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Survey on Brain-Computer Interface Enabled Mobile Vehicles

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Abstract

A brain-computer interface allows people to communicate or control a device using their thoughts or other brain activity. BCIs are based on the idea that the brain generates electrical signals in response to various stimuli, such as thoughts, movements, and sensory experiences. These signals can be measured and analysed using specialized sensors to control devices or perform other tasks. BCIs can be used in various applications, including medical rehabilitation, assistive technology, and research into brain function.[1] Brain-computer interfaces (BCIs) have the potential to revolutionize the way we interact with vehicles. Allowing drivers to control their vehicles using their thoughts or other brain activity, BCIs could make driving safer, more efficient, and more enjoyable. There are several different ways that BCIs could be used in vehicles.[2] For example, a BCI might allow a driver to control a car's acceleration, braking, and steering using their thoughts. This could be particularly useful for drivers with disabilities who may have difficulty using traditional controls. BCIs could also improve safety by detecting changes in a driver's brain activity that may indicate fatigue, stress, or other factors affecting their driving ability. In addition, BCIs could enhance the driving experience by allowing drivers to customize their vehicle's settings or access information and entertainment using their thoughts. [3]

Keywords. Neural Commands, BCI, Arduino, Automation, Smart Automobile, BCI Sensors

1. Introduction to Brain-Computer Interfaces (BCI)

A brain-computer interface (BCI) is a system that allows a person to communicate or control a device using their thoughts or other brain activity. BCIs are based on the idea that the brain generates electrical signals in response to various stimuli, such as thoughts, movements, and sensory experiences. These signals can be measured and analysed using specialized sensors to control devices or perform other tasks.[2]

BCIs can be used in various applications, including medical rehabilitation, assistive technology, and research into brain function. For example, a BCI might be used to help a person with paralysis communicate or control a computer or to help a person with a movement disorder perform everyday tasks more efficiently. Several BCIs include invasive, partially invasive, and non-invasive systems. Invasive BCIs involve the insertion of electrodes directly into the brain, while partially invasive systems use electrodes placed on the brain's surface or scalp. Non-invasive BCIs use sensors placed on the scalp, forehead, or other body parts to measure brain activity.[1] BCIs have the potential to revolutionize the way we interact with computers and other devices and could have a significant impact on a wide range of fields, including healthcare, education, and entertainment. However, there are also several challenges to overcome in the development and use of BCIs, including reliability, cost, and ethical concerns.

2. Introduction to Computer-Controlled Mobile Systems

Computer-controlled vehicle systems refer to systems that use computers to control various aspects of a vehicle's operation, such as propulsion, steering, and braking. These systems can be used in various vehicles, including cars, trucks, buses, and aircraft. One typical example of a computer-controlled vehicle system is an electronic stability control (ESC) system, designed to help a vehicle maintain stability and control during turns or other manoeuvrings. An ESC system uses sensors to monitor the vehicle's speed, steering angle, and other factors and then uses this information to adjust the brakes and engine output as needed to help keep the vehicle on its intended path.[7]

Examples of computer-controlled vehicle systems include:

- Anti-lock braking systems (ABS to control the brakes and prevent the wheels from locking up during hard braking.
- Automatic transmission systems to select the appropriate gear ratio based on the vehicle's speed and load.
- Adaptive cruise control systems to maintain a set speed and a safe following distance from other vehicles.
- Fuel injection systems to control fuel flow to the engine based on various factors, such as engine speed and load.

Computer-controlled vehicle systems have greatly improved modern vehicles' safety, performance, and efficiency. However, these systems can also be complex, and it is essential for vehicle owners to understand how they work and to maintain them properly.

3. Types of Brain Waves compatible with BCI Sensors

The human brain generates electrical signals in response to various stimuli, such as thoughts, movements, and sensory experiences. These electrical signals can be measured and analysed using specialized sensors, such as electroencephalography (EEG), which are placed on the scalp to measure the brain's electrical activity.[3] The brain's electrical activity is typically divided into five different types of brain waves based on their frequency:

- Gamma waves (30-100 Hz): Gamma waves are associated with high levels of consciousness, alertness, and focus.
- Beta waves (12-30 Hz): Beta waves are associated with ordinary waking consciousness and are typically present when a person is alert and engaged in mental activity.
- Alpha waves (8-12 Hz): Alpha waves are associated with a state of relaxation and are typically present when a person is awake but not focused on a task.
- Theta waves (4-8 Hz): Theta waves are associated with a state of deep relaxation, such as when a person is meditating or falling asleep.
- Delta waves (0.5-4 Hz): Delta waves are associated with deep sleep and are typically present when a person is in a deep, dreamless sleep.

Brain waves can be measured and analysed to understand how the brain functions and diagnose certain conditions, such as sleep disorders and epilepsy.

4. Types of BCI Sensors

There are several types of sensors that can be used for a brain-computer interface (BCI). Some of the most commonly used include:

- Electroencephalography (EEG) sensors: These sensors measure the electrical activity of the brain and are typically placed on the scalp. They are non-invasive and can be used to detect changes in brain activity in response to specific tasks or stimuli.
- Functional near-infrared spectroscopy (fNIRS) sensors: These sensors measure changes in blood oxygenation levels in the brain and are also non-invasive. They can be used to detect changes in brain activity in response to specific tasks or stimuli.
- Electrocorticography (ECoG) sensors: These sensors are implanted directly on the surface of the brain and measure electrical activity from the cerebral cortex. They are invasive but provide a higher resolution of brain activity than non-invasive sensors.
- Intracortical microelectrodes: These are invasive sensors that are implanted directly into the brain tissue, they are able to record the activity of single neurons and provide the highest resolution of brain activity.

These are some of the most commonly used sensors in BCI research, but new technologies are being developed all the time.

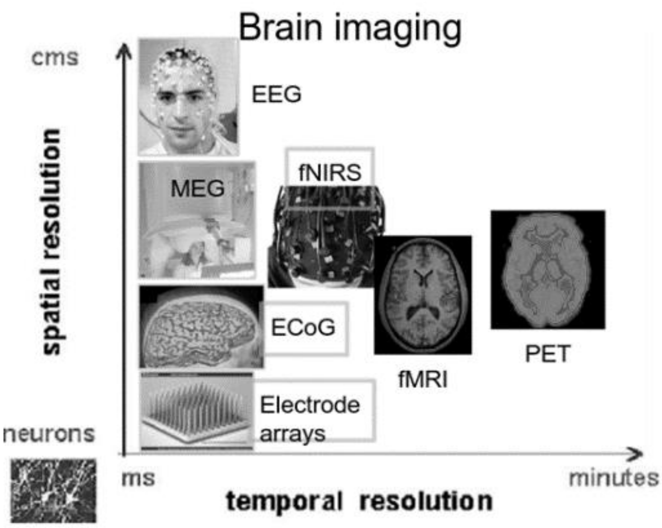

Fig 1 Types of BCI Sensors

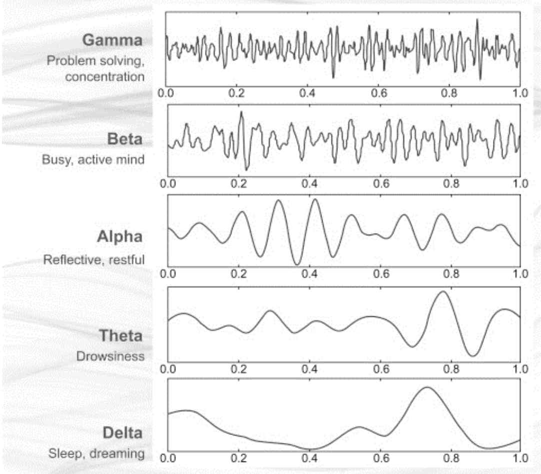

Fig 2 Types of Brain Waves and their patterns

5. Configuration Steps to Analyse Brain Waves using MATLAB

Several steps are involved in configuring brain-computer interface (BCI) sensors with MATLAB, a programming language and software platform commonly used for data analysis and visualization. Here is a general outline of the process:[16]

1. Choose a BCI hardware platform: There are many different types of BCI hardware platforms available, each with its own set of sensors and features. We must choose a platform compatible with MATLAB that meets specific needs.
2. Install the necessary software: Install MATLAB and any additional software or drivers to interface with your chosen BCI hardware platform.
3. Connect the BCI hardware to the computer: Follow the instructions provided by the manufacturer to connect the BCI hardware to the computer. This may involve connecting the sensors to a headset or other device and then connecting the device to the computer using a USB or cable.
4. Load the necessary data: Once the BCI hardware is connected to the computer, we will need to load the data from the sensors into MATLAB. This can typically be done using a specific function or command provided by the manufacturer.
5. Analyse and visualize the data: Once the data is loaded into MATLAB, we can use the software's various tools and functions to analyse and visualize the data. This might involve plotting the data over time, performing statistical analysis, or creating visualizations such as bar charts or heat maps.

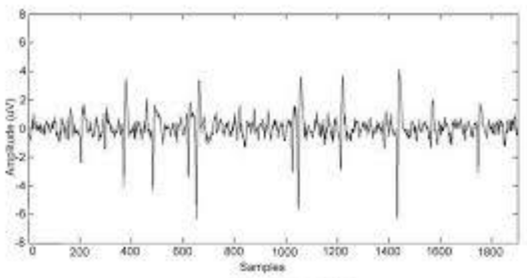

Fig 3 Amplitude of Signal versus time

6. Configuration of BCI Sensors with Arduino

Several steps are involved in configuring brain-computer interface (BCI) sensors with Arduino, an open-source electronics platform commonly used for prototyping and building electronic devices. Here is a general outline of the process:[12]

1. Choose a BCI hardware platform: There are many different types of BCI hardware platforms available, each with its own set of sensors and features. You must choose a platform compatible with Arduino that meets your specific needs.
2. Install the necessary software: You will need to install the Arduino Integrated Development Environment (IDE) and any additional software or drivers required to interface with your chosen BCI hardware platform.
3. Connect the BCI hardware to the computer: Follow the instructions provided by the manufacturer to connect the BCI hardware to the computer. This may involve connecting the sensors to a headset or other device and then connecting the device to the computer using a USB or cable.
4. Load the necessary code: Once the BCI hardware is connected to the computer, we must load the code into the Arduino IDE. The manufacturer might provide this code, or we may need to write it using the Arduino programming language.
5. Upload the code to the BCI hardware: Once the code is loaded into the Arduino IDE, we can use the software to upload it to the BCI hardware. This will allow the sensors to communicate with the Arduino and perform the tasks specified in the code.

Overall, configuring BCI sensors with Arduino requires a combination of hardware setup, software installation, and programming skills. It is essential to follow the instructions provided by the manufacturer carefully and to have a good understanding of the tools and functions available in the Arduino IDE.

7. Controlling Vehicles with BCI

Controlling a vehicle using brain-computer interfaces (BCIs) involves using sensors to measure brain activity and then using this information to control various aspects of the vehicle's operation, such as propulsion, steering, and braking.[6]

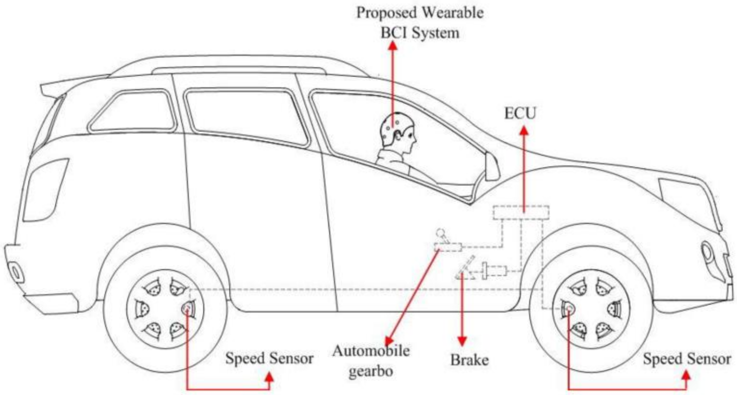

Fig 4 Experimental vehicle interfaced with BCI

There are several ways that BCIs could be used to control a vehicle:

1. Direct brain control: In this approach, the BCI would detect specific brain signals associated with particular actions, such as accelerating, braking, or turning. The BCI would then interpret these signals and send commands to the vehicle's controls to execute the desired action.
2. Indirect brain control: In this approach, the BCI would detect brain signals related to the driver's intentions or goals rather than specific actions. The BCI would then use machine learning algorithms to interpret these signals and determine the most appropriate course of action for the vehicle to take.
3. Hybrid brain control: The BCI would combine direct and indirect brain control elements in this approach. For example, the BCI might use specific brain signals to control certain actions while using more general signals to guide the overall direction of the vehicle.

7.1. Direct Brain Control to control vehicles

Direct brain control refers to a brain-computer interface (BCI) type that allows users to control a device or system by detecting specific brain signals associated with particular actions or commands. In the context of vehicles, direct brain control BCIs could be used to control various aspects of a vehicle's operation, such as propulsion, steering, and braking, by detecting specific brain signals associated with these actions.[7]

There are two ways that direct brain control BCIs could be used to control vehicles:

- Electroencephalography (EEG): EEG is a non-invasive technique that uses sensors placed on the scalp to measure the brain's electrical activity. EEG could be used to detect specific brain signals, such as those associated with movement or intent, and to use these signals to control the vehicle.
- Invasive brain-machine interfaces (BMIs): Invasive BMIs involve the implantation of electrodes or other sensors directly into the brain. These sensors can detect more specific and clear brain signals but also come with more significant risks and challenges than non-invasive techniques.

7.2. Indirect Brain Control to control vehicles

Indirect brain control refers to a brain-computer interface (BCI) type that allows users to control a device or system by detecting brain signals related to the user's intentions or goals rather than specific actions or commands. In the context of vehicles, indirect brain control BCIs could be used to control various aspects of a vehicle's operation, such as propulsion, steering, and braking, by interpreting more general brain signals related to the user is desired destination or route.

Using BCIs to control vehicles can significantly improve road safety, efficiency, and enjoyment. However, there are also several challenges to overcome in the development and use of BCIs in vehicles, including reliability, cost, and ethical concerns.

8. Effect Of Various Parameters on BCI

8.1. Effect based on the concentration of the user

A user's concentration can significantly affect the performance of brain-computer interfaces (BCIs). BCIs rely on detecting and interpreting brain activity, typically brainwaves, to allow users to communicate or control a device using their thoughts or other brain activity. Suppose a user is highly concentrated and focused. In that case, they are likely to generate more specific and consistent brain activity, making it easier for the BCI to detect and interpret the signals.[8] This can lead to improved performance and accuracy of the BCI. On the other hand, if a user is not focused or distracted, their brain activity may be less clear and consistent, making it more difficult for the BCI to detect and interpret the signals. This can lead to lower performance and accuracy of the BCI.[9]

Maintaining a high concentration level can be essential for maximizing the performance and accuracy of BCIs. However, it is also important to note that other factors, such as the specific type of BCI being used and the user's skill and experience with the system, can also influence the performance of the BCI.[10]

8.2. Effect based on the age of the user

A user's age can impact the performance of brain-computer interfaces (BCIs), as brain activity tends to change with age. Research has shown that brainwave patterns change with age, with older adults typically showing slower brainwave frequencies and less synchrony between different brain regions. These changes may affect the ability of BCIs to detect and interpret brain activity, which could impact their performance. For example, older adults may have more difficulty using BCIs that rely on detecting higher-frequency brainwaves, such as gamma waves, associated with focus and attention.[1] On the other hand, older adults may have an advantage in using BCIs that rely on detecting lower-frequency brainwaves, such as alpha and theta waves, which are associated with relaxation and meditation.

Overall, the impact of age on the performance of BCIs is likely to be complex and may depend on the specific type of BCI being used, as well as the individual characteristics of the user.[21]

8.3. Effect based on the gender of the user

There is limited research on the effect of gender on the performance of brain-computer interfaces (BCIs). Some studies have suggested that there may be differences in brainwave patterns between men and women, with men generally showing higher levels of alpha activity (associated with relaxation and meditation) and lower levels of beta activity (associated with alertness and focus) compared to women.[15] However, the extent to which these differences may affect the performance of BCIs needs to be better understood. Other factors, such as age, education, and overall health, may also impact BCI performance more than gender. In addition, the specific type of BCI being used and the user's skill and experience with the system may also play a role in determining performance.[11]

8.4. Effect based on the health of the user

Certain health conditions or factors, such as sleep deprivation, stress, and fatigue, can affect brain activity and the ability of BCIs to detect and interpret brain signals. For example, sleep deprivation has been shown to reduce the accuracy and reliability of BCI systems. At the same time, stress and fatigue can also impair cognitive function and affect the ability of BCIs to detect and interpret brain activity. On the other hand, good overall health and well-being may be associated with more consistent and reliable brain activity, which could improve the performance of BCIs.[12]

9. Future Scope Of BCI in Transportation

Some potential applications of BCIs in transportation include:

1. Autonomous vehicles: BCIs could be used to control the operation of autonomous vehicles, allowing users to specify their desired destination or route using their thoughts alone. BCIs could also be used to monitor the driver's level of attention or fatigue and take control of the vehicle if necessary.
2. Drones: BCIs could be used to control the operation of drones, allowing users to specify their desired flight path or mission using their thoughts alone. BCIs could also be used to monitor the operator's level of attention or fatigue and take control of the drone if necessary.
3. Augmented reality: BCIs could enhance the driving experience by overlaying information or graphics onto the driver's field of view in real-time. For example, BCIs could provide turn-by-turn directions, alert the driver to potential hazards, or display other relevant information.
4. Public transportation: BCIs could be used to improve the efficiency and convenience of public transportation systems, such as trains or buses. For example, BCIs could allow users to purchase tickets or select their desired route using their thoughts alone.

Overall, the future scope of BCIs in transportation is vast, and the technology is still in its early stages. As technology evolves and improves, BCIs will likely play an increasingly important role in the transportation industry.

10. Conclusion

Brain-computer interfaces (BCIs) have the potential to revolutionize transportation by allowing users to control vehicles using their thoughts or other brain activity rather than traditional input methods such as steering wheels or pedals. BCIs could be used to control the operation of autonomous vehicles, drones, and other types of transportation and enhance the driving experience through augmented reality.

However, several challenges need to be overcome to realize the full potential of BCIs in transportation. These challenges include issues related to reliability, cost, and ethical concerns. In addition, using BCIs in transportation raises questions about liability and responsibility in the event of accidents or other incidents.

Overall, the development and use of BCIs in transportation have the potential to significantly improve safety, efficiency, and convenience on the road. However, careful consideration will need to be given to this technology's potential risks and challenges to ensure its responsible and effective use.

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