

# Utilising EEG Signals for Modulating Neural Molecular Communications

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## ABSTRACT

A major challenge in neuronal molecular communications lies in modulating signals through the neuronal network of the cortex that will minimize interference with the natural signalling. In this paper, we propose the use of Electroencephalogram (EEG) signals as a sensing mechanism to determine spiking interval gaps that can be used to stimulate artificial data transfer in the cortical micro-column.

## CCS CONCEPTS

• **Applied computing** → **Life and medical sciences**; *Telecommunications*; *Computational biology*; *Systems biology*;

## KEYWORDS

Nanonetworks, Molecular Communication, Information Theory, EEG, Optogenetics

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## 1 INTRODUCTION

Recent studies in molecular communication have investigated the maximum capacity of sending information through neurons. A question remains as to how stimulation of neurons to transmit information can be achieved while minimizing interference with natural signalling process. In particular when miniature nanoscale implantables such *Wireless Optogenetics Nanonetworks (WiOptND)* are used to stimulate the neurons. One possible approach is to

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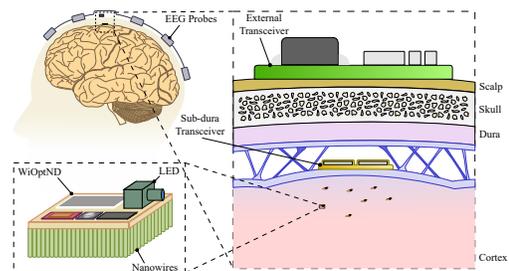


Figure 1: System Architecture.

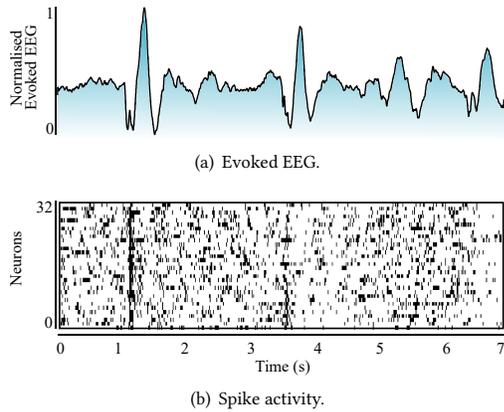
integrate a sensing system within the cortex that will sense the neural activities, however, this leads to increased complexity.

The objective of this paper is to present a new form of Brain-Computer Interface (BCI), where the EEG measurements are used to determine the activity of the cortex, which in turn can provide new forms of neuronal molecular communication modulation. The overall proposed system is illustrated in Figure 1. There is a relationship that exists between the neuron firing patterns and the EEG signalling, as shown in Figure 2. A neuron can slow down or speed up its firing rate depending on tasks being performed by the subject. Therefore, based on this, our aim is to transmit information through the low spiking patterns of the neurons, and in particular during the gaps.

## 2 CORTICAL COLUMN ARTIFICIAL DATA TRANSFER

The Micro-column activity (MCA) depends on parameters regarding its structure such as number, type and configuration of the cells and topology of the column. The EEG signal is measured passed through a band-pass filter for both the *delta* and *gamma* frequency bands with which the power of the *gamma* signal and the phase of the *delta* signal are determined. The multi-unit activity is then predicted by the model proposed by [4] and represented as  $S = W_\gamma \omega_\gamma + \Theta_\Delta \omega_\Delta + \epsilon$ , where  $\omega_{\gamma,\Delta}$  are the weights of power and phase,  $W_\gamma$  and  $\Theta_\Delta$  are oscillatory power and phase and  $\epsilon$  is a constant error term. Further details regarding the statistical estimation of the weights and the use of only *gamma* and *delta* signals can be found in [4].

The probability that  $k$  spikes are fired during a giving time interval in which  $S$  spikes are expected, is given by  $P(k \in S) = S^k e^{-S}/k!$ . Therefore, the probability of communication gap,  $P_{gap}$ , would be



**Figure 2: Relationship between the (a) normalised evoked EEG and the (b) spike raster plot data from visual stimuli.**

equal to the probability of  $k = 0$  spikes. Thus,  $P_{gap} = p(x = 0) = e^{-S}$ . Time intervals, with duration  $\tau$ , are discrete time slots in which a single bit is transmitted, and is defined as  $\tau = T/N_b$ , where  $T$  is the total time of observation and  $N_b$  is the total number of bits. The information rate,  $R$ , which is used to analyse the ability of a sender to communicate multiple bits of information to a receiver, is the maximum average amount of information transferred per unit time and is given as  $R = C(X; Y)/\tau$ , where  $C(X; Y)$  is the maximum average mutual information.

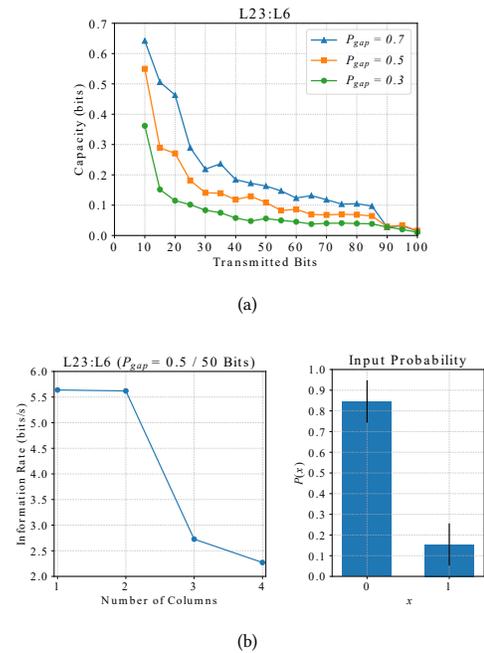
### 3 RESULTS AND DISCUSSION

In this section, the results obtained from simulations performed using NEURON and Python are presented [1]. The cells models are arranged according to their respective layers and connection probabilities based in [2]. Each column is arranged with one cell per layer and a fractional noise parameter is set to zero so it would be possible to evaluate the interference caused by the free spreading of spikes fired in both single- and multi-unit arrangements. The EEG readings of neuronal activity are based on recordings from a 10-20 electrode system [3]. The data is analysed through a signal processing algorithm to detect gaps that can be used to modulate signals. Based on this, we simulate the neurons to transmit artificial data within these gaps.

Figure 3(a) depicts how a larger number of transmitted bits along with a lower  $P_{gap}$  implies more interference across the column, considering bit sequences randomly generated in relation to  $P_{gap}$ , which represents a decrease in the channel capacity between  $T_x$  (L23) and  $R_x$  (L6). This decay follows the shape of an exponential function getting very close to zero when it approaches 100 transmitted bits.

Figure 3(b), on the left side, shows that neighbouring columns, simulated for 50 transmitted bits and a  $P_{gap} = 0.5$ , resulting in more interference in the channel which leads to a decrease, by a factor of approximately 2, in the capacity and information rate. The right side illustrates an input probability collected from real EEG readings.

The columnar arrangements were kept the same for all simulations, but any change in their position, connection probability or



**Figure 3: Analysis of the channel regarding the relationship between the (a) capacity and the number of transmitted bits in a 1000 ms simulation and the (b) influence of the number of cortical columns in the information rate (left) and the input probability of the system (right).**

the number of dendrites, represents a cascade of events that would lead to performance changes.

### 4 CONCLUSIONS

Our proposed artificial data transfer system results demonstrates how neighbouring cells represent a significant level of interference even if only one cell is firing spikes. At the same time, the correlation between the EEG signals and spiking activity may vary across situations requiring a careful approach for interpreting the signals. The proposed work can lead to a new form of BCI for neural communication systems and pave the way towards new applications and a more reliable process to enhance the capabilities of the brain by inserting artificial data without interfering with the natural flow of neuronal information.

### ACKNOWLEDGMENTS

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