Assessing the Mean Neuronal Firing Rate Information Hypothesis via Mutual Information

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Abstract

While it is currently well accepted that the mean neuronal firing rate (MNFR) is a key parameter encoding information about sensory and motor events, in some cases the measured information due to MNFR is not adequate to explain the total neuron signal information content. **[4]** In this study, several auditory neuron responses and corresponding MNFR-generated surrogates are analyzed using mutual information (MI) as a metric of information content. **[3]** Results showed that for particular inter-spike gaps (ISG), data MI exceeded two standard deviations of the surrogate MNFR MI, indicating that spike spacing and order also encode information.

Background

Understanding how neurons encode information is a topic of great interest in neuroscience; however, in order for this to be possible, first the information content of neural signals must be quantified. **[1]** A well-accepted parameter encoding information for sensory and motor neurons is the mean neuronal firing rate (MNFR), which can be described by the following equation:

$$MNFR = \frac{\sum spikes}{time\ interval} \quad (1)$$

Work by Stein and colleagues has suggested that the MNFR does not account for all information content in neural signals. **[2]** Consequently, the purpose of this research was to test the MNFR information content hypothesis using MI. Specifically, a null hypothesis stating that all information is encoded via the MNFR was defined, and then comparison or surrogate data was generated based on this null hypothesis, allowing for testing the null hypothesis with the MI results from the actual data.

Neuronal Data

Auditory neuron response data from a single marmoset monkey auditory neuron was obtained from Ross Snider at the John Hopkins Laboratory of Auditory Neurophysiology.

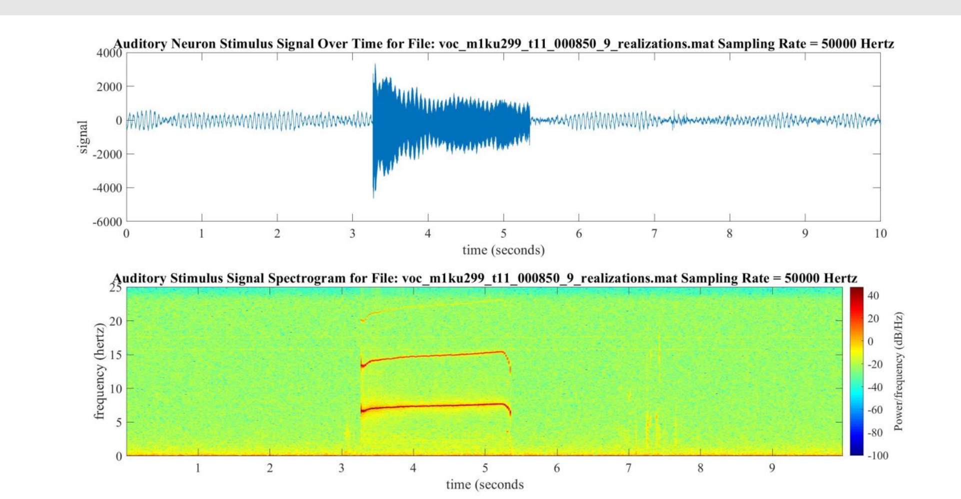


Table 1.

Number of files	Number of realizations
23	> 3 (unused)
10	3 (unused)
2	9 (used)

Figure 1. The left upper plot shows one of the auditory neuron stimulus signals (phee vocalization) in time domain while the left lower plot shows a spectrogram (window size = 1024) of the signal. On the right, Table 1 shows the number of realizations, defined as a new instance of stimulus application, for all available data; note that only two of the data files were usable.

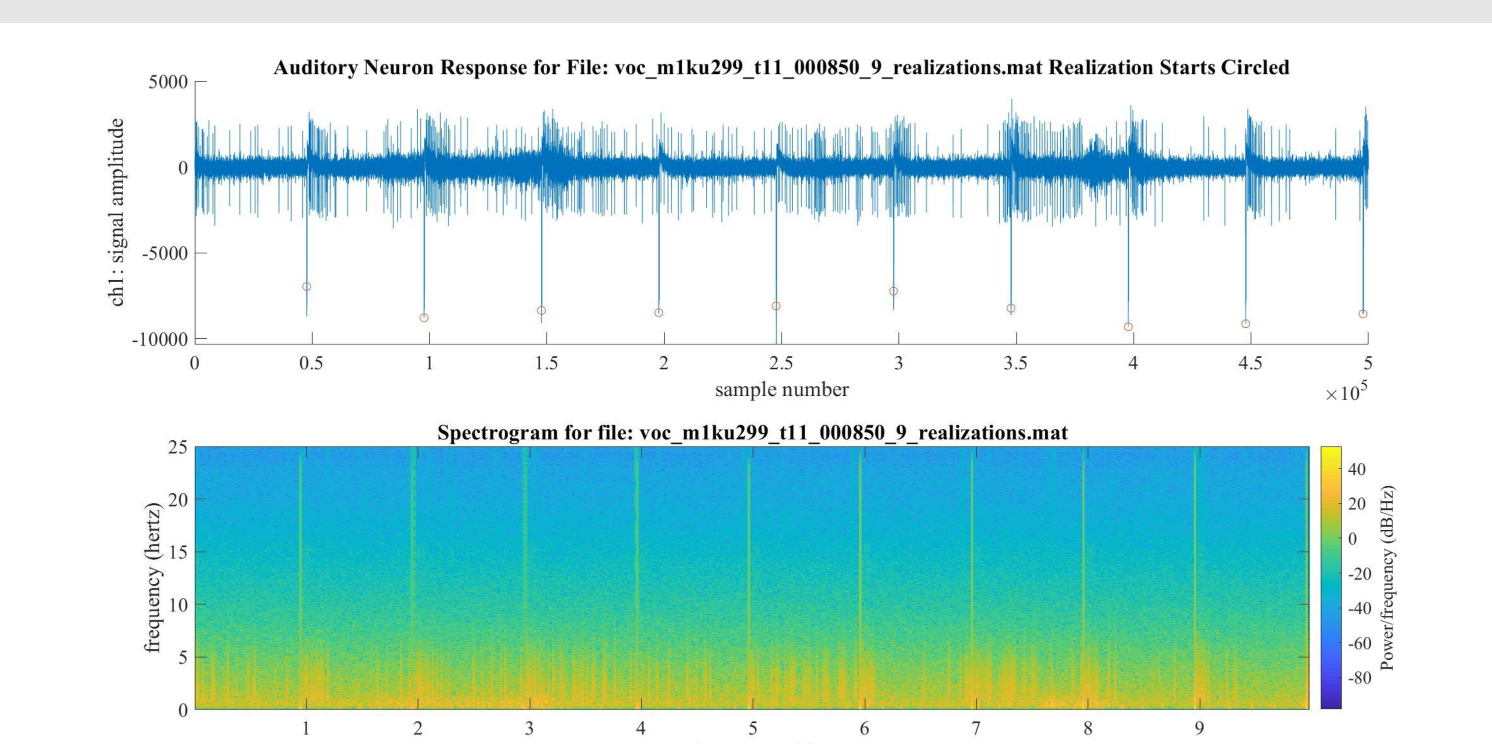


Figure 2. The top panel shows the auditory response signal data; the circled red data markers between (-6000 to -8000) denote a new instance of stimulus application or realization. The bottom panel is a spectrogram of the same response data.

Methodology

Realization and Peak Detection

Data was categorized according to the number of realizations present, as Table 1 (left) shows. Realization detection was performed using a constant threshold determined by inspection. Individual neural spike detection was then performed using a constant threshold set by observation, as seen below. Upon finding spike indices, ISG widths were calculated, creating a time series of events on which to calculate MI.

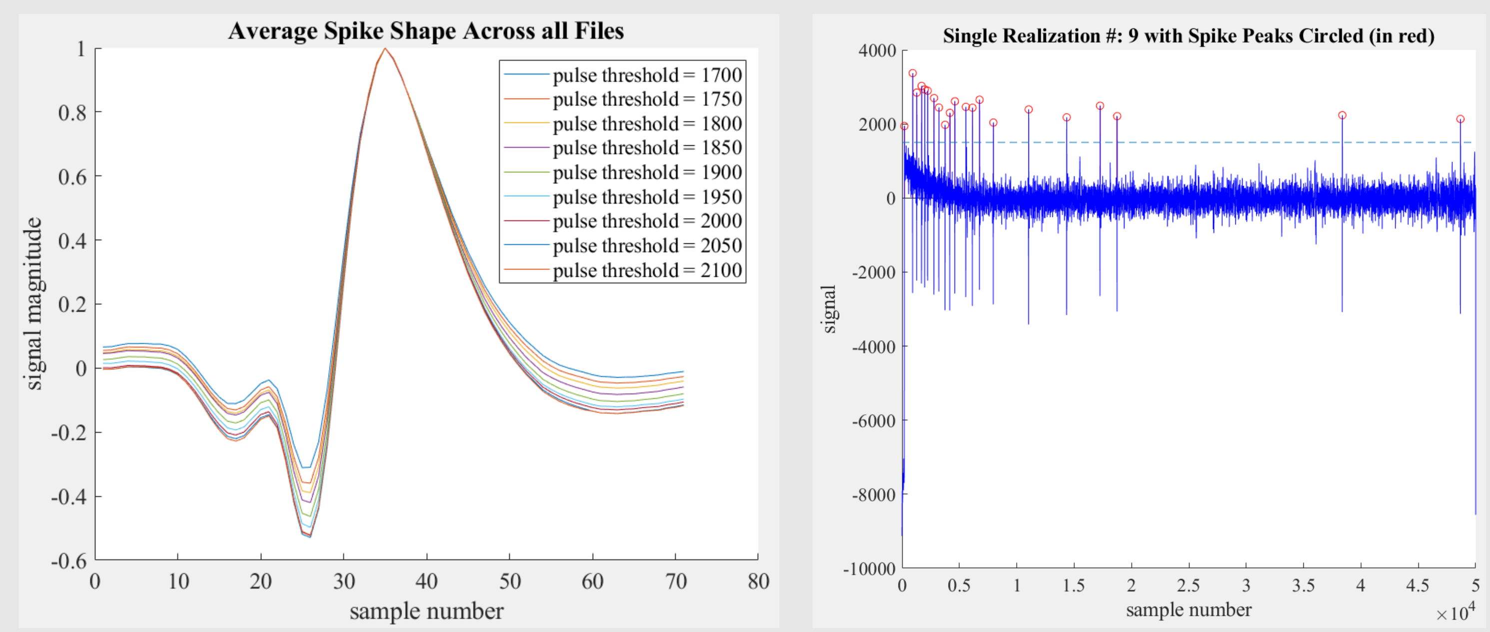


Figure 3. The left plot shows the consistent spike shape across all 35 data files while the right plot shows threshold peak detection, where the dashed line denotes the detection threshold.

Look-ahead and Mutual Information

Using the array of ISG widths, a list of ordered pairs, $\{(\Delta_1, \Delta_{1+\tau}), (\Delta_2, \Delta_{2+\tau}), \ldots\}$, was constructed with some look-ahead or tau $\boldsymbol{\tau}$. This array of ISGs should not contain any specific structure at any given look ahead so long as the ISG time series is fully random and independent. With mutual information (MI) as the metric to measure the amount of structure in the ISG time series, MI was calculated using

$$MI = H(X) + H(Y) - H(X,Y) \quad (2)$$

Where H(X) is the Shannon Entropy: $-\sum P(X_i)\log(P(X_i))$. Significant non-zero MI indicates an interdependence of spikes on previous spikes. By varying the look ahead, the distance that MI extends into future time was measured.

Surrogate Data Generation

In order to compare the MI values calculated for the ISG time series with the MNFR hypothesis, comparison data was constructed using equation (1). Evenly distributed random values in a range of (0 1) were generated and the values equal or less to the MNFR were defined as spikes, whereupon the same MI calculation procedure used for the data was then applied.

Comparison of Distributions

Surrogate data and actual data was binned and the number of spikes per bin (SPB) calculated along realization length. Since the total number of spikes in the surrogate and the actual data should be approximately equal due to the MNFR, SPB values were integrated along realization length to verify surrogates were representative of the MNFR hypothesis.

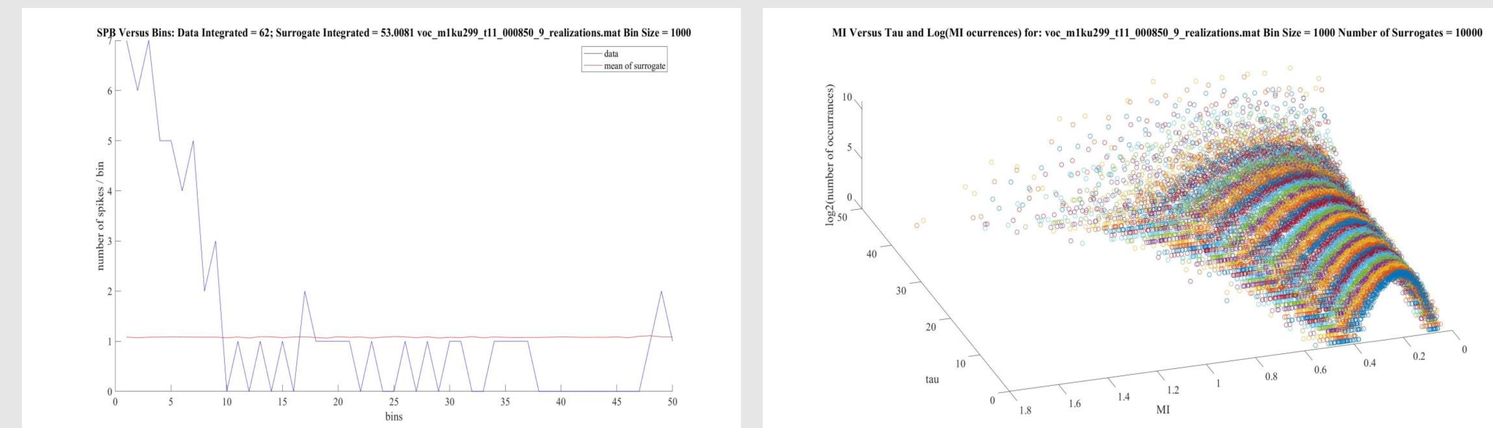
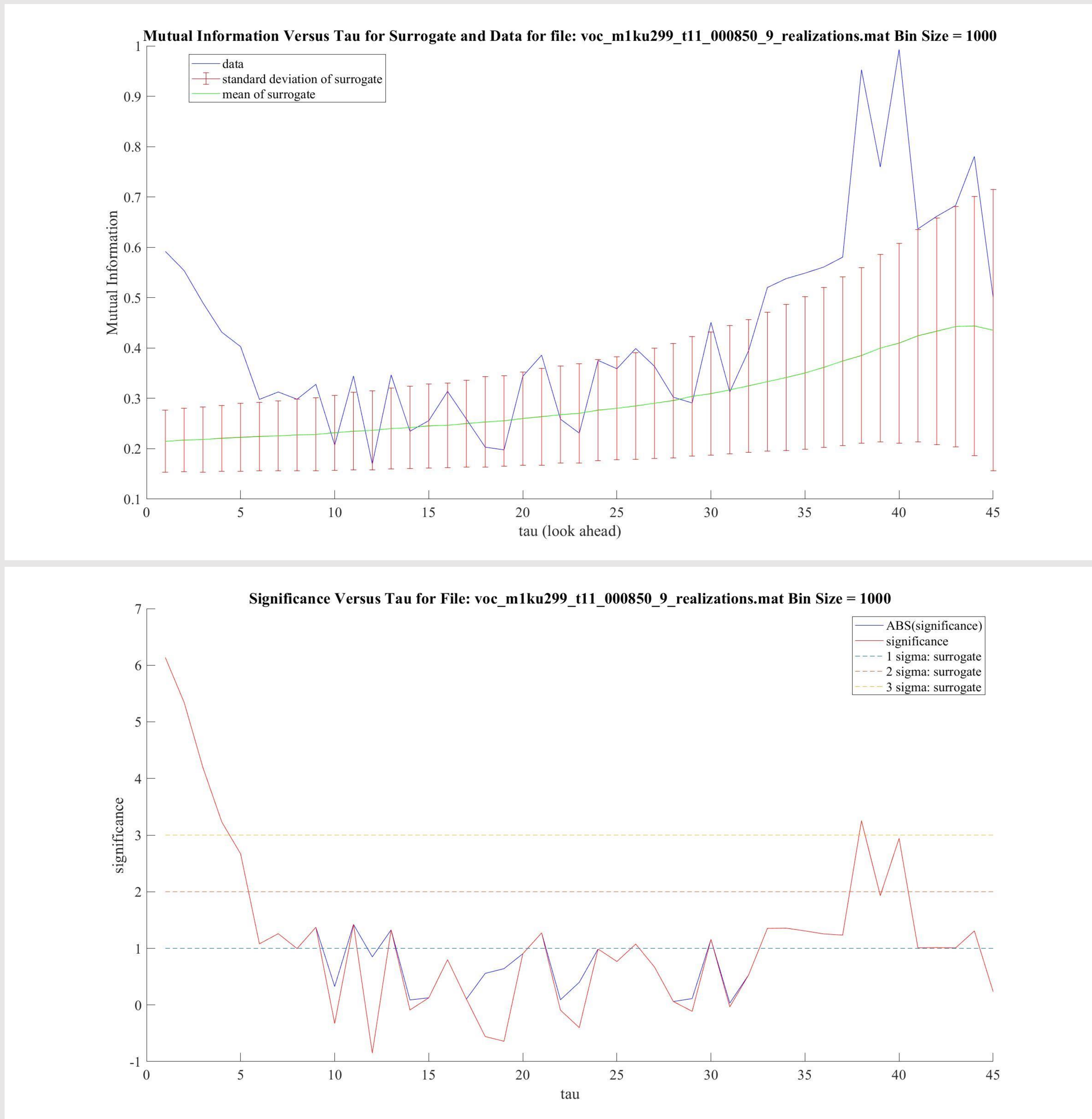


Figure 4. The left plot shows spikes per bin versus bins for both surrogate (red) and the actual data (blue); the right plot shows the surrogate data (10,000 surrogates) MI values as a function of tau and number of occurrences, and verifies they are normally distributed.



Results

Figure 5. In the upper panel the MI of both data and the mean of 10,000 surrogates is plotted as a function of tau or look ahead. The lower plot shows the significance of the actual data versus the mean of the surrogate (surr), calculated via $\frac{MI(data) - MI(surr)}{SD(surr)}$ where SD denotes standard deviation. From the significance plot, it is clear that for a look ahead of from 1 to 5 and 38 and 40 the data MI exceeds the surrogate MI by over 3 standard deviations, disproving the null hypothesis at those look ahead values.

Conclusions and Future Work

Results showed spikes had a significant impact on predicting subsequent spikes for large timescales of (0.6 to 0.8 seconds) and short time scales (0.02 to 0.1 seconds). Subsequently, we have shown that the MNFR hypothesis does not account for all information in the considered data set. However, since the considered data set was only two data files, future work will include expanding the data set and increasing number of and length of realizations per data recording. Since the MATLAB analysis scripts for this project were written in a manner to handle variable number of input files, this research has also resulted in the development of a scalable tool others may deploy in neuron signal analysis.

References

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