DIRECT ENTROPY AND INFORMATION IN SIMULATED MULTI-UNIT NEURAL SPIKE TRAINS

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ABSTRACT

Information content was analyzed in simulated Poisson neural spike trains. Multi-unit spike trains were created by summing pairs of spike trains. The direct method of entropy calculation was used to estimate the rate at which these multi-unit responses conveyed information about the stimulus. These methods yield results quantitatively different from those achieved using an indirect method, but the general conclusions remain. Information seems to decrease linearly with contaminating spike error. Rather than eradicating information in the neural activity, summing responses appears to conserve information from the individual units when they encode similar information (or encode the same stimulus features). Information loss appears to be additive.

1. INTRODUCTION

An understanding of neural encoding requires the study of activity from populations of neurons and their relation to the stimulus that caused the responses or the behavioral output caused by the activity. With tens of thousands of neurons synapsing on each neuron, one question that arises is how a summation of responses affects the transfer of information. This question is also of interest from the perspective of acquiring extracellular signals as recorded in a brain-machine interface (BMI). Current multi-neuron data acquisition systems go through the painstaking and costly process of discriminating action potentials from multiple neurons detected on the same electrode. This process is known as spike sorting. The cost-benefit relationship of spike sorting has only begun to be questioned and explored.

In a previous simulation study [**?**], integrate-and-fire model neurons were simulated and combined to represent different types of multi-unit signals, as might be acquired on a single electrode. The results showed that the information of units is preserved when they encode similar information, while information is corrupted when the responses summed are from units which encode disparate information. The different cases could also be seen as scenarios of recombining sorted spike trains, in which case the benefit of having discriminated spikes is lost to the information loss due to spike sorting error.

That study employed simplifying assumptions and an indirect method of calculating information. In the present study, a linear system is not assumed, nor is Gaussianity assumed. Instead of estimating a lower bound of the mutual information between stimulus and response indirectly from the optimal reconstruction of the stimulus, the entropy rates were calculated directly from empirical probability distribution computation.

2. METHODS

Using the methods given in Strong et. al., the spike trains were segmented into non-overlapping words of length T_{word} ranging from 5ms to 75ms. Both the total entropy rate and the noise entropy rate were extrapolated using a least squares regression fit to find $H_0 = H(T_{word} \to \infty)$ and $H_{n0} = H_n(T_{word} \to \infty)$

These simulations are designed to explore the information about some stimulus of interest s_{int} transmitted by 2-unit spike trains. First, a set of responses is generated from s_{int}, and this serves to simulate the control neuron whose response is denoted by ρ. The simulations were divided into four categories depending on the relationship of the responses being combined with ρ. In case A, the outputs ρ_A were generated in response to a random stimulus s_{rand} independent of s_{int}. To get the multi-unit response ρ_{UA}, ρ_A was added to ρ. In case B, the spike trains ρ_B were generated from s_{int}, and $\rho_{UB} = \rho_B + \rho$. In case C, the spike trains ρ_C were corrupted by spike error. The amount of spike error was quantified as a ratio of false positives and negatives to the total number of spikes and ranged from 0 to 0.5. The multi-unit signal ρ_{UC} was the sum of an uncorrupted spike train ρ with ρ_C. Finally, case D units were created in the

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same manner as ρ_C, and the multi-unit signal was created from two corrupted spiketrains; i.e., ρ_{UC} = ρ_C + ρ_D. The single-unit spike trains in cases C and D were equivalent.

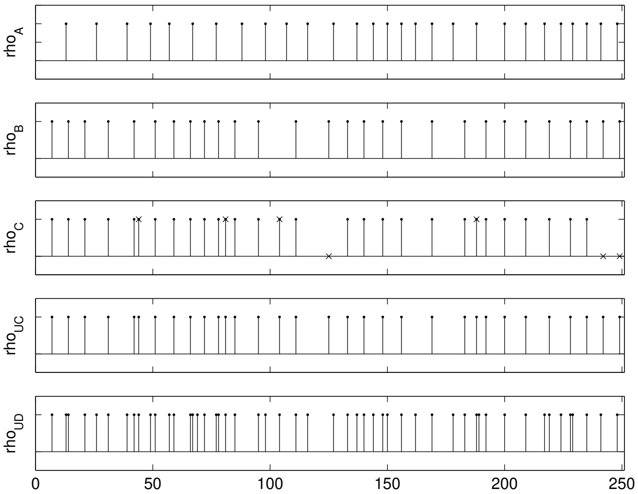


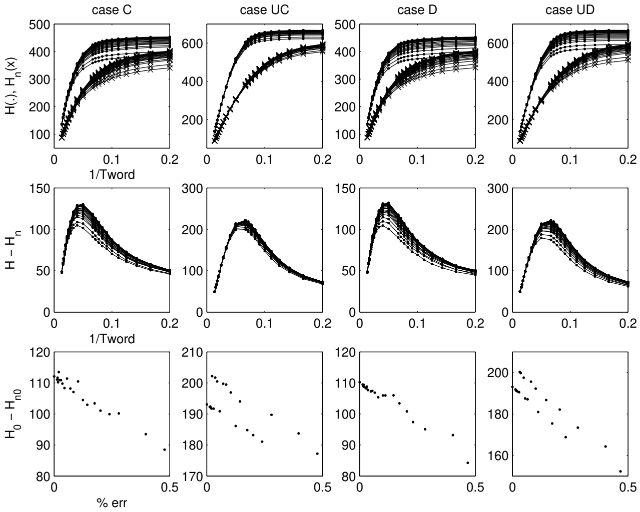
Fig. 1. Examples of Poisson spiketrains: Case A - A spike train is generated independently of the stimulus of interest. Case B - A neuron's response is generated in response to s. Case C - False negatives and false positives (x) corrupt ρ_B. The multi-unit response is generated by the union of a type B response with a type C response, i.e. $\rho_{B1} \bigcup \rho_{C2}$ Case D - the multi-unit response $\rho_{UD} = \rho_{C1} \bigcup \rho_{C2}$, i.e. two type C responses.

3. RESULTS

A family of curves was generated from $\dot{H}(T_{word})$ and $\dot{H}_n(T_{word})$ as percent error was varied. As expected, the entropy rates dropped below the Ma bound as the word length is increased to the point beyond which probability distributions of symbols cannot be accurately estimated because of limited data size (I did not actually calculate Ma bound). The difference in total and noise entropies as a function of word length reveal a peak at roughly $T_{word} = 15ms$. Information determined by extrapolating the entropy rates to $T_{word} \rightarrow \infty$ reveals a linear dependence on percent error. The information in single-unit spike trains corrupted by error (ρ_C, ρ_D) decreases without much deviation from a monotonically decreasing linear function. The multi-unit spike trains show much more variability. Information rates appear to be roughly additive:

- $\dot{I}_{UC} \approx \dot{I}_C + \dot{I}_B$
- $\dot{I}_{UD} \approx \dot{I}_C + \dot{I}_D$

But $\dot{I}_{UC} - (\dot{I}_C + \dot{I}_B) < 0$ and $\dot{I}_{UD} - (\dot{I}_C + \dot{I}_D) < 0$, showing some degree of redundancy.



(a) Result 1

Fig. 2. Direct entropy calculations. Top row: total entropy rate $\dot{H}(T_{word})$ (.) and noise entropy rate $\dot{H}_n(T_{word})$ (x) plotted as a function of the inverse word length ($1/T_{word}$, ms^{-1}). Middle row: Difference in total and noise entropy rates $\dot{H}(T_{word}) - \dot{H}_n(T_{word})$, showing a potentially optimal word length. Bottom row: Information rates estimated from the difference between projected entropy rates H_0 and H_{n0}.

4. DISCUSSION

The measurements obviously lead to incorrect results. This could indicate that the assumption that extrapolating the entropy curve to $T_{word} \rightarrow \infty$ yields the true information does not hold or that using non-overlapping words does not give the correct answer. Rather, another common assumption seems more feasible: neurons have a characteristic response time, and this would give us the word length that should be used to directly calculate entropies.

5. CONCLUSION

5.1. Subheadings

5.1.1. Sub-subheadings

6. FOOTNOTES

7. COPYRIGHT FORMS

8. REFERENCES