode for intensity resolution. We believe that such work is an essential first step in the development of a biologically plausible general model of auditory pattern (category) recognition. Our goal was to construct a system that exhibits the general properties of human performance in roving level discrimination tasks. The evidence from human subjects experiments suggests that this requires performing auditory discrimination without using a special comparison buffer (and the specialized buffer-transfer operations that are implied). Instead, our system measures input signal intensity and then stores that value for the first stimulus while decaying slowly

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[1] In a roving discrimination task, ΔI is fixed and I varies between trials. For example, the subject might be asked to discriminate between 50 and 52 on one trial and between 40 and 42 dB on the next trial.

toward the equilibrium of the system (located near 0 intensity). When the second stimulus arrives, it re-excites the system to a value corresponding to the intensity of the second stimulus. A differentiation module computes a criterion variable based on information available just after the onset of the second stimulus.

A Model of Memory and Discrimination

The model presented here for intensity discrimination (see Figure 1) consists of two components: (1) a model of auditory short-term memory adapted from a model proposed by (Zipser, 1991) for cortical neurons that incorporates random output fluctuations; and (2) a decision model that generates a criterion variable used to decide when two stimuli differ based on the local change in the output of the memory module.

Memory Model. The memory model consists of 2 linear input units and 9 fully connected logistic units representing auditory short-term memory (STM), as shown in Figure 1. The inputs have connections to all STM nodes. The input units are a binary cue input and a real-valued stimulus representing intensity in the range $[0, 1]$. It is known that the rate of neural firing is an important cue for perceived loudness (Moore, 1989) and this corresponds to the activation level of individual units in this model. One of the STM units is the Output unit for the dynamic memory—the only unit trained directly during the learning phase of the simulations. All of the memory units have the activation function

$$y_i(t+1) = \phi(\sum_j w_{ji} y_j(t) + w_{si} x_s + w_{ci} x_c + \theta_i) + X_i(t)$$

where $\phi(x) = (1 + e^{-x})^{-1}$; the cue and stimulus inputs and weights are subscripted with c and s, respectively. X is a random variable drawn, on each time step for each unit, from a Gaussian distribution with mean and standard deviation μ and σ. The random variable X was included during testing trials to simulate random neural excitation of unit activations (Zipser, 1991). It was not included during training. In all of the simulations discussed in this paper, the biases θ_i were fixed at negative values in the range $[-1.0, -2.5]$, as in (Zipser, 1991), to avoid spontaneous unit activity. Also, the dynamics of $\phi(x)$ are only interesting when the biases are negative (McAuley, 1992).

Decision Model. The decision model implements a form of comparison without using buffers. The model consists of a set of several time-delayed connections from the output unit of short-term memory to the response unit. The weights on the connections between the two units are pre-wired and were not adjusted during training. The links effectively implement a low-pass filter that approximates the scaled derivative of the output unit's activation over 5 time steps. We anticipated that if short-term memory is effective in retaining past input values, then a following stimulus will perturb the memory model to the extent it differs from the initial input value. Of course, perfect memory is impeded by the imperfect initial encoding of the sensory stimulus, the internal noise of the trace memory, and the relaxation ("forgetting") of trace memory over time.

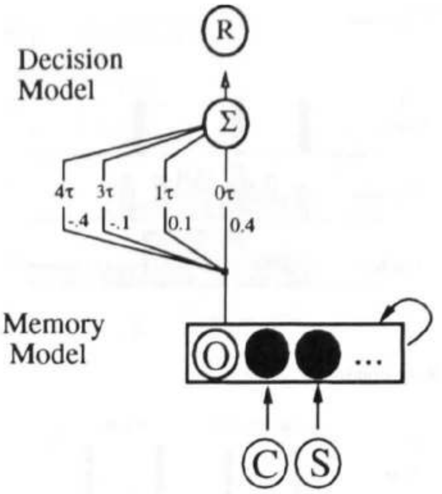

Figure 1: Network architecture. The cue (C) and stimulus (S) input units are shown below. Each unit connects to all units in the recurrent layer. The units of the memory module are fully interconnected and all weights are learned. The response unit R is connected to the output unit O via a set of weighted time-delay connections. The values of the time delays are shown on each connection along with the corresponding weights.

Training the Memory Model. The training task, shown in panel A of Figure 2, was to store in short-term memory a cued intensity value for an unspecified duration. During a training sequence, the network was presented with a cue input of 1.0 plus a random stimulus input from the interval $[0, 1]$. The cue may be thought of as representing a signal from some other part of the nervous system indicating that the value of the simultaneous external stimulus should be remembered. The network was trained to autoassociate the current stimulus input for a random number of time steps. For each trial the number of time-steps was drawn from a uniform distribution from 2 to 12. Following the initial stimulus and cue pair, up until the next stimulus and cue pair, the cue unit was set to 0.0 and the stimulus unit varied randomly within the range $[0, 1]$.

The network was trained using the real-time recurrent learning algorithm (Williams & Zipser, 1989) to update weights. All forward weights between the input and recurrent layers and all weights within the recurrent layer were modified during training. Training lasted for 400,000 iterations or

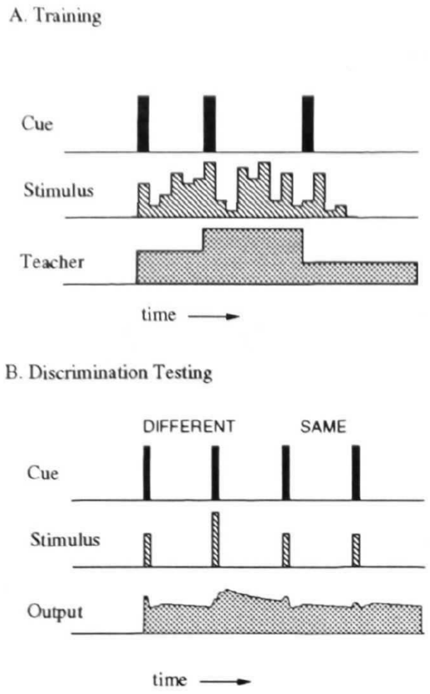

Figure 2: **A.** Cue, stimulus, and teacher values for a hypothetical training sequence. **B.** Actual testing data from a Different followed by a Same trial. The first two stimuli presented are Different (0.6 followed by 1.0). The next two stimuli are the Same (0.6 and 0.6). Note that all input values decay over time and are momentarily affected by introduction of the cue signal.

approximately 60,000 training trials. Final mean squared error approached 0.01 on the network examined below.

The training task is fairly difficult to learn because the stored input is real-valued and because the interstimulus interval varies between trials. The network has finite capacity, and cannot resolve all the possible real-valued inputs on the unit interval. The randomly varying ISI prevents anticipation of the time of occurrence of the next stimulus.

Simulations

Memory Dynamics. The basis for memory in this model is its very slow relaxation to equilibrium following presentation of the stimulus. The qualitative dynamics of the trained model were explored by setting the cue and stimulus units to 0.0, randomizing the initial activations, and then letting the network run for the 50 randomly chosen initial conditions. Graphs of the results of these tests are shown in Figure 3. All graphs show only one dimension of trace memory, the Output unit (with the range $[0, 1]$) for 50 time steps. Similarities were observed between hidden unit activity and single unit recordings in the auditory cortex of monkeys performing a memory task, as described in (Zipser, 1991). Panel A of Figure 3 shows that memory decay to equilibrium is very slow. For most initial conditions, decay is approximately linear. Even though during training, the network stored stimuli for at most 12 iterations, for some ('high intensity') initial conditions the network is still relatively far away from its asymptote after 50 iterations.

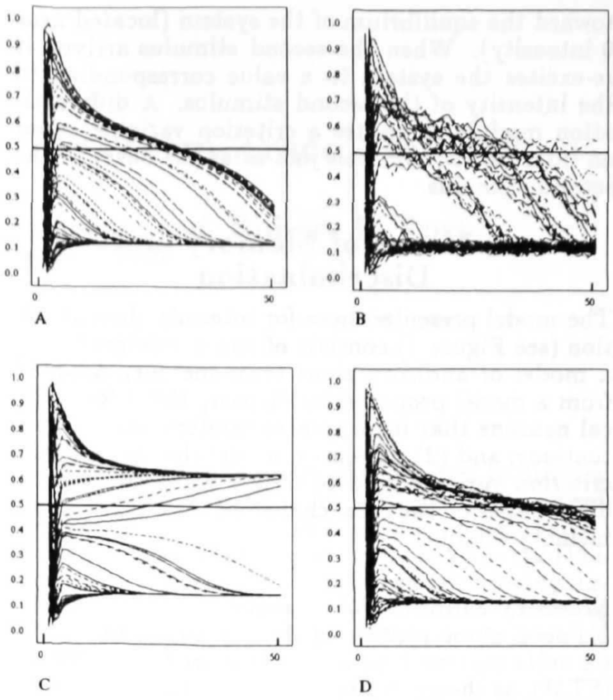

Figure 3: Qualitative dynamics of the model. Each plot shows the activation of the Output node in the range $[0, 1]$ for 50 time steps from 50 random initial conditions. **A.** without noise. **B.** with Gaussian noise, $\mu = 0$, $\sigma = 0.01$, the maximum amount of noise. **C.** with Gaussian noise, $\mu = 0.01$, $\sigma = 0.0$. **D.** with Gaussian noise, $\mu = 0.0025$, $\sigma = 0.005$

The effect of noise was also explored by adding a Gaussian distributed random variable to the output of each unit on each time step. The variance of this distribution is an important parameter in determining the qualitative dynamics. Panels B and D of Figure 3 represent standard deviations of 0.01 and .005, respectively. Compare the activation levels in these panels at iteration 50 with panel A. Increasing the noise variance slows memory decay, but, as we show below, this results in degraded resolution of the original stimulus intensity. Possibly then, optimal performance is a compromise between sensitivity (improved by less noise) and memory (improved by greater noise variance). Panel D would be a candidate for such a compromise. Panel C shows that the addition of a sufficient amount of 0-variance noise (equivalent to the addition of a sufficiently large constant) creates a second equilibrium point in the system. This suggests that the system achieves a longer memory span (as in Panel B and D) by operating near a bifurcation point.

Because the rate at which the network approaches equilibrium is, at high and low activations, proportional to its overall level of activity, one might suspect that intensity discrimination is better at lower activations, in accordance with Weber's Law ($\Delta I/I = k$). While this is somewhat true for the network, the midrange of the output unit has a rather linear decay, and we found that Weber's law does not hold very well throughout the range of intensities encoded by the memory units of this model.

Memory Span vs Resolution in Intensity Discrimination. Network memory was evaluated using a same-different between-trial roving discrimination task. Panel B of Figure 2 shows two sample trials, one Different and one Same. I varied between 0.1 and 0.9 *between* trials, while ΔI and the interstimulus interval (ISI), measured in discrete time steps, remained fixed. Testing blocks consisted of 1800 trials. Blocks were run for all combinations of ΔI in the set $\{0.02, 0.04, 0.06, 0.08, 0.1\}$ and ISI in the set $\{3, 7, 9, 11, 15, 19, 29\}$ of time steps. The model's performance on a block of trials was measured by computing hit and false alarm rates for a range of response thresholds applied to the response unit. d' was found to be roughly constant, excluding edge effects, indicating that the response unit approximately obeys the assumptions of signal detection theory (Swets, 1961). The graph in Figure 4 depicts the ΔI required to achieve performance of $d' = 1$ (implying 71% correct with no response bias) as a function of ISI. Four different noise conditions are plotted corresponding to fixed $\mu = 0.0025$ and σ between 0 and 0.01. All four plots show results consistent with human performance on a roving level discrimination task; stimulus sensitivity degrades with increasing ISI. The rate at which sensitivity decreases is inversely related to the amount of noise variance. For large variances (shown with the filled circles in Figure 4), sensitivity is lost for shorter ISIs (where the change in intensity at threshold is .10) yet there is little degradation with increasing ISI. On the other hand, with no noise (shown in the open triangles), an intensity difference of only .04 can be resolved at short ISIs yet performance at longer ISIs is *worse* than the noisier conditions.

In the context of the underlying dynamics shown in Figure 3, these results can be explained. A relatively large internal noise variance can slow memory decay to equilibrium and consequently slow loss of resolution over time. In this model, there is a trade-off between memory and resolution. Memory is improved at the cost of resolving power and improved resolution sacrifices memory performance. Optimal discrimination in a task in which ISI varies within trials might be best achieved by a noise condition which produces a weighted balance between memory span and resolving power.

Discussion

These simulations bear on at least two issues: the nature of human memory for intensity of sensory stimulation, and the role of noise in facilitating the memory function of a dynamic system.

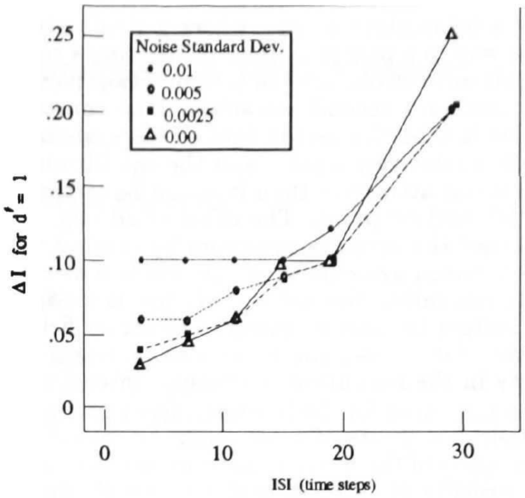

Figure 4: ΔI required for d' of 1 (or maximum percent correct discrimination of 71%) as a function of interstimulus interval. Each line represents a condition with neural noise added, having a mean of ($\mu = 0.0025$) and standard deviation as specified in the legend. The filled circles have the most noise variance and the open triangle has the least variance

Comparison with Human Sensory Memory. We have attempted to model certain properties of human performance on auditory discrimination tasks. Although we only modelled performance for a single tone, our model can easily be extended by creating a bank of identical modules, covering the entire auditory spectrum. The results of these simulations exhibit some critical properties of human performance on analogous roving-standard discrimination tasks. Our model is able to store the intensity of a stimulus for a short while and exhibits decay with accompanying loss of performance. The critical effect of interstimulus interval on our model's performance is analogous to results with human subjects found by Berliner and Durlach (1973).

One aspect of the current model that seems incorrect is that it confounds decay with intensity—inputs stored longer evolve in state-space through representations of less intense inputs, since the fixed point of the system lies near 0 intensity. A more appropriate consequence of decay would seem to be greater uncertainty about intensity—rather than weaker perceived intensity. This may be achievable within our current model by using several trace memory modules with equilibria at different locations in activation space. A stimulus would decay towards lower intensities in some modules, but to higher intensities in others. The mean activity, or population code, of the modules would then represent the stimulus trace, with variance representing the level of stimulus uncertainty.

The Role of Noise in Trace Memory. In our model, a dynamic system has learned to function near a bifurcation point—where a single attractor gives way to a pair of attractors. Adding a constant to unit activations acts as a bifurcation parameter and creates a second attractor. One consequence of this is that the vector field of the system state-space is relatively weak—and the equilibrium near zero is less attractive than it would be farther from the bifurcation point. The effect of adding noise is to 'tease' the memory dynamics by causing vacillation between systems with one and two attractors. Thus relaxation toward equilibrium is slowed and the system behaves as though the vector field were flatter. Of course, the noise also increases uncertainty in the resolution of stimulus intensity.

As suggested for the intensity decay problem, the undesirable effects of noise might be minimized by replication of the memory module, while preserving the benefits (improved performance at long ISI). For example, if several independent modules were used to store the intensity of a single frequency band, their mean would provide a much better estimate of the original intensity than a single module could. It is interesting to hypothesize that the well-documented noisy behavior of real neural systems functions in part to improve memory span in a way similar to that of our model, by slowing relaxation to equilibrium.

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