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A Novel Three-Dimensional Multilayer Electroencephalography Paradigm

Frank Edughom Ekpar

Abstract

Contemporary electroencephalography systems operate on a two-dimensional single-layer paradigm where signals from multiple layers of neuronal populations under an electrode are aggregated and recorded by that single electrode, leading to noisy signals and a lack of insight into neurological processes and keeping brain-to-brain communication, practical brain-computer interfaces and a host of applications in domains ranging from medicine to computing out of reach. Here, we introduce a novel three-dimensional multilayer electroencephalography (3D Multilayer EEG) paradigm – unlike the contemporary single-layer or two-dimensional (2D Single-layer EEG) paradigm – that leverages a nature-inspired conceptual framework in which approximations to carefully selected features of the source of the bio-signals are harnessed for characterization and manipulation of the underlying biological system. Effected through the simultaneous capture of distinct signal streams from multiple layers of neurons, this novel multilayer EEG paradigm could lead to effective computer-mediated brain-to-brain communication systems, a clearer understanding of neurological processes both in normal functioning and in disease as well as several orders of magnitude improvements in the information transfer rate in brain-computer interface systems – making these systems practical – as well as enabling a broad range of novel applications in domains ranging from medicine to social interactions, human factors including workplace optimization, economics, generic computing and human-machine interactions. Recent work demonstrating the direct imaging of signals propagating through myelinated axons and direct evidence that scalp EEG recordings can detect subcortical electrophysiological activity confirms the correctness of the principles underpinning our framework. We demonstrate the effectiveness of our novel 3D Multilayer EEG paradigm by formulating the null and alternative hypotheses for simultaneous multilayer EEG signal capture and relying on the results of analysis of a set of carefully designed experimental measurements to falsify the null hypothesis and validate the alternative hypothesis.

Keywords: Electroencephalography (EEG), Three-dimensional Multilayer Electroencephalography (3D Multilayer EEG), Ekpar Electroencephalography (Ekpar EEG, EEEG), Brain Computer Interface (BCI), Brain-to-brain Communication, Artificial Intelligence (AI), Deep Learning (DL), Ampullae of Lorenzini

Introduction

Human communication is essential for the smooth functioning of human society. Throughout history, human communication has been

Affiliation:

Scholars University Ltd, Rivers State University, Topfaith University, Nigeria

***Corresponding author:**
Frank Edughom Ekpar, Scholars University Ltd, Rivers State University, Topfaith University, Nigeria.

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mediated by language in verbal, written and sign formats. As a result, there has been a proliferation of languages and dialects with the attendant confusion and deficiencies in communication. Cooperation, especially international cooperation, has also been hampered by this babel of languages and more significantly, persistent, intractable, costly, violent and fatal conflicts have often resulted from our inability to communicate effectively. The brain plays a central role in human communication. Enabling brain-to-brain communication would permit us to communicate and collaborate more effectively, resolve conflicts, create more peaceful societies, control our environment via thought and gain unique insights into the workings of the human mind – leading to a wide range of remedies for brain communication-related problems.

Brain-computer interface (BCI) systems are poised to become more ubiquitous. It is plausible to induce desired states and sensory perceptions in associated biological systems through signals emanating from BCIs. Systems for the acquisition of brainwave data generally fall into two broad categories--invasive and non-invasive. Invasive methods and systems are typically characterized by the utilization of surgical procedures to insert sensors directly into biological tissue. On the contrary, non-invasive methods and systems do not require surgical procedures or direct contact with the cells within the biological substrate associated with the signals. Electrocorticography (ECoG)-based systems such as those presented by Leuthardt et al. [1] are invasive. Examples of non-invasive systems include positron emission tomography (PET) [2], single photon emission computerized tomography (SPECT), functional magnetic resonance imaging (fMRI), electroencephalography (EEG) [3], magnetoencephalography (MEG) [4], including MEG devices employing ultrasensitive superconducting quantum interference device (SQUID) arrays [5], and functional near-infrared spectroscopy (fNIRS) systems. Although invasive techniques generally provide more accurate representations of neuronal activity, they are inconvenient, typically require risky brain surgery and pose ongoing risks to biological tissue during operation. In 2019, the Royal Society (United Kingdom) published a Perspective Article entitled "iHuman: Blurring the lines between machine and mind" providing an extensive review of the state of the start as well as a historical perspective on neural interfaces including brain-computer interfaces and EEG systems [6]. Based on the Royal Society's review, it is obvious that while tremendous progress has been made, numerous challenges remain and in particular practical systems for effective human level communication using neural interfaces still appear unattainable. signals are applied in a very broad range of settings including clinical and non-clinical environments. In clinical settings and in the practice of medicine, the EEG is used for a wide variety of tasks including, but not limited to, psychiatric studies and the diagnosis and management of neurological impairments such as epilepsy as well as in the evaluation of medical and psychological therapies. Uses of the EEG in psychology and neuroscience include the study of the brain processes underlying memory, learning, perception and attention. The EEG can also be applied to the study of social interactions. Other applications relate to human factors including factors pertaining to workplace optimization, neuromarketing and economics and the aforementioned brain computer interfaces (BCIs) and human-machine interaction. The EEG can also be applied to the study of non-human primates, other animals as well as comparative studies between species of animals.

Schiller et al [7] examined the relationship between the temporal dynamics of resting EEG networks and pro-sociality while Packheiser et al [8] investigated real-life emotions in romantic couples using a mobile EEG study. The Neuralink Interface [9] currently under development holds out the promise of permitting brain-to-brain communication in the future but requires surgical implants that are at best inconvenient and expensive and at worst could cause harm to the subject. Traditionally, the majority of non-invasive BCIs were based on the well-known electroencephalography (EEG) technique owing to its relative portability, low cost, high temporal resolution and ease of operation. Examples of BCIs based on EEG and/or other non-invasive recordings include those disclosed by Katz et al [10], Wolpaw et al [11] and Toshimitsu [12]. The system described by Katz et al [10] groups together multiple modalities including EEG, near-infrared spectroscopy (NIRS), electromyography (EMG) and galvanic skin response (GSR) on the basis of classification techniques and is designed to assess the brain state of a patient while determining the present will (defined broadly to include not only desires and wishes but also emotions) of a subject using characteristic values of the subject such as a set of EEG signals that can be augmented by a combination of signals from scalp potential, muscle potential, heart-rate, eye-movement and frequency of eye blinks is the goal of the work described by Toshimitsu [12].

The spatial resolution of contemporary EEG-based BCIs is quite low--with systems typically comprising between 1 and 256 electrodes, each of which aggregates signals from massive neuronal populations. Furthermore, the signals are heavily attenuated on their journey through the skull and are thus susceptible to corruption by noise from other signal-emitting physiological processes in the subject and disturbances from the environment. As revealed by the Royal Society's review6, the current state-of-the-art in ambulatory (portable), relatively inexpensive non-invasive BCIs still relies on the well-known single-layer EEG technique where signals from all layers of neuronal populations under an electrode are aggregated to a single electrode, leading to noise and distortion of signal information. Techniques,

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algorithms and systems that remedy the shortcomings of EEG-based BCIs are well known and widely reported in the literature. Wolpaw et al. [11] describe an adaptive algorithm that uses a simple linear combination of relevant features to improve the effectiveness of a non-invasive BCI designed for 2-dimensional computer cursor control. Although the method described by Wolpaw et al. [11] provides better results than some competing methods by adapting the features selected for classification to the specific features that the user is best able to control, it is still hampered by the major drawback of high sensitivity to individual brainwave characteristics and the requirement for long training periods. The information transfer rate of EEG-based BCIs is currently in the range of 5 to 25 bits per second which is too low to permit widespread use of such BCIs in practical applications.

Recent research has been focused on harnessing the advantages of deep-learning neural networks and other artificial intelligence (AI) methods to the challenge of processing brainwave signals, classifying patterns therefrom and generating actionable information for use in a wide range of applications. For example, Dolmans et al [13] describe a system for the classification of perceived mental workload using intermediate fusion multimodal deep learning. Similarly, Kwon et al [14] applied convolutional neural networks to the creation of BCIs based on subject-independent functional near-infrared spectroscopy. A two-level domain adaptation neural network for EEG- based emotion recognition was introduced by Bao et al [15]. Aldayel et al [16] carried out research on the recognition of consumer preference through the analysis and classification of EEG signals. Improvements in classification performance for motor imagery EEG using channel-level recombination in a data augmentation system were achieved by Pei et al [17] while Hosseini et al [18] introduced an optimized deep learning method for EEG big data and seizure prediction BCI via Internet of Things. The enhancements in continuous neural tracking for robotic device control using noninvasive neuroimaging reported by Edelman et al [19] can be significantly improved using the multilayer EEG paradigm and signal processing techniques presented here Jiang et al [20] presented a system comprising a multi-person brain-to-brain interface for direct collaboration between brains that combines EEG brainwaves with transcranial magnetic stimulation (TMS) to achieve its goals. This system is limited by the shortcomings of the current 2D EEG paradigm and uses an intrusive modality in the form of TMS, the long-term effects of which are not completely understood. By utilizing a computer mediated brain-to-brain communication configuration such as that depicted in Fig. 1 and based on our novel 3D Multilayer EEG paradigm, full-fledged brain-to-brain communication can be achieved without the potentially deleterious effects of TMS or similar intrusive modalities.

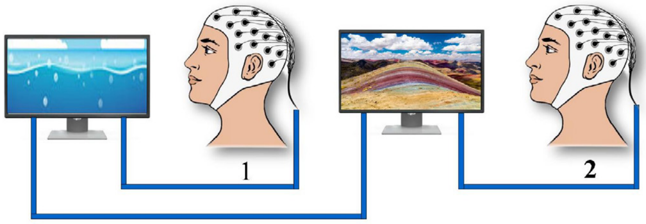

Figure 1: Schematic of Computer-mediated Brain-to-Brain Communication System.

In Fig. 1, 1 and 2 represent human participants each wearing a computer-linked EEG headset. Note that the linkage between the computer and the EEG headset could be accomplished with or without wires. To send a message to 2, the computer linked to 1 captures the EEG brainwaves emitted by 1, decodes and identifies the pattern(s) they represent and then selects the appropriate symbol(s) or representations(s) from a pre-arranged language understood by both participants for transmission to the computer linked to 2 which displays or presents the symbol(s) or representations to 2. This process is simply reversed in order to send a message to 1 from 2. The pre-arranged language could be a simple visual language. For example, in a situation where a Japanese speaker wishes to communicate the idea of a river ("kawa" in Japanese) to an English speaker, an image or movie of a river could be displayed on the receiver's screen after the brainwave signal patterns representing a river are detected from the sender. Similarly, the same Japanese speaker could communicate the idea of going on a hike in the mountains ("yama" in Japanese) by simply imagining the hike in the mountains and having an image of a mountain displayed on the receiver's computer screen. In this way truly universal and full-fledged brain-to-brain communication could be achieved using a mutually understood language which itself could be pictorial. Note that the computing resources could be distinct or shared with local or distributed communications and that there could be as many participants as dictated by necessity and availability if resources.

Nagel et al [21] reported the fastest documented BCI in the relevant literature in 2019, achieving an information transfer rate (ITR) of 1237 bits per minute or about 21 bits per second using deep learning. By introducing the simultaneous multilayer signal acquisition approaches we have introduced in this paper, we can significantly increase the information transfer rate of BCIs by several orders of magnitude, potentially recording ITRs in the range of megabits per second or higher depending on the count and density of EEG electrodes and the computing resources available. It is a goal of the work presented here to establish a novel 3D Multilayer EEG paradigm by formulating the null and alternative hypotheses for simultaneous multilayer EEG signal capture and relying on the results of analysis of a set of carefully designed experimental measurements to falsify

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the null hypothesis and validate the alternative hypothesis. This work also suggests a pathway towards full-fledged and effective brain-to-brain communication based on research on nature-inspired signal processing by Ekpar [22, 23]. Zhang et al [24] recently demonstrated the direct imaging of signals propagating through myelinated axons while Seeber et al [25] provided direct evidence that scalp EEG recordings can detect subcortical electrophysiological activity. These results confirm the correctness of the principles underpinning the conceptual framework on which our work is based and confirm all three related predictions reported by Ekpar22, 23 with far-reaching implications.

In summary, the main contributions of the work reported in this paper are:

1. Explaining how the recent direct imaging of signals propagating through myelinated axons by Zhang et al [24] and direct evidence that scalp EEG recordings can detect subcortical electrophysiological activity by Seeber et al [25] confirm the veracity of the principles underpinning the conceptual framework on which our work is based and confirm all three related predictions by Ekpar [22, 23]. This has far-reaching consequences.
2. Enabling three-dimensional multilayer electroencephalo graphy (3D EEG) in a novel paradigm unlike the contemporary single-layer (2D single-layer EEG) paradigm, potentially leading to new insights into the underlying physiological processes and new and improved applications of EEG in a broad range of application domains.
3. Demonstrating the simultaneous capture of distinct signal streams from neuronal populations located at different layers at the signal capture site by formulating the null and alternative hypotheses for simultaneous multilayer EEG signal capture and relying on the results of analysis of a set of carefully designed experimental measurements to falsify the null hypothesis and validate the alternative hypothesis.
4. Providing a pathway towards effective brain-to-brain communication and other hitherto difficult-to-achieve brainwave data-based applications.

The rest of this paper is organized as follows. Section 2 presents our conceptual framework, showing how it enables multilayer 3D EEG and explaining how recent results obtained by Zhang et al [24] and Seeber et al [25] confirm the correctness of the principles underpinning the conceptual framework on which our work is based and confirm all three related predictions by Ekpar [22, 23]. Materials and Methods are described in Section 3 while Hypotheses and Experiments to test the hypotheses appear in Section 4. Section 5 presents results which are discussed in Section 6 while Section 7 contains concluding remarks.

Three-Dimensional Multilayer Electroencephalo graphy (3d Multilayer Eeg)

The Need for a 3D Multilayer EEG Paradigm

Although invasive brain-computer interfaces currently provide a pathway to practical brain- machine interaction, they are severely limited because they require risky, inconvenient and undesirable surgery and implantation of electrodes which can be rejected by biological tissue and are costly to implement. Existing non-invasive electroencephalography (EEG) systems, while being more responsive, cost effective and easier to implement than alternatives such as functional magnetic resonance imaging (fMRI), exhibit poor performance and noisy signals – depending as they do on the aggregation of signals from large collections of neuronal populations, making them impractical for real-world applications. Furthermore, contemporary EEG systems do not provide a viable pathway to viable brain-to-brain communication, which as mentioned earlier could permit us to communicate and collaborate more effectively, resolve conflicts, create more peaceful societies, control our environment via thought and gain unique insights into the workings of the human mind – leading to a wide range of remedies for brain communication-related problems. Ekpar [23] recently introduced a nature-inspired signal processing system that when adapted to EEG sensor ensembles, permits the simultaneous capture of distinct EEG brainwave signals from neuronal populations located at different depths within the brain thus enabling 3D multilayer EEG systems. Combined with robust signal processing, pattern recognition and artificial intelligence techniques, we now have a system with a clear pathway towards more robust and practical BCIs, computer-mediated brain-to-brain communication, clearer insights into the workings of the brain and mind, clinical applications, and so on. The utility of the system would be limited primarily by the ability to manufacture sensor ensembles (and associated electronics, photonics or other processing modalities) with sufficient electrode counts and densities to adequately capture information about the underlying physiological processes.

In the remainder of this section, we highlight the theoretical framework underpinning the system and explain how the recent direct imaging of signals propagating through myelinated axons by Zhang et al.24 and direct evidence that scalp EEG recordings can detect subcortical electrophysiological activity by Seeber et al.25 confirm the correctness of the principles underpinning the conceptual framework on which our work is based and confirm all three related predictions by Ekpar [22, 23].

Conceptual Framework

As elucidated by Ekpar 22, 23, our model utilizes approximations to carefully selected representative features

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of the source of the bio-signals for characterization and/or manipulation of the underlying biological system. Fig. 2A is a schematic representation of our model and outlines the relationship between the source of the signals and the corresponding or counterpart environment, mediated by the boundary while Fig. 2B illustrates a specific instantiation of our model.

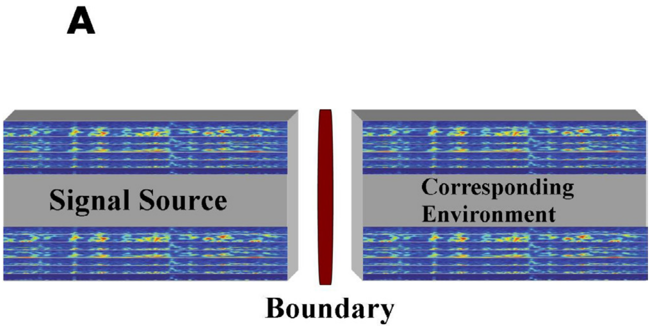

Figure 2A: Outline of model

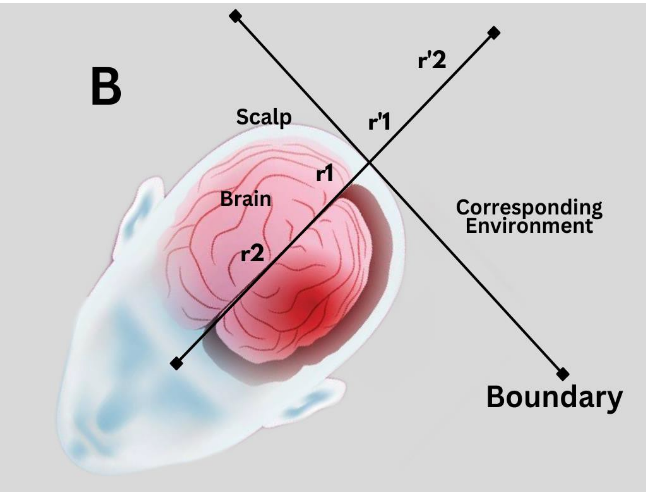

Figure 2B: Signals within the source (brain) and their detected images in the counterpart or corresponding environment.

In Fig. 2B, the source of the signals represents the brain while the corresponding environment represents the system of sensors built to non-invasively record data streams from the brain. The boundary between the two systems is the scalp. The detected or measured counterpart to the predominant source signal labeled r1 is r'1 while the detected or measured counterpart to the predominant source signal labeled r2 is r'2. Generally, in our model, the characteristics of the boundary between the source and the generated counterpart environment that are incorporated into the model are informed by a consideration of the nature of the source and the corresponding environment. Furthermore, the application of the model informs the choice of characteristics that need to be approximate as well as the manner in which those characteristics would be estimated.

Confirmation of Correctness of Conceptual Framework

On the basis of this conceptual framework, Ekpar22, 23 made three predictions, namely:

PREDICTION I: Since signals from sources at locations deeper in the brain are likely to reach the scalp later than signals originating from neuronal populations or brain regions closer to the scalp, sensors in the corresponding environment closer to the boundary (in a radial direction from the scalp) are likely to detect signals in which contributions from neuronal populations at shallower locations within the brain predominate. Conversely, sensors located farther from the boundary are likely to detect signals in which the contributions of neuronal populations that are farther from the boundary predominate. Generally, the farther the sensor, the lower the ratio between the contribution of near compared to far sources.

PREDICTION II: Sensors placed over the same site but separated from each other (in a radial direction from the scalp, such as sensors located at r'1 and r'2 in Fig. 2B) are likely to detect signals in which contributions from different levels within the brain predominate.

PREDICTION III: Sensors embedded directly at different levels within the brain should detect signals similar to those detected by sensors located at corresponding positions within the corresponding environment.

Consequently, with reference to Fig. 2B, our model predicts that a sensor located at r'1 is likely to detect signals in which the contributions of neuronal populations closer to r1 predominate while a sensor located at r'2 is likely to detect signals in which the contributions of neuronal populations closer to r2 predominate. This is because the farther the sensor, the lower the ratio between the contribution of near compared to far sources. Expressed differently, the signal detected by a near sensor (r'1) would be almost entirely due to the near source (r1), while a farther sensor (r'2) would be influenced by both sources since the sources-sensor distances would be comparable. Recent work by Zhang et al [24] permits the direct imaging of signals propagating through myelinated axons and demonstrates conclusively that electrical signals propagate through different neurons at finite, measurable and disparate speeds and consequently are likely to be detected at different layers of neuronal populations at different times. This is direct confirmation of PREDICTION I made by Ekpar [22, 23] on the basis of our framework and reproduced here with an expanded description of the distribution of signals. Furthermore, Seeber et al [25] provided direct evidence that scalp EEG recordings can detect subcortical electrophysiological activity. This is direct confirmation of **PREDICTION III** made by Ekpar [22, 23] on the basis of our framework and reproduced here.

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PREDICTION II follows naturally as a consequence of **PREDICTION I** and **PREDICTION III** which have been confirmed by the results reported by Zhang et al. [24] and Seeber et al [25]. Confirmation of all three predictions made by Ekpar [22, 23] on the basis of our framework by the recent results disclosed by Zhang et al.24 and Seeber et al.25 provides independent validation of and support for the foundations of our conceptual framework and model and has far-reaching consequences.

Materials and Methods

Bio-Signal Acquisition System

Here we describe the bio-signal acquisition system we created based on our conceptual model and inspired generally by some of the characteristic features of Ampullae of Lorenzini. Signals propagate through a biological signal source and cross the intervening media to reach the components or boundaries of the source (such as the scalp in the case of the human brain) that are in contact with or connected operatively to our signal acquisition system at finite, measurable speeds. It has been shown that EEG signals (including intracranial EEG or iEEG signals) can provide anatomically precise information about the selective engagement of neuronal populations at the millimeter scale and about the temporal dynamics of their engagement at the millisecond scale25, 34. Our system leverages these temporal dynamics engendered in the corresponding or counterpart environment (permitted by the appropriate source-sensor coupling model between the two environments) to effect the simultaneous acquisition of distinct signals from disparate layers within the signal source. In broad outline, system comprises a grid of sensor ensembles, each sensor ensemble comprising a collection of sensors disposed on an arbitrarily shaped N-dimensional (N = 1, 2, 3, and so on) surface with each sensor in contact with a suitable medium (conducting medium for applications such as EEG) which in turn is in contact with a surface associated with the source of the bio-signals [22, 23]. Elasmobranchs (cartilaginous fish belonging to the group that comprises sharks, rays and skates) are known to possess electroreceptive units referred to in the literature as Ampullae of Lorenzini that comprise jelly-filled canals usually found on the head of the animal which form a system of sense organs, each of which receives stimuli from the external environment through the dermis and epidermis. The lengths of canals exhibit variability from species to species and even within one fish but show an approximately species-specific distribution pattern. A group of small bulges lined by the sensory epithelium terminates each jelly-filled canal in an ampulla. Furthermore, each ampulla is innervated by a small bundle of afferent nerve fibers. Our signal acquisition system is inspired by some of the features associated with the ampulla. Murray26, 27, Kalmijn28, 29 and Brown30 provide more nuanced discussions of Ampullae of Lorenzini.

Experimental Setup: Sensor Ensemble

We constructed a sensor ensemble comprising two sensors or electrodes – SE1 and SE2 -- placed orthogonally with a separation of 10.0 mm along the axis of a containing plastic (non-conducting) cylinder with an inner diameter D, of 10.0 mm, an outer diameter of approximately 14.0 mm, and a height or length L, of 20.0 mm. The height (distance from scalp) of the first electrode (SE1) – HSE1 was 5.0 mm and the height (distance from scalp) of the second electrode (SE2) – HSE2 was 15.0 mm – giving an inter-electrode distance of 10.0 mm. Fig. 3 illustrates the sensor configuration. For the purposes of our experiments, we filled the interior of the cylindrical container with a sponge medium and soaked the sponge in a saline (NaCl) solution. We used a stainless-steel wire with a diameter of 1.1 mm for the electrodes or sensors. The model of sensor-source coupling in our sensor ensemble is resistive conduction. The inter-sensor impedance for the two sensors SE1 and SE2 was approximately 240 KΩ while the boundary-sensor impedance for SE1 was about 200 KΩ when the sensor ensemble was fully wetted with normal saline, that is, 0.9% saline solution. The impedances increase with time – reaching 1 MΩ or higher -- as the wetness of the ensemble decreases with time. Based on our conceptual framework, the sensor ensemble constitutes part of the counterpart or corresponding environment, the brain is the signal source while the scalp serves as the boundary between the source of the signals and counterpart environment. Signal (such as action potential (AP)) propagation within the intervening medium in the brain engenders or induces corresponding signal (such as AP) propagation in our counterpart environment due to the resistive conduction sensor-source coupling. We have chosen this sensor ensemble topography and configuration because it is relatively simple to set up and is effective. However, researchers and practitioners could experiment with a wide variety of alternative topographies and configurations in the generation of suitable sensor ensembles in accordance with our conceptual framework [22, 23]. In order to acquire EEG data, we connected each electrode or sensor in the sensor ensemble to an electrode on the Emotiv EPOC headset – a wireless ambulatory EEG headset equipped with 14 electrodes positioned approximately in accordance with the international 10-20 system. Note that the sponge medium in our sensor ensemble was the same material (felt) utilized in the unmodified Emotiv EPOC electrode and that forms the boundary between the scalp and the unmodified electrode in the traditional 2D EEG configuration. We connected SE1 to AF3 and SE2 to F3. We chose these electrodes for convenience as they are readily identifiable and accessible from the front end of the headset. During EEG data stream capture, the electrodes AF3 and F3 were prevented from making contact with the scalp at their original positions by placing an insulator between them and the scalp. Contact between the electrodes (AF3 and F3) and the scalp could only be effected via our sensor ensemble at the site at which the sensor ensemble was placed over the scalp.

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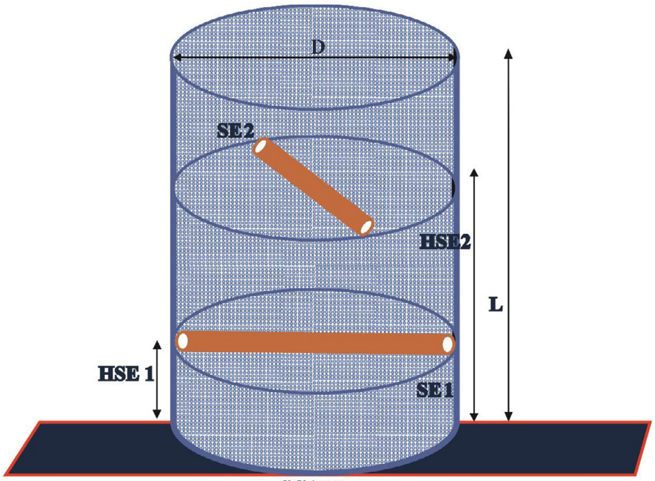

Figure 3: Sensor ensemble harnessed for three-dimensional multilayer EEG recordings

Matching Features in Ampullae of Lorenzini

As mentioned earlier, some of the features of our sensor ensemble are inspired by characteristics reminiscent of Ampullae of Lorenzini found in elasmobranchs. For example, the saline-filled sponge medium in our sensor ensemble could correspond to canals in the ampullae while the sensor casing (in this case a non-conducting plastic cylinder) could correspond to the sensor-containing basal region or alveoli of the ampullae. Note that as the walls of the sensor-containing basal region or alveoli of the ampullae are typically composed of high resistive or non-conducting material, so is the wall of the sensor casing in our sensor ensemble composed of non-conducting plastic. Natural ampullae feature canals filled with a jelly or hydrogel which could serve as a counterpart to the saline-soaked sponge medium that fills the interior of our sensor ensemble. In the ampullae of elasmobranchs, we typically find a group of sensors (as opposed to a single sensor) arranged in an omni-directional fashion that could optimize signal coverage. Similarly, our model allows omni-directional configurations of sensors for optimum signal coverage. The sensor ensembles we have created (as well as collections of such sensor ensembles) bear similarities to the system disclosed by Ekpar31 albeit lacking focusing elements in this specific configuration. In order to generate image-based representations of the EEG data streams that could be subjected to further processing and eventual application by utilizing deep learning neural networks and other suitable artificial intelligence (AI) algorithms and methodologies, we could interpret the signal values for individual sensors as pixel intensity values. In summary, Ekpar31 describes systems, methods and devices including a versatile image acquisition device comprising at least one grid of one or more focusing elements disposed on an N- dimensional and arbitrarily shaped surface, at least one grid of one or more sensor elements disposed on an N-dimensional and arbitrarily shaped surface, and optionally, at least one grid of one or more stimulus guide elements disposed on an N-dimensional and arbitrarily shaped surface, where N can be chosen to be 1, 2, 3, or any other suitable quantity.

Corresponding or Counterpart Environment

Our sensor ensemble (or grid of sensor ensembles) constitutes part of the corresponding or counterpart environment we have created to match selected features of the signal source (the brain in this case) for manipulation/characterization. The boundary in this case is the scalp which is in contact with both the signal source (brain) and the corresponding or counterpart environment (sensor ensemble). Just as the signal sources (neuronal populations) within the brain are enclosed in an intervening medium that permits signal propagation, the sensors or electrodes in our sensor ensemble are correspondingly enclosed in a medium (the saline-soaked sponge medium) that permits propagation of signals so that the sensors can be responsive to the signals generated by the neuronal populations within the signal source. Note that we could create a counterpart or corresponding environment in which the medium containing the sensors is comparable to the intervening medium within the brain and is placed in contact with any desired part (or the whole) of the scalp. As a result of the resistive conduction source-sensor coupling between the brain and our ensemble, the ensemble behaves as an approximate continuation of the intervening medium within the brain, permitting the signals to propagate through ensemble in a manner that is similar to the manner in which they propagate within the brain, ultimately enabling simultaneous acquisition of distinct signal streams from different layers of neuronal populations within the brain.

Data Acquisition

We acquired EEG data by positioning the sensor ensemble on a subject's scalp at a location close to the position indicated generally as AF4 or FC6 in Fig. 4 on the Emotiv EPOC headset. EEG data was acquired after ensuring a good contact quality indication for the reference electrodes and the electrodes (AF3 and F3) on the Emotiv EPOC headset that were connected to the sensors (SE1 and SE2) on our sensor ensemble. We used the TestBench software bundled with the headset to record and store the data and ultimately convert it to text format for further analysis. Raw EEG data are stored by the Emotiv EPOC TestBench tool in standard binary European Data Format (EDF) files which are compatible with many EEG data analysis programs and can be converted into human readable text in comma-separated values (CSV) files.

Data Availability

The data (including raw EEG data) that support the findings of this study are available from **GitHub** at https://github.com/frankekpar/ekpar_eeg/blob/main/dataset.zip.

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Reproducibility

The Emotiv EPOC wireless EEG device harnessed for the measurements is a relatively affordable research and consumer grade EEG device and is accessible to the research and development community. Furthermore, we have provided the details required to reconstruct our sensor ensembles and reproduce our experiments. As stated earlier, all the data (including raw EEG data) that support the conclusions of our study are available from GitHub at https://github.com/frankekpar/ekpar_eeg/blob/main/dataset.zip. Researchers have validated the Emotiv EPOC wireless EEG device for the acquisition of research-grade EEG data comparable with the leading research EEG systems, attesting to its precision and accuracy in event-marking for event-related potential (ERP) research [35, 36, 37].

Data Analysis

We can utilize a wide range of mathematical tools to evaluate the contributions of the topography of the transducer ensemble to the distinctness (or lack thereof) of the data streams linked to the biological substrate from which signals are captured or in which signals are generated by the transducers in the ensemble. In the ensemble employed in this study, the transducers have been configured or adapted to serve as sensors or electrodes and in particular, to record EEG data streams that can be gleaned from the scalp and that originate from disparate layers of neuronal populations within the brain. Mathematical tools that can be harnessed in this case include an analysis of measures of the electrical distances between sensors or electrodes, scatter plots for sensor pairs and the Pearson product-moment correlation coefficients between pairs of EEG data streams corresponding to sensor pairs within the ensemble [22, 23].

Computing Correlation Coefficients

Given a pair of sensors, Equation 1 illustrates how we can compute the Pearson product-moment correlation coefficient (r).

$$r = \frac{\sum_{i=1}^{n}(X_i - X)(Y_i - Y)}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad (1)$$

In Equation 1, X represents the sample mean for the data $\{X\} = \{X1, X2, \dots, Xn\}$ (EEG data stream in this case) recorded at the first electrode, Y denotes the sample mean for the data $\{Y\} = \{Y1, Y2, \dots, Yn\}$ (EEG data stream in this case) recorded at the second electrode while n represents the number of samples.

Measuring Electrical Distance Using the Hjoth Laplacian

The Hjorth algorithm [32] provides a linear approximation to the surface Laplacian. For the expression for the Hjorth waveform H_i (t, N), the contribution to the signal from each sensor is expressed as the difference between the time-varying potential P_i(t) and the scaled sum of the potentials P_j(t) at each of N neighboring sensors. Equation 2 describes the relevant relationships.

$$H_i(t,N) = P_i(t) - \sum_{j=1}^{n} P_i(t) W_{i-1}(N) \quad (2)$$

In Equation 2, W_{i-j}, as expressed in Equation 3 is inversely proportional to the distance d_{i-j} between the sensors and represents a weighting factor for each neighbor.

$$W_{i-j}(N) = \frac{1/d_{i-j}}{\sum_{k=1}^{N} 1/d_{i-k}} \quad (3)$$

Note that the non-spatial electrical distance D_{i-j} denoting the electrical similarity between sensors i and j replaces the spatial distance d_{i-j} in the intrinsic Hjorth algorithm. Equation 4 expresses the potential difference waveform P_{i-j} (t) between two sensors i and j.

$$P_{i-j}(t) = P_i(t) - P_j(t) \quad (4)$$

Equation 5 demonstrates how to calculate the electrical distance.

$$D_{i-j} = \frac{1}{T}\sum_{t=1}^{T}(P_{i-j}(t) - \overline{P_{i-j}(t)})^2 \quad (5)$$

Limiting the consideration of electrical distances to the detection of the single nearest neighbor is sufficient for the detection of electrolyte bridges between sensors. This is comparable to setting N = 1 in employing the Hjorth algorithm [32] to the computation of a linear approximation to the surface Laplacian.

Hypotheses and Experiments

Null Hypothesis

We can state the Null Hypothesis as follows:

Multiple electrodes or sensors placed at distinct layers within the same sensor ensemble record identical or similar EEG signal streams when placed above the same location on the scalp.

For simplicity, we consider two EEG data streams to be identical or similar if their correlation coefficient is statistically indistinguishable from 1.00 with a margin of 0.05. This means that two EEG data streams are identical or similar if their correlation coefficient is equal to or greater than 0.95. We will carry out measurements using carefully designed experiments with sensor ensembles configured in the manner described earlier to determine if the Null Hypothesis is true or false.

Alternative Hypothesis

Now we can state the Alternative Hypothesis as follows:

Multiple electrodes or sensors placed at distinct layers within the same sensor ensemble record distinct EEG signal streams when placed above the same location on the scalp.

Here again, for simplicity, we consider two EEG data streams to be distinct if their correlation coefficient is statistically distinguishable from 1.00 with a margin of 0.05. This means that two EEG data streams are distinct if their correlation coefficient is less than 0.95. We will carry out measurements using carefully designed experiments with sensor ensembles configured in the manner described earlier to determine if the Alternative Hypothesis is true or false.

Main Experiments

We measured three pairs of data streams each lasting just over 3 minutes from three separate adult subjects (A, B and C) using the Emotiv EPOC wireless headset. Informed consent was obtained from each of the participants and the studies complied with all relevant ethical regulations and were approved by the Research Ethics Committee at Topfaith University. All participants were healthy without any known history of neurological pathologies.

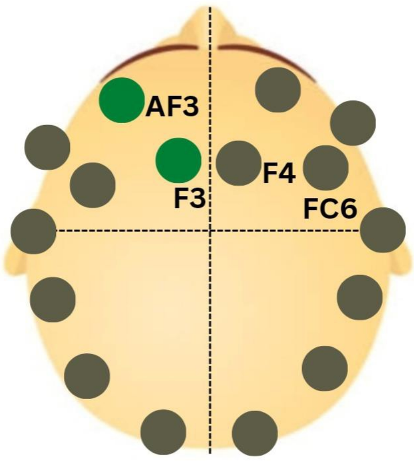

Figure 4: Original positions of electrodes on Emotiv EPOC connected to sensor ensemble (AF3 to SE1, F3 to SE2) and approximate locations on subject's scalp during EEG data recordings (F4 for Subject A and FC6 for Subject B and Subject C). The electrodes AF3 and F3 were prevented from making contact with the scalp at their original positions by placing an insulator between them and the scalp.

For Subject A, the sensor ensemble was positioned near the location generally indicated as AF4 on the scalp as illustrated in Fig. 4 while for Subject B and Subject C, the sensor ensemble was placed on the scalp near the point indicated as FC6 in Fig. 4. The subjects were placed in a relatively quiet environment and were recorded in a relaxed and sitting position. They were not engaged in any special tasks and were recorded with their eyes open.

Control Experiment

The ideal control experiment would involve the use of a sensor ensemble in which the two sensors (SE1 and SE2) would be placed at exactly the same layer and position within the ensemble. Since this is not very practical without actually fusing the electrodes together, we utilize a proxy in the form of the consequences of the results reported by Zhang et al.24 and Seeber et al.25. Relying on direct evidence from Zhang et al.24 that electrical signals propagate through different neurons at finite, measurable and disparate speeds and direct evidence from Seeber et al.25 that scalp EEG recordings can detect subcortical electrophysiological activity, we conclude that sensors placed at exactly the same layer and position within the sensor ensemble measure the same EEG data stream with an effective correlation coefficient of 1.0 and a scatter plot that would appear as a straight line with an effective gradient of 1.0.

Results

To evaluate the proposed hypotheses, we computed Pearson product-moment correlation coefficients and visualized scatter plots for the pairs of EEG data streams (for the SE1-SE2 sensor or electrode pair) captured from the three subjects who participated in the experiments. Each recording lasted approximately 3 minutes or 180000 milliseconds. Note that this duration is orders of magnitude longer than the typical signal recording duration of 100-500 milliseconds utilized in event-related potential (ERP) configurations.

Fig. 5 depicts the scatter plot for the recordings obtained from Subject A. The corresponding correlation coefficient for Subject A was 0.2951.

In Fig. 6, the scatter plot for the recordings captured from Subject B is visualized. The corresponding correlation coefficient for Subject B was 0.3337.

Fig. 7 shows the scatter plot for recordings from Subject C with a corresponding correlation coefficient of 0.062689.

The correlation coefficients and scatter plots obtained demonstrate the distinctness of the two signal streams comprising each pair of signal streams recorded simultaneously.

As can be inferred from the results of the experiments, the EEG data stream captured by each sensor (SE1 or SE2) in the pair of sensors in the ensemble is clearly distinct from the EEG data stream captured by the other sensor even though both sensors were housed within the same ensemble (at different layers) and placed over the same location on the subject's scalp.

For the Null Hypothesis to be true, the correlation coefficient for the pair of EEG data streams should be very close to 1.0 and the scatter plot should indicate very close clustering of

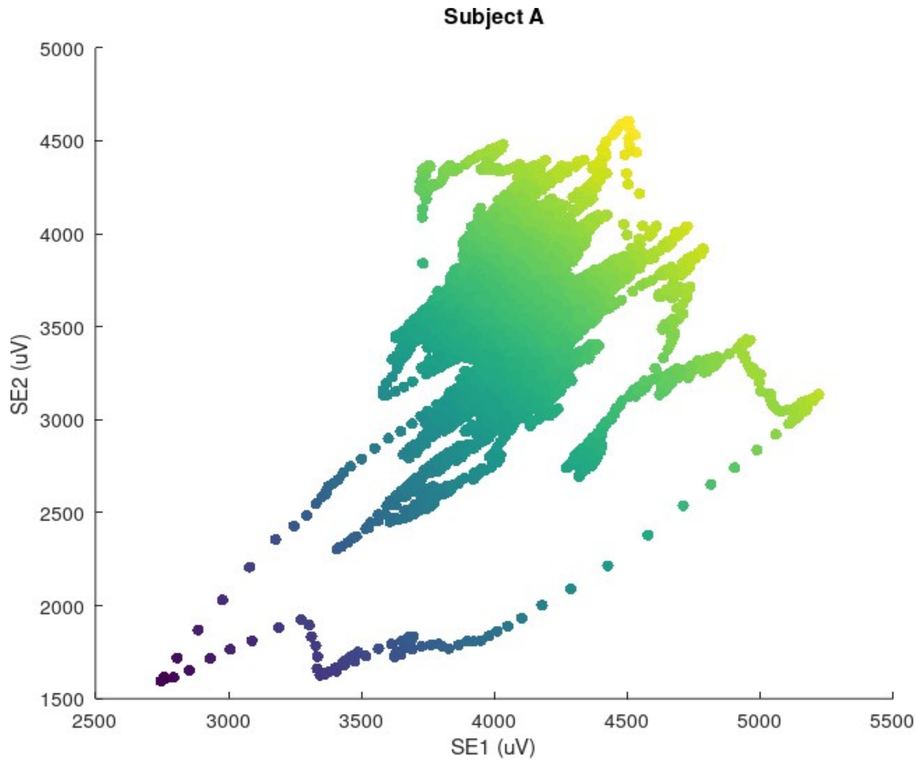

Figure 5: Subject A: Scatter plot of EEG data (in microvolts) for SE1-SE2 electrode pair. Correlation coefficient, r = 0.2951.

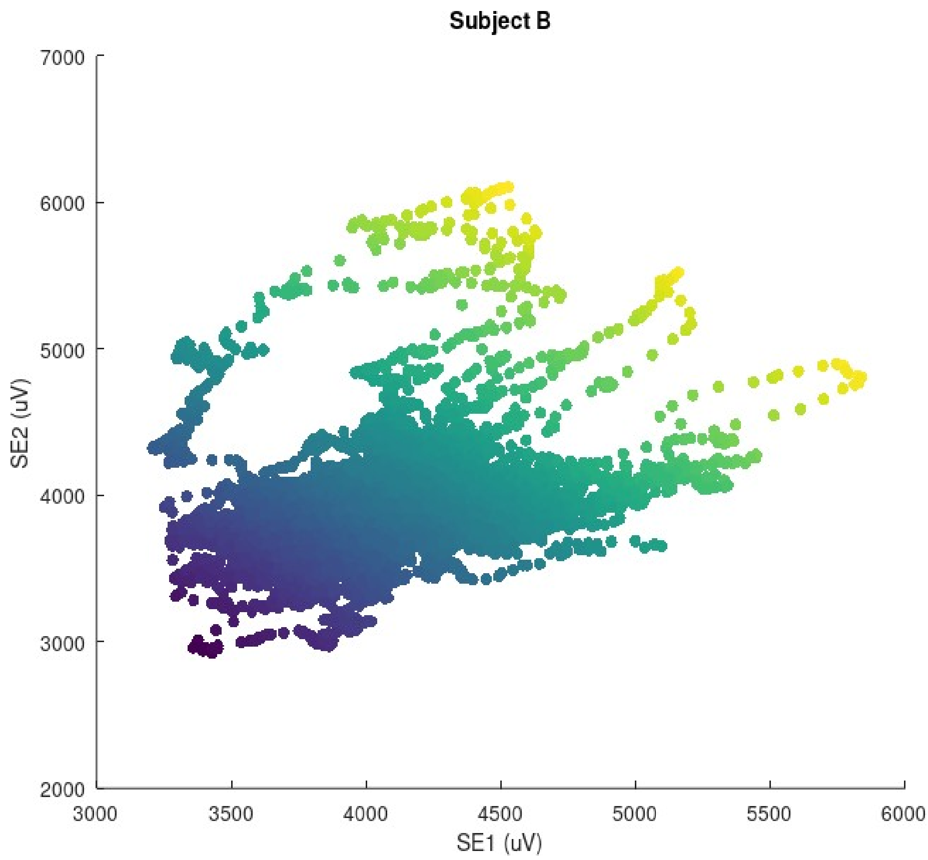

Figure 6: Subject B: Scatter plot of EEG data (in microvolts) for SE1-SE2 electrode pair. Correlation coefficient, r = 0.3337.

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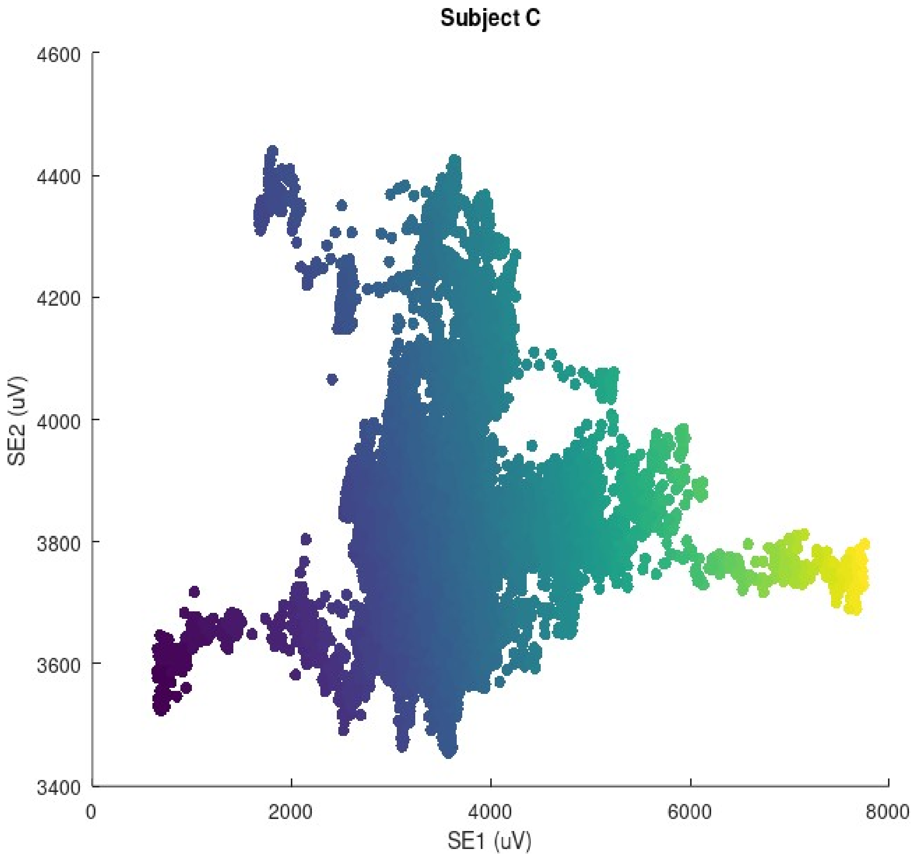

Figure 7: Subject C: Scatter plot of EEG data (in microvolts) for SE1-SE2 electrode pair. Correlation coefficient, r = 0.062689.

the data points for each subject. We observe just the opposite of these features in the measurements. Conversely, for the Alternative Hypothesis to be true, the correlation coefficient for the pair of EEG data streams should be less than 1.0 and the scatter plot should display dissimilarities between the data streams -- indicating that they are distinct – for at least the majority of subjects. This is the exact set of features we observe in the measurements for all subjects. Choong et al.38 computed Pearson correlation coefficients for pairs of electrodes by utilizing the Emotiv EPOC in the traditional 2D EEG configuration in the context of EEG data representing emotional states and obtained correlation coefficients as high as 0.8142 in the alpha band. Here, we have adapted the Emotiv EPOC to our three-dimensional multilayer sensor ensemble and obtained correlation coefficients for pairs of sensors ranging from 0.062689 for Subject C to 0.3337 for Subject B.

In a comparison of time domain measures of EEG correlations, Bonita et al.39 set out to apply EEG correlation measures to discriminate between two behavioral states, namely, eyes open no task (similar to the experimental setup we used to measure EEG data) and eyes closed no task. The results reported by Bonita et al.39 indicate that the Pearson product moment correlation coefficient (also utilized in this work) could discern the correct one of the two behavioral conditions with epoch durations greater than or equal to 2 seconds or 2000 milliseconds. Crucially, Bonita et al.39 demonstrated that the Pearson product moment correlation coefficient was robust to noise. Note that the recording duration in our experiments was approximately 180000 milliseconds. Thus, our measurements of Pearson product moment correlation coefficient in this present work were robust to noise, ruling out alternative explanations of our results that are based on the presence of noise in the signals. Given the backdrop of the results reported by Zhang et al.24 and Seeber et al.25, these results confirm PREDICTION II by Ekpar22, 23 and demonstrate that sensors placed at different layers above a given location on the scalp capture EEG data streams emanating from different layers of neuronal populations within the brain. Furthermore, these results, combined with the findings of Zhang et al.24 and Seeber et al.25, confirm all three predictions (PREDICTION I, PREDICTION II and PREDICTION III) by Ekpar22, 23 on the basis of our conceptual framework through direct measurements. The results are robust and hold true across subjects and over a very long recording duration (approximately 180000 milliseconds for each recording) that is orders of magnitude longer than the typical 100 - 500 millisecond duration of event-related potential (ERP) configurations.

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These results conclusively falsify the Null Hypothesis and confirm the Alternative Hypothesis. It can be inferred from the findings of Parvizi et al.34 and Seeber et al.25 that EEG signals (including intracranial EEG or iEEG signals) can provide anatomically precise information about the selective engagement of neuronal populations at the millimeter scale and about the temporal dynamics of their engagement at the millisecond scale. The sampling rate of the device used in our experiments was 128 samples per second – sufficient to resolve signals emanating from neuronal populations separated by an arrival interval of 7.8 milliseconds. By utilizing higher sampling rates, sensor ensembles with more densely packed sensors, faster processing systems (for example, electronic or photonic systems) and robust signal processing algorithms, significantly more information can be extracted from EEG data streams (for example, through the resolution of data streams emanating from neuronal populations separated by smaller arrival intervals) with improved signal-to-noise ratio (SNR) metrics.

The fact that sensors placed at disparate layers within the sensor ensemble are able to capture signals from neuronal populations within the brain can be explained by the direct physical contact between the scalp of the subjects and the saline-soaked medium within which the sensors are housed, allowing signals to propagate to the sensors. It is well known – as can be gleaned from results published by Plonsey et al.41, De Munck et al.42 and Tenke et al.33 – that resistive conduction is an accurate model of source-sensor coupling in an EEG sensor ensemble such as our system, and it occurs with virtually no delays or phase shifts. Furthermore, our sensor ensemble creates an environment effectively approximating the insertion of electrolyte bridges between the electrodes. Consequently, the electrodes should be expected (assuming that the signals emanate from the same source locations or layers) to measure similar or identical signal streams. As demonstrated by Bonita et al.39, the correlation coefficient metric we have employed is robust to noise, ruling out noise in the signals as the source of the distinctness. Note that since the material used for all electrodes in the sensor ensemble is the same and all sensors are housed in the same saline-soaked sponge that is comparable to the sensor pads used in the regular single-layer configuration, there is no reason to expect the buildup of an ion cascade or peculiar non-linearities or distortions within the ensemble. The presence of effective electrolyte bridges between the electrodes should be expected to lead to the measurement of similar or identical signals and to nullify any "cross-talk" effects. By operating the sensor ensemble under a wide variety of conditions with the measured impedance ranging from tens to hundreds of KΩ, stabilizing around 1 MΩ and going beyond that as the wetness of the medium decreased, our system has effectively run with characteristics that could be associated with different sets of materials, obviating the need for additional experiments with multiple design parameters. Ekpar22 published research in which a sensor ensemble similar to the one described in this study was configured with four (4) separate electrodes in distinct layers with similar results.

Given the temporal resolution of the phenomena under consideration (see Seeber et al.25 and Parvizi et al.34) and the use of the correlation coefficient as a similarity metric, the sampling frequency of the Emotiv EPOC (with an inbuilt high-pass filter) is sufficient. The spatial resolution of the Emotiv EPOC does not play any role in this study since the original Emotiv EPOC electrodes are bypassed and the novel sensor ensemble described in the study used instead. The effectiveness of the Emotiv EPOC as a research-grade EEG device has been demonstrated in studies including those carried out by Badcock et al.35, 37 and Williams et al.36 including characterization of the device. Note that all raw EEG data measurements in the dataset used for the study are reference-compensated, obviating the need for separate measurement of the reference signals and subsequent compensation. Based on the foregoing explanations and clarifications, the most plausible explanation of the observed distinctness of the signals is that they can be localized to disparate sources or layers within the brain. As explained via the predictions, this can be justified by relying on the results reported by Zhang et al.24 regarding direct imaging of signals propagating through myelinated axons and by Seeber et al.25 regarding direct evidence that scalp EEG recordings can detect subcortical electrophysiological activity. We have hereby clearly demonstrated the acquisition of distinct signal streams from neuronal populations located at different depths at the same electrode site and consequently established a system enabling three-dimensional multilayer electroencephalography (3D Multilayer EEG) with far-reaching implications for a broad range of novel applications.

Discussion

We have established a system enabling non-invasive three-dimensional multilayer electroencephalography (3D Multilayer EEG – for which we propose the name Ekpar Electroencephalography or Ekpar EEG or eEEG) with far-reaching implications for a broad range of fields from medicine to computing. We formulated the Null and Alternative Hypotheses and carefully designed experiments and carried out measurements that clearly falsify the Null Hypothesis and validate the Alternative Hypothesis, thus directly demonstrating the simultaneous acquisition of distinct signal streams from neuronal populations located at different depths at the same electrode site. The results of our measurements are robust and hold true across subjects and over a very long recording duration (approximately 180000 milliseconds for each recording) that is orders of magnitude longer than the typical 100 - 500 millisecond duration of event-related potential (ERP) configurations.

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We have also explained how the recent direct imaging of signals propagating through myelinated axons by Zhang et al.24 and direct evidence that scalp EEG recordings can detect subcortical electrophysiological activity by Seeber et al.25 confirm the veracity of the principles underpinning the conceptual framework on which our work is based and confirm all three related predictions by Ekpar 22, 23.

Further research is needed to characterize the wide variety of sensor ensemble topologies and configurations that could be utilized, to quantify the difference in the signal-to-noise ratio (SNR) of EEG measurements based on our system compared to contemporary systems, to quantify the difference in the information transfer rate as well as any differences in spatial resolution possibly via comparison with other source localization techniques reported in the literature. and more broadly, comparative studies between our 3D Multilayer EEG system and contemporary systems. Research is also required to elucidate the influence of temporal dynamics and related phenomena on the mechanism of operation of sensor ensembles based on our system possibly via investigations into the role of coupling, delay, noise and other factors in resting brain fluctuations40. With the additional information about neuronal activity that could be gleaned from the vastly increased electrode count and density permitted by our 3D Multilayer EEG system, vast improvements in the signal to noise ratio (SNR) of EEG measurements could potentially be obtained.

Our work suggests a pathway to full-fledged brain-to-brain communication with the attendant benefits to human society including greater collaboration, conflict resolution, greater inter-cultural understanding, more peaceful communities and greater insights into the workings of the human brain. We can also build practical non-invasive BCIs (and more generally, human-machine interfaces) and unlock novel non-invasive applications by relying on the vastly improved SNR and information transfer rate afforded by our 3D Multilayer EEG system. In the field of medicine, insights gleaned from our 3D Multilayer EEG system could enable more accurate diagnosis and therapies for brain-related and psychiatric conditions as well as an improved understanding of the workings of the human brain in healthy and pathological conditions, possibly leading to the discovery of hitherto unknown conditions and the development of novel and effective therapies. Additionally, the rehabilitation of those living with brain-related impairments could be rendered practical and cost-effective using our novel 3D Multilayer EEG system.

Our 3D Multilayer EEG system could be applied in psychology and neuroscience in the study of the brain processes underlying memory, learning, perception and attention and in the study of social interactions, human factors including factors related to situational awareness and workplace optimization, neuromarketing and economics. This system could be utilized in the study of non-human primates, other animals as well as comparative studies between species of animals, leading to a better understanding of what it means to be human. Given sensor ensembles with sufficient sensor count and density and associated processing systems and algorithms, we could decipher the content of dreams using our non-invasive 3D Multilayer EEG system. Our novel non-invasive 3D Multilayer EEG system could be harnessed in a broad range of conceivable applications.

Conclusion

This paper introduced a novel paradigm involving three-dimensional multilayer EEG – in contrast with the contemporary single-layer (2D single-layer) paradigm – with the novel paradigm potentially enabling effective brain-to-brain communication and other hitherto hard-to-realize applications such as a clearer understanding of neurological processes both in normal functioning and in disease, orders of magnitude improvements in the information transfer rates of brain- computer interfaces (BCIs) that could lead to practical BCIs, potentially significant improvements in the signal-to-noise ratio (SNR) of EEG recordings as well as a broad range of novel applications and demonstrated that the system works through experimental results with evidence that distinct signal streams can be recorded from EEG sensor ensembles placed over the same site on the scalp but responding to bio-signals from neuronal populations at different depths. More specifically, we have demonstrated the effectiveness of our novel 3D Multilayer EEG paradigm by formulating the null and alternative hypotheses for simultaneous multilayer EEG signal capture and relying on the results of analysis of a set of carefully designed experimental measurements to falsify the null hypothesis and validate the alternative hypothesis. We have explained how the recent direct imaging of signals propagating through myelinated axons by Zhang et al. 24 and direct evidence that scalp EEG recordings can detect subcortical electrophysiological activity by Seeber et al. 25 confirm the correctness of the principles underpinning the conceptual framework on which our work is based and confirm all three related predictions by Ekpar 22, 23. This has far-reaching implications for a broad range of fields from medicine to computing. By combining more efficient information processing techniques with the ability to capture three-dimensional multilayer EEG signal streams, the results also suggest a pathway towards more robust and practical BCIs and other applications of EEG signals as well as a viable pathway to effective computer-mediated brain-to-brain communication with its attendant benefits. We propose the name Ekpar Electroencephalography or Ekpar EEG or eEEG for our novel 3D Multilayer EEG system.

Conflicts of Interest

We have no conflicts of interest to disclose.

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