

The Uniqueness of the Message in a Retinal Ganglion Cell Spike Train and its Implication for Retinal Prostheses*

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Abstract— We sought to determine whether the messages conveyed in the spike trains of individual retinal ganglion cells are unique or whether, as has been reported for other neurons, they depend in some way on a neuron's state. Our data show convincingly that the messages are unique.

I. INTRODUCTION

A remaining challenge of neuroscience is to unravel the neural code [1-5], and the retinal output is an attractive place to investigate this problem, because of our deep knowledge of the retina's physiology and the robust techniques available to the experimenter for its study. A particular topic in the area of neural coding that has become of interest in recent years is the extent to which neurons may be able to switch states and adjust their messages to reflect context [6]. This phenomenon has been demonstrated experimentally by the observation that in some neurons the same stimulus can evoke a discrete set of responses, predicated on the internal state of the neuron. Could this apply to signals leaving the retina? To investigate this question we have studied whether the message conveyed to the brain by a retinal ganglion cell in response to repeated presentations of the same stimulus is unique. The fuzzy K-means method was used to evaluate the presence of clusters in the responses of individual cells to white noise visual stimuli. Since these broadband stimuli encompass the full range that the retina could encounter, one would expect that stimulus-evoked state changes would be revealed, if they exist.

II. METHODS

A. Data

The spike trains analyzed were collected by Passaglia and Troy [7]. Well-isolated spikes of single cat X and Y retinal ganglion cells were recorded from their axons in the optic tract. The spike trains used for our analysis were responses to high contrast spots or annuli whose luminance was varied according to a pseudo-random sequence. Spike times were recorded to 0.1 ms accuracy. The cat viewed the visual stimulus through 4-5 mm

artificial pupils. All animal procedures were approved by the Northwestern University IACUC.

B. Cluster Analysis

Spike trains were collected from the same cell in response to many repeats of the same stimulus and cluster analysis performed on the set of trains obtained to determine the number of distinct spike patterns they contain. A fuzzy K-means algorithm for cluster identification was implemented as a program in Matlab. The reliability of the program in uncovering patterns was checked against a set of artificially generated data sets known to contain multiple spike patterns buried in noise.

Briefly, the method involves the calculation of a similarity matrix of the set of spike trains and from this a covariance measure, R , determined. R could range from 0 (spike trains are uncorrelated) to 1 (spike trains are identical). High values of R ($R > 0.8$) indicate that there is just one pattern of response. Intermediate values of R suggest the potential presence of more than one pattern of response. The fuzzy K-means method is used to uncover these patterns and sort the set of responses into distinct groups.

We compared spike trains collected for the same cell to repeats of the same stimulus and spike trains collected from different cells of the same type to the same stimulus, in some cases cells of like type recorded in different animals.

III. RESULTS

A. Testing the Algorithm

Figure 1 demonstrates that the clustering algorithm can pull out distinct firing patterns from a set of artificial spike trains. The upper panel shows 100 spike trains arrayed on top of one another. Each dot is a spike. The lower panel shows the set of spike trains ordered to reveal three distinct patterns after the cluster analysis. This set was generated to have three clusters. A similar analysis was performed on 19 other artificial spike trains, each with a known number of clusters. In all cases, the algorithm revealed the hidden clusters. For every case it was impossible through visual inspection of the trains in shuffled order (like the upper panel of Figure 1) to see any of the hidden patterns of spiking.

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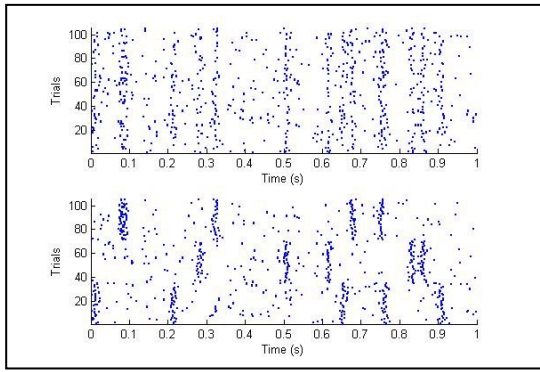


Figure 1. Fuzzy K-means algorithm reveals three spike patterns. Lower panel shows the spike trains in the upper panel ordered to reflect similarity of adjacent spike trains

B. Cluster Analysis of Spike Trains from the Same Cell

Data from 43 (13 ON-Y, 13 OFF-Y, 12 ON-X and 5 OFF-X) cells of nine cat experiments were analyzed. The average value of R was 0.94, so it is little surprising that we found no evidence of more than one cluster in the spike trains of any of these cells. Figure 2 illustrates this point well for a representative OFF-X cell.

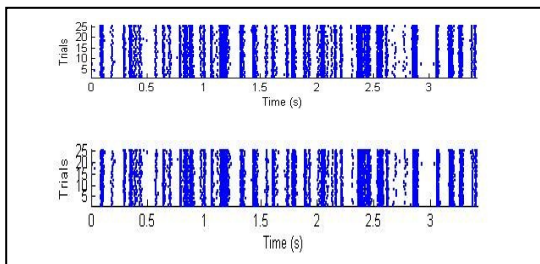


Figure 2. The spike trains of this OFF-X cell contain just one pattern of firing. The top panel shows 25 spike trains in response to the same stimulus, arranged in the order in which they were recorded. The bottom panel shows the same 25 panels arranged in order of similarity.

C. Cluster Analysis for Spike Trains of Different Cells

To determine how similar are the messages carried by different ganglion cells of the same type to the same stimulus we performed a similar cluster analysis to that described above for spike train records of different cells combined as one set of records. We could perform this analysis for 8 cells from the same cat and for 15 cells from different cats. Figure 3 shows a representative example for data assembled from three ON-X cells.

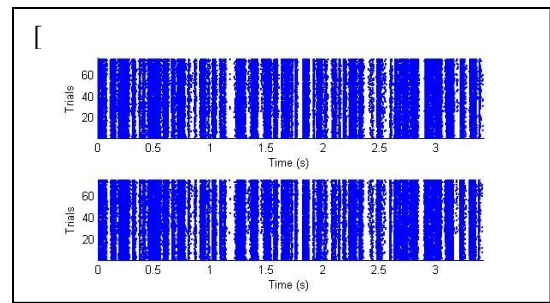


Figure 3. The spike trains of three ON-X cells are essentially identical. The top panel shows 75 spike trains in response to the same stimulus, arranged in the order in which they were recorded. The bottom panel shows the same 75 panels arranged in order of similarity.

IV. DISCUSSION

Our results indicate that the responses of cat retinal ganglion cells to stimuli are unique, implying that an individual retinal ganglion cell does not employ more than one state and more than one neural coding scheme. The responses from different cells of the same type are also quite stereotyped. These observations are important both for simplifying the task of characterizing the retinal output and for the development of visual prostheses where the artificial stimulation of retinal ganglion cells is needed to mitigate the effects of inner retinal degeneration. The transduction of visual stimuli into patterns of spike trains is straightforward.

Recent work [8] has found that biophysical diversity in the same neuronal population may endow them with advantages in terms of information transmission. This would not seem to be true for well-identified sub-types of retinal ganglion cells which show little variation in their information rates [this work, 7].

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