Quantum Based Brain-Computer Interface Performance Analysis for Next-Generation Metaverse

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ABSTRACT

The study discussed observations from 8-electrode brain-control interface (BCI) recordings and investigated its connectomic structure. The subject repeatedly controlled the operating system by concentrating creatively and producing recordable signals. The research problem was to understand recorded psychometric data and prove its validity. Sample observational size (n = 6’825) was selected using clustering sampling from successfully recorded stimulations (N >= 200’000) in a Virtual Reality (VR) development environment. The empirical Structural Equation Model (SEM) was modeled. Through SEM, rotated data was simplified with Factor Analysis (FA). Hypothesis testing reveals distinctions and correlation predictions in non-invasively placed electrodes on the cerebral hemisphere. In conclusion, the β-values of electrodes placed to the right instead predict adverse effects to the left electrodes during processing visual sensory inputs.

Keywords: brain-computer interfaces, structural equation modeling

INTRODUCTION

Today, an ambitious general initiative is far beyond the current state of the virtual metaverse. Generally, corporation managers see that bringing metaverse to life lies within implementation of reaching the goal within embodied Internet. The goal has become more and more familiar since the development of the Internet after the II World War. Metaverse is a vision for a successor to the mobile Internet. Instead of viewing its content, you are in it. Related technologies integration standard requires a more ergonomic and virtual approach to control equipment. This is accompanied by the motivation for compilation on this paper – how a more convergent communication-based embedded-systems-method can be used and further developed. The paper discusses how industrial VR applications can validate an instruction stimulation read directly from the subject's hemisphere. This is accomplished by analyzing data from successful stimulation cases. To understand this data, we discuss relevant hemispheric anatomy and measurement equipment. Emphasis is on positioning the research on the philosophical foregrounding. The method for analyzing data is validated by approaching factoring the data and estimating the variance magnitudes. When it is found that the model has middling capabilities, we gain insights into the regressors for how used variables in the multivariate analysis correlate. Let's first dive into the biological world of learning to understand better how we review the world around us.

THEORETICAL FRAMEWORK

Nature of learning

Human brains are made up of special nerve cells (neurons) and supporting glial cells. Learning from the outer world is transformed as feedback (electrical and chemical signals) that gradually modify associations between neurons. Affective networks are located at the core of the Brain. The outermost cortex involves understanding – recognition of information. The prefrontal brain area has specialized nerve cells for strategic activity. The neuron model can be classified in the model, which consists of dendrites, a body cell, and an axon. Dendrites receive chemical indicators from other neurons as a response to experience. The assigned indicator is relayed to the nucleus with DNA within the cell body. If telegram potential is above the threshold, it triggers electric operating potential. This fires up action potential bridging down to the axon while releasing other indicating chemical potentials to the other cells' dendrites. (Hinton & Fischer 2010, 116-118.) Let's look at what kind of learning environment we are in from a medical science classified perspective.

Cerebral hemisphere basic anatomical structure and function

The cerebral hemisphere can be classified into four main areas (frontal, parietal, occipital, and temporal lobes), of which two are the most meaningful for this research. The parietal lobe is found from the uppermost vertex. The occipital lobe is located behind the neckline, to the lower inion. Parietal and occipital lobes have recognized functions; See table 1.

Table 1. The use of specific cerebral areas (Duvernoy 2005; Guy-Evans 2021).

Substructure definition	Associated functions
Parietal lobe:	Primary sensory processing center
Precentral gyrus	Somatosensory sensations
Postcentral gyrus	Object recognition and memory
Superior parietal lobule	Visual and sensory signals from the hands
Inferior parietal lobule	Language, calculus, body image, visuomotor, auditory and emotions
Occipital lobe:	Visual processing center
Superior occipital gyrus	Vision and spatial data transmission to dorsal/ventral streams
Middle occipital gyrus	Vision-based decision making
Inferior occipital gyrus	Visual processing of patterns and objects (especially facial)

The lateral area of the parietal lobes is separated into the intraparietal sulcus into two entities. The pre-and postcentral gyrus is bounded as an entity with superior parietal lobule (PZ, P3, P4) and inferior (P7, P8) parietal lobule. Lower occipital area is separated from each other by superior (OZ), middle (O1, O2) and inferior (O7, O8) occipital sulci. The central middle occipital gyrus is subclassified into superior and inferior areas by the lateral occipital sulcus. (Duvernoy 2005.) The primary visual cortex is located within the superior occipital area (Guy-Evans 2021). The secondary visual cortex area immediately surrounds the primary area. Visual cortexes coordinate optical tract streamlines flow, i.e., to parietal lobes by ventral and out by dorsal streams. In principle, when visual data is forwarded from the retinas, it travels through an optic tract of the ventral stream to the central thalamus that relays to several points within the cerebral hemisphere and completes its journey to the parieto-occipital lobes. The produced vision per se, within the visual cortex's information within the superior occipital area, is sent to other brain parts to be analyzed to recognize objects and patterns. The visual cortex's nerve cells continuously react to changes with low latency within the visual field and is a worthy area to consider for connecting the assistive device and monitoring the area. It has been stated that there is a correlation between the subject's ability to recognize an object and activate complex occipital lobes (small stimulus on activation) (Grill-Spector *et al.* 2001.) Let's learn how synthesized human learning can be captured and analyzed in different technological ways next.

Computer aided demonstration of stimulation

The trade-off between extremes, a subject is learning or cannot learn – is separable by monitoring the hemispheric sensory stimulation. Capturing on/off cerebral activities can be done in many ways. It has been revealed in various tomographic methods (Hsieh *et al.* 2011). The method chosen depends on the nature and scale of the experiment. Consideration may be affected by, e.g., availability, reliableness, and cost-effectiveness. In recent innovation awards, non-invasive electroencephalography (EEG) based BCI devices are said to almost surpassing the reliableness (86 %) compared to equipment placed by surgical methods (88

%) (CES 2020). EEG's markets will grow tremendously by the end of 2027 (The Insight Partners 2021). EEG-based BCI's are very available for various use, e.g., monitoring the brain's activities controlling a PC mimicking its manipulation. To benefit from using intrinsic brain activities and controlling a standalone assistive program in real-time, the signals from the visual cortex are to be considered. The visual cortex represents a Bioelectric Resonance Frequency (BRF) band at 25 Hz. Images in the brain signals are observable while information feed is bypassing through retinas to a processing activity and new memory. All BRF below 20 includes Motor Control (10 Hz), Auditory (15 Hz), and Somatosensory Cortex (9 Hz), as well as subconscious thoughts (20 Hz). (Mongan *et al.* 2015, 330.) The frequencies of the signals need to be learned and attached to the areas of the protocol by the program to utilize the sensor memory; the talk about processing is relevant.

BCI manufacturers have different pre-and postprocessing signals measured from the brain (Fiscon *et al.* 2018). Pre-processing the captured information considers both high- and low-pass filtering techniques (H- and LPF) in real-time to capture initial decision-making. Postprocessing, in turn, is formally the subject of the paper, found in the results chapter. Processing on a wireless EEG data acquisition can happen under any database-oriented operating system (OS) control. As in Red Hat Enterprise OS with interacting its Bluetooth Network Manager daemon. Daemon maintains control of all Networking devices, whereas modem acts as Bluetooth. To capture intermediated pulses of serial communication processors requires a database. Of the available packages, Berkeley Database (BDB) fulfills soft-ware paradigms for embedded database support in the duplex client-server manipulative application to log the sensor feedback history (pkgs.org 2021). Now that the information sources integrate with hardware, data searching for information can begin in the research question.

Research problematization

Performing electrodes predictions positioned in the left and right cerebral hemisphere, on occipital and parietal areas, is the focus of this paper. The problematized research question is as follows. *Whether the use of the left cerebral hemisphere differ to predict the function of the right cerebral hemisphere during creative learning?* Could latent hypotheses tests reveal distinctions between cerebral areas? In the empirical part, let us examine it next, starting with the scientific-philosophical side note.

RESEARCH METHODOLOGY

Philosophy of science

Research is deducted as a self-experimentation. The researcher's role is at the center of the study as an external objective observer (Weisse 2012). The self-experimenter research is rarely problematized as it is self-evident in everyday work. From the metaphysics viewpoint, ontology explains what reality is independent of the observer. Thus, we find ourselves crossing the path of subjectivism and objectivism. In many scientific fields, a practical rule for relying upon scientific, philosophical principles is based on the literature perceptions of forming suitable analyses for a quantifiable number of observations to explore the phenomenon. Independently of subjectivism on an ontological basis, the explored condition of this paper exists despite the observer. Critical epistemology, in turn, answers how the explored condition is measured and what validity. The framework (Williams 2008) has criticized the epistemologies of the standard validity that is applied. Therefore, the overall process is being shaped by objectivistic and interpretivistic meanings – where objectivists tend to segment the research for a group, and the interpretivistic approach integrates human interest into the study.

DATA-ANALYSIS

Data-acquisition

8-guide acquisition transducers were used to record EEG in order as the International 10-20 system specifies, limited to Parietal (P), Occipital (O), and electrodes placed on the midline (Z) lobe. Contacts were fitted into the brain scalp. Applied electrodes were PO3, PO4, PO7, PO8, O1, O2, OZ, and POZ. Electrodes were made with a unique polymer material that sensor heads conduct amplifiable and transferable signals. Electrodes placed on the head are designed to respond to sensory memory feedback. The used equipment interface was non-invasive. Sampling capturing standard classifies as Ultra-High Frequency (UHF) 1024 MHz rate within bit depth of 24 Bit at 2.4 GHz wireless interface ISM band (Carmo *et al.* 2007). Considered minimum acceptable sampling rate is 2.5 times greater than the highest frequency of interest (Smith 2021), is met. The saved output of filtered recording is saved in a database image during measurement periods in .raw binary format. For statistical interpretation, binary data was processed into a 64-bit hexadecimal string representation and IEEE 754 floating-point number values. Variables were treated as square root extraction to conduct normalized concepts. Variables were formed accordingly from arithmetic means.

Experimental structural equation modeling and factor analysis

FA was considered for the study if the captured and clustered data was appropriate. Method of analysis is chosen intentionally to provide information on the dependencies of the variables (Creswell 2015; Edmonds & Kennedy 2012). Rotation of Principal Component Analysis (PCA) was used for dimensional reduction. The FA experiment showed that the sum variables formed a reasonable variance but not a significant substance. The adequacy of the Kaiser-Meyer-Olkin (KMO) sampling measure of the correlation matrix was middling (.708); Bartlett's weighting test was significant ($p <.001$); and the sample size was sufficient ($n> 40$ per variable); X2 = 23541.313 – good fit was expected for the model and the test is valid to proceed. Table 2 represents factor loadings and communalities. Factor loadings are within an acceptable range. Contingency tables on factor loadings smaller than .8 should be considered deletion due to incoherent model convergence. As the covariance structure fits the model, the model converges successfully.

Table 2. Factor loading and communalities

	1	2	3	4	Communalities
O1	0.806				0.650
POZ	0.812				0.660
PO3		0.827			0.684
PO7		0.823			0.678
OZ			0.822		0.676
O2			0.825		0.680
PO4				0.815	0.665
PO8				0.815	0.665

SEM with CFA tackles as a conservative way to improve model fit. CFA helps understand latent variables relations, addressing the validation for regression testing. Possible errors are due to correlational measurements' randomness. SEM explains complex relationships between independent and dependent variables. Implementation with useful metrics emphasized a coherent sample size, where the most reliable way is to test variables as a model. Indices refer to a middling fit: Comparative Fit Index, Tucker-Lewis Indice, Root Mean Square Error of Approximation, and Goodness of Fit Index (CFI=0.929, TLI=0.899, RMSEA=0.064 and GFI>=0.95) are acceptable. The Cronbach's α-coefficients for EEG signals are derived from sum variables. α-coefficients range as reliable (standardized) reliability values (.844-.860) and with composite reliabilities ranging from (.764-.808) (Taber 2018). Overall, the model can be applied to test hypotheses.

Construct empirical, convergent and discriminant validity

The stimulation data were not chosen for analysis if the computed recorded data points were not completed successfully in the test. Empirical validity indicates whether measures generate utilizable results that consider solutions as a response to the research problem. The validity of the electrodes inputs was assessed using FA with acceptable reliability levels. The average variance extracted (AVE) measures the amount of variance captured by each factor. Table 3 shows that each Fc's AVE exceeds 0.6, exceeding latent variables regressors, and thus is acceptable for discriminant validity.

Table 3. Construct Correlations and average variance extracted

	Fc1	Fc2	Fc3	Fc4
Fc1	(0.654)			
Fc2	.078**	(0.681)		
Fc3	.508***	-.080**	(0.678)	
Fc4	.069**	-.545***	.087**	(0.664)

EMPIRICAL RESULTS

Structural equation model

As model fit indices refer to a middling fit, the model can be applied to test high validity regression hypotheses. β is positive and statistically significant between factors and latent variables. Latent external variables are exemplified. Hypotheses between factors were estimated. Yet comparing factors together reveals rather negative β between Fc2-Fc3 and Fc2-Fc4. The embedded regressor model determinant processed by the Bareiss Algorithm (.498>.0001) was also calculated, indicating noncollinearity.

SEM summary

Regression test on generalized hypotheses for measurable factors with meaningful relationships between variables. The rotation space of the component plot is dividing the scores into classes as shown. Hemispheric is divided into two halves into four measurement areas ranging from Parietal to Occipital. The empirical testing indicates that right inferior-to-middle parietal-occipital cerebral hemisphere electrodes predict negatively (β varies from -.069 to -.545) for the left inferior-to-middle parietal-occipital areas activities during one unit increase.

DISCUSSIONS AND CONCLUSIONS

The research problem was whether the use of the left cerebral hemisphere differs from predicting the function of the right during creative learning. The potential dataset of hemispheric activities was recorded within the standardized testing protocol to solve this significant problem. Learning frameworks were applied in convergence to the predicted results. Data transformation into wisdom procedure was approached by utilizing SEM with FA supporting validity angles. Rotation formed loadings for measured events within primary sensory and visual processing areas. Data capturing with higher resolution systems utilize together parietal (P) and occipital (O) lobes of the brain with fewer electrodes (as concluded in Oostenveld & Praamstra 2001) by predicting visual and sensory signals processing.

In conclusion, there are many statistically significant relations between theoretically and empirically identified variables. The left hemisphere seems to be less used during creative processing as theory dictates (Fink & Benedek 2014). Effectiveness can be supported by developing noise emission filtration to increase prediction accuracy and model fit. The experiment found that activation areas are associated with multilevel task-processing converging through scientific theory based on regressors. In practice, the device enables control of the Unix-based real-time operating system. As self-criticism, the TLI does not quite reach its target readings (over .9 is acceptable according to Hu & Bentler 1999) and remains a marginal error. Crossing model marginal errors are suggested to be due to misfit per degree of freedom randomness (as Dexin & Taehun 2018 suggested) that was not eliminated by low- and high-pass filtering.

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