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Current Sensing Trends and Future Views on Brain Machine Interfaces

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***Abstract*— Brain machine interfaces, or BMIs, are rehabilitation instruments that use feedback to control neurological processes like walking, talking, hearing, and seeing. The feedback is initiated by either decoded external perception or stimulation of the brain. A number of the main obstacles to using BMI as a rehabilitation tool are related to the processing of physiological signals. Signals and sensing devices that can effectively discriminate between different patient states over time and conditions are needed to solve these problems. Features such as implantability, spatiotemporal resolution, and invasiveness are critical for BMI sensing. In BMI, sensing is necessary to either regulate the brain's perception or its actions. Therefore, the focus of this review is on those who use brain activity to control neuro-motor activities in order to improve, attenuate, or restore bodily function in individuals with disabilities. Furthermore, the view proposes future perspectives on BMI sensing. Despite the increase in BMI research, the key obstacle is still getting findings into practical applications. This paper sheds lighter on the limits in sensing technology that have mostly impeded these changes. It is hoped that in the future, BMI applications would use paradigms that integrate electrical activity and metabolic sensors to obtain real-time brain responses. This improves information content and illness identification by increasing spatiotemporal resolution.**

***Keywords*— Bio-signal processing, Brain machine interface, Deep brain stimulation, Feedback algorithms, Neural activity measurement.**

INTRODUCTION

The brain and a machine can communicate with one another through the brain-machine interface (BMI), which translates brain signals. The machine and the brain can each play a part in the sender and recipient. An idealized BMI system's bidirectional communication is shown in Fig. 1. BMIs can generally be categorized in a number

of ways, including according to their function, degree of invasiveness, source of brain signal, and design [33]. However, in this review more focus will be on the classification of BMI based on function. They can be roughly separated into two types when categorized according to functions. Perception assistive BMI is the initial classification. These are gadgets that use relevant brain regions to stimulate sensory information

Fig 1: Brain Machine Interface Bidirectional Communication

Sensory information by emulating the neurological activity of the key brain regions related to different sensations, such as sound or vision. Actuation assistive devices fall under the second group. These are gadgets that use real-time neural activity decoding to control prosthetic limbs, motor impairments, pain, and other impairments or disabilities. Between the two categories, the former uses sensory data to drive brain perception, while the latter uses recorded neural activity from the brain to direct actuation to a bodily part or prostheses.Electrical signals are used by both types to transmit actuator and sensory data, respectively [33] .Human sensory-motor functions can also be strengthened, restored, and assisted by them[11].A rise in BMI research has been attributed to developments in brain science. But the main obstacle is translating research to practical applications still remains.The primary obstacles to this transformation have been poor control tactics, unreliable algorithms for signal processing and interpretation, and limits in sensor technologies [33].To address a few of the issues, appropriate to understand which BMI Technology is required.

Selecting feedback signals and the appropriate signal gathering technique has proven to be a significant obstacle in the analysis of physiological signals. In order to reduce neuro-motor

diseases or control a prosthetic limb, the sensing stage counts brain activity.Cutting-edge methods that reach far-reaching and deep brain regions are necessary for efficient neural recording [20].The development of compact recording devices with high spatiotemporal resolution has increased as a result. One prominent illustration of this is the encapsulated neural acquisition chip, which captures electrical activity from the brains [20]. It offers a high spatiotemporal resolution, which may contribute to a deeper understanding of brain processes.[46], significant progress in the understanding of neurophysiological dynamics depends on improvements in the gathering of BMI data. This is because obtaining brain signals without sacrificing their quality is a prerequisite for developing an effective algorithm for detecting BMI. For this reason, a variety of feedback signals and signal collecting methods are examined. While not all-inclusive, the list showcases the most often used signal collecting methods in BMI applications. A number of studies have examined BMI applications[47].The paper examines the practical concerns pertaining to BMI's usability as well as its applicability in many domains[41]. The overview in discusses the potential and constraints of invasive and non-invasive techniques to effectively interface of the brain. Additional research has looked into paradigms[11], algorithms, and objective techniques for comparing different BMI devices[47]. By concentrating on sensing methods and feedback signals that can be obtained from the brain—that is, signals that are not available from the outside world—this work adds a new dimension. The majority of investigations have concentrated on exterior signals since inside signals require a higher degree of invasiveness. The analysis also suggests future directions for BMI sensing.

PERCEPTION ASSISTIVE SENSING

These signals are used to help individuals with visual, auditory, or other sensory impairments improve their sensory abilities. Signals from outside the brain are mostly used to initiate stimulation. Cochlear and retinal implants are examples of visual and auditory prostheses that fall under this category. Cochlear implants function by translating sound into electrical stimuli that are given to the auditory nerve fiber located on the cochlea's basilar membrane using a collection of implanted microelectrodes. The processing chain of a cochlear implant,

a common example of a BMI that improves percepts, is summarized in Fig. 2 by replacing the neural system with the auditory nerve and the percepts with sound. The first effective prosthesis was the sound-enhancing one. They were created by Miller Hutchinson as early as the 19th century[40]. They were therefore the first BMIs to be offered for sale. The first retinal implant was authorized by the Food and Drug Administration (FDA) in 2013 [19]. Similar to the cochlear implant, the retinal implant stimulates the optical nerve using a series of electrodes after using decoded collected images as control signals. As seen in Fig. 2, the processing chain used by the retinal implant is comparable to that of the cochlear implants. Perception is vision with retinal implants, and the optical nerve is the neural system that needs to be adjusted. Although retinal implant research is still in its infancy and has showed great potential, low resolution remains a challenge, making it challenging for blind patient to use it daily life.

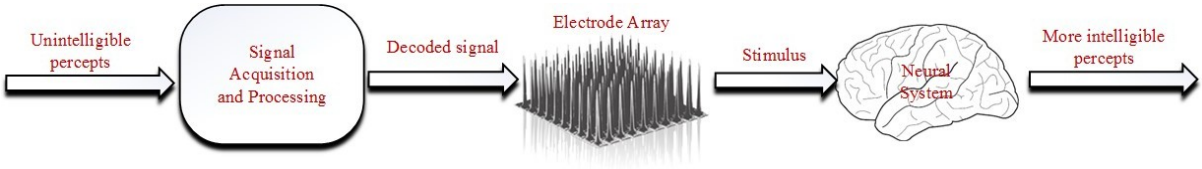

Fig 2: Perception assistive BMI Processing chain

ADAPTIVE ACTUATION SENSING

These comprise the collection of brain signals that are used to correct, restore, and enhance external physical functions, primarily motor impairments. A BMI controlling a prosthetic limb with brain impulses is shown in Fig. 3. These prosthetic limbs help severely damaged patients, who may be completely paralyzed or have significant neuro-motor difficulties, regain their grasp and gait abilities. More neuronal information can be obtained in the process of recovering body functions employing creative methods with high spatial earliest BMIs to be commercially available. The first retinal implant was authorized by the Food and Drug Administration (FDA) in 2013 [19]. The retinal implant employs decoded recorded images as control signals, just like the cochlear implant, and uses a series of electrodes to stimulate the

optic nerve. As seen in Fig. 2, the processing chain used by the retinal implant is comparable to that of cochlear implants. The optical nerve is the neurological system that will be influenced by the retinal implants, which also affect perception and vision (Niketeghad & Pouratian, 2019). Although retinal implants are still in their infancy and have showed great potential, their low resolution makes it challenging for blind patients to use them for everyday tasks[38].Methods to measure various brain processes or temporal resolution [45]. This review divides cerebral activity measurements into two general categories: electrical activity and metabolic activity. The several techniques utilized to extract electrical and metabolic activity from the brain are briefly described below.

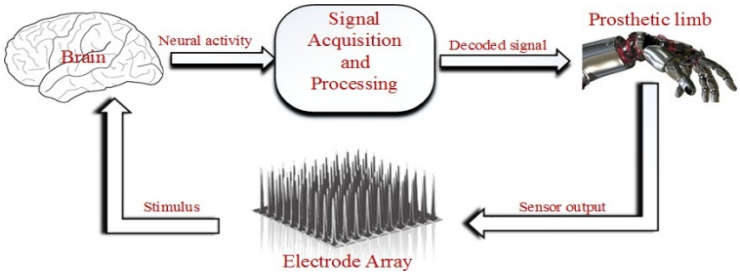

Fig 3:BMI with actuator assistance utilizing brain impulses to operate a prosthetic arm

SENSING BRAIN THROUGH ELECTRICAL ACTIVITY

The bio-electrical characteristics of brain cells and tissues have been studied using neuro-electrophysiology. Among these was the groundbreaking finding of action potentials in squid axons made by Hodgkin and Huxley in 1952, which ultimately earned them a Nobel Prize. The contribution of individual neurons to visual processing was later discovered by Hubel and Wiesel in 1977. In the field of neuro-electrophysiology, these groundbreaking investigations set the standard. A thorough understanding of the brain development of neuro-electrophysiological signals is necessary in order to extract meaningful information from them. Neuro-electrophysiological data typically depict the mean potentials of a large neural ensemble, the mall neural ensemble, and the spiking behavior of a single neuron. The

amplitudes increase with the size of the neuronal population because more neurons contribute additively to the signal.

There are several uses for neuro-electrophysiological
signals in clinical settings. They have mostly been employed as feedback signals in brain-machine-interfaceIn BMI, brain impulses are recorded and decoded by implanted devices, which are then utilized to control external devices, such as prosthetic limbs[17]. Furthermore, in both medically treatable and incurable epilepsy, electrophysiological signals are used to pinpoint the locations where seizures start.
They have been shown to be useful indicators for movement disorders, including dystonia, essential tremor, and Parkinson's disease (PD) (Little & Brown, 2012). They are also being used to trace neuropsychiatric illnesses, including Alzheimer's disease (AD), dementia, attention deficit hyperactivity disorder (ADHD), obsessive compulsive disorder (OCD), and schizophrenia (SZ) [48].

Essentially, the degree of invasiveness, resolution, signal substance, and clinical relevance should all be taken into consideration while choosing feedback signals. In the end, the choice of signals will be determined by how the system is designed overall in respect to the available signal processing capacity. The sensing methods and signals made possible by electrical activity in the brain are briefly described in the sections that follow.

NEURO-ELECTROPHYSIOLOGY RECORDING

The measuring of voltage or current inside a cell's membrane is known as intracellular recording. An electrode inside the cell and a reference electrode outside the cell are inserted to do this. A voltage or current clamp could be used for this [33]. A current clamp measures the increased membrane potential that results from injecting current through the intracellular electrodes. In contrast, the voltage clamp measures the current passing through the intracellular electrode while maintaining the membrane potential at a constant value. Current,

potential, and conductance measurements are the main methods utilized in intracellular recordings.However, the primary technique for assessing in vivo brain activity is extracellular recording. Extracellular recording for a single neuron is accomplished by positioning an electrode near the neuronal soma so that the number of spikes indicates the neuron's firing rate [6]. Because extracellular recording may provide neural activity and is relatively easy to use compared to intracellular activity, it has become more popular.Research on how a network of neurons affects different processes like vision, movement, and cognition is expanding in addition to studying single neuron activity. Multi-electrode arrays (MEA) have been used mostly for extracellular recordings in these investigations. Information from extracellular potentials is made up of high frequency spiking activity (> 500 Hz), also known as multi-unit activity (MUA), which originates from several neurons close to the recording electrode. Additionally, the local field potentials (LFP) comprise the low frequency potentials. The standard setup for monitoring extracellular activity from a neuronal population is shown in Fig. 4. A perfect measurement method must be able to provide both single-neuron activity and whole-brain activity on a microsecond time scale [7]; this may only be possible by integrating recordings from several methods.

UNIT ACTIVITY

Action potentials are often taken from a single neighboring neuron (single-unit recording) or from an unidentified population of surrounding neurons (multi-unit recording) using sharp extracellular electrodes, as shown in Fig. 4 [17]. The majority of these are extracellular potentials with high frequencies (>500 Hz). To learn how a neuron reacts to a particular stimulus or to comprehend the interaction between different neurons, a single unit activity is utilized. This has led to their usage as biomarkers for closed-loop deep brain stimulation (DBS) by shedding light on patterned activity in the globus pallidus internus (GPi) and subthalamic nucleus (STN) in connection to movement, cognition, and memory.DBS is a method used to treat neurodegenerative illnesses like Parkinson's disease (PD), tremor, and dystonia that are not treatable with medication. Therefore, feedback signals are used by

closed-loop DBS to monitor changes in the patient's condition and modify stimulation accordingly to enhance it. One example of BMI is closed-loop DBS. However, they are hampered by the necessity for accuracy on the target neuron, the inaccuracy of recording over prolonged use, and

recalibration (caused by drift in neural characteristics) [7].Though they have greater sample rate needs, deterioration at the neuron-electrode interface, and challenges in preserving recordings from the same neuron for prolonged periods of time, single neuron recordings do capture some movement aspects. However, the size of the recording electrodes has made it difficult to continue recordings since it primarily detects neuronal ensemble activity rather than the necessary single unit activity [8]. As a result, further processing units, like spike sorting, are required to help separate single unit operations from multiunit activities. Because great spatial resolution is needed in brain-machine interface (BMI) applications, unit activities are more valuable than other neuro-electrophysiological outputs. The use of spikes in BMI for prostheti climbs has demonstrated a clear correlation between them and behavioral and motor functions. Their application as biomarkers for controlling stimulation in closed-loop DBS has resulted from this [37].

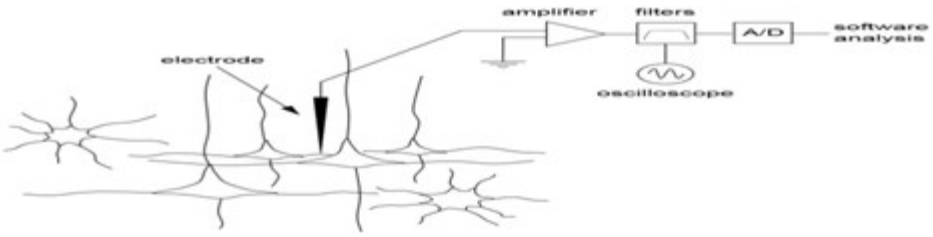

Fig 4: The fundamental setup for extracellular brain signal measurement and analysis (Lewicki, 1998). The analogue to digital converter (ADC), band pass filter (BPF), and low noise amplifier (LNA) are displayed in the setup.

LOCAL FIELD POTENTIALS

LFPs are extracellular potentials that are low frequency (less than 500 Hz) and are derived from sampling a local population of neurons.LFPs are produced by summated postsynaptic potentials coming from stimulation in basal ganglia and cortical neurons, and they are easily

recorded using a typical electroencephalography (EEG) amplifier coupled to the implanted DBS electrode. They are more stable and dependable than unit activity since they don't tend to drift with time [8].Compared to other neuro-electrophysiological signals, they provide a better trade-off between high spatial resolution (found in unit activity) and large spatial scale (found in global field potentials), and their population-based character makes them more informative due to their time and frequency response. The long-term experience researchers have gained in signal processing for EEG-like signals, especially LFPs, is another benefit of a confined population of neurons. Figure 5 shows the area where LFP recording is possible.LFP processing algorithms are perfect for use in implanted devices since they are simple to implement on microchips. There is no need for extra effort or processes because LFP processing microchips have been used in several investigations. Because of this, they are perfect for a wide range of applications that need feedback from brain signals. Current research supports the idea that LFP activity varies according to the clinical condition of the patient, making it a biomarker for closed-loop DBS. Very-low frequencies (2–8 Hz), beta frequencies (8–20 Hz), alpha frequencies (20–35 Hz), gamma frequencies (60–80 Hz), and very-high frequencies (250–350 Hz) are among the frequency regions in which basal ganglia LFPs oscillate. Because beta frequencies appear to represent the patient's motor state, they are the most researched and discussed LFP oscillations.Variations in betaLFP activity are correlated with motor performance and mostly reflect dopamine-induced reactions in the basal ganglia[49].

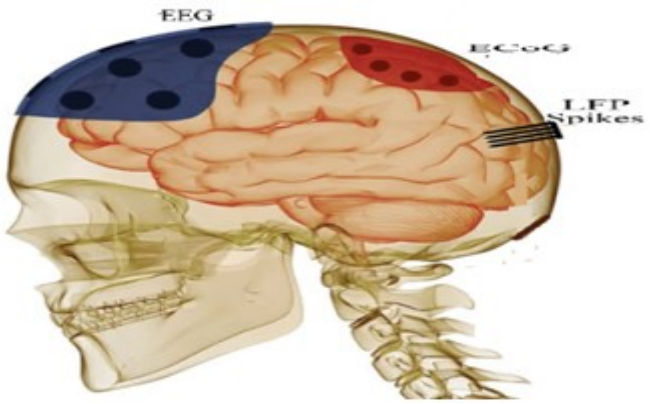

Fig.5.Neuro-Electrophysiological Signals and their recording sites

METABOLIC ACTIVITY SENSING

Vital brain information could be obtained from hemodynamic or neurotransmitter response in BMI. In neuro-motor disorders, stimulation and improved circumstances lead to the excitation and inhibition of neural impulses. Other side effects include altered blood flow, neurotransmitter modulation, neurogenesis, and a variety of other metabolic processes [24]. Because of this, it is crucial to look into metabolic activity for BMI.

Blood releases glucose to active neurons more quickly than it does to inactive neurons in the hemodynamic response [50].Oxyhemoglobin levels in the veins surrounding the active region rise as a result of the glucose and oxygen delivered into the bloodstream.Since both DBS and PD cause cortical hemodynamic abnormalities in patients, hemodynamic changes in PD patients can be useful biomarkers in DBS[5]. Techniques like near infrared spectroscopy (NIRS), diffusion magnetic resonance imaging (dMRI), and functional magnetic resonance imaging (fMRI) can be used to identify these alterations. Similar to hemodynamic responses, neuro-transmitter response measurement techniques are relevant since the majority of neuromotor illnesses, such as Parkinson's disease, cause cells that use dopamine as a neurotransmitter to degenerate[5].

There have been reports of tracking dopamine traces from cerebral metabolites[36], however a significant obstacle is the shrinking size of chemical analysis.

Responses to particular molecules are measured using optical micro-imaging techniques, primarily by employing fluorescence measurements, in addition to monitoring neurotransmitter and hemodynamic responses. Functional neuroimaging, which employs a two photon microscope, has single-cell resolution thanks to recent developments in optical imaging techniques[23].Using closed-loop DBS and BMI to record body functions requires an understanding of diseased brain processes down to the single neuron level. Optical procedures are superior to other methods because they are substantially less intrusive (about 1

to 2 mm in depth) and have strong spatial localization. Nevertheless, their primary drawback is their poor temporal resolution in contrast to neuro-electrophysiological techniques. Their strong demand for data analysis and signal processing is partially to blame for this [24]. Table I summarizes the main techniques for examining and determining metabolic activity from the brain that can be used in BMI applications.

FLUORESCENCE MEASUREMENTS

When certain chemicals, such as calcium, potassium, or sodium, are present, fluorescence measurements react in a unique way.There are two types of fluorescent measures of neural activity: those that detect changes in intracellular calcium concentration and those that are sensitive to membrane voltage. Action potentials cause relatively little signals to be produced by sensors that are sensitive to membrane potentials.

At the moment, calcium-sensitive sensors are orders of magnitude more sensitive than those that are sensitive to sodium or potassium. [4], the start and propagation of action potential can theoretically result in a calcium concentration that is around a hundred times higher than it would be at rest. This can be used to quantify the brain's active and dormant neurons.

NEAR-INFRAREDSPECTROSCOPY(NIRS)

NIRS measures changes in brain metabolism due to toneural activity using optical spectroscopy based on infrared light. Infrared light can reach a depth of around 1 to 3 centimeters beneath the human skull [27]. This allows NIRS to use light attenuation (absorption and scattering) to estimate the concentration of oxyhemoglobin [2]. Light's poor penetration makes it less than suitable for applications that track biomarkers in deep brain areas. However, because vascular alterations take place approximately 100 milliseconds after the corresponding cerebral activity, it is a prospective diagnostic tool to study neurovascular linkage, for instance in epilepsy to create novel electroencephalogram detection methods. This, according to Coyle, Ward, and Markham , is a suitable temporal resolution for BMI applications.Furthermore, its spatial resolution is within 1 cm. The main benefit of using

optical modalities, suchas fluorescence measurements and NIRS, to capture brain activity is their high specificity, which will help to provide artifact-free BMI implementations[17]. If used NIRS in DBS patients.The results indicated that alterations in oxyhemoglobin levels in the prefrontal cortex were indicative of treatment outcomes. Because of its capacity to precisely measure neuronal activity, which is indicative of the severity of symptoms, NIRS has been suggested as a viable signal to modify the parameters of DBS in a closed loop configuration, despite its bulkiness [45]. The use of this technology for BMI applications is still in its infancy. To prove its viability, further research with a sufficient number of patients and positive outcomes is needed.

MAGNETIC RESONANCE IMAGING(MRI)

A new technique for detecting neuronal activity in the living brain is magnetic resonance imaging (MRI). Applications such as blood-oxygen-level-dependent (BOLD) functional magnetic resonance imaging (fMRI), a non-invasive technique for tracking brain activity, have enormous potential for its use.Similar to NIRS, fMRI provides a millimeter-scale spatial resolution and is a measurement based on hemodynamic changes. Research has demonstrated that it provides significant understanding of the fundamental workings of the human brain [15]. Furthermore, knowing the fundamental processes can help explain why the brains of various patients react differently to comparable stimulation levels. In addition to fMRI, diffusion magnetic resonance imaging (dMRI) can provide a detailed picture of the intricate activity in the brain's white matter [21].It records the displacement of water molecules within a voxel. Based on the directional diffusion of water, this is used to determine the position and orientation of white matter tracts.The internal functioning of the brain has been understood through changes in the white matter fiber tract. The study by verified that in healthy patients, alterations in the white matter fiber tract connection were associated with subject performance on particular tasks[21].

FAST SCAN CYCLIC VOLTAMMETRY (FSCV)

FSCV is a voltammetry technique that uses carbon fiber microelectrodes (CFM) to apply a linearly variable potential. This causes redox chemical reactions around the electroactive molecules. The size of the evoked current peaks to the redox reaction at the electrode surface is used to determine the analyte concentration. A chemical signature for the presence of specific neurotransmitters or analytes is provided by the relationship between the applied voltage and the resultant current.Electroactive analytes, such as dopamine (a PD biomarker), adenosine (a sleep biomarker), and oxygen (a symptom of anoxic brain injury), are the primary targets of FSCV detection. The bulkiness and short lifespan of CFMisafew months are the main drawbacks of FSCV, which limits its use to intraoperative methods. The Mayo Investigational Neuromodulation Control System (MINCS) in was interfaced with FSCV for closed-loop DBS utilizing an anesthetized rat model[34].

INTRACRANIAL MICRO-DIALYSIS

The most popular technique for determining the chemical concentration of analytes in the brain is microdialysis It makes use of an adialysis probe that can reach the brain's tiny chemicals. Artificial cerebrospinal fluid is pumped into the brain, and the amount of molecules that diffuse into the dialysate and probe are measured and examined offline. Because a specific volume of dialysate must be collected before any analysis can be conducted, which hinders time resolution, its spatiotemporal resolution is not high. On the other hand, its sensitivity and chemical selectivity are extremely high. Microdialysis is only useful for measuring long-term changes in analytes or neurotransmitters for use in closed-loop or BMI applications because of its limited temporal resolution. In essence, its selectivity and sensitivity make it appropriate for uses such as PD patient home monitoring.This could significantly lower the number of in-person visits for individuals with neuro-motor diseases or prosthetics. Some of the features of different feedback signals that are appropriate for BMI applications are compiled in Table 1.[42]

ELECTRICALVERSUSMETABOLICACTIVITY

Advanced methods that reach remote and deep areas of the brain are necessary for efficient neural recording (Haet al., 2017).These might provide additional understanding of brain dynamics. However, methods with spatial coverage are equally important. Advances in brain signal capture are essential for a significant breakthrough in our understanding of neurophysiological dynamics (Muraskinetal., 2017).This is the fundamental prerequisite for effective BMI systems.

Alterations in the brain's biochemical environment can serve as a proxy for patients' actual and intended behaviors.Metabolic activity sensing is appropriate for measuring brain activity because of these features. Notable examples of methods used to measure biochemical activity include fluorescence measures, FSCV, intracranial dialysis, NIRS, and fMRI. Researchers have looked into using metabolic activity as a biomarker [45]. Metal artifacts and safety issues like MRI compliance are their main drawbacks.Other metabolic activity sensors, such NIRS, have a lower temporal resolution than electrophysiological activity, but they are not impacted by metal artifacts. One of the main obstacles to fully implanted BMI systems is their size. In general, metabolic activity offers many advantages over electrical activity recording, aside from sensitivity to metal artifacts in fMRI. These advantages include the lack of electrical noise, the ability to image many neurons at once, and the ability to selectively record from genetically-targeted brain regions [30]. Their high specificity, selectivity, and signal to noise ratio can greatly aid in the development of artifact-free BMI systems.

EEG and single unit activities are at the extreme of the spectrum; EEG has the highest spatial scale and the lowest temporal resolution, whereas single unit activities have the highest temporal resolution and the least spatial coverage. Information content for electrical activity is reliant on spatiotemporal resolution. In terms of spatiotemporal resolution, LFP and ECoG provide a compromise.They are very desirable feedback signals for BMI applications due to their long-term stability at the electrode-tissue interface [36]. The legitimate question is how

informative they are in comparison to other neuro-electrophysiological signals in order to employ them as universal feedback signals. Thus, it is clear that the selection of BMI feedback signals appears to depend on the application.

ElectricalActivityMeasurements	**Spike** (Gold et al.,2006),(Buzsáki,2004),(Rosinetal., 2011)	**LFP** (Urrestarazuetal.,2009),(Kühnet al., 2006)	**ECoG/iEEG**(Rowlandetal.,2013)	**EEG**(Schwartzetal.,2006),(Schalk&Leuthardt,2011)	
ActivityMeasured	Unitactivity	averagepotentialofa localised neural population	corticalorintracranialactivity	Electricalactivityfromscalp	
TemporalResolution	<1ms	~1 ms	~3ms	~50ms	
SpatialResolution	~50µm	~0.5mm	~1 mm	~10mm	
LevelofInvasiveness	Invasive	Invasive	Minimallyinvasive	Non-invasive	
PracticabilityinBMI	Implantable	Implantable	Implantable	Bulky,butcheap	
MetabolicActivityMeasurements	**Fluorescence Measurements** (Schultzetal.,2017), (Berridgeetal.,2000)	**NIRS** (Alt et al.,2017),(Sakataniet al., 1999)	**fMRI** (Muraskin et al.,2017),(Fouragnanetal., 2015)	**FSCV** (Lee et al.,2007),(Changetal.,2013)	**Intracranialdialysis** (Robinsonetal.,2003)
ActivityMeasured	Ca^{2+}, Na^{+} or K^{+}concentrationinthebrain	Concentrationofoxyhemoglobin	blood-oxygen-levelandmolecular displacementofwater	Concentrationofneurotransmitter(dopamine)	Concentrationofneurotransmitter(dopamine)
TemporalResolution	~30ms	<1s	~1 s	~1 s	~1 s
SpatialResolution	~10µm	~ 5mm	~1mm	~30µm	~200µm
LevelofInvasiveness	Invasive	Non-invasive	Non-invasive	Invasive	Invasive
PracticabilityinBMI	Implantable(withvery highdataanalysiscost)	Bulky	Bulky(amajorhindranceisDBSdevicesarestillMRconditional)	Bulky(with high specificityandselectivity)	Bulky (with highspecificityandselectivity)

FUTURE TRENDS OF BMI

Neural activity measurements consisting of metabolic and electrical activity are the preferred choice for use as feedback signals. While metabolic activity measurements are more selective, specific, and quantifiable than electrical activity measurements, electrical activity has a faster response than metabolic activity. Of all electrical activity measurements, LFP has the optimal trade-off in spatio-temporal resolution as well as stability, making it a prime candidate for non-invasive BMI. BMIs are rehabilitation tools in which neural functions are modulated through feedback that is triggered by either decoded external percepts or brain activities.

The primary objective of BMI sensing is to give the brain-attached gadget enough information to enhance patients' usage of their body parts. In the most advanced BMI devices, prosthesis rejection is a significant obstacle. Poor feedback signals have been the primary cause of this. a prosthesis should be placed in the body both physiologically and sensorially to guarantee better integration. Numerous research have looked into using a prosthetic device for daily tasks[12]. But in a lab setting, the majority of this has been accomplished with an external computer. One of the main challenges of BMI applications has been converting research into practical implementations.

These have mostly been caused by weak feedback signals and insufficient data collection.External and non-invasive sensing modalities should be included in BMIs in order to get more comprehensive sensory data and more meaningful information. This can be achieved by supplementing other internal measures derived from electrical and metabolic activity with variations in temperature, vibration, and mechanical pressure. Simple feedback techniques can be employed to construct BMI systems with this type of approach. which might reduce the computational burden of the systems and make them better suited for chronic.

CONCLUSION

This review makes it abundantly evident that the two main obstacles to physiological signal analysis are feedback signals and sensing equipment. Feedback signals that clearly identify messages for various behaviors and intentions are necessary in BMI. These signals ought to be reliable throughout time and indicative of different topic activities. Nevertheless, implanted, non-invasive sensing devices with the best spatiotemporal resolution are needed for this to be fully implemented. BMIs can potentially reach the required performance levels without compromising the patient's quality of life by combining the appropriate sensing modalities.

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