ÓBUDAI EGYETEM
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DOCTORAL (PhD) THESIS BOOKLET

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Innovative Brain-Computer Interface Systems: Robotics Control through EEG Signals

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Summary

A doktori kutatás célja olyan innovatív, nem-invazív agy-számítógép interfész (BCI) rendszerek fejlesztése, amelyek EEG jeleken alapulva képesek különféle robotikus aktuátorok – például robotkarok és mobil robotok – pontos és hatékony vezérlésére. A kutatás két fő irányvonalat követett:

(1) a mentális parancsok megbízható felismerése gépi tanulási módszerekkel.

(2) ezek parancsokká történő átalakítása különféle robotikus eszközök irányításához.

Az első célkitűzés a gépitanulási algoritmusok (SVM, neurális hálózatok és ANFIS) alkalmazása volt a hullámtranszformációval történő jellemzőkinyerés mellett, az EEG jelek osztályozásának pontosságának növelése érdekében. A módszerek átlagosan 93%-os osztályozási pontosságot eredményeztek, ami megalapozza a BCI rendszerek megbízható működését valós környezetben.

A második célkitűzés a BCI rendszerek aktuátorvezérlési alkalmazásainak kidolgozása volt. Három különálló rendszer került megtervezésre és megvalósításra:

1- HITI Brain alapú rendszer – 6 szabadságfokú (DOF) robotkar vezérlése:
A rendszer képes volt 12 különböző mentális parancs alapján vezérelni egy 6 DOF robotkart, amely az emberi kar természetes mozgásait képes utánozni. Ez a megoldás magas fokú intuitivitást és pontosságot biztosított.

2- Node-RED alapú rendszer – innovatív vezérlés magas DOF esetén:
Egy új eljárást dolgoztam ki, amellyel egy nagy szabadságfokú robotkart lehet vezérelni mindössze 4 agyi jel alapján. Ez a módszer csökkenti a felhasználó mentális terhelését, és hatékonyabbá és kényelmesebbé teszi a robotvezérlést.

3- Node-RED alapú rendszer – kerekes robot vezérlése:
Ez a rendszer lehetővé teszi mobil robotok (pl. intelligens kerekesszékek, kerékpárok, járművek) irányítását EEG jelek segítségével, így új távlatokat nyit a mozgáskorlátozottak segítésében és a jövő intelligens közlekedési eszközeiben.

A kutatás tudományos és gyakorlati jelentősége kiemelkedő, különösen az asszisztív technológiák és az ember-gép interakció területén. A nem-invazív megközelítés biztonságosabb, etikusabb és hozzáférhetőbb alternatívát nyújt az invazív rendszerekkel szemben. A jövőbeli fejlesztési irányok között szerepel a szabadságfokok további növelése, multimodális vezérlési megoldások (pl. hang, szemmozgás) integrálása, valamint a felhasználóhoz alkalmazkodó, tanuló rendszerek létrehozása.

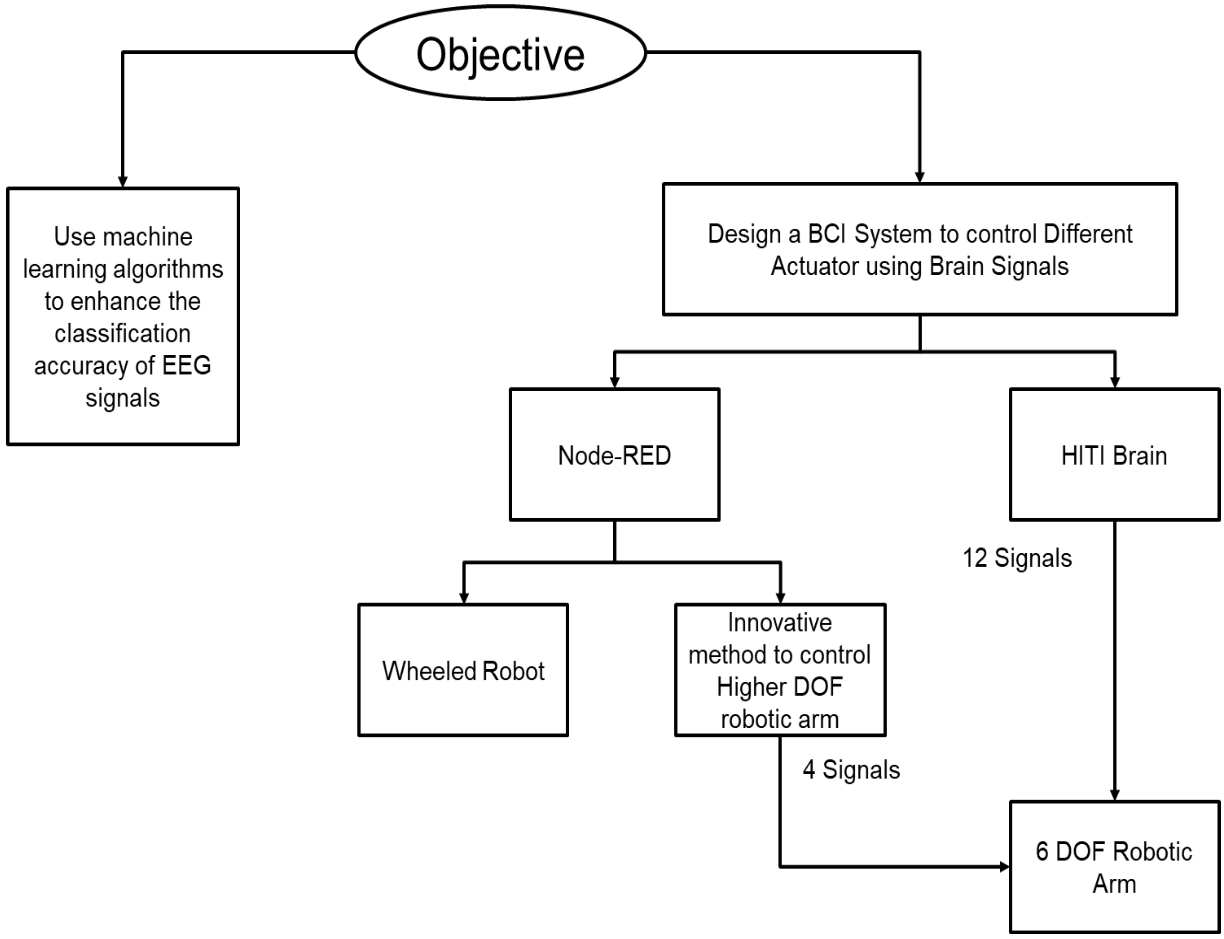
1. Antecedents of the Research

The origins of this study on Brain-Computer Interface (BCI) systems for robotics control via EEG signals are founded in the increased need for assistive technology, especially for those with physical limitations. BCIs have historically progressed from invasive to non-invasive techniques, with non-invasive EEG-based systems gaining popularity owing to their safety, accessibility, and ethical benefits. Previous research has investigated EEG signal categorization utilizing machine learning methods, such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and supervised learning approaches, to enhance the accuracy of translating brain signals into robotic instructions. However, there are still gaps in attaining intuitive control of high-degree-of-freedom (DOF) robotic systems while requiring low cognitive strain. This study expands on these foundations by suggesting novel approaches to improve EEG signal analysis, such as wavelet transformations for feature extraction and ANFIS for classification. Furthermore, it solves the difficulty of commanding complicated robotic arms and mobile robots with fewer mental instructions, increasing usability and efficiency. The work is further supported by its emphasis on real-world applications, such as assistive robots, where non-invasive BCIs have practical and ethical advantages over invasive alternatives. By incorporating these advances, the study adds to the overarching objective of making BCI technology more accessible, accurate, and user-friendly for those with mobility disabilities.

2. Objective

This work`s aim is divided into two parts:

1- Use machine Learning algorithms to enhance the classification accuracy of EEG signals.
2- Design a BCI System to control Different actuator using Braiin Signals.



3. Research Methods and Challenges

1- The process of classifying EEG signals starts with artifact reduction, which eliminates noise generated by physiological interferences such as eye blinks, muscle movements (itchiness), and external disruptions. The cleaned signals are next preprocessed, which involves computing statistical characteristics like as mean, variance, skewness, and kurtosis to define signal qualities. Wavelet Transform (WT) decomposition is then used to divide the EEG signals into frequency sub-bands, isolating important components such as the beta band (13-30 Hz), which is critical for motor imagery identification. Following that, feature extraction detects discriminative patterns in the decomposed signals, improving the separability of various mental states. Finally, the collected characteristics are input into a classification algorithm (e.g., SVM, ANN, or ANFIS) that divides EEG signals into discrete groups, allowing for reliable interpretation of brain activity in applications such as BCI-controlled robots. This organized technique guarantees that the EEG signal analysis is robust and noise resistant.

2- Three different BCI systems were built for the control of the robotic actuators:

- The first system was built using the HITI brain software. It is GUI software that used as a medium to enable communication between the BCI device and the Robotic arm. With this method the control of the robotic arm was executed using 12 different types of signals from the brain, based on mental commands and facial expressions 9 each joint require two type of signals to rotate it in both directions).
- The first system problem was the large number of brain signals needed to be created, which leads to a high training required for the patient. The solution for it is with the design of the second system. In this system the Node-RED software was used for communication instead of HITI-Brain. With the new system the control of the robotic arm was executed only with four different type of brain signals, two to control the rotation of each joint and two for the transition between joints.
- The success of using the Node-RED software opened a new idea to design a new system to control wheeled robots. The node-red is a GUI -IoT software. With this feature we an control the Wheeled robots from two different places in the world using Brain signals.

4. New Scientific Results

The following theses encapsulate the essence and significance of my scientific research conducted during my Ph.D. studies:

Thesis No. 1

I have demonstrated the practicality, safety, and applicability of non-invasive BCIs in real-world robotic applications, with a particular emphasis on assistive technologies for the disabled users. (Chapter 7/7.1 [4],[5], [**6**])

Discussion

The following important elements are emphasized in my statement:

1. Real-World Applications: Non-invasive BCIs are more practicable and easier to use, making them more suitable for deployment in practical, everyday contexts. This is consistent with the requirements of incapacitated users, who need systems that are both user-friendly and dependable.
2. Safety Benefits: Non-invasive BCIs mitigate the health risks and complications that are linked to invasive and semi-invasive technologies, such as long-term maintenance, infection risks, and surgical procedures. This renders them a more acceptable and secure option for a broad user base, particularly for assistive purposes.
3. Emphasize Disabled Users: The objective is to establish systems that prioritize safety, comfort, and simplicity of adoption for individuals with disabilities. These criteria are more effectively met by non-invasive BCIs than by their invasive counterparts.
4. Adoption and Accessibility: Non-invasive BCIs are more likely to be widely adopted due to the fact that they do not necessitate specialized expertise for setup and maintenance or complex medical procedures. This renders them more suitable for mass-market assistive devices.

I reaffirm the thesis that non-invasive BCIs are not only technologically viable but also ethically and socially preferable options for assistive robotic systems

Thesis No. 2

I have proven the effectiveness of combining advanced feature extraction techniques with robust classification methods in EEG data analysis, specifically for applications in BCI-controlled robotic systems (Chapter 7/ 7.1 [1], [3]).

Discussion:

The following is illustrated by my statement:

1. Wavelet Transforms for Feature Extraction: I have demonstrated that wavelet transforms are highly effective in the extraction of meaningful and relevant features from EEG signals. This is of particular significance due to the fact that EEG data are frequently complex and chaotic, necessitating sophisticated preprocessing methods to enhance the signal-to-noise ratio and emphasize patterns during classification.
2. ANFIS for Classification: I demonstrated that the accuracy of EEG data analysis is considerably improved by employing the Adaptive Neuro-Fuzzy Inference System (ANFIS) as a classification method. This implies that ANFIS is an exceptional candidate for the classification of mental commands from EEG signals, as it is well-suited for the interpretation of nonlinear and equivocal data.
3. Supervised Machine Learning Applicability: The fact that supervised machine learning algorithms can similarly improve classification accuracy demonstrates that a variety of advanced methods, in addition to ANFIS, can be effectively employed for the classification of EEG signals. This broadens the scope of my findings, demonstrating that the results are not constrained to a single approach but rather to a general framework that integrates sophisticated classifiers and feature extraction.
4. Improved Accuracy: Your research demonstrates that the integration of sophisticated preprocessing (wavelet transformations) with potent classifiers (e.g., ANFIS or supervised machine learning algorithms like SVM and neural networks) leads to a substantial increase in classification accuracy. This enhancement is essential for real-world applications that require precision and reliability in the interpretation of EEG signals.

Thesis No. 3:
I have demonstrated the practicality and efficacy of employing Brain-Computer Interfaces (BCIs) to attain intuitive and precise control of intricate robotic systems, specifically a six-degrees-of-freedom (DOF) robotic arm (Chapter 7/7.1 [2], [**8**].

Discussion:
The following important elements are emphasized in the statement:

1. Human Arm Movement Replication: Your demonstration of the ability of BCIs to reconcile the divide between human intention and robotic execution was achieved through the use of a 6-DOF robotic arm that closely resembles human arm movements. This results in a more intuitive and natural control of the robotic limb for the user.

2. Intuitive Control: The capacity to operate a robotic arm through mental commands enables users to operate it without the need for extensive physical interfaces or manual

inputs. The interaction is simplified, and cognitive and physical distress are reduced, which is particularly beneficial for users with disabilities.

3. Robotic Control Precision: The robotic arm's high degree of accuracy demonstrates that BCIs are capable of translating mental commands into precise, fine-grained movements. This is essential for applications that necessitate delicate or coordinated duties, such as industrial automation, prosthetics, or assistive devices.

4. Developing BCI Applications: Your research underscores the potential of BCIs to evolve from basic robotic duties to more complex systems with greater degrees of freedom. You contribute to the body of evidence that supports the scalability and versatility of BCIs in robotics by demonstrating successful control of a 6 DOF robotic arm.

5. Practical Significance: The emphasis on intuitive and precision control demonstrates the practical applicability of this technology in real-world scenarios, particularly in assistive technologies for individuals with motor impairments or in environments that necessitate seamless human-robot interaction.

Thesis No. 4:
By using a simple approach, I demonstrated a new method to control a higher degree of freedom robotic arm with only four commands. Instead of assigning two mental commands to every joint in the robotic arm which leads (which leads to the fact that the higher DOF the more double Number mental commands required) only four mental commands used. With this method (Chapter 7/ 7.1 [**7**]).

Discussions:
I demonstrated that:
1- Complex tasks can be managed by fewer mental commands.
2- This method could be applicable for different fields, like assistive devices.
3- The reduction in cognitive loads highlights the potential for reducing mental fatigue.

Thesis No. 5:
I endorsed a statement emphasizing the prospective advantages of using Brain-Computer Interface (BCI) technology for the control of mobile robots. The assertion indicates that BCI may improve the efficiency and efficacy of robotic control by enabling direct brain inputs that control robot motions and commands. This integration may enhance accessibility and engagement with robots, particularly for those with physical disabilities (Chapter 7/7.1 [**7**]).

5. The Possibility to utilize the results:

The findings of this brain-controlled robotic system have major practical implications, particularly in the domains of assistive technology and human-robot interaction. The system can be adapted to assist individuals with motor impairments by allowing them to control a robotic arm using only non-invasive EEG signals and minimal mental commands. This allows them to perform essential tasks such as object manipulation, mobility assistance, or prosthetic control. Furthermore, the modular and scalable design, which employs platforms such as HITI Brain, Node-RED, and Arduino, facilitates integration into a variety of robotic systems, including wheelchairs, smart home devices, and industrial manipulators.

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7. Publications

7.1 Scientific Publications Related to the Thesis Points

[1] I. A. Satam, “EEG signal ANFIS classification for motor imagery for different joints of the same limb,” Military Technical Courier, vol. 72, no. 1, pp. 330–350, 2024, doi: 10.5937/vojtehg72-46601.

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[6] I. A. Satam and R. Szabolcsi “Ethical and Safety Challenges of Implantable Brain - Computer Interface” Interdisciplinary Description of Complex Systems 23(2):82-94 (January 2025) http://dx.doi.org/10.7906/indecs.23.2.1
[7] I. A. Satam and R. Szabolcsi Advanced Brain-Controlled Actuation: Harnessing EEG Signals for Multi-Actuator Coordination In Robotics May 2025 Technium Romanian Journal of Applied Sciences and Technology 30:1-11 http://dx.doi.org/10.47577/technium.v30i.12808
[8] A. Satam and R. Szabolcsi Cortical Signal-Driven Kinematic Control: Implementing Human-Arm Like Movements in A 6-Dof Robotic Manipulator Via Non-Invasive BCI Technium Romanian Journal of Applied Sciences and Technology 29:84-95 (May 2025) DOI: 10.47577/technium.v29i.12807