JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Unveiling Human Intentions: EEGNET's Hybrid Role in Motion Detection

1st **Dr. Deepthi V S**
Assistant Professor,
Department of CSE(Cyber Security),
Dayananda Sagar College of Engineering,
Bangalore, Karnataka, India
deepthivs86@gmail.com

2nd **Dr. Vagdevi S**
Professor & Head,
Department of AI & ML,
City Engineering College,
Bangalore, Karnataka, India
vagdevi0721@gmail.com

***Abstract*— The burgeoning interest in harnessing electroencephalography (EEG) signals for non-muscular communication and control has spurred extensive research in pattern recognition. Recent years have witnessed a surge in efforts to extract meaningful features from EEG data, aiming to elucidate the intricate connections between brain activity and behavior. However, conventional vectorization-based feature representations, be it vector-like or matrix-like, are hampered by pervasive signal noise and the challenge of leveraging signal correlations among neighboring EEG sensors.**

A crucial preliminary step in integrating EEG signals into a learning model entails standardizing them into a unified frequency representation. Disregarding specific frequency components of EEG signals can undermine activity recognition, as different frequencies hold varying degrees of relevance in discerning distinct activities. The proposed approach hinges on three fundamental pillars: data preprocessing, feature extraction, and model training.

Data preparation encompasses artifact avoidance and linear filtering to mitigate noise interference. Notably, the Common Spatial Domain emerges as the predominant choice for feature extraction. Subsequently, the Hybrid EEGNET model is deployed for model training, demonstrating superior performance compared to the commonly employed alternatives, namely CNN and LSTM. Remarkably, the proposed method achieves an impressive success rate of 97.52 percent.

Keywords*— *Electroencephalography (EEG), Inertial Measurement Unit (IMU), Motion intention recognition.

I. Introduction

Unveiling the intricacies of human intention has long been a quest at the forefront of neuroscience and technology. The advent of electroencephalography (EEG) signals as a means to decode these intentions has ignited a paradigm shift, promising novel avenues for understanding and harnessing human motion. In recent years, the fusion of EEG signals with advanced neural network architectures, notably EEGNET, has emerged as a pioneering approach in deciphering human motion intentions.

Human motion intention detection holds profound implications, not merely in rehabilitation and assistive technology, but also in the realms of human-computer interaction and robotics. By tapping into the neural signatures underlying motor intentions, researchers aim to bridge the gap between the human mind and external devices, enabling seamless communication and control.

However, traditional approaches to motion intention detection have encountered formidable challenges, from signal noise to the limitations of feature representation. Vectorization-based methods, though prevalent, often falter in capturing the nuanced dynamics of EEG signals, thereby impeding accurate intention decoding.

In this context, the hybrid role of EEGNET—a neural network architecture tailored for EEG signal analysis—presents a transformative solution. By integrating EEGNET with innovative methodologies, this hybrid approach promises to unravel the intricacies of human intentions with unprecedented fidelity and efficiency.

This paper delves into the realm of human motion intention detection, shedding light on the novel hybrid EEGNET-based approach poised to revolutionize the field. Through a comprehensive exploration of data preprocessing, feature extraction, and model training, we unveil the potential of EEGNET in decoding human intentions, paving the way for a new era of seamless human-machine interaction.

II. LITERATURE REVIEW

Rapid and accurate forecasting of human intentions is paramount for the success of collaborative robotic applications [1]. This necessitates the gathering and interpretation of body signals, a task integral to Human Intention Detection (HID). HID operates in two primary stages: the motor driver adjusts the motor's output (speed or torque), followed by the regulation of the robot's impedance or admittance. While impedance control is crucial, existing model-based approaches, such as the one-joint, two-link model, are impractical for many assistive robot applications due to their time-intensive operation [2].

To enable effective utilization of exoskeletons, it's imperative to detect the pilot's intentions accurately. This involves gathering and analyzing joint signals, including velocity, angular rate of change, and torque of the upper body [3]. Traditional AI systems like optical flow, while effective, require stationary setups for reliable data collection and are unsuitable for mobile devices. In contrast, Inertial Measurement Unit (IMU) based systems offer a wearable solution, allowing subjects to move freely and are thus better suited for use with exoskeletons [4].

The recorded signals are then processed using simple methods to extract bodily positions and motion data, establishing thresholds for movements [6]. Anticipated benefits of Physical Human-Robot Interaction (pHRI) include enhancing the efficiency of production jobs and operations, particularly those requiring human-like dexterity [9]. pHRI-equipped cobots can interpret human intentions and respond appropriately, as demonstrated by studies utilizing object velocity to adjust control parameters based on the operator's intent [7].

Surface Electromyography (sEMG) signals, which capture muscle activity, offer valuable insights into human intentions, especially in the context of exoskeletons and therapeutic robots [10]. sEMG-based human motion intention identification, on the cusp of mainstream adoption, offers comprehensive and non-invasive insights [12]. Machine learning (ML) algorithms, including Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and Deep Learning (DL), are commonly employed for motion intention recognition [14].

Proposed strategies include using DL models, such as Convolution Neural Networks (CNNs) and Stacked Auto-Encoders (SAEs), for gesture intent determination [15]. Additionally, prediction strategies leveraging Inertial Measurement Unit (IMU) and sEMG signals have demonstrated high accuracy in forecasting user intentions [17]. However, challenges persist, particularly in accurately predicting steady-state motion patterns [17].

Efforts to mitigate these challenges include feature engineering to interpret noisy signals and autonomous feature extraction for stable algorithms [18]. Advanced frameworks, such as Expectation Maximization (EM), are utilized to extract human motion patterns for precise mobility predictions [20]. Overall, the goal is to model human intent using familiar environmental structures, thereby enhancing the transferability of prediction algorithms to novel environments [21].

III. PROPOSED METHODOLOGY

Before Navigating an exoskeleton could pose challenges or risks if the human operator's intended gait pattern clashes with the exoskeleton's control systems. Extensive research has been conducted to identify the optimal gait operation. However, the timing of recognition plays a critical role in this process. Instantaneous or delayed pilot intent detection can adversely affect the performance of an exoskeleton. As a departure from conventional motion detection methods, this study explores the viability of real-time detection through gait recognition.

A. Preprocessing

In the preprocessing stage of the Brain-Computer Interface (BCI) system, EEG signals undergo filtering to remove random noise that may arise from various anomalies. This section explores some of the cutting-edge filtering techniques recently employed in BCI settings.

1) Artifacts Avoidance:

Achieving high-quality EEG recordings involves careful placement of the EEG cap on the patient and positioning any additional devices that may affect the recording area. This technical step precedes signal filtering for physiological artifacts and is essential for collecting accurate data.

2) Linear Filtering:

Linear filtering is a commonly employed technique to eliminate artifacts in signals that do not share frequency components with brain signals. Among linear filtering methods, lowpass and highpass filtering are the most prevalent [22]. EOG artifacts typically necessitate a high-pass filter due to the presence of low-frequency components, while most EMG components exhibit high frequencies and can be attenuated with a low-pass filter.

One of the primary strengths of linear filters is their ease of implementation, both in software and hardware. For instance, to remove EOG or EMG noise from an EEG signal, a linear filter can be applied without the need to define specific characteristics of the artifact signal beforehand. However, in cases where EEG and EOG (or EMG) signals overlap, linear filters may prove ineffective in isolating EEG data and removing artifacts from the EEG signal.

B. Feature Extraction:

While originally proposed for binary classification tasks, the Common Spatial Patterns (CSP) technique has demonstrated utility in EEG data analysis involving Event-Related Synchronization/Desynchronization (ERS/EDS). However, when faced with scenarios involving a large number of classes, the CSP algorithm may require refinement.

The CSP algorithm operates by spatially projecting the original EEG signal, aiming to find the axis along which the variation of one signal type is maximized while the variance of the other signal type is minimized. This results in a projection axis that optimally separates the two signal types [23].

Once the EEG signal has been preprocessed, including the removal of the DC component $V \times W$, the resulting matrix E can be utilized. Assuming V channels of EEG data, each channel is sampled W times. Consequently, the covariance matrix of the EEG data can be calculated as follows:

$$G_P = \frac{BB^W}{trace(BB^W)} \quad (1)$$

The transposition of the BB^W matrix is denoted by BWT. The average covariance of the individual EEG signals is represented by GP, where $p \in \{1,2\}$. Thus, the overall mean of the covariance matrix can be expressed as:

$$G_g = G_1 + G_2 \quad (2)$$

Upon decomposing the eigenvalues of Gg, the following insights are gained:

$$G_g = M_g \mu_g M_g^W \quad (3)$$

After constructing the whitening matrix, Mg represents the eigenvectors of the complex conjugate matrix Gg, while g denotes the corresponding eigenvalues.

$\mathrm{I} = \sqrt{\mu_g^{-1}} M_g^W$ that:

$$P = I G_g I^W \quad (4)$$

After transforming $G1$ and $G2$, it is established that:

$$Z_p = I G_p I^W, p \in \{1,2\} \quad (5)$$

As the eigenvectors $Z1$ and $Z2$ share identical eigenvalues, their combined sum equals 1. While $Z2$ boasts the largest eigenvalue, $Z1$ possesses the smallest. Consequently, the direction associated with the smallest eigenvalue aligns with that of the largest eigenvalue.

If

$$Z_1 = E \mu_1 E^W \quad (6)$$

It can be established:

$$\begin{cases} Z_1 = E \mu_1 E^W \\ \mu_1 + \mu_2 = P \end{cases} \quad (7)$$

Projection matrices are

$$T = E^W I \quad (8)$$

The original signal B is projected onto a $V \times V$ matrix T, yielding a new signal:

$$S = TB \quad (9)$$

The projection of the first u rows and last u rows of the table yields the number u. The subsequent steps involve processing a new signal to extract the ultimate eigenvalue:

$$D_q = \left[\frac{Var(S_q)}{\sum_{o=1}^{2u} Var(S_o)}\right] \quad (10)$$

C. Training the Model: ***Hybrid EEGNET Model***

This section illustrates the operation of the Hybrid EEGNet model, comprising two independent TensorFlow networks. Specifically, the HybridEEGNet model integrates two separate CNN-based components, each featuring 8 convolutional layers and 8 max-pooling layers. These independent CNN models share the same softmax layer and four fully connected layers across all submodels.

SynEEGNet is dedicated to learning synchronous EEG data, while RegEEGNet focuses on learning regional EEG features. Together, they constitute the complete model. The "Layer Size" columns provide formulas for calculating the number of neurons at the input or output of each layer: channels * data points * feature maps. Each layer in SynEEGNet shares identical input and output sizes with its counterpart in RegEEGNet, thereby avoiding redundancy in representation.

Regarding "Filter Size," it denotes the largest pooling size or convolutional filter size. These filters, named Syn for learning synchronous EEG properties and Reg for learning regional EEG characteristics, traverse both the l and r axes simultaneously. The input to the first layer comprises a 2D matrix of G channels, with F representing the total number of data points.

During convolutional filter application, the l and r coordinates shift by one unit. Zero-padding is applied to the input if the filter size does not perfectly match. Max-pooling filters subsequently shift the input data at regular intervals, moving one unit along the l axis and two units along the r axis.

Overall, this detailed description outlines each stage of the Hybrid EEGNet model, elucidating its architecture and operational mechanisms.

IV. RESULTS AND DISCUSSION

After Recent advancements in collaborative robot (cobot) technology have facilitated enhanced collaboration between robots and humans in manufacturing environments. This progress opens up opportunities for improved efficiency and flexibility in factories, driven by the ability to recognize human intent and enable seamless cobot-human collaboration.

Despite significant strides in physical human-robot interaction (pHRI), interpreting human intent and adjusting the cobot's controller accordingly remains one of the most challenging obstacles to overcome.

TABLE I. COMPARISON OF MODELS(%)

Models	Precision	Accuracy	F1-Score	Recall
LSTM	87.13	88.65	88.91	86.32
CNN	92.37	93.81	93.27	91.68
Hybrid EEGNET	96.34	97.52	97.14	95.76

Table 1 presents a comparison of precision, recall, and F1-scores achieved by LSTM, CNN, and Hybrid EEGNET models. The performance of the proposed model is juxtaposed against previously utilized models. Notably, the proposed model demonstrates superior performance, surpassing state-of-the-art models by an impressive margin of 97.52%.

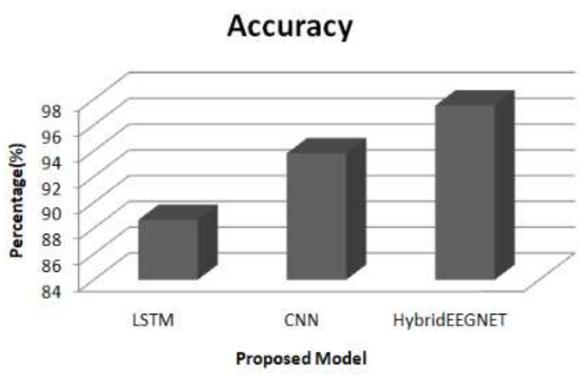

Fig. 1. Accuracy Comparison of the Models

Figure 1 illustrates a comparison between the existing system and the proposed one. The proposed system achieved an overall accuracy of 97.52% in detecting human motion intentions, showcasing enhanced classification accuracy compared to the existing system.

Figure 2 depicts the decrease in loss over time with an increasing number of iterations. The training loss stabilizes after 10 epochs before data augmentation and after 5 epochs thereafter.

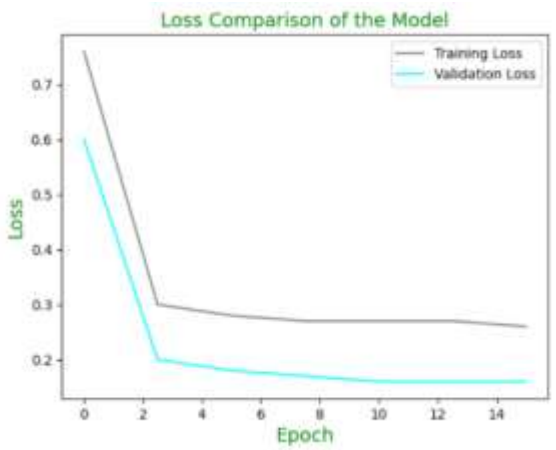

Fig. 2. Loss Comparision of the Model

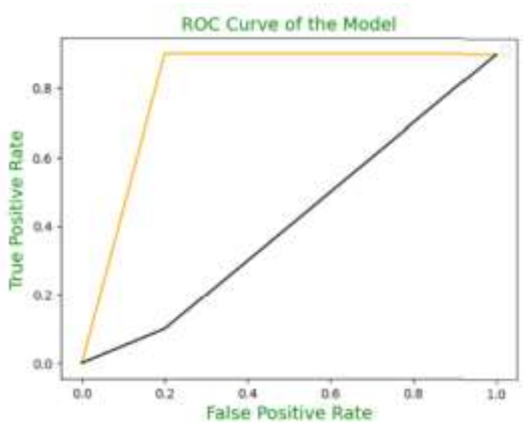

Fig. 3. ROC Curve of the Proposed Approach

Figure 3 displays a ROC curve (Receiver Operating Characteristics) illustrating our model's effectiveness in diagnosing multiple diseases. This curve serves as a validation strategy, assessing the efficacy of a classification method by comparing the true positive rate with the false positive rate. Notably, the proposed model demonstrates superiority, as indicated by its performance curve positioned in the top left corner.

V. CONCLUSION

The Brain-Computer Interface (BCI) represents a groundbreaking device facilitating direct communication between the human brain and electronic devices, including computers. Electroencephalography (EEG) signals play a crucial role in BCI systems due to their non-invasive nature, allowing comfortable acquisition from users.

Developing a high-performance system capable of accurately identifying motion intentions from EEG data across different subjects and multiple categories presents a significant challenge. In this paper, we propose employing a convolutional recurrent neural network to address this challenge effectively. To preserve spatial and temporal features, the raw EEG streaming is transformed into an image sequence based on the position of the primary sensorimotor area.

Data preparation involves techniques such as artifact avoidance and linear filtering. Feature extraction primarily relies on the Common Spatial Domain method. The Hybrid EEGNET architecture is utilized for model training, which demonstrates superior performance compared to both CNN and LSTM models.

REFERENCES

[1] L. Zhang, G. Liu, B. Han, Z. Wang, and T. Zhang, “SEMG Based Human Motion Intention Recognition,” J. Robot., vol. 2019, 2019, doi: 10.1155/2019/3679174.

[2] F. Sado, H. J. Yap, R. A. R. Ghazilla, and N. Ahmad, Exoskeleton robot control for synchronous walking assistance in repetitive manual handling works based on dual unscented kalman filter, vol. 13, no. 7. 2018. doi: 10.1371/journal.pone.0200193.

[3] M. Jiang, J. Dong, D. Ma, J. Sun, J. He, and L. Lang, “Inception Spatial Temporal Graph Convolutional Networks for SkeletonBased Action Recognition,” Proc. - 2022 Int. Symp. Control Eng. Robot. ISCER 2022, pp. 208–213, 2022, doi: 10.1109/ISCER55570.2022.00042.

[4] A. F. Bobick and J. W. Davis, “The recognition of human movement using temporal templates,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 23, no. 3, pp. 257–267, 2001, doi: 10.1109/34.910878.

[5] A. Taheri, O., Salarieh, H., & Alasty, “Human leg motion tracking by fusing imus and rgb camera data using extended kalman filter,” arXiv Prepr. arXiv2011.00574, pp. 1–18, 2020.

[6] D. P. Losey, C. G. McDonald, E. Battaglia, and M. K. O’Malley, “A review of intent detection, arbitration, and communication aspects of shared control for physical human–robot interaction,” Appl. Mech. Rev., vol. 70, no. 1, pp. 1–19, 2018, doi: 10.1115/1.4039145.

[7] G. Kang, H. S. Oh, J. K. Seo, U. Kim, and H. R. Choi, “Variable Admittance Control of Robot Manipulators Based on Human Intention,” IEEE/ASME Trans. Mechatronics, vol. 24, no. 3, pp. 1023–1032, 2019, doi: 10.1109/TMECH.2019.2910237.

[8] H. Y. Li et al., “Stable and Compliant Motion of Physical Human-Robot Interaction Coupled with a Moving Environment Using Variable Admittance and Adaptive Control,” IEEE Robot. Autom. Lett., vol. 3, no. 3, pp. 2493–2500, 2018, doi: 10.1109/LRA.2018.2812916.

[9] K. Wakita, J. Huang, P. Di, K. Sekiyama, and T. Fukuda, “Human-walking-intention-based motion control of an omnidirectional-type cane robot,” IEEE/ASME Trans. Mechatronics, vol. 18, no. 1, pp. 285–296, 2013, doi: 10.1109/TMECH.2011.2169980.

[10] L. Bi, A. Feleke, and C. Guan, “A review on EMG-based motor intention prediction of continuous human upper limb motion for human-robot collaboration,” Biomed. Signal Process. Control, vol. 51, pp. 113–127, 2019, doi: 10.1016/j.bspc.2019.02.011.

[11] W. Huo, S. Mohammed, J. C. Moreno, and Y. Amirat, “Lower Limb Wearable Robots for Assistance and Rehabilitation: A State of the Art,” IEEE Syst. J., vol. 10, no. 3, pp. 1068–1081, 2016, doi: 10.1109/JSYST.2014.2351491.

[12] M. Yokoyama, R. Koyama, and M. Yanagisawa, “An Evaluation of Hand-Force Prediction Using Artificial NeuralNetwork Regression Models of Surface EMG Signals for Handwear Devices,” J. Sensors, vol. 2017, 2017, doi: 10.1155/2017/3980906.

[13] M. Sartori, M. Reggiani, D. Farina, and D. G. Lloyd, “EMGDriven Forward-Dynamic Estimation of Muscle Force and Joint Moment about Multiple Degrees of Freedom in the Human Lower Extremity,” PLoS One, vol. 7, no. 12, 2012, doi: 10.1371/journal.pone.0052618.

[14] F. Bian, R. Li, and P. Liang, “SVM based simultaneous hand movements classification using sEMG signals,” 2017 IEEE Int. Conf. Mechatronics Autom. ICMA 2017, no. February 2019, pp. 427–432, 2017, doi: 10.1109/ICMA.2017.8015855.

[15] K. Asai and N. Takase, “Finger motion estimation based on frequency conversion of EMG signals and image recognition using convolutional neural network,” Int. Conf. Control. Autom. Syst., vol. 2017-Octob, no. Iccas, pp. 1366–1371, 2017, doi: 10.23919/ICCAS.2017.8204206.

[16] K. B. Huang, H., Zhang, F., Hargrove, L. J., Dou, Z., Rogers, D. R., & Englehart, “Continuous locomotion-mode identification for prosthetic legs based on neuromuscular–mechanical fusion,” IEEE Trans. Biomed. Eng., vol. 58, no. 10, pp. 2867–2875, 2011, doi: 10.1109/TBME.2011.2161671.Continuous.

[17] C. Pew and G. K. Klute, “Turn Intent Detection for Control of a Lower Limb Prosthesis,” IEEE Trans. Biomed. Eng., vol. 65, no. 4, pp. 789–796, 2018, doi: 10.1109/TBME.2017.2721300.

[18] M. Z. ur Rehman et al., “Multiday EMG-Based classification of hand motions with deep learning techniques,” Sensors (Switzerland), vol. 18, no. 8, pp. 1–16, 2018, doi: 10.3390/s18082497.

[19] H. L. Jae, T. Tsubouchi, K. Yamamoto, and S. Egawa, “People tracking using a robot in motion with laser range finder,” IEEE Int. Conf. Intell. Robot. Syst., pp. 2936–2942, 2006, doi: 10.1109/IROS.2006.282147.

[20] M. Bennewitz, W. Burgard, and S. Thrun, “Using EM to learn motion behaviors of persons with mobile robots,” IEEE Int. Conf. Intell. Robot. Syst., vol. 1, pp. 502–507, 2002, doi: 10.1109/irds.2002.1041440. [

[21] M. Bennewitz, W. Burgard, and S. Thrun, “Learning motion patterns of persons for mobile service robots,” Proc. - IEEE Int. Conf. Robot. Autom., vol. 4, pp. 3601–3606, 2002, doi: 10.1109/ROBOT.2002.1014268.

[22] N. Elsayed, Z. Saad, and M. Bayoumi, “Brain Computer Interface: EEG Signal Preprocessing Issues and Solutions,” Int. J. Comput. Appl., vol. 169, no. 3, pp. 12–16, 2017, doi: 10.5120/ijca2017914621.

[23] M. Zhao, H. Gao, W. Wang, and J. Qu, “Research on HumanComputer Interaction Intention Recognition Based on EEG and Eye Movement,” IEEE Access, vol. 8, pp. 145824–145832, 2020, doi: 10.1109/ACCESS.2020.3011740.

[24] Z. Wan, J. Huang, H. Zhang, H. Zhou, J. Yang, and N. Zhong, “HybridEEGNet: A Convolutional Neural Network for EEG Feature Learning and Depression Discrimination,” IEEE Access, vol. 8, pp. 30332–30342, 2020, doi: 10.1109/ACCESS.2020.2971656.