NOISE TOLERANCE AS A MEASURE OF CHANNEL DISCRIMINATION FOR MULTI-CHANNEL NEURAL INTERFACES

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***Abstract*-Spatial selectivity can be obtained when recording the activity of a peripheral nerve [1-4] or corticospinal pathways of the spinal cord [5] by circumferential placement of the metal contacts around the axon bundle. Selectivity indices that have been proposed [1-3], however, do not measure how the channel discriminability deteriorates in the presence of noise. The pattern of amplitude distribution across the recording sites during a neural firing (a vector) can be considered as a symbol received at the end of an information channel. Thus, the performance of the neural interface/recording method can be quantified for the noisy case and compared with others using the classic formulaé for the information channels. Monte Carlo simulations in this study show that the decay of information transfer rate with noise can differentiate between neural interfaces that have identical spatial selectivity indices based on the Euclidian distance measure [2]. Noise tolerance can be the method of choice to assess the performance of multi-channel neural interfaces in terms of channel discrimination.**

***Keywords*-selective nerve recording, neural interface, signal-to-noise ratio, information rate.**

I. INTRODUCTION

Several spatial selectivity measures have been proposed for multi-channel recordings of peripheral neural activity [1-4]. The Euclidian distance measure [2] has been adapted as a measure of selectivity for multi-contact recordings of the spinal cord [5]. However, the information provided by these measures is not very practical since it does not convey how discriminable the channels would be in the presence of noise. In a noiseless system, any level of selectivity is perfect since all the channels can be distinguished without error. In a neural prosthetic application, however, the noise tolerance will determine the effective rate of information transfer for neural signals.

Information transfer rate was proposed as a standard measure of performance for brain-computer interfaces based on the accuracy of the selections made by the subject [6]. In this paper, we apply this analysis to quantify the performance of the neural interface alone without the subjective component. We assume that the noiseless version of the neural data is available. In several hypothetical cases, the Euclidian distances between the symbols, i.e. parameter vectors, are calculated and Gaussian distributed white noise is superimposed to simulate the background thermal noise and/or neural contamination. The simulations indicate that the decay in the information rate with noise is sensitive to the location of individual symbols in the vector space. Using this analysis, one can find the theoretical information transfer rate for any amount of background noise and thereby compare multi-channel recording interfaces /techniques based on their noise tolerance.

II. SIMULATIONS

A. Correct Classification of Symbols/Vectors with Noise

Let us consider a case where we have a set of **m** dimensional **n** orthogonal vectors with unit lengths. Each vector consists of a set of characteristic measurements (amplitude, temporal duration, slope, etc.) taken from the neural signals. Although neural signals are analog in nature, any analog signal can be represented with discrete samples. In this analysis, the measurement vectors will be considered as symbols transferred through a noisy channel, i.e. the neural interface. During the transfer, the vectors are contaminated with Gaussian distributed white noise. The probability of correctly classifying a newly generated (received) vector at the end of the channel will be 1 for zero noise and it will decrease as the noise is increasing. One can statistically find this probability using the Monte-Carlo approach, i.e. with many realizations of the noise component superimposed on the original vectors. The probability of correct classification is shown in Fig. 1 for m=n=2,3,4, and 5 for noise varying from zero to hundred percent. Notice that the larger the number of vectors in the set, the lower the probabilities are despite the fact that the vector dimension (**m**) is also increased along with the number of vectors in the set (**n**).

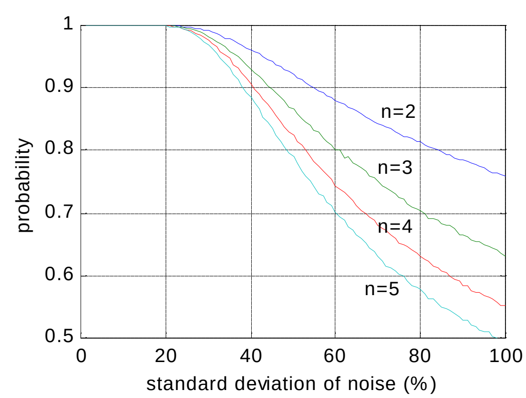

Fig. 1. Probability of correctly classifying a new vector that is identical to one of the vectors in a set of n dimensional n orthogonal vectors with unit lengths. Standard deviation of the Gaussian distributed noise that contaminates the new vector is varied from zero to hundred percent of unity. Probability of correct classification is the same regardless of which vector is generated in the orthogonal set and therefore only one vector is shown.

B. Classification of Non-Uniform Distribution of Symbols in the Vector Space

Let us now consider the two different vector configurations in Figs. 2a and 2b. The Euclidian distance measure [2] gives the same selectivity value in both cases (45.4%), and therefore does not make any distinction between them. We now calculate the probability of correct classification for each case for various levels of random noise as shown in Fig. 3a and 3b respectively. Unlike the orthogonal set in Fig. 1, the probabilities are different depending on which vector in the set is generated. The probability of correct classification is higher for those vectors on either side of the distribution than the ones in the middle. A comparison of Fig. 3a and 3b reveals that the vectors of each set have different levels of noise tolerance.

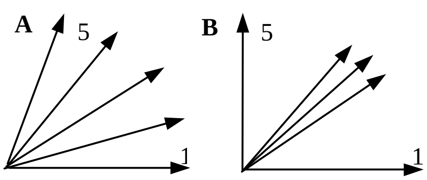

Fig. 2. Two different configurations of five unit vectors in 2 dimensional space. Vector angles from horizontal are A) 0, 20, 40, 60, and 75 degrees, B) 0, 39, 45, 51, and 90 degrees.

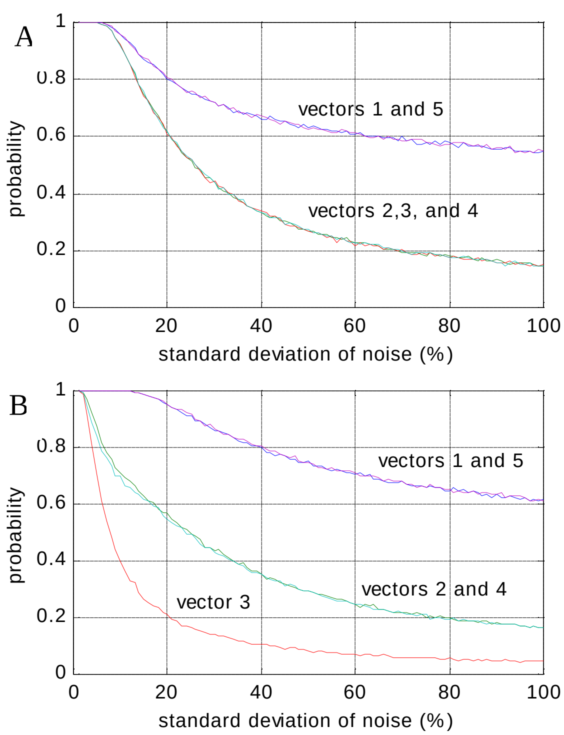

Fig. 3. Probability of correct classification for the vectors shown in Fig. 2a and 2b are plotted in A and B respectively using the Monte-Carlo method (10,000 realization of the noise component for each point). Labels indicate which vectors in Fig. 2 are generated.

C. Information Transfer Rate vs. Noise

The probability of generation for each vector in the alphabet and the rate at which these vectors will be generated are the functions of the source, i.e. dependent on the subject who generates the signals volitionally, or the task that is being conducted. Thus, we will assume that all the vectors are generated with equal probability and will use bit rate/trial rather than bits/second to eliminate the subject/task dependency of the analysis. Having found the probabilities of correct (p_{ii}) and false (p_{ij}) classification statistically, one can calculate the bit rate/trial using the classic formula given by Shannon for the information rate[7]:

$$
\begin{aligned}
BitRate = & -\sum_{i=1}^{N} P_i \log_2 P_i + \\
& P_1\left(p_{11}\log_2 p_{11} + p_{12}\log_2 p_{12} + \ldots + p_{1N}\log_2 p_{1N}\right) + \\
& P_2\left(p_{21}\log_2 p_{21} + p_{22}\log_2 p_{22} + \ldots + p_{2N}\log_2 p_{2N}\right) + \ldots \\
& + P_N\left(p_{N1}\log_2 p_{N1} + p_{N2}\log_2 p_{N2} + \ldots + p_{NN}\log_2 p_{NN}\right)
\end{aligned}
$$

where N is the number of vectors (symbols), P_i is the probability of generation for each vector (here all are assumed to be equal to 1/N), and p_{ij} indicates probability of classifying i^{th} vector as j^{th} vector.

The corresponding bit rates to the cases shown in Figs. 3a and 3b are plotted in Fig. 4. The theoretical maximum information transfer rate for a channel that has an alphabet of 5 symbols is 2.32 bits for zero noise as shown in Fig. 4. The bit rate falls as the noise is increasing. Notice the large difference in the bit rates for noise levels lower than 20%. This is due to difference in the location of the vectors in the two dimensional space (Fig. 2).

A plot of information transfer rate vs. noise may not be convenient to describe the effectiveness of a neural interface. Instead, one may prefer to take a representative value from the information transfer rate vs. noise graph and convey that single value. For instance, one may use the noise value at which the bit rate drops to 90% of the maximum theoretical bit rate. The noise tolerances that correspond to 90% of the maximum bit rate (2.088 bits/trial) are 3.22% and 8.54% respectively for the cases A and B in Fig. 4.

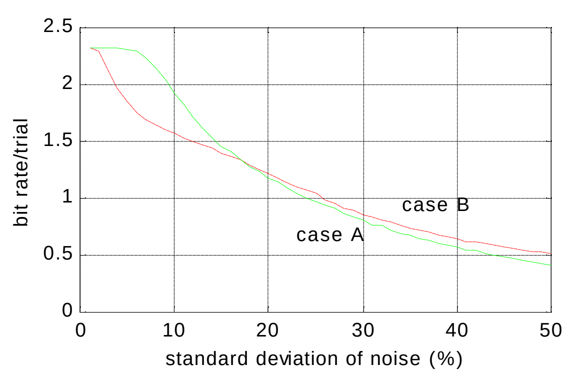

Fig. 4. Information rate against varying amounts of noise for the cases in Fig. 2.

III. CONCLUSIONS / DISCUSSION

This simulation shows that any measure of selectivity for a multi-channel neural interface should account for noise. The location of each symbol in the vector space determines the discriminability of that channel at the given noise level, which in turn has a contribution to the overall information transfer rate for the interface. Noise tolerance may be a more practical measure for channel discrimination of neural interfaces than selectivity measures that do not account for noise [1-3].

This analysis assumes that all the symbols (or measurement vectors) are generated with equal probability (P_i). One can calculate the maximum transfer rate (i.e. channel capacity) by adjusting the probabilities of the source and thus matching it to the channel for each different level of noise. The channel capacity can be plotted as a function of noise to study the noise tolerance of the interface. However, one usually does not have the flexibility to change the probabilities of occurrence for each symbol once the channels are dedicated to certain tasks in a neural prosthetic application. Thus, here we assumed that all the channels are used with equal probability.

The signals here could be the neural signals obtained from sensory peripheral nerves that are used to close a control loop in a neural prosthetic device or could be the signals recorded from the central nervous system as a means of generating voluntary command control. In either case, the theoretical analysis described in this paper can be adopted to compare various selective recording methods/interfaces in terms of their performance.

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