Digital modulation and achievable information rates of thru-body haptic communications

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ABSTRACT

The ever increasing biocompatibility and pervasive nature of wearable and implantable devices demand novel sustainable solutions to realize their connectivity, which can impact broad application scenarios such as in the defense, biomedicine, and entertainment fields. Where wireless electromagnetic communications are facing challenges such as device miniaturization, energy scarcity, limited range, and possibility of interception, solutions not only inspired but also based on natural communication means might result into valid alternatives. In this paper, a communication paradigm where digital information is propagated through the nervous system is proposed and analyzed on the basis of achievable information rates. In particular, this paradigm is based on an analytical framework where the response of a system based on haptic (tactile) information transmission and ElectroEncephaloGraphy (EEG)-based reception is modeled and characterized. Computational neuroscience models of the somatosensory signal representation in the brain, coupled with models of the generation and propagation of somatosensory stimulation from skin mechanoreceptors, are employed in this paper to provide a proof-of-concept evaluation of achievable performance in encoding information bits into tactile stimulation, and decoding them from the recorded brain activity. Based on these models, the system is simulated and the resulting data are utilized to train a Support Vector Machine (SVM) classifier, which is finally used to provide a proof-of-concept validation of the system performance in terms of information rates against bit error probability at the reception.

Keywords: Body area networks, device-to-device networks, wearable sensor networks, haptic communications, somatosensory evoked potentials, electroencephalogram, communication system modeling, neural field theory

1. INTRODUCTION

Body Area Networks (BANs) are based on cutting-edge communication technologies for the interconnection of devices on, in, or around the human body for a variety of possible uses, including medical, entertainment, fitness, and defense.[1,21,26,40] The latest wearable and implantable devices are pushing the limits of these technologies by providing ubiquitous sensing of human body parameters and actuation capabilities coupled with enhanced biocompatibility and ergonomics.[4,37] While most research efforts around BANs[26] have been focusing on electromagnetic (EM) wireless technology and the propagation of EM waves around the body, as expressed in the standard IEEE 802.15.6,[1] technologies able to propagate information inside the body, or Intra Body Communication (IBC),[38] such as ultrasound,[35] and galvanic coupling,[22] are limited in their applicability, especially due to their invasiveness and unnatural characteristics, which could lead to negative effects on health.[3]

Although IBC solutions based opto-ultrasonic communications[36] and Terahertz band communications[2] have been proposed as possible alternatives to reduce the aforementioned invasiveness through the use of nanoscale communication devices and very short-range EM technologies, a potentially transformative direction stands in the utilization of natural biochemical processes already at the basis of communications inside our body.[3,24] In particular, the study of the nervous system and its neurons as means to propagate information between future wearable and implantable devices is encouraged by their ubiquitous distribution within the body and the existence

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of well-established techniques for external interfacing.[13,25] Moreover, the utilization of natural communication channels in the nervous system has the potential to enable self-sustainable and more secure communications with respect to other aforementioned technologies, since signal propagation is realized by natural biochemical reactions and it is confined within or in close proximity of the body tissues. These reasons, amongst others, make such a technology particular promising for defense applications, such as the interconnection of wearable devices for military personnel.[10] To realize this goal, novel interdisciplinary research at the frontier of communication engineering and neuroscience is needed to develop communication theoretical tools and models that could exploit the wealth of knowledge built in recent years around modeling the physiological processes in the nervous system.

In this paper, we propose a communication system based on the propagation of haptic (touch) stimuli through the nervous system and its components. Throughout this paper we use haptic to refer to the application of tactile sensation to the cutaneous, or touch, receptors at the skin. This system is based on an information-transmitting tactile stimulation, realized at the index finger pad, its propagation along the nerves of somatosensory system, and the reception of the resulting brain's somatosensory cortex activity through an ElectroEncephaloGraphy (EEG) device. Where in a traditional system the message is transformed into an electrical signal by an encoder device, and in optical system the message is translated into a light signal, in our system we can only modulate the signal by use of the timing and pressure of skin taps. The non-invasive nature and the availability of well-established techniques for EEG signal acquisition and analysis, as well as previous neuroscience literature on the modeling of somatosensory system processes, makes this an ideal system to study for the aforementioned IBC goals. In particular, in this paper we develop an analytical modeling framework based on diverse computational neuroscience models of the somatosensory signal propagation[11,12] the somatosensory cortex at the brain,[8] and the generation of EEG signals.[5,28]

Some similarities with this approach can be found in very recent literature,[15,39] where the cortex representation resulting from Braille tactile stimulation through the somatosensory system is studied through EEG recording and analyzed. Nevertheless, these studies do not aim at building analytical models, and are not placed in the context of IBC engineering. The latter applies also to[41] where a conceptual network model of each signal transduction step in human nervous system from a sensory neuron to brain astrocytes is detailed, but this model does not include an overall model of touch receptive fields and the cortex, nor the signal reception through EEG. Although an attempt has been made to model the overall touch propagation through the somatosensory system in,[33] this paper does not include numerical data, nor experimental data or validation of the presented models, which are based on finite state machines rather than physiological models from neuroscience.

The rest of the paper is organized as follows. In Section 2 we present a high-level description of the proposed communication system, and its main elements. In Section 3 we detail an analytical modeling framework that is based on the mathematical formulation of the main processes underlying the propagation of information-bearing tactile stimulation through the somatosensory system and the EEG device. In Section 4 we describe our simulation framework and the parameters we utilized to evaluate the performance of the proposed system, while in Section 5 we present the numerical results. Finally, with Section 6 we conclude the paper.

2. A THRU-BODY COMMUNICATION SYSTEM BASED ON HAPTIC INFORMATION TRANSMISSION

In Fig. 1, we show a graphical sketch of the communication system proposed in this paper, based on the following main elements. The **Transmitter** encodes information into a somatosensory signal through tactile stimulation of the skin. The **Channel** is identified with the somatosensory signal propagation through the nervous system, which transduces the aforementioned tactile stimulation into brain activity. Finally, at the **Receiver** an ElectroEncephaloGraphy (EEG) device is used to record the brain's somatosensory cortex activity, and the transmitted information is decoded from the resulting data. In the following, we describe each element with further detail.

2.1 Transmitter

Information *bits* are encoded into a *somatosensory signal* by modulating the parameters of a **tactile stimulation** operated by a device. In this preliminary work, we consider a stimulation device that operates a tapping of the skin, where we can control the time instant t_0 and the duration T of a skin tap at a precise location, which is

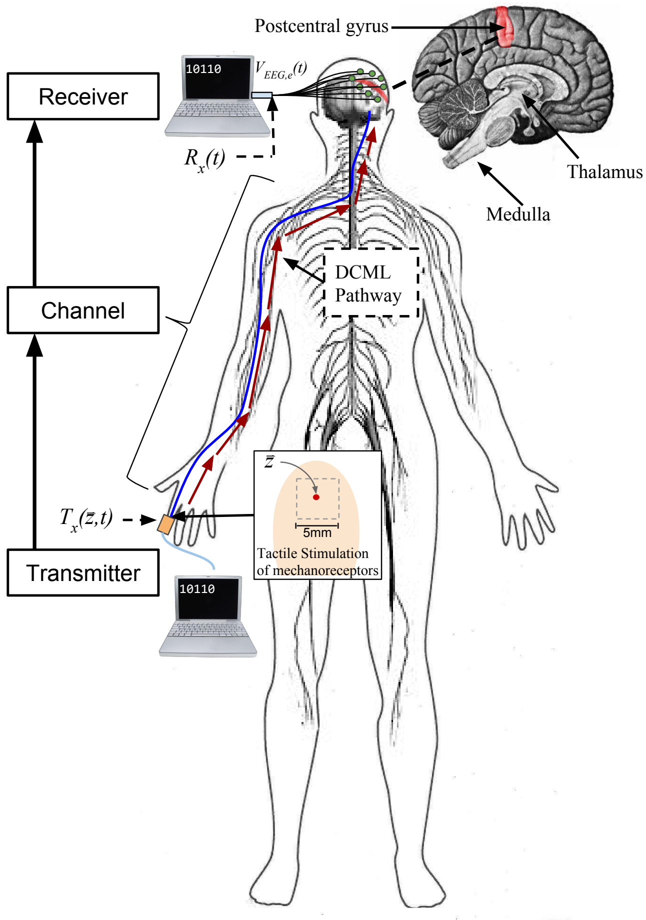

Figure 1. Scheme of the proposed communication system based on haptic information transmission.

inline with current off-the-shelf devices, *e.g.*, for Braille reading.[34,39] **Digital modulation** is achieved via an On-Off Keying (OOK) scheme where each bit is transmitted into a time slot, with duration equal to the inverse of the bitrate of the system, where bit 1 is transmitted with a tap, and bit 0 is transmitted with no tap. Since the tap is realized by protruding a pin with a diameter of 2 mm, we approximate the tapping location with a point on the skin surface. In the rest of the paper, we also assume that the tapping location is roughly at the center of the right index finger pad, denoted with the two-dimensional location coordinate $\vec{z}_{in}$, considered one of the most touch-sensitive skin locations of the human body.[18] The transmitted signal $T_x(\vec{z}, t)$, as function of the time t and the two-dimensional skin location $\vec{z}$, is expressed as follows:

$$T_x(\vec{z}, t) = \delta\left(|\vec{z} - \vec{z}_{in}|\right) A\,\mathrm{rect}\left(\frac{t - t_0}{T} - \frac{1}{2}\right), \tag{1}$$

where $\delta(.)$ and rect(.) are the Dirac delta and the rectangular function, respectively, A corresponds to the intensity of the tap, which is considered constant and equal to 1 within the scope of this paper, as explained in the following, and $||\vec{z} - \vec{z}_{in}||$ is the Euclidian distance on the skin surface between a skin location $\vec{z}$ and the tapping location $\vec{z}_{in}$.

2.2 Channel

In the proposed communication system, the channel abstracts the *somatosensory signal propagation* in the nervous system from the aforementioned tapping location until reaching the brain, which is operated by the mechanoreceptors at the finger pad, the Dorsal Column-Medial Lemniscus (DCML) pathway, and the somatosensory cortex, respectively.

First, **mechanoreceptors** present on the skin surface transduce a mechanical deflection at the finger pad, operated by the tapping, into an electrochemical signal.[12, 18]

Second, the **DCML pathway** is an interconnection of three orders of neurons that relay this electrochemical signal to the brain by propagating and regenerating the signal along their cell body projections, or axons.[32] The axons of the first order neurons begin at the finger pad mechanoreceptors, and continue up the arm past the shoulder, into the spinal cord, and ascend the posterior column of the cord until reaching the caudal portion of the brainstem, called the medulla. At the medulla, the first order neurons relay the propagated signal to the second order neurons through synapses, junctions between nerve cells where electrochemical signals are relayed through neurotransmitters diffusing in gaps between the two cell bodies. The second order neurons send their axons to the thalamus, a central region of the brain where nerve fibers project out to the cerebral cortex in all directions, where they also cross the midline to the opposite side of the spinal cord with respect to their origin side, in a region of their axons called medial lemniscus. At the Ventral Posterior Lateral (VPL) nucleus region of the thalamus, a second set of synapses connect the incoming second order axons to the third order neurons. The third order axons relay the incoming electrochemical signals via a third set of synapses into cortical neurons located at the postcentral gyrus of the brain, which is a region in the upper side of the brain opposite (at the left side in this case) to the side of the tapping location. There is evidence that a localized tactile stimulation corresponds to a localized set of cortical neurons receiving the resulting signal in a point-to-point fashion, where different stimuli locations correspond to different signaling locations in the brain.[27]

Third, the signal propagation along the cortical neurons stimulates correlated **somatosensory cortex** activity, where neighboring neurons react with electrochemical excitatory and inhibitory responses to the signals incoming from the DCML pathway.[28] These electrochemical responses of brain cortex neurons, organized into minicolumns and functional columns interconnected through thalamocortical and corticocortical networks,[7] result into ionic currents flowing across the brain cortex that cause the emission of electromagnetic waves, which are subsequently received at the EEG electrodes.

2.3 Receiver

The Receiver uses an **EEG system** with electrodes placed on the scalp at different locations to measure voltage fluctuations induced by the aforementioned ionic currents at the brain cortex. We consider a number E of electrodes placed on the scalp at predetermined standard locations.[20] The voltage fluctuations read by each electrode are affected not only by the somatosensory cortex activity correlated to the input tap in (1), but also by other brain activities, such as those related to higher-level cognitive functions. In the communication system presented in this paper, we aim to recognize the voltage fluctuations induced by the aforementioned tap-related somatosensory cortex activity. For this, we utilize a standard technique called **SomatoSensory Evoked Potential (SSEP)**,[29] where the voltage fluctuations from each electrode correlated to an event, *i.e.*, tapping, are preprocessed through averaging and filtering, resulting in the voltage signals $V_{\text{EEG},e}(t)$, for each electrode e. In addition, we take into consideration only the electrodes around the left postcentral gyrus region of the brain,[14] denoted with the set $\mathcal{G}$, since, as also explained above, other electrodes will not be able to read SSEP voltage fluctuations from the tap. As a consequence, the received signal $R_x(t)$, as function of the time t, is defined as follows:

$$R_x(t) = \{V_{\text{EEG},e}(t) | e \in \mathcal{G}\} \; . \tag{2}$$

In this communication system, we are interested in SSEP signals $V_{\text{EEG},e}(t)$ minimally dependent from the particular characteristics and state of each individual's nervous system. Based on experimental evidence,[29, 30] *the SSEP signals in* (2) *show an overall standard pattern across different experiment realizations within the first 100 ms from the occurrence of a tap, characterized by local maxima and minima around precise time instants.* In the rest of this paper, we detail an analytical modeling framework capable of reconstructing this standard pattern from mathematical formulations (Sec. 3). These findings and results provide preliminary yet fundamental tools to design communication systems based on haptic information transmission.

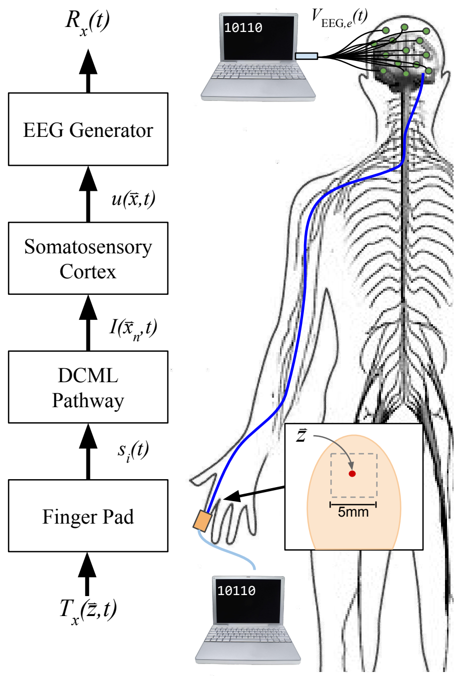

Figure 2. Schematic with the main models of the analytical framework for the proposed communication system.

3. ANALYTICAL MODELING

In this section, we detail an analytical modeling framework that is based on the mathematical formulation of the main processes involved in the communication system described in Sec. 2. In particular, as shown in Fig. 2, this framework is composed of four main analytical models, namely, the Finger Pad model, the DCML Pathway model, the Somatosensory Cortex model, and the EEG Generator model. The first two models are developed with reference to recent work in computational neuroscience from,[11,12] where the authors built a computational model of the aforementioned cortical neuron reception of somatosensory signals upon tactile stimulation of the finger pad. The Somatosensory Cortex model is based on a formulation of the global theory of neocortical dynamics in.[8] Finally, the EEG Generator model is inspired by the dipole neuron models studied in,[5,28] which provide mathematical expressions underlying the electromagnetic wave generation based on neural activity. These models are detailed next, together with the description of implementation details.

3.1 The Finger Pad

The Finger Pad model converts the transmitted signal $T_x(\vec{z},t)$ from (1) into the response $s_i(t)$ for each mechanoreceptor $i = 1, \ldots, \mathrm{I}$ placed on the finger pad skin. With reference to,[16] the response $s_i(t)$ can be approximated for any time t with a Gaussian function of the distance between the tapping location $\vec{z}_{in}$ and the location $\vec{z}_i$ of the mechanoreceptor i for the duration of the tap. This is computed from (1) with the following convolution operation:

$$\begin{aligned} s_i(t) &= T_x(\vec{z},t) * a \exp\left(-\frac{1}{2\sigma^2}|\vec{z}-\vec{z}_i|^2\right)\delta(t) \\ &= Aa\,\mathrm{rect}\left(\frac{t-t_0}{T}-\frac{1}{2}\right)\exp\left(-\frac{1}{2\sigma^2}|\vec{z}_{in}-\vec{z}_i|^2\right), \end{aligned} \tag{3}$$

where $*$ denotes the convolution operation with respect to the time t, a and σ are the intensity of the mechanoreceptor response and the decay of the skin deflection with the distance from the tapping location, respectively, considered equal for every mechanoreceptor.[16]

3.2 The DCML Pathway

The DCML Pathway model takes the response $s_i(t)$ of each mechanoreceptor $i = 1, \ldots, \mathrm{I}$ in input, and outputs the somatosensory signal $I(\vec{x}_n, t)$ that is received by a neuron n at the two-dimensional location $\vec{x}_n$ in the brain cortex, as explained in Sec. 2. The index n identifies signal-receiving neurons, a total of N, present in a localized region of the postcentral gyrus, *i.e.*, the signaling location, also known as receptive field, that receives tactile stimuli from the right index finger pad.[18] With reference to,[11,12] the real DCML pathway behavior can be approximated by computing for each neuron n the average distance between receptor responses $s_i(t)$ and feedforward weights $w_f^i(\vec{x}_n)$ associated to the neuron itself. This model is expressed as follows:

$$I(\vec{x}_n, t) = 1 - \frac{1}{\mathrm{I}} \sum_{i=0}^{\mathrm{I}} \left| s_i(t) - w_f^i(\vec{x}_n) \right| . \tag{4}$$

While the relation in (4) expresses an instantaneous propagation from the mechanoreceptor responses to the somatosensory signals at the cortical neurons, in reality there is a propagation delay in the DCML pathway as the somatosensory signals go through the first, second, and third order of neurons and their synapses, as explained in Sec. 2. In the scope of this paper, since the inclusion of a realistic model for the generation of this delay would imply the detailed knowledge of physiological parameters of each individual's nervous system, we limit ourselves to an empirical estimation from experimental data found in the literature.[29] We report in Table 1 an average estimate of the delays at different DCML locations experienced by the first peak in the pattern of the resulting SSEP, called the N20 component.

Table 1. Commonly observed average delays of the N20 component at different DCML pathway locations

Time (ms)	**Event**
0	Stimulus occurs (tap)
9	N20 at shoulder
13	N20 at fifth cervical spine
20	N20 at somatosensory cortex

3.3 The Somatosensory Cortex

The Somatosensory Cortex model computes the somatosensory cortex activity $u(\vec{x}, t)$ at each two-dimensional location $\vec{x}$ within the left postcentral gyrus of the brain at time t from the somatosensory signal $I(\vec{x}_n, t)$ received by the each neuron at location $\vec{x}_n$ within the aforementioned right index finger pad receptive field, function of the time t. According to the neural field model of the neocortical dynamics (see Table 2), this computation can be approximated through the Nunez-Amari integro-differential equation,[11,12] and it is expressed as follows:

$$\begin{aligned} \tau \frac{\partial u(\vec{x}, t)}{\partial t} = & - u(\vec{x}, t) + \int_{\Gamma} w_l(\vec{x}, \vec{y}) f\left(u\left(\vec{y}, t - \frac{|\vec{x} - \vec{y}|}{v} \right) \right) d\vec{y} \\ & + I(\vec{x}_n, t) \delta(|\vec{x} - \vec{x}_n|) , \end{aligned} \tag{5}$$

where τ is the membrane time constant, v is the speed of propagation of cortex activity between neighboring neurons, Γ is the set of two dimensional coordinates included in the postcentral gyrus, $w_l(\vec{x}, \vec{y})$ is the lateral connection function between two neurons located at $\vec{x}$ and $\vec{y}$, respectively, and $f(u(\vec{x}, t))$ is the firing rate, as function of the cortex activity u at location $\vec{x}$ in the postcentral gyrus, and time t.

The lateral connection function $w_l(\vec{x}, \vec{y})$ expresses the interplay between excitatory neurons, which respond to neighboring neuron activities with a positive signal, and inhibitory neurons, which respond to the same activities with a negative signal. The neural field theory (see Table 2) and the Nunez-Amari equation model cortex activity as a continuum on the cortex surface, and excitatory and inhibitory neurons are modeled as part of a homogeneous mixed population,[8] resulting in the following expression:

$$w_l(\vec{x}, \vec{y}) = K_e \exp\left(-\frac{1}{2\sigma_e^2} |\vec{x} - \vec{y}|^2 \right) - K_i \exp\left(-\frac{1}{2\sigma_i^2} |\vec{x} - \vec{y}|^2 \right) \tag{6}$$

Table 2. Neuroscience Terminology

N or P and a number (e.g. N20,P60)	A standard in the neuroscience community for describing features on plots of EPs. N or P refers to whether the feature is a local minima or maxima respectively, and the number represents the location in time (following the related stimulus).
Evoked Poential (EP)	An electric response in the nervous system following the presentation of a stimulus.
Somatosensory Evoked Potential (SSEP)	An SSEP is an EP caused by a physical stimulus which can be detected through EEG readings. SSEP tests are often used clinically for detection of the speed of information travel across the spinal cord.
Epoching	A process through which continuous signal data is cut into numerous constant length segments.
Dorsal Column Medial Lemnicus (DCML) pathway	The DCML is a key pathway in the nervous system which transmits information related to touch from the skin and joints to postcentral gyrus of the brain.
Neural Field Theory	Uses tissue-levels models to describe the spatiotemporal characteristics of variables such as the synapse firing rate and membrane potentials.

where K_e and K_i quantify the strength of excitation and inhibition of a neuron, respectively, and σ_e and σ_i express the intensity of excitation and inhibition, respectively, as function of the distance between two neurons. Commonly, (6) models the experimentally observed short range excitation and long range inhibition, which results in the condition $\sigma_i \gg \sigma_e$.[12]

The firing rate $f(u(\vec{y}, t - |\vec{x} - \vec{y}|/v))$ models the non-linear behavior underlying the excitability of a cortex neuron at location $\vec{y}$. This is usually expressed through a sigmoidal function of the cortex activity propagated at location $\vec{y}$ from location $\vec{x}$ at time t with velocity v.[8] For simplicity, as suggested in,[17] we approximate the firing rate function f as follows:

$$f(u) = \begin{cases} u & u \geq 0 \\ 0 & u < 0 \,. \end{cases} \tag{7}$$

3.4 The EEG Generator

The EEG generator model takes as input the somatosensory cortex activity $u(\vec{x}, t)$ at each location $\vec{x}$ within the left postcentral gyrus as function of the time t, and returns as output the received signal $R_x(t)$ expressed in (2). In agreement with,[5,28] from the point of view of the aforementioned generation of electromagnetic waves by ionic currents associated to the neocortex activity, and the consequent voltage recorded at the EEG electrodes, the somatosensory cortex can be modeled as a two-dimensional layer of electromagnetic-wave-emitting dipoles. In this model, the EEG electrodes are approximated as point-wise locations immersed in the conductive medium of the scalp, to which they are electrically connected through an electrolytic saline solution, gel, or paste.[23] As a consequence, in agreement with,[5] the voltage signals $V_{\mathrm{EEG},e}(t)$ read by the electrode e as function of the time t can be expressed as

$$V_{\mathrm{EEG},e}(t) = \frac{\sigma_{in}}{4\pi\sigma_{ex}} \int_{\mathrm{surf}} k_v u(\mathbf{P}\vec{r}, t) d\Omega(\vec{r} - \vec{r_e}) \,, \tag{8}$$

where σ_{in} and σ_{ex} are the intracellular and extracellular conductivity, respectively, $\mathbf{P}$ is the orthogonal projection matrix equal to $[100; 010; 000]$,[6] $\mathbf{P}\vec{r}$ projects the three-dimensional coordinate $\vec{r}$ into the two-dimensional coordinate $\vec{x}$ of the somatosensory cortex, and $d\Omega(\vec{r} - \vec{r_e})$ is the solid angle that an infinitesimal surface unit (surface differential) subtends at the three-dimensional location $\vec{r_e}$ of the EEG electrode e.[5] The constant parameter k_v converts the somatosensory cortex activity into a proportional electrical potential of the cell membrane of the cortex neurons at the same location and time. Within the scope of this paper, we estimate the parameter k_v by scaling the received signal computed through the analytical model to that obtained from the experiments, as explained in Section 5.

4. SIMULATION

To simulate the data we developed a MATLAB script using the equations provided in Section 3 and the associated parameters, which are summarized in Table 3.[5,12] Using this model, we produced 12,600 seconds of simulated EEG data corresponding to frequencies between 10 and 100 Hz. For each test, we produced a pseudo-random sequence of bits which determined whether the simulation would simulate a tactile tap or not at each time slot, as explained in Section 2.1. This simulation produces essentially noiseless data, the only impairment occurring inherently caused by inter-symbol interference, Figure 4.

In order to probe the capacity of our system in the presence of noise, we utilized one of the most simple and commonly used noise models, the diagonal model for noise covariance. Through this model we consider the noise to be uncorrelated and parameterized by diagonal elements made up of the EEG sensor variances.[19] We have not yet determined a reasonable standard deviation for the noise, and so presently we have tested several noise values to show how our system holds up. Additionally, for our study we are interested in the somatosensory cortex activity that is localized to a specific part of the brain (the post-central gyrus), and so even in clinical settings we need only at most a few electrodes to record the related voltage signals. For this reason, as well as for computational simplicity, we only considered a single EEG electrode in our simulations.

Table 3. Model Parameters

K_e	Excitation strength	3.65
K_i	Inhibition strength	0.1 mm
σ_e	Excitation intensity	2.40
σ_i	Inhibition intensity	1.0 mm
τ	Membrane time constant	1 s
dt	Time change	1 ms
T	Tap duration	1 ms
a	Intensity of response	1
σ	Decay of skin deflection	1
v	Cortical Propagation velocity	750 cm/s
σ_{in}	Intracellular conductivity	1 S/mm
σ_{ex}	Extracellular conductivity	1 S/mm
k_v	Proportionality constant	*est*

5. NUMERICAL RESULTS

To evaluate the performance of the system through the aforementioned simulation, we broke the simulated EEG data into 39,100 epochs. The epoch length corresponds to the length of each OOK time slot, and its inverse is the bit rate (*e.g.* for a transmission frequency of 10 bits per second, the continuous EEG signal is chopped into lengths of 100 ms each), and each epoch contains either a tap stimulus or a silence period. After this preprocessing, we utilize the obtained epochs in combination with a Support Vector Machine (SVM) binary classifier.[9] The SVM classifier works by determining an optimal hyperplane to separate binary data (in our case the presence or absence of a tactile stimulus). We implemented the SVM classifier using the built in SVM toolbox in the standard MATLAB library. The results are summarized in Figure 4. In order to get a reliable accuracy score, we averaged the results of 10 SVM classification scenarios for each bt rate, where each scenario

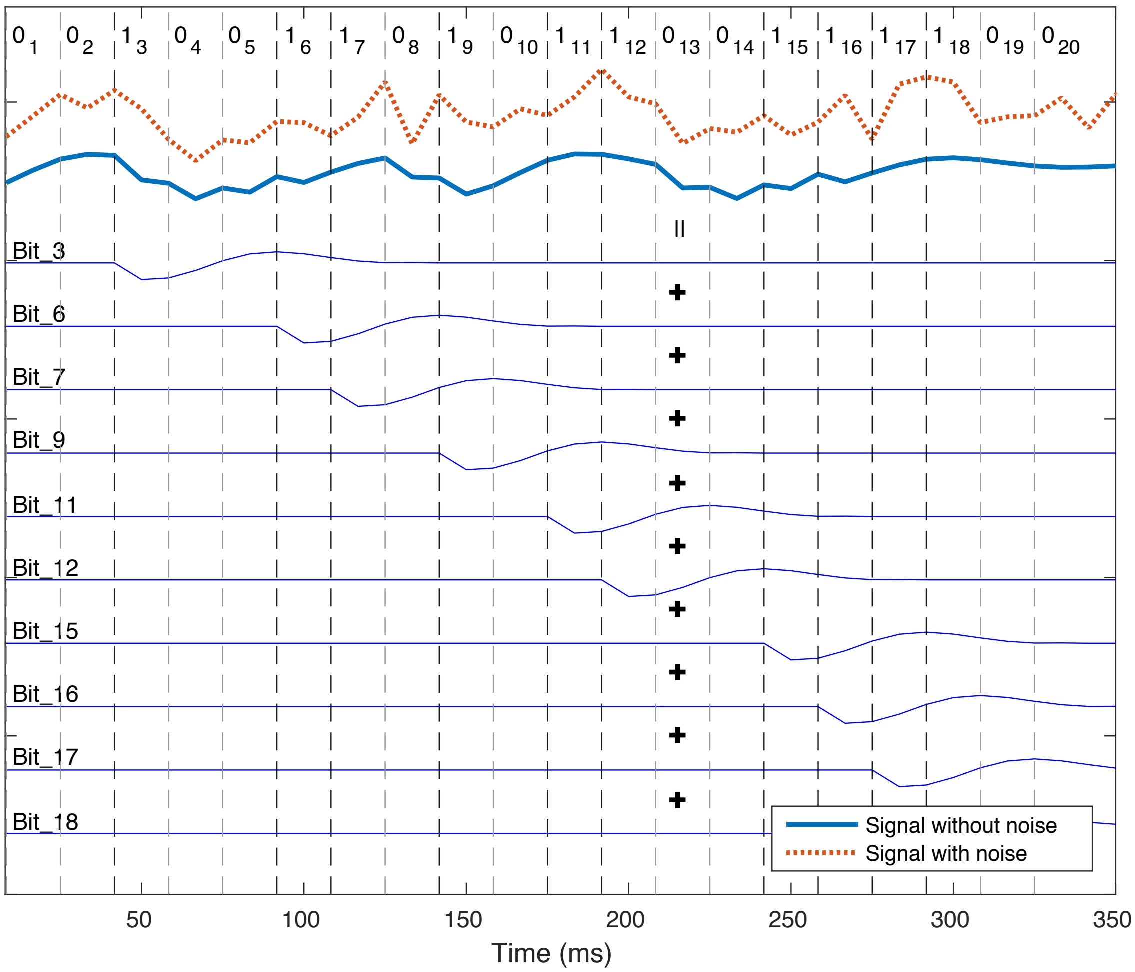

Figure 3. Example of simulated data. From upper to lower, we show a pseudo-random sequence of bits to be transmitted, each bit with the corresponding slot sequence number, the resulting EEG signal output from the haptic information transmission system in the case without noise, and with noise, and the decomposition of individual contributions, one for each bit, that make up the signal.

included using different collections of training and testing data. We used a constant training data set of 5000 samples for each test (*e.g.* for 10 Hz data we would have a training set consisting of 5000 epochs of 100 ms long each).

We quantify the results from the classification in two ways. The accuracy score which is defined as the ratio of correct classifications to the total number of samples classified. Mathematically we write

$$accuracy = \frac{\#p_{1,1} + \#p_{0,0}}{\#p_{1,1} + \#p_{1,0} + \#p_{0,1} + \#p_{0,0}}$$

where $\#p_{i,j}$ represents the number of occurrences of a prediction of having received bit i given that the transmitted bit is j. The second form of evaluation is the scoring function which represents the distance between a given sample and the decision boundary. This is done by computing the optimal posterior probabilities using Platt's Method.[31] This is the built in scoring function provided with the SVM resources in MATLAB.

In the classification of the noiseless simulated EEG data, we see perfect classification for bit rates varying between 10 and 60 bits per second, with a slow drop off after that. This is reasonable given that for lower bit transmission rates there is minimal intersymbol interference, but as the rate increases each symbol may be confused with the next. As we add greater amounts of noise to this data, the overall accuracy drops, but the general trend continues. With the inclusion of noise, we see the best accuracy ratings between 10 and 20 bits per second, and a linear decrease in accuracy occurs around 40 bits per second.

The confidence scores for each level of noise start low and then reach an optimum above 30 bits per second (with the exception of the noiseless data which finds an optimum at 60 bits per second). This is likely because for lower frequency data, the period (and thus the epoch) length is very high and so more data points are considered for each classification. This issue could be alleviated by increasing the training set size.

Based on the provided results, it appears that we can transmit bits at rates of up to 40 bits per second before there is any significant drop-off in terms of the error rate. Based on our simulated results, the optimum transmission rates appear to be either in the peaks between 15 to 25 bits per second, or around 40 bits per second, but not higher. Although these bit rates are much lower than those normally required for interconnecting wearable devices, we believe this study can serve as a proof-of-concept for more advanced implementations that, *e.g.*, make use of more complex modulation and encoding schemes. Further investigation is left to future work.

6. CONCLUSION

In this paper, we proposed a communication system based on the propagation of haptic (touch) stimuli through the nervous system and its components. This system is motivated by the ever increasing number of wearable and implantable devices that demand novel sustainable solutions to realize their connectivity. In particular, this system is based on an information-transmitting tactile stimulation, realized at the index finger pad, its propagation along the nerves of somatosensory system, and the reception of the resulting brain's somatosensory cortex activity through an ElectroEncephaloGraphy (EEG) device. The non-invasive nature and the availability of well-established techniques for EEG signal acquisition and analysis, as well as previous neuroscience literature on the modeling of somatosensory system processes, makes this an ideal system to study for the aforementioned goals.

We developed an analytical modeling framework based on diverse computational neuroscience models of the somatosensory signal propagation, the somatosensory cortex at the brain, and the generation of EEG signals. Preliminary simulation results in these models reveal that it is possible to reach a bit rate of 30-40 bits per second with this system by utilizing OOK digital modulation of tactile stimulation taps at the index finger. Future work will be focused on an in-depth analysis of this system when more complex modulation and encoding schemes are employed, as well as a further investigation on the noise sources affecting the received signal. In addition, we plan to experimentally validate our proposed system in a neurophysiology lab.

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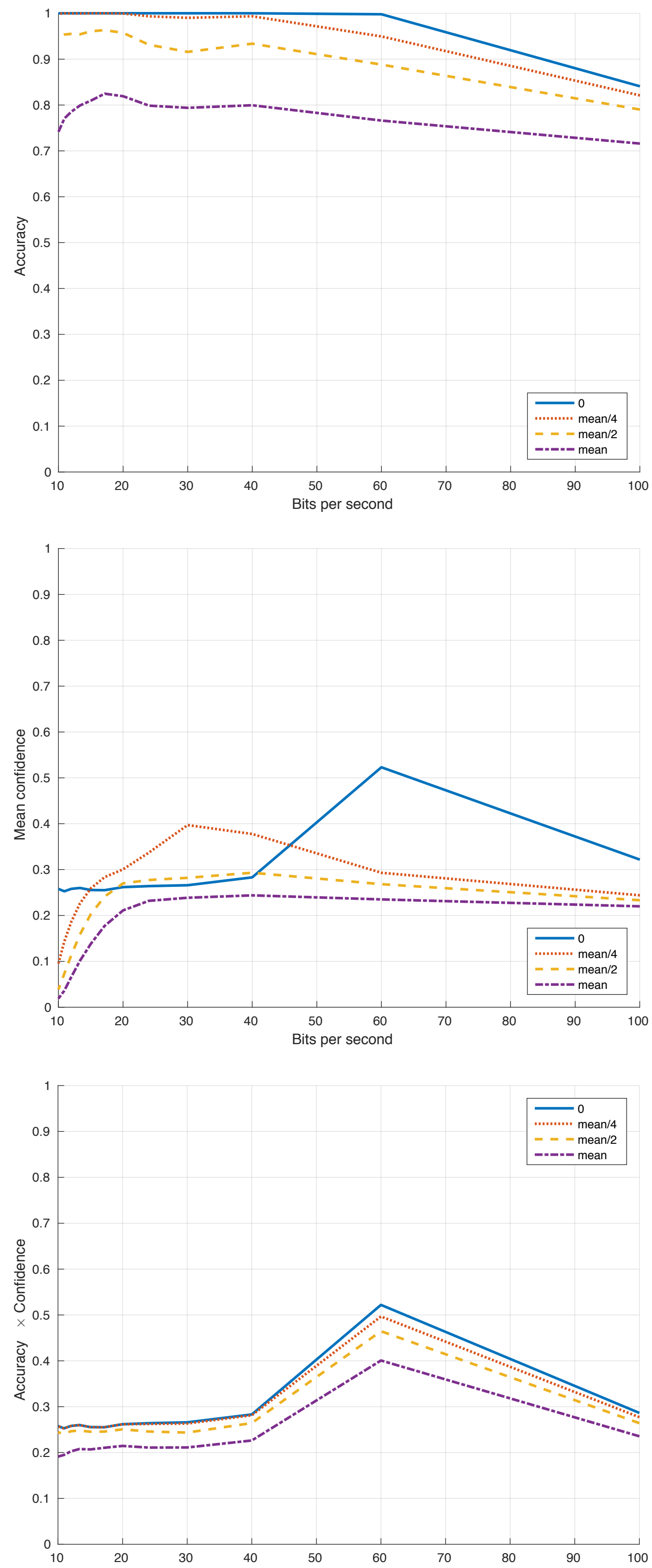

Figure 4. Performance of the communication system in terms of accuracy and confidence in the estimation of the received bits. Different curves correspond to different values for the standard deviation of the noise, ranging from 0 to a value equal to the mean of the simulated received EEG signal.

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