EEG Controlled Robots

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1. Abstract

We introduce an advanced EEG-based control system for drones and robots that synergistically combines a Variational Autoencoder (VAE) for noise reduction and latent feature extraction with a Transformer model for high-level command sequence prediction. By leveraging the VAE's capability to distill noise-invariant features and the Transformer's proficiency in modeling temporal dependencies, this approach offers a significant advancement in the field of EEG-based control systems.

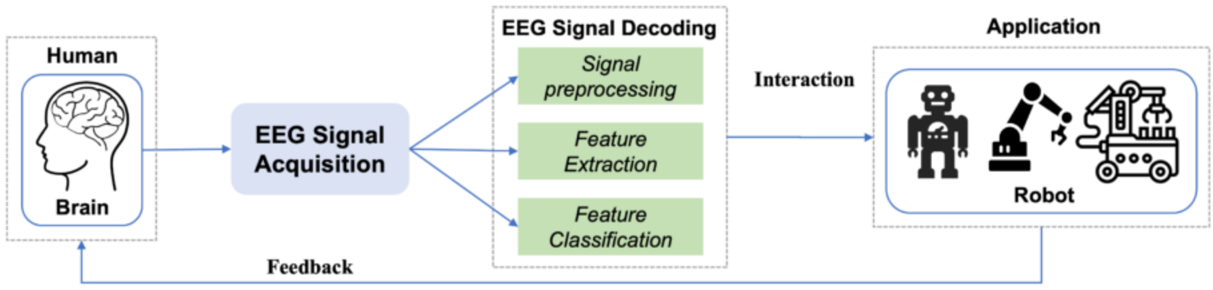

Figure 1: The common framework of a complete BRI system utilizing EEG..

2. Literature Review

EEG-based BCIs are widely used, yet their accuracy is hindered by noise and variability, as noted in [4]. Traditional methods rely on handcrafted features, which are less effective in dynamic environments [5]. Recent works use deep learning for better performance, such as CNNs for robot control [5] and cooperative systems for robot-drone interaction [1]. VAEs have shown promise in extracting noise-invariant EEG features [7], while Transformers excel at modeling temporal dependencies [3, 6]. However, most systems treat denoising and command prediction separately, leading to suboptimal results. This proposal integrates VAEs and Transformers to address these gaps.

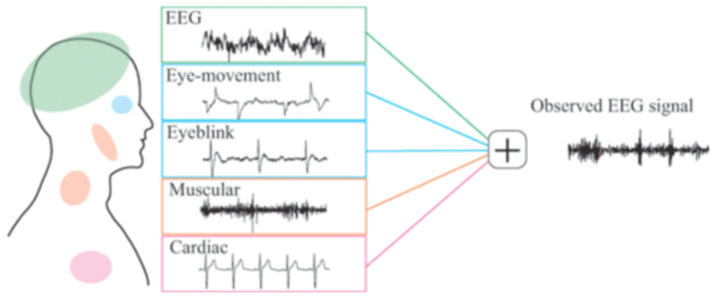

Figure 2: Illustration of the components contributing to an observed EEG signal. The signal is a combination of neural activity (EEG) and various noise sources, including eye movement, eyeblinks, muscular activity, and cardiac signals, which must be filtered for accurate analysis.

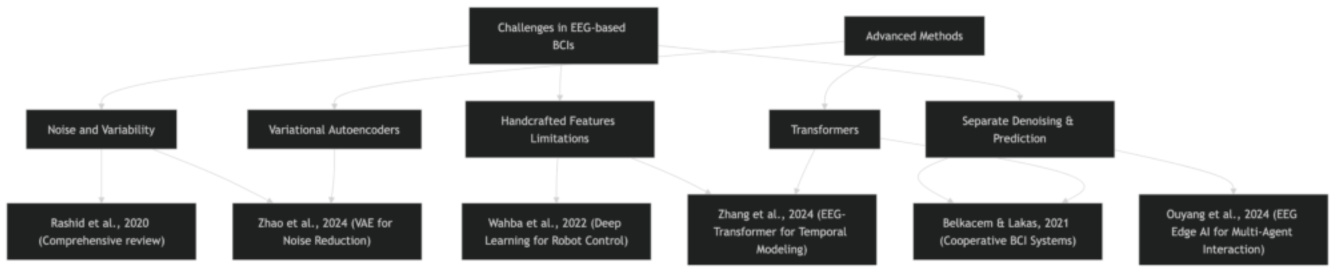

Figure 3: Key challenges in EEG-based BCIs, including noise, feature limitations, and separate denoising and prediction, are mapped to corresponding research contributions. Advanced methods like Variational Autoencoders (VAEs) and Transformers address these issues, enabling improved noise reduction and temporal modeling.

3. Research Methodology

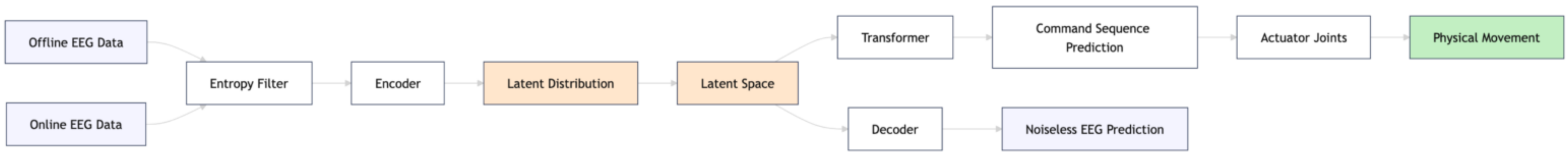

Figure 4: The proposed brain–computer interface pipeline begins by applying entropy-based filtering to both offline and online EEG signals, effectively reducing noise. These filtered signals are then processed through a Variational Autoencoder (VAE), which extracts noise-invariant latent features and reconstructs clean EEG signals for training purposes. Subsequently, the latent features are input into a Transformer model that predicts command sequences, enabling real-time control of robotic actuators.

Three stages of the proposed system:

1. **Signal Preprocessing: Raw EEG data (offline/online) is filtered using entropy-based methods to remove noise [7].**
2. **VAE-Based Denoising:**
   - **Encoder: Maps filtered EEG to a latent distribution.**
   - **Latent Space: Regularized to capture noise-invariant features.**
   - **Decoder: Reconstructs clean EEG signals for training.**
3. **Transformer for Command Prediction: The latent features are fed into a Transformer to predict high-level commands (e.g., "ascend," "turn left") for controlling robots [3, 6].**

Innovations

- **Combines VAE's noise reduction and latents space representation with Transformer's sequence modeling for robust real-time control.**
- **Uses entrophy filtering to remove irrelevant time points.**

Evaluation

- **Datasets: EEG data from [9] and drone-control paradigms from [2].**
- **Implementation: Validated using the Genesis robotics simulator [8].**

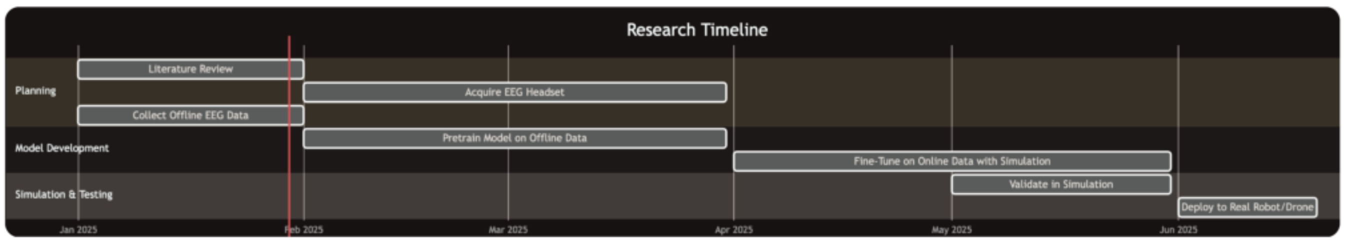

Figure 5: A Gantt chart (or similar timeline) detailing the major phases of the proposed research, including preliminary literature review, data collection, model development, simulation testing, and final evaluation. Each phase is aligned with a projected time window, illustrating the workflow from planning to dissemination.

Simulation environment

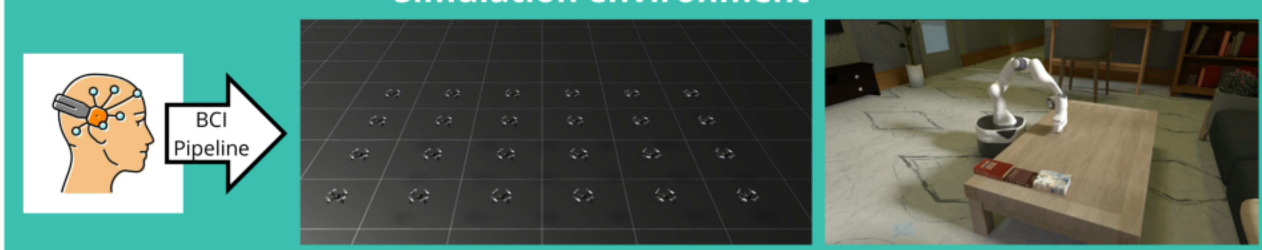

Figure 6: Screenshot of the Genesis simulation environment [8], depicting drones and robots managing commands derived from EEG signals.

Figure 7. Ethical Aspects of EEG-Based Robot Control – Key ethical challenges include user safety (device risks and dependence), privacy (data security and hacking), autonomy (informed decisions and manipulation), and responsibility (liability and ethical use).Addressing these interconnected concerns is crucial for the responsible deployment of EEG-based robot control systems.[10]

4. Conclusion

This proposal addresses critical challenges in EEG-based BCIs by integrating VAEs for noise reduction and latent feature extraction with Transformers for robust sequence modeling
By enabling accurate and reliable real-time control of drones and robots, the system paves the way for transformative applications in assistive robotics, search-and-rescue missions, and neurorehabilitation therapies. This innovative approach holds the promise of advancing the capabilities and impact of BCIs in dynamic, real-world environments.

5. Acknowledgements

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