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Psycho Gundam: система управления роботом в режиме реального времени на основе электроэнцефалографии и глубокого обучения

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Корреспондентский авторВклад этих авторов в работу одинаков.Вклад этих авторов в работу одинаков.Эта статья была принята к публикации на 13-м Международном симпозиуме по изучению культуры и технологий ACG (U-ACG 2024). Подробнее на https://u-acg.com/archives/29015.

Абстрактный

Психорамка — сложная система, которая в основном используется в мобильных костюмах серии Universal Century (U.C.) для пилотов NEWTYPE ({CJK}UTF8minニュータイプ), — стала неотъемлемым компонентом для использования скрытого потенциала ментальной энергии. Ее способность усиливать психические способности пилота и резонировать с ними обеспечивает мысленное управление в режиме реального времени, что позволяет создавать уникальные технологии, такие как психомагнитные поля и сенсорное оружие. В этой статье представлена разработка новой системы управления роботами, вдохновленной устройством Psycho Frame [1], которая сочетает в себе электроэнцефалографию (ЭЭГ) и технологии глубокого обучения для управления роботизированными системами в режиме реального времени. Считывая и интерпретируя данные об активности мозга с помощью ЭЭГ, система преобразует когнитивные команды человека в действия робота, обеспечи-

данных и обеспечивая более глубокое и интуитивное управление сложными роботизированными системами.

Ключевые слова Глубокое обучение · Классификация ЭЭГ · Интерфейс «мозг — компьютер» · Гандам · Управление робототехникой

1 Введение

Идея использования ментальной энергии для управления сложными механизмами уже давно является ключевой темой в научной фантастике, особенно в серии игр U.C. Gundam. Психорамка — технология, специально разработанная для пилотов «Ньютайпов», — воплощает эту идею, позволяя пилоту управлять мобильным костюмом с помощью ментальной синхронизации, что повышает не только его боевую эффективность, но и способность машины реагировать на ментальные стимулы. Эта технология усиливает ментальную мощь пилота, создавая психомагнитные поля и позволяя осуществлять атаки на большом расстоянии с помощью дистанционного управления. С эволюцией «Психо Фрейма» в систему NT-D умственные способности пилота еще больше усиливаются, что позволяет использовать его в таких продвинутых областях, как квантовые манипуляции и концептуальное вмешательство в физические системы.

Inspired by this futuristic vision, we explore the real-world implications of mental control using EEG-based robotic systems. Electroencephalography captures brainwave signals that are processed by deep learning algorithms to establish real-time control over robotic platforms [2]. This work builds upon the concept of the Psycho Frame to develop a control system where mental inputs can direct robot actions. Our system, drawing from advanced AI and neurotechnology, aims to emulate the seamless interaction between human thought and robotic behavior, as seen in the Gundam universe. The paper outlines the design, training, and deployment of this EEG-based control system, analyzing its potential for applications in fields such as prosthetics, robotics, and augmented human-machine interfaces.

The contributions of this work are stated as follows:

2 Related work

2.1 EEG-based robotic control

evoked potentials, to map user intentions to robotic actions [4]. However, these systems faced limitations in terms of signal clarity, processing speed, and user adaptability.

Recent advancements in deep learning have significantly enhanced the both capabilities of EEG-based control systems and EEG encoders [5, 6]. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been applied to EEG signal classification with greater accuracy, enabling more precise and fluid control over robotic systems [7]. Moreover, transfer learning techniques have been utilized to reduce the amount of training data needed for each user, addressing the challenge of individual variability in brainwave patterns.

In parallel, research in neuroprosthetics has explored the integration of BCI systems with robotic limbs, allowing users to control prosthetic devices via neural signals. These systems have demonstrated promising results in enabling individuals with motor impairments to perform complex tasks (Brauchle et al., 2018). The combination of BCI and robotic control holds potential not only for assistive technologies but also for enhancing human-machine interaction in various fields, including teleoperation, gaming, and exoskeletons.

This work builds upon these developments, utilizing deep learning models to enhance the real-time processing of EEG signals for precise control of robotic systems. By drawing inspiration from science fiction's portrayal of mental-robotic synchronization, this approach seeks to push the boundaries of intuitive, thought-based robotic control.

3 Methodology

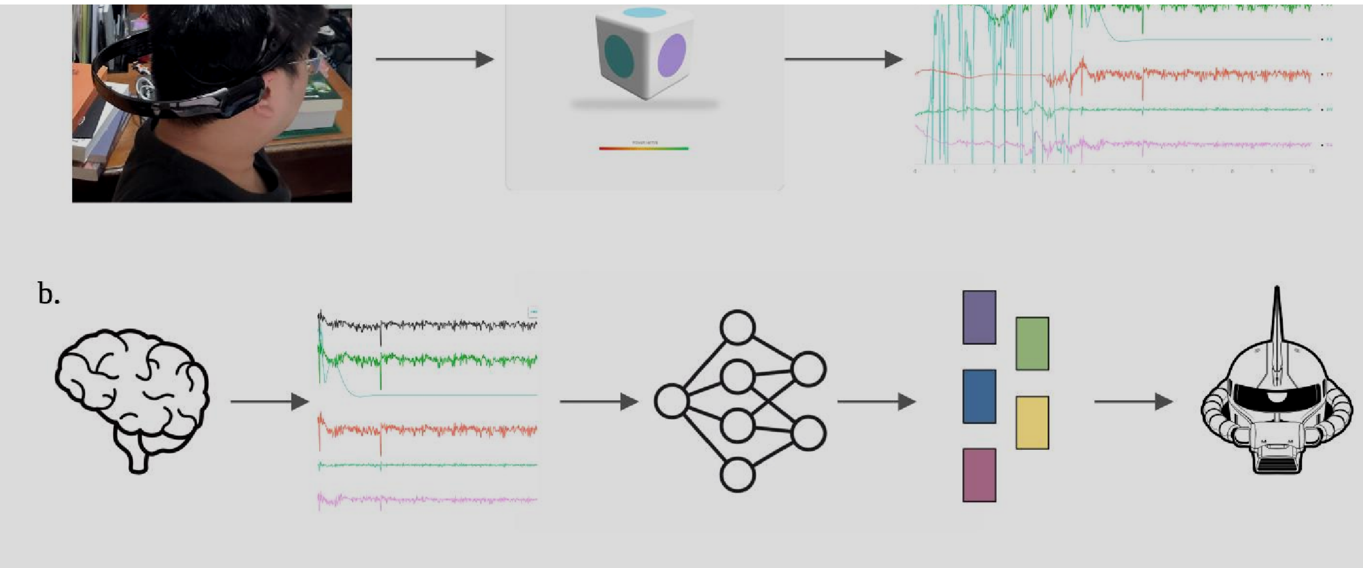

Figure 1: BCI-based Robotic Control System for Motor Imagery (MI) Training and Signal Decoding. (a) In the MI training stage, the user visualizes pushing or pulling a virtual box in five directions by using the action of the cockpit to imagine: forward, backward, left, right, and upward. This generates five distinct types of MI signals, and the raw EEG signals are recorded for training purposes. (b) A neural network is trained to decode these EEG signals into five control commands, which are transmitted to the robot. The robot then executes actions based on the one-hot decoded commands, enabling real-time control through mental visualization.

3.1 Overview

This section describes the methodology employed to develop the *Psycho Gundam* system, an Electroencephalography (EEG)-based real-time robotic control system using deep learning. The system leverages the EMOTIV+ EEG cap to capture brainwave signals and translate them into robotic control actions through a series of preprocessing, feature extraction, and deep learning-based classification steps. The goal is to enable real-time, accurate control of a robotic system by leveraging cognitive signals from human subjects.

3.2 EEG Data Acquisition

3.2.1 Equipment

EEG data was collected using the EMOTIV+ EEG cap, a non-invasive, wireless EEG headset. The cap is equipped with multiple electrodes placed according to the International 10-20 system to record electrical activity in the brain. The EEG signals were sampled at a frequency of 128 Hz for

One participant, aged 27 years, left-handed, was selected for the study. The participants were trained on the intended mental tasks, such as imagining left or right hand movements, or focusing on specific visual targets to invoke corresponding EEG patterns.

3.2.3 Experimental Setup

Each subject wore the EMOTIV+ EEG cap while seated in front of the robotic system. During the experiment, subjects were instructed to perform mental tasks corresponding to specific robotic actions, such as moving the robot arm forward, backward, left, or right. Data was recorded in sessions lasting 10 minutes, with rest intervals to prevent mental fatigue.

3.3 Signal Processing

3.3.1 Standard Procedure

Before analysis, raw EEG data is typically subjected to the following preprocessing steps to remove noise and artifacts:

Band-pass filtering: A band-pass filter between 1 Hz and 50 Hz is usually applied to eliminate powerline noise and non-relevant low/high-frequency components.

Artifact removal: Independent Component Analysis (ICA) is used to remove artifacts such as eye blinks, muscle movements, and other physiological noise.

Normalization: The signals are normalized to ensure consistency across different sessions and participants.

3.3.2 Current Practical Approach

Since the latest free version of the EMOTIV software no longer supports exporting raw EEG data, we have switched to recording the screen to capture raw EEG data as video files, which now serve as the primary data source for analysis.

Denoising After converting the screen-recorded EEG signals into images, we first manually remove frames with noise, such as those containing unintended windows from accidental mouse clicks or frames where unrelated visuals obstruct the EEG recording screen.

3.4 Feature Extraction

- **Power Spectral Density (PSD)**: Extracted using Welch's method to capture frequency band power.
- **Time-domain features**: Statistical measures such as mean, variance, and skewness were calculated over sliding windows.
- **Wavelet Transform**: Applied to capture non-stationary EEG signal properties, particularly in the alpha and beta bands.

3.4.2 If Viewing EEG as Images from Video

In this approach, EEG data is treated as sequences of images extracted from recorded video. A neural network is used for feature extraction, allowing for spatial-temporal analysis and leveraging deep learning methods typically applied in computer vision to capture complex patterns and dynamics in the data.

3.5 Deep Learning Model for EEG-to-Robot Mapping

3.5.1 Model Architecture

A deep learning model was developed to map EEG signals to corresponding robot control commands. The architecture consists of:

- **Input Layer**: The processed EEG feature vectors serve as input to the model.
- **Pre-trained Vision Transformer (ViT) [8]**: The EEG feature vectors are fed into a pre-trained Vision Transformer model, which leverages self-attention mechanisms to capture both spatial and temporal dependencies within the EEG data, providing a comprehensive understanding of the signal patterns.
- **Fully Connected Layer**: The output embeddings from the ViT model are passed through fully connected layers to map the transformed features to robot control actions (e.g., move left, right, forward, backward).
- **Output Layer**: The final layer provides categorical outputs corresponding to discrete robotic control commands.

3.5.2 Training Procedure

The model was trained on a dataset comprising EEG data paired with labeled control actions:

20% validation sets.

3.6 Robotic System Integration

3.6.1 Robotic Platform

The EEG-based control system is integrated with a robotic platform designed for multi-axis movement (Figure 2), the more details are introduced in [1]. The control interface receives EEG-based commands in real-time via a USB connection between the robot controller and the computing system. To minimize excessive mechanical jitter, EEG-based commands are processed through a specially designed low-pass filter. The overall motion design of the robot is inspired by classic fighting games. To enhance the real-time control experience like playing the fighting games, the low-pass filter includes an integrator, which accumulates non-responsive signals and triggers specific actions once a threshold is reached.

3.6.2 Robot Motion Control

The robot control system simplifies EEG signals into five types: forward, defense, punch, heavy punch and kick. It also supports some classic fighting game combos, though the operational complexity has been simplified due to signal limitations(Table 1). Each of these actions activates a pre-defined motion control trajectory. The motors themselves provide angle feedback control, so the controller is only responsible for transmitting the angle signals.

Figure 2: A robot made by hollowing out a MEGA size gundam and putting a motor in it.

2	forward	right pedal
3	punch	left Handle
4	heavy punch	both handle
5	kick	right Handle
6	punch combo	forward + punch
7	Uppercut	forward + heavy punch
8	kick combo	forward + kick
9	Hadoken	punch + heavy punch

Table 1: A mapping table of robot moves.

T), we achieved an overall classification accuracy of ulate the Psycho Gundam cockpit environment. The our raw EEG data did not undergo traditional signal ally applied in EEG analysis. Nevertheless, as a pioneering Motor Imagery (MI) dataset, this represents a novel approach and serves as an important first step in exploring this unique application. Due to the high variability of brainwave patterns across different individuals and sessions, achieving smooth and reliable mapping to control outputs remains a significant challenge. EEG signals are inherently noisy and vary with factors like mental state and external distractions, which complicates the model's ability to generalize. This variability underscores the need for more advanced methods in feature extraction and model training to ensure stable, responsive performance in real-time applications.

5 Conclusion

In this work, we introduced the first Motor Imagery (MI) dataset based on a Gundam cockpit simulation and developed a real-time EEG-controlled robotic system. This pioneering approach demonstrates the potential for integrating EEG-based control into complex robotic applications, paving the way for future advancements in brain-machine interfaces. Our results highlight both the challenges and opportunities presented by raw EEG data in real-time control scenarios, especially within unique, non-traditional contexts. Additionally, recent advancements in quantum computing for EEG processing and AI [9, 10] provide promising avenues for further exploration. The integration of quantum machine learning could bring us closer to transforming the science fiction

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Appendix A Appendix

A.1 More experiment details

The project code is available at https://github.com/ChiShengChen/PSYCHO_GUNDAM.

Category	Label	Number of Images
Pull Forward with Both Hands	0	18052
Left Leg on the Pedal	1	18020

Table 2: The details of the whole dataset.

A.2 Update

This paper has been accepted by 2024 13th International Symposium on ACG Culture and Technology Studies (https://u-acg.com/archives/29015).