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Investigating the effect of Cortical Discharge Variability on the accuracy of population decoders

Mehdi Aghagolzadeh*[1] and Karim Oweiss[1,2]

Address: [1]Department of Electrical and Computer Engineering, Michigan State University, Michigan, 48824, USA and [2]Neuroscience Program, Michigan State University, Michigan, 48824, USA

Email: Mehdi Aghagolzadeh* - aghagolz@msu.edu; Karim Oweiss - koweiss@msu.edu

* Corresponding author

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Estimation of the response properties of cortical neurons from within a recorded population is an essential component in a cortically-controlled brain machine interface application. The response properties of interest typically include precise spike timing, mean firing rate and any inherent correlation in the activity of the recorded ensemble. These response properties are essential for the operation of a neural decoder that translates the observed cortical activity to command signals for controlling robotic arms. In this work we investigate the effect of cortical discharge variability on the decoding performance. Specifically cortical discharge variability was induced in two types of cortical network models. The first one is a probabilistic model in which the activity was modeled as an inhomogeneous Poisson process with firing probability that depends on the neuron's own firing history and those of other neurons connected to it through time-varying synaptic couplings. The second is a biophysical leaky integrate and fire model. Neurons in both models were cosine-tuned to movement direction with random tuning widths.

We examined the performance of three types of decoders to response variability expressed in terms of variations in the size of the observable neural population used for decoding and also in terms of the contaminating network noise. These variations may be indicative of recording stability in any given experiment. The first is a maximum likelihood decoder, in which the probability of the intended movement given the response is estimated through Bayes rule. Independent Gaussian models were utilized to model the conditional probability of the intended movement based on the observed response.

$$EstStim = X(j) \equiv \arg\max_j \left\{ P\left(D_j \mid R\right) \right\} = \arg\max_j \left\{ \prod_{i=1}^{N} P\left(D_j \mid R_i\right) \right\} \quad -P\left(D_j \mid R_i\right) = \frac{1}{\sqrt{2ps_i^2}} e^{-\frac{(r_i - m_i)^2}{2s_i^2}}$$

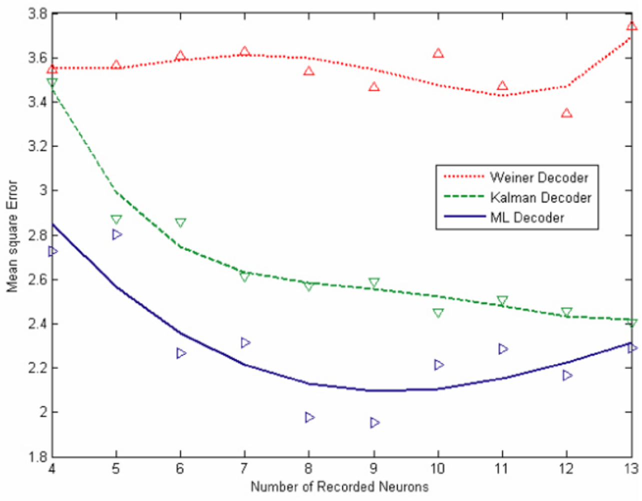

Figure 1
Accuracy of different decoders versus the size of the recorded population *N*. A total of 45 neurons were involved in encoding the simulated movement at any given experiments. Only *N* of these were used for decoding.

where r_i is the number of spikes for the i^{th} neuron over a fixed bin width. The mean and variance of each Gaussian model is defined through the training process. The other two decoders are the Wiener and the Kalman filters. The entire population was 45 neurons and we used a random subset of these for decoding. The maximum likelihood decoder demonstrates a superior performance compared to the Weiner and Kalman based decoders (Fig. 1).