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This paper describes a novel network architecture developed to classify multiple successive echoes from targets ensonified by a dolphin echolocating in a naturalistic environment. The inputs to the network were spectral vectors of the echo plus one unit representing the start of each scan. This network combined information from successive echoes from the same target and reset between scans of different targets. The network was trained on a small subset (4%) of the total set of available echoes (1,335). Depending on the measure used to assess it, the network correctly classified between 90% and 93% of all echo trains. In contrast, a standard backpropagation network with the same number of units and variable connections performed with only about 63% accuracy in classifying echo trains. The integration model seems to provide a better account of the dolphin's performance than a decision model that does not combine information from multiple echoes.

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Recognizing Successive Dolphin Echoes with an Integrator Gateway Network

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Abstract

A novel network architecture was developed to classify multiple successive echoes from targets ensonified by a dolphin echolocating in a naturalistic environment. The inputs to the network were spectral vectors of the echo plus one unit representing the start of each scan. This network combined information from successive echoes from the same target and reset between scans of different targets. The network was trained on a small subset (4%) of the total set of available echoes (1,335). Depending on the measure used to assess it, the network correctly classified between 90% and 93% of all echo trains. In contrast, a standard backpropagation network with the same number of units and variable connections performed with only about 63% accuracy in classifying echo trains. The integration model seems to provide a better account of the dolphin's performance than a decision model that does not combine information from multiple echoes.

Introduction

Bottlenose dolphins (*tursiops truncatus*) possess a unique biological sonar which is highly adapted to their aquatic environment (Moore et al, 1990). Using this sonar the dolphin can readily identify many characteristics of submerged objects by sending out broad-band high frequency clicks and processing the returning echoes (see Nachtigall, 1980, for a review).

The specific processes by which the dolphin extracts acoustic information about the targets is unknown and particularly interesting questions concern how the animal performs feature extraction from a set of returning echoes (Nachtigall & Moore, 1988)

Behavioral methods

Our subject is a highly experienced male bottlenose dolphin, housed in a floating enclosure in Kaneohe Bay at the Hawaii Laboratory of the The NavalCommand, Control and Ocean Surveillance Center (RDT&E Division). During the echolocation tests the animals' eyes are covered with soft removable eyecups that occlude its vision. Echolocation data were recorded while the animal was performing a delayed matching-to-sample (DMTS) object recognition task.

In this task, the dolphin must select from a set of three alternatives the one target that is the same as (matches) a previously presented sample target. The identity and location of the targets vary randomly from trial to trial, so performance on this task requires the animal to recognize the sample, remember its identity, and to recognize the matching target. To perform this task the dolphin stationed under water in the center of an observing aperture, located directly in front of the sample target array. Three sets of comparison targets were suspended in front of the animal from a bar located 4.3 m from the underwater aperture. Echolocation clicks were detected by B&K 8103 hydrophones located 2 m from the observing aperture between the aperture and the targets. Echoes from the targets were recorded using a custom-built hydrophone with a flat response up to 200 kHz. Recordings were made using a RACAL store-4 tape recorder, with a 300 kHz dynamic range, from which clicks and echoes were digitized at 1 MHz. Figure 1 is a schematic of the testing configuration.

The present study used three targets. (a) a PVC plastic tube open at both ends (15 cm long, 7.5 cm diameter, 30 mm wall thickness), (b) a water-filled stainless steel sphere (5 cm diameter), and (c) a solid aluminum cone (10 cm diameter base, 10 cm height), each presented approximately 100 cm below the water's surface. Four examples of each target were used, one as sample, and the other three as alternative comparison targets. Each trial began with the dolphin stationed in the observing aperture with the acoustic screen closed. One of the sample targets was then lowered into the

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water, the screen was lowered, and the dolphin was

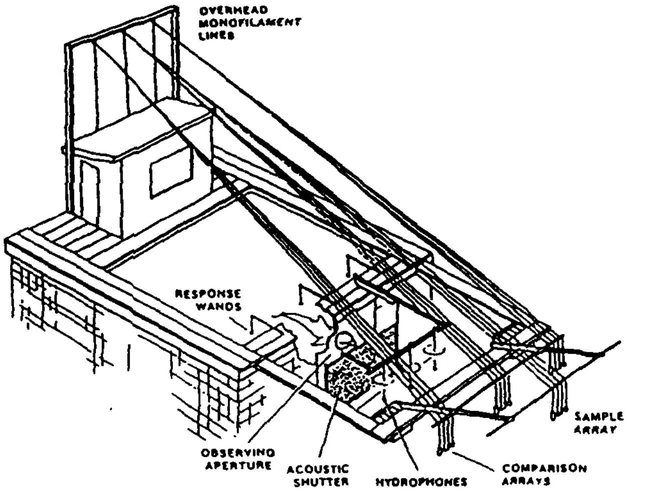

Figure 1. A schematic of the test-pen. The animal is shown stationed facing the acoustic screen, measuring hydrophones and the comparison and the sample target arrays. The hydrophone used to collect the echoes from the targets was placed on the right side of the animal.

allowed to echolocate ad lib. The acoustic screen was then raised, the sample was removed from the water and three alternative targets were then presented. The screen was then again lowered and the dolphin was allowed to echolocate on the comparison targets. The animal indicated his choice by contacting a small ball on the end of a response wand at the water surface, and directly in front of each comparison target array. The dolphin's choice accuracy averaged nearly 95% correct.

Echo analysis using a counterpropagation network

A selected sample of echoes collected from this experiment was submitted to a counterpropagation network (Hecht-Nielsen, 1987, 1988; see also Grossberg, 1976) trained to classify a subset of these echoes into categories corresponding to each of the stimuli (see Roitblat, Moore, Nachtigall, Penner, & Au, 1989; for a description of this work). This network learned to classify the spectral information from the echoes with considerable accuracy above 95% correct (including novel exemplars). Although the network could identify the target with only a single echo, the dolphin concurrently performing the same task emitted many more clicks in identifying the same targets. We also noticed that the dolphin was more variable in terms of the number of clicks and the number of scans used to identify the correct match than was predicted by a sequential sampling model of his performance (Roitblat, et al., 1990).

The sequential sampling model assumed that the echoes were drawn from a stationary distribution, which may have been an inappropriate assumption in light of the variability in the dolphin's click production. Because of the sampling procedure (echoes were selected largely on the basis of their intensity), the echoes submitted to the neural network may not have been typical of the population of echoes the dolphin actually used. This possibility could have led to an overestimate of the ability of the models to recognize targets on the basis of dolphin echolocation returns.

In response to these considerations we extended our analysis to include every echo available to the dolphin. In contrast to our previous studies concerning the classification of echoes, in which echoes were selected for inclusion if they were sufficiently intense, in the present study we captured the echo resulting from every click the animal emitted in the sampled trials.

The integrator gateway network

A new network architecture was developed in order to model the dolphin's extraction of information from trains of echoes. The model incorporates the assumption that the dolphin averages or sums spectral information from successive echoes and continues to emit clicks and collect returning echoes until it can classify the target producing those echoes with sufficient confidence. The inputs to this network were patterns of spectral intensity (i.e., amplitude in each frequency band). The outputs of the network were stimulus classes. One output corresponded to each stimulus class, sphere, cone, and tube. The resulting activations of each of these output classes were taken to be an estimate of the likelihood that the echo resulted from the particular stimulus type (Qian & Sejnowski, 1988). Figure 2 shows the overall structure of the Integrator Gateway Network.

Inputs to the network consisted of 30 bins of relative amplitude spectral information, 3.91 kHz per bin, ranging from 31.25 kHz to 146.5 kHz. Each echo was also marked as to whether the echo was (1.00) or was not (0.00) at the start of an echo train. The first input to the network contained the start-of-train marker, the remaining elements contained the amplitude of a specified frequency range. The frequency inputs were then passed to a scaler unit and to the integrator layer.

The integrator layer (grey circles) also contained 30 units, connected to the frequency units in the input layer in a corresponding one-to-one pattern. The connection weights from the inputs to the integrator layer were fixed at 1.00. The connections to the scaler unit were fixed at 1/n, where n is the number of frequency inputs (i.e., 30).

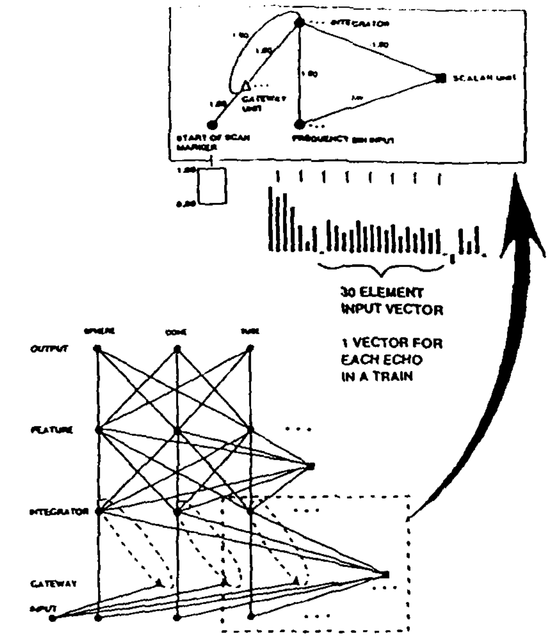

Figure 2. A schematic of the Integrator Gateway Network. The bottom part of the figure shows one echo in the form of relative amplitude and a start-of-scan marker. Elipses indicate that the full network contains additional units of the same type.

The output of the scaler unit, which was simply the sum of all of its inputs, was passed to each of the units in the integrator layer via a fixed weight of -1.00. The effect of this scaler unit was to subtract the average activity of the input layer (neglecting the start-of-train marker) from the inputs to the integrator layer.

The elements in the integrator layer computed a cumulative (running) sum of the inputs they received. One echo was presented per time step. The activation of each unit in the integrator layer was the sum of the activation it had during the previous time step, plus the activation it received from the scaler unit, plus the activation it received from its respective input, plus the activation of its corresponding gateway unit. The role of the integrator layer was to accumulate and integrate information from successive echoes. The outputs of the integrator layer were passed back via fixed connections with 1.00 weights to corresponding units in the gateway layer (open triangles). Each unit in the gateway layer acted as a reset for the corresponding unit in the integrator layer.

The connection between each gateway unit and its corresponding integrator unit was fixed at -1.00. The output of the gateway unit was the product of the output of its corresponding integrator unit and the start-of-scan marker. The activation from the gateway unit received by the integrator unit consisted of the product of the connection weight (-1.00), the activation of the start-of-scan marker, and the activation during the previous time step of the corresponding unit in the integrator layer. Because the marker had 1.00 activity at the start of a click train and 0.00 activity otherwise, this marker allowed the gateway unit to function as a reset signal, causing the units in the integrator layer to be reset to 0.0 at the start of every scan.

During each time step, the output of the integrator layer also led via variable-weight connections to each of the elements in the feature layer. The outputs of the elements in the Feature Layer then led via variable-weight connections to the output or classification layer. The elements in these two layers contained sigmoid transfer functions and were trained using a standard cumulative backpropagation algorithm (McClelland & Rumelhart, 1988; Rumelhart, Hinton, & Williams, 1986) with the epoch size set to the number of training samples (60).

The network was trained with six sets of ten successive echoes selected from the ends of haphazardly chosen echo trains. Two sets of echoes were chosen for each stimulus in the set. The network was trained with declining learning-rate parameters. The network converged to a criterion RMS output error of 0.05 after 12,300 iterations.

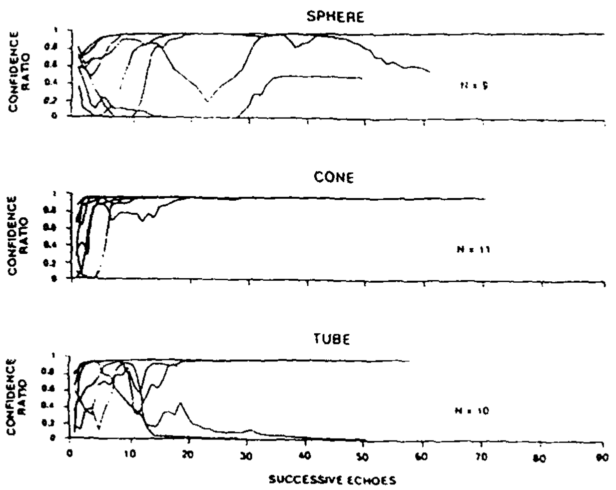

Figure 3. Results of generalization testing of the network in the form of the confidence of the network in assigning the echo train to the proper category.

Integrator gateway results and discussion

Figure 3 shows the results of generalization testing of the network. The complete, original set of 1,335 sequential echoes was presented to the network and the network was allowed to classify each echo train. Figure 3 shows the confidence of the network in assigning the echo train to the proper category as a function of the number of echoes received. "Confidence" was defined as the ratio of the activation level of the correct classification versus the total output of the three classification units. These confidence ratios correspond to intermediate likelihood ratios (Qian & Sejnowski, 1988). Overall, the animal's performance is better than that of our network. Roitblat, et al. (1990b) reported that the dolphin was 94.5% correct at selecting the correct match. This level of performance required the animal to identify the sample correctly and to identify comparison stimuli correctly. The probability of both occurring was observed to be 0.945. Therefore, on the assumption that the two identifications were independent of one another, the probability of identifying both is simply the product of the probabilities of identifying each target individually. Therefore, the probability of each identification can be estimated at $p = \sqrt{0.945} = 0.972$ (assuming that each occurred with equal probability). By no measure was our network 97.2% accurate at identifying the stimuli, but when it did identify the stimuli it tended to do so with fewer echoes than were used by the dolphin.

According to our model, on a substantial number of trials the dolphin continued to emit echolocation signals beyond the rational stopping criterion prescribed by sequential sampling theory, and failed to emit sufficient clicks on one scan (the first scan of tube targets). There could be several reasons why the dolphin continued to sample after the network had reached its confidence criterion. Among these are the possibility that the dolphin considers a broader range of targets in making its classification. This dolphin was highly experienced having served in various forms of the experiment with many different targets for more than 5 years. Although this experiment was designed to present only the same three targets at all times, the dolphin may have persisted in classifying the echoes relative to a much larger set of targets. More echoes may be necessary to discriminate among this broader range of targets.

Another possibility is that the dolphin uses other information besides that used by the network. For example, although the network was trained to classify targets on the basis of relative-amplitude echo spectra, the dolphin may use absolute target "strength" or a variety of time-domain features (Au, 1988) as discriminative cues.

A third possibility is that the dolphin may not be able to represent the echo spectra with the same fidelity that was available to the network. The dolphin may occasionally "forget" or fail to attend to some of the echo information. We also time-windowed the echoes and thereby focused the network's "attention" specifically on these intervals. The dolphin may not be capable of such rigid timing and may need to emit some clicks simply to determine target distance in order to extract other information.

The final possibility that has occurred to us is that the dolphin may not have been as task-focused as the neural network. The echoes were collected in a natural environment containing, for example, many moving fish, other dolphins, etc. It is possible that at least some of the clicks may have been directed at targets other than those presented explicitly by the experimenters, or that the dolphin continued to click at the target while actually attending elsewhere.

A simple backpropagation network

The architecture of the integrator gateway network is substantially more complicated than that of some more standard networks architectures. By way of comparison, therefore, we trained a backpropagation network on the same data in order to determine whether this additional structure contributed to the performance of the network. The backpropagation network contained exactly the same number of inputs, hidden units, outputs, and adjustable connections as the integrator network. The only difference between the networks was the presence of the integration apparatus in the integrator network and its absence in the backpropagation network. The backpropagation network was trained to the same 0.05 RMS error criterion using the same training parameters and then tested on the full set of echoes.

Backpropagation results

Figure 4 shows the confidence of the network in assigning the echo train to the proper category as a function of the number of echoes received. Compared to the categorization performance of the integrator network, the backpropagation network was much more variable. Whereas the integrator network was trained to recognize integrated combinations of echoes, the backpropagation network was trained to recognize individual, independent examples of echoes.

As Figure 4 illustrates, the individual echoes were highly variable, and frequently assigned to an erroneous category.

These data suggest that the integrator network added significantly to the ability to classify sequentially produced echoes. In other words, by implementing a signal "averaging" mechanism in the neural network we allowed the system to take advantage of the redundancy inherent in the use of multiple echoes from the same source and in the stochastic properties of the noise in which those echoes are embedded.

In contrast, the backpropagation network was

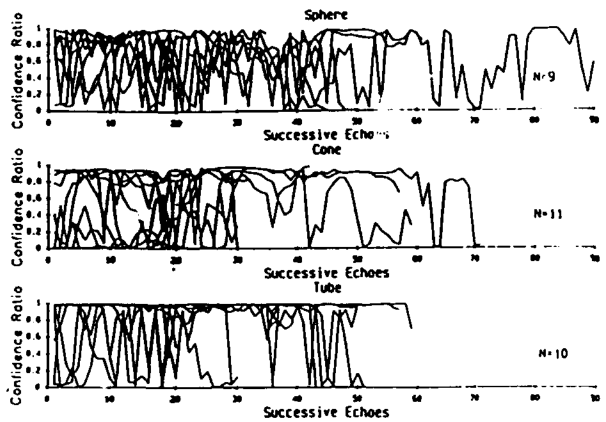

Figure 4. Confidence of the backpropagation network in assigning the echo to train to the proper catagory as a function of the number of echoes recived. N is the number of trains classified from each target.

required to process not only the characteristics of the echoes themselves, but also the characteristics of the noise. This results in many spurious classifications. Presumably, if a larger training set had been employed, the backpropagation network would have learned to "abstract" the salient properties of the echoes, but within the constraints of a relatively small training set (60 of 1,335 or just 4% of the total number of echoes), the integrator network does a much better job of separating the signal from the noise.

The gateway integrator network adds a level of complexity to the standard backpropagation network architecture that contributes substantially to its performance. Its design is inspired by properties of the dolphin's performance and it represents one step along a development path that seeks to include more of the mechanisms that we can identify from the neurobiology of echolocation (e.g.,Suga, 1990) and from the performance of dolphins in their aquatic environment. Although the results of the present study do not prove that dolphins perform similar integration, this integration model seems to provide a better account than a decision model that does not integrate.

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