A review on the evolution of EEG- based Brain Computer Interfaces

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Abstract:
Brain-computer interfaces, or BCIs, are a new technology with a promising trajectory in the field of neuroscience and biomedical engineering. Neurological disorders such as Parkinson's disease, stroke, epilepsy, spinal cord injuries and disorders of consciousness affect the nervous system and can impair motor control, communication, sensory function, or cognition. BCIs help restore or compensate for lost functions by enabling movement through prosthetics or restoring communication. Brain-computer interfaces hold the potential to improve patients' quality of life and help them reclaim independence. BCIs can assist in symptom management such as reducing tremor in patients with Parkinson's disease. Despite brain-computer interfaces still being in the early stages of development, they show great potential in transforming treatment for neurological disorders. Research on BCIs pushes the development of new and innovative medical devices that can transform the medical field and lead to more effective treatments for neurological disorders. The research also raises important questions about privacy, autonomy and ethics in biomedical innovation which is an impactful part of making sure new technology is developed responsibly.

Introduction:

What is a BCI?

In 2023 the National Center for Health found that strokes,along with other neurological disorders, were the fourth most common cause of death in the U.S. A new study released by *The Lancet Neurology*, showed that more than 3 billion people worldwide were living with a neurological condition. *The World Health Organization* stated that 1 in 3 people are affected by neurological conditions becoming the leading cause of disability worldwide.

This rise in this rate of disability called for needed improvement in treatment to increase quality of life. As the need for improved treatment arose, the BCI was found.

The idea of a BCI was long-established but had only begun to gain significant popularity in the 21st century. Research began in 1973 by Jacques Vidal ending only in 1977 proving the concept of a BCI but failing to create one. The first BCI was implanted in the late 1990s as the field began to see advancements in neural signal processing and machine learning.

What is EEG?

The groundwork for electroencephalogram or EEG was laid by early researchers such as Luigi Galvani in the late 18th century, who discovered "animal electricity." By the 19th century, Richard Caton had built on Galvani's research and recorded electrical activity from the exposed brains of an animal. In 1924, Hans Berger, a German psychiatrist, recorded the first human electroencephalogram (EEG) from the scalp. At first, his findings were met with disbelief and doubt due to the primitive technology during the time, but after different researchers began to replicate Berger's findings in 1934, the scientific community started to accept EEGs.

An electroencephalogram or EEG is a test that measures electrical activity in the brain. Electrodes are attached to the scalp and detect electrical charges produced by brain cells. These charges are then amplified and displayed as brain waves on a computer or paper.

The "argument."

This review intends to highlight the evolution in scientific studies of EEG based BCIs.

Methodology:

1977: Jacques J. Vidal demonstrated the first EEG-based control of a cursor.

The intention of Vidal's experiment was to find out if brain activity (EEG signals) could be used to detect specific mental responses in real time. He aimed to use this disovery to control computers or devices. The results will be explained later on in the review.

In the experiment, he placed the subjects in front of a display of diamond-shaped red checkerboards that flashed briefly with fixation points. Electrodes were placed on the scalp of the subjects in five locations, mostly in the areas where the occipital/parietal lobes are found in addition to the earlobes. The event-related potential, ERP, data was collected every 4 milliseconds and was analyzed within 400 milliseconds after each flash. This setup allowed the researchers to capture ERPs associated with the brain's response to each stimulus.

To classify the stimulus each participant was focusing on, the system processed the live EEG data in real time. This involved rapidly recording and preprocessing the signals, then applying machine learning algorithms to identify which fixation point triggered the response.

1991: Cheng et al introduced motor imagery based control where users adjust mu rhythms to move cursor vertically in real-time

The goal of the experiment was to determine whether EEG signals (specifically the mu rhythm 8-12 Hz) could be used to move a cursor accurately among four possible targets on a screen.

Subjects sat in front of a screen with 4 vertical targets. EEG data was recorded from 64 scalp electrodes, referenced to the right ear, sampled at 160 Hz. Data was collected from 3 subjects for over 10 sessions where the first 6 consisted of training. Each trial lasted approximately 2.3 seconds.

The EEG data was analyzed using a three stage algorithm: spatial filtering, feature extraction and classification. The spatial filtering consisted of Common Average Reference (CAR) to reduce noise common across all EEG channels and enhance localized brain activity, and Common Spatial Subspace Decomposition (CSSD) to isolate and enhance brain signal components to identify which target the subject focused on. Feature extraction involves two components, a power feature and a time feature, that are independent but work together to improve classification accuracy. The power feature measures the strength of mu rhythm in specific frequency bands using spectral analysis to capture how much mu rhythm activity is present. The time feature tracked how mu rhythm changed over time during a trial based on an energy accumulation function based on the Fisher ratio and was designed to be independent of the power feature. Lastly, a 2-dimensional linear classifier was adopted in the algorithm to minimize the number of trials misclassified.

2022: Pan et al proposed an LSTM-based network to decode continuous 2-D velocity

The goal of this experiment was to develop a real-time brain-computer interface system that allows users to control a 2D cursor noninvasively using EEG signals. They integrated both active (motor imagery) and passive (P300 error-related) brain signals for improved control accuracy.

Ten subjects participated in the study and a 64-channel cap, focused on 10 motor-related channels, were placed on their heads. The participants were instructed to imagine moving the cursor left, right, up, or down based on the on-screen cues. These imagined movements generated specific brainwave patterns (specifically mu rhythms), which the system used to move the cursor in real time. If the cursor moved incorrectly, P300 signals (passive error detection) were triggered causing the system to recognize its mistake and correct the control.

The EEG patterns were used by a deep learning model (stLSTM) to decode intended movement direction and velocity that contained two feature extractions: spectral features and temporal features. The spectral features focused on mu rhythm and were extracted using autoregressive (AR) modeling. The temporal features captured P300 components that were enhanced using wavelet convolution to emphasize event-related potentials.

2025: Forenzo et al used deep learning to help subjects control a robotic arm

Forenzo and his team aimed to investigate whether adding a “click” signal to a motor imagery based EEG BCi system could enable users to perform more complex tasks such as reaching, grasping, and placing objects with a robotic arm. They evaluated whether healthy and stroke-affected individuals could simultaneously control movement and clicking using only motor imagery.

Seven healthy and 3 stroke-survivors participated in the study. EEG data was recorded using a 64-channel Neuroscan Quik-Cap and data was placed according to a modified international 10/20 system. The subjects performed motor imagery tasks to generate brainwave patterns: imagining left hand movement to move left, right hand for right, both hands for up, rest for down, and foot movement for clicking. The subjects were tasked with moving a cursor to a target and clicking using foot motor imagery, moving a robotic arm using the same “click”, and using the robotic arm to move physical cups across vertical shelves.

To interpret the EEG signals, the system used deep learning models based on EEGNet. This system also included two decoders. One was used for predicting 2D movement velocities and the other was used for detecting a Boolean click signal. Both models were calibrated to fit the subject

Results:

1977: Jacque J. Vidal

Vidal was able to observe that when a subject looked at flashing visual stimuli (the checkerboard), distinct EEG responses (visual evoked potentials or VEPS) appeared in the occipital region. These VEPS occurred consistently but varied depending on where the subject focused their attention. This supported his hypothesis that if different stimuli could produce these distinguishable EEG signals, the computer could interpret those signals and determine user intent.

Vidal also explored slow cortical potentials (slow shifts in EEG voltage) that were 0.5 Hz or less. These are known to be related to motor preparation and intention. Vidal found that these SCPs could be changed by the subject, highlighting that a subject could learn to produce a specific SCP pattern to correlate with a particular movement. If the subject could learn to control these SCPs intentionally, these patterns could be input into a computer interface to allow them to move as wanted.

Lastly, Vidal found that event-related potentials or ERPs changed based on task demands and mental focus. When subjects were told to expect a stimulus their ERP responses were stronger meaning the brain's response was influenced by attention and anticipation.

Overall, Vidal successfully used EEG features to trigger computer responses proving that it was possible to "speak" to a machine using only brain signals. He coined the term "BCI" and proved the feasibility of a BCI system proving that EEG signals could be used to control devices.

1991: Cheng et al

Cheng observed that when subjects attempted to move the computer cursor, the mu rhythm exhibited distinct patterns based on which target they were aiming for. Using spectral analysis they found that different target choices produce distinguishable changes in mu rhythm power, particularly in the 12-14 Hz and 24-25 Hz frequency bands. These variations in power confirmed that mu rhythm amplitude could accurately reflect the subject's intent in the direction of the cursor.

Cheng also explored the time course of mu rhythm activity and how the amplitude changes over time during a trial. This was specifically shown in the intermediate targets (2 and 3) where subjects would actively change the rhythm. This observation supported the idea that subjects could learn to produce distinct patterns of brain activity to move where intended.

Additionally, Cheng found that spatial filtering techniques improved classification accuracy. By applying CSSD, they enhanced task-specific EEG signals and reduced noise, resulting in unclear values for different targets. When both power and time features were combined in a two-dimensional linear classifier, accuracy increased notably in the training data for some subjects.

However, when the same models were applied to test setting, classification accuracy dropped revealing variability in EEG signal strength. Despite this, Cheng's work demonstrated that users could intentionally generate distinguishable mu rhythm patterns to control a cursor with success.

2022: Pan et al

Pan observed that users could continuously and intuitively control the 2D cursor using only motor imagery showing that the BCI system enabled reliable and accurate real-time control using noninvasive EEG. The system was able to successfully separate horizontal and vertical directions, by using a velocity-constrained loss function, allowing precise control.

When the cursor moves incorrectly, the subject's brain automatically generates P300 signals in response to errors that were detected by the system without requiring additional commands from the users.

The spectral-temporal LSTM model accurately decoded both movement intentions and error signals, and by combining mu rhythm features with P300 responses, the system achieved adaptable control over time. Quantitative performance metrics, including Root Mean Square Error (RMSE), accuracy, and mean absolute ratio showed marked improvements compared to baseline linear regression model.

Overall, by integrative active motor imagery and passive error-related brain signals Pan was able to enhance accuracy, stability allowing noninvasive BCIs to control a 2D cursor in real-time.

2025: Forenzo et al

Forenzo and his team observed that users could continuously and simultaneously control a robotic arm's 2D position and initiate grasping actions using only motor imagery. However, performance varied widely between subjects and variability was also observed within and between sessions for a single subject, a known issue in BCI research.

When users performed foot motor imagery, the BCI detected this as the "click" signal, replacing older methods. The click-based paradigm allowed users more natural interaction with physical targets.

The deep learning models effectively decoded both continuous movement and click commands. By adjusting models mid-session for EEG variability, the system maintained consistent performance. Quantitative performance metrics, including hit count and hit-to-click ratio, showed subjects could move up to 7 cups in 5 minutes.

Overall, by integrating voluntary movement and action control into a single BCI framework, the system enhanced accuracy and usability of noninvasive EEG based control, bringing BCI assisted robotics closer to clinical and daily applications.

Discussion:

Vidal's experiment served as a proof of concept for BCI technology by being able to translate EEG data to the computer proving that EEG signals could be used to control devices. Cheng took Vidal's findings one step further by demonstrating that users could intentionally generate specific EEG signals (mu rhythm patterns) to control a device. Pan also added on by integrative active motor imagery and passive error related brain signals to enhance BCIs. Lastly, Forenzo integrated all this research into building a BCI to control a robotic arm and adding to it by integrating voluntary movement and action control.

These results highlight the evolution of EEG based BCIs. From the discovery of EEG signals in humans in the late 20th century, the usage of EEG signals has evolved to allow people to use these signals to control an object.

In Vidal's demonstration of EEG-based control he acknowledges the problem that the BCI system is not generalizable and what works for one subject may not for another. However, Vidal does not address this further, emphasizing there may be an issue with BCI development. Technology was rudimentary when the paper was written in 1977, causing the EEG data to be "noisy" and not as clear.

Additionally, in Cheng's experiment EEG signals varied not only between people but over time as well. Factors such as electrode placement, mental fatigue and even small movements can cause shifts in the signal's amplitude, proving to be a problem.

Also, in Pan's paper, the deep learning model (stLSTM), requires careful tuning of multiple parameters for different datasets and subjects, which limits its practicality and generalizability in real-world BCI applications. This is also seen in Forenzo's work that relies heavily on controlled lab conditions that are not viable due to the real world's variability, making it impractical to replicate his experiments outside of a laboratory setting.

Conclusion:

From Vidal's early EEG-controlled cursor to modern deep learning powered robotic control, BCI research has developed significantly. The accuracy, complexity and usability has improved throughout the years bringing BCI technology one step forward in becoming a practical tool for everyday use and a viable solution for assisting people with neurological conditions.

However, challenges still exist today. Signal variability and user-specific calibration limit real-world practicality. Along with these challenges comes neuroethics, which raises concerns about privacy, autonomy and the responsible use of brain data, prompting important questions.

Despite challenges, these systems hold immense potential to restore communication and mobility for people with neurological disorders in addition to opening doors for mental health monitoring.

Currently, EEG based BCI's are widely used for non-invasive brain signal monitoring, including assistive communication, neurofeedback therapy, gaming, cognitive monitoring and research purposes. Two widely recognized EEG-based BCIs include the Muse Headband and the Emotiv Epoc X. The Muse Headband is a consumer-friendly, wearable EEG device used for meditation. The Emotiv Epoc X is a wireless EEG headset used for research, neurogaming, and assistive technology and provides professional-grade data.

Emerging BCI technology includes AI-driven decoding algorithms allowing deep learning models to adapt to users in real time, reducing calibration time. Several companies and research groups are actively working on achieving this. These advancements bring us closer to a future where BCIs are not only more accurate and user friendly but also seamlessly integrate into daily time, restoring independence and enhancing human capabilities.

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