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Evaluating the feasibility of Fall Detection using Single-channel EEG

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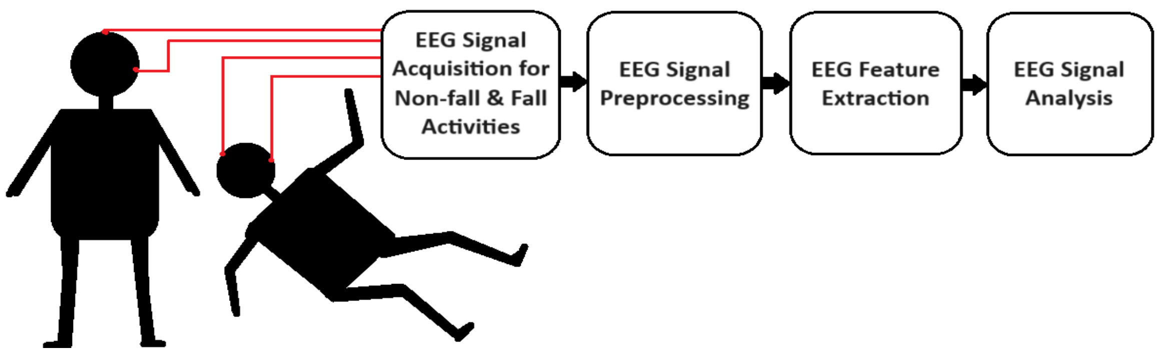
Article

ABSTRACT



Human Falls are a significant cause of fatal, non-fatal injuries and mortality worldwide in all age groups, especially in older adults, according to WHO. Falls are the major cause of hospital admissions, which impose substantial financial burdens on individuals, the healthcare system, and society. An automatic & accurate fall monitoring system is necessary for fall detection and early assistance to reduce fall after-effects. It has been a hot topic among researchers for the last two decades. Vision, wearable, ambient, and muti-model techniques are used for fall detection, but the wearable technique is more suitable due to its cost-effectiveness and no area restriction on the subject. Most wearable techniques use accelerometers and gyroscope sensors, whereas little research is going on muscular & cortical bioelectrical activity for fall detection and Brain-computer interface. This research analyzes single-channel EEG signals for various non-fall and fall activities. This research aims to evaluate the feasibility of fall detection using morphological, statistical, and spectral analysis of EEG signals during non-fall and fall activities. The study shows significant variations in EEG signals for various non-fall and fall activities. The single-channel EEG signal technique can successfully discriminate fall events from non-fall events.

Keywords: Falls, Fall detection, Fall detection techniques, Single-channel EEG, EEG feature extraction

INTRODUCTION

WHO defines fall as "inadvertently coming to rest on the ground, floor or other lower level, excluding intentional change in position to rest in furniture, wall or other objects".[1] Human falls are a major cause of accidental injury and death. The second leading cause of accidental or unintentional injury deaths all over the world is falls, and an estimated 6,84,000 individuals each year die from falls worldwide.[2] Falls count for more than 30% of people aged 65-70 years and about 50% of people over 80 years, making them the leading cause of injury-related deaths and non-fatal injuries in all age groups.[3] The Centers for Disease Control and Prevention found that one in four Americans aged 65 and older falls every year.[4] Falls are a prime cause of hospitalizations. The CDC highlights that more than 95% of hip fractures are due to a fall, and nearly everyone falls sideways. WHO report 2004 shows that globally, 424000 deaths occur due to falls, where 95000 occur in India alone, which is equal to 20%; this number increased to 160000 in India in 2005. [5] From 2015 to 2050, the proportion of older adults above 60 rises from 12% to 22% worldwide.[6] With the increase in age and frailty level,

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fall frequency increases. Every year, 28-35% people of age 65 and over fall; it increases to 32-42% for people over 70 years.[1] As age grows, a person's cognitive, sensory, and physical ability reduces, increasing the chances of falling.[7] Falls and consecutive injuries are prime public health risks for all age groups. Falls and successive injuries require hospitalization & medical assistance, which increases the financial burden on the family & healthcare system. So, accurate fall detection is crucial in fall study, prevention, and treatment of post-fall injuries. Timely fall detection is helpful in medical assistance and minimizes the fall consequences. The latest research in automatic fall detection systems may enable early fall detection, reducing fall-related injuries and burden on the healthcare system.

RELATED LITERATURE REVIEW

Different approaches used for fall detection are Vision-based, Wearable, Ambient, and Multi-model. The wearable approach is widely used due to low cost, user privacy preservation, and no area constraints. Our research focuses on the feasibility of fall detection using EEG signals. All the voluntary and involuntary movements are monitored & controlled by the brain. Movement-related EEG potentials(MRPs) include Bereitschaftspotential(BP), Event-related synchronization(ERS), Event-related desynchronization(ERD), Pre-motion positivity(PMP), and Motor potential(MP).[8] Three movement-related brain potentials before voluntary movement of the finger were recorded from the scalp surface(FP1, FP2, P3, P4, Pz, C3, C4) using time-reversed averaging along with EMG and analyzed that Bereitschaftspotential, Pre-motion positivity, Motor potential occurs 750ms, 90ms, 60ms respectively before finger movement.[9] Scalp recorded μ-rhythm(8-12 Hz) of EEG activity from the somatosensory cortex(C3, C4) using Common average reference and large Laplacian method successfully controls the cursor movement on the screen.[10] The location of recording electrodes and reference is crucial for detecting MRPs from scalp surfaces for diagnostic, rehabilitative, and BCI applications. The performance of the BCI system can be improved by choosing SMA(FCz, Fz) as an optimal reference location in the motor imaginary task of finger movement.[11] Unpredictable body perturbation results in balance corrections leading to large negative cortical evoked potential recorded at midline electrode locations (FCz, Cz, CPz) compared to predictable body perturbation.[12] Considering SMA as a reference & M1 as recording location, C3-FCz & C4-FCz are shown as optimal locations for identifying motor imaginary task of hand movement for BCI.[13] EEG-based driver fatigue detection was investigated using an ensemble deep random vector functional link (edRVFL) network by applying two strategies using InterpretableCNN features to input of network and improving the feature learning ability of the network using FGloWD-edRVFL approach.[14] The ICNN and FGloWD-edRVFL hybrid approach shows good cross-subject driver fatigue detection results. EEG-based(Fp1) fall classification using genetic programming for machine learning pipeline with Wavelet, Polynomial, and PCA-based feature extraction on Preliminar Fall-Up dataset was done, achieving an average accuracy of 90.52% with inference time 0.019 sec.[15] Single-channel EEG and EMG-based low-cost systems are designed to provide real-time user feedback for fall prevention.[16] MRCP detects the movement intention at the Cz location, which enables the EMG analysis and matches the EMG template with a pre-characterized user profile to alert the user for fit to move or stop moving. Using EEG and Heart rate variability, the reoccurrence of falls can be detected by detecting similarities from previous fall data to warn the user or caretaker about the possibility of falls.[17] The author also proposed a fall detection system using an RFID tag mounted on the user's belt & RFID reader on the user's hand by received signal strength, which varies with sudden hand movements when a fall occurs. Fall risk prediction with Bispectral EEG Fp1 & Fp2 in delirious elders using Random forest for EEG feature extraction and Kernalized SVM for classification yield 89% accuracy.[18] EEG-EMG-based Multi-sensor architecture is used for pre-impact fall detection with a time of 370.62 ± 60.85 ms and 96.21% accuracy.[19] EMG computation for specific movement triggers the EEG analysis, which jointly extracts thresholds and uses a logical condition network to classify the loss of balance. For the safety of construction workers, an IoT-based helmet is designed that uses prefrontal EEG(FP1, FP2) to detect sleep deprivation and IMU for fall detection of onsite workers with an emergency alert to the supervisor.[20] Wavelet energy & Hjorth parameters are used for feature extraction, and Random forest is used as a classifier, providing 98% accuracy. From EEG analysis of MRCPs and ERD during unilateral wrist extension, motor potential during movement execution & contingent negative variation during movement preparation has the largest amplitude at Cz, whereas μ-ERD during movement execution was smallest at Cz.[21] FPGA-based architecture is used for real-time hand movement prediction using EEG MRCP and EMG.[22] Integration of BSN and Vehicular ad-hoc Network architecture is proposed using EEG (Fp) to detect driver attention level & trigger alert for low attention level toward traffic safety.[23] A cyber-physical system is designed using EEG-EMG coupling to assess involuntary movement for fall prevention by providing user feedback.[24] BP, μ, β-rhythm, and EMG co-contraction are used as a basis for possible fall risk detection. A wearable wireless system with feedback is designed to detect and prevent falls using simultaneous monitoring of EEG and EMG.[25] BP increases before voluntary movement and is absent during involuntary movement. BP and EMG are used for involuntary movement detection using a matchmaking algorithm, and feedback is provided to the user to maintain posture for fall prevention. A fall detection system using a smartphone was developed for the safety of construction workers.[26] EEG and motion sensors of smartphones are used to get workers' physiological status and provide alerts for any unsafe action. The motor imaginary task of ankle movement is detected using MRCPs by a self-paced asynchronous BCI system that triggers peripheral electrical stimulation.[27] Such a system is useful for deliberate skill acquisition in normal people and rehabilitation of brain-damaged people. Bioelectric signals[28,29] and imaging[30] have been successfully used for disease prediction, diagnosis, and treatment. According to the above studies, EEG signal varies significantly for voluntary and involuntary movements. This study analyzes EEG signals for various fall and non-fall activities to find the possibility of fall detection using EEG.

METHODOLOGY

In this study, we acquired unipolar EEG signals from subjects for various non-fall and fall activities, preprocessed the signal, and performed feature extraction for analysis of EEG. Safety precautions were taken during the experiment.

Subjects

Two healthy subjects (33±0.2 years, 63±2 kg, Male) participated in this study. Both the subjects gave their consent before participation.

Experimental Setup

Unipolar Electroencephalographic (EEG) signals were recorded from the scalp with Ag/AgCl surface electrodes. EEG acquisition hardware was placed on the subject's chest with an active electrode placed on the primary motor cortex area[16] and a reference electrode on the right mastoid (RM) according to the 10-20 system, as shown in Figure 1. A wireless EEG acquisition system was used to acquire EEG signals during non-fall and fall activities, which wirelessly transmits the data to a laptop via Bluetooth. EEG signals were sampled at a frequency of 100Hz, amplified with a gain of 40000, and bandpass filtered at 0.8-48 Hz.

Figure 1. EEG acquisition hardware, Placement and Setup

Experimental Protocol

EEG signal was recorded for three non-fall activities and five fall activities. Subjects were asked to perform the following activities as mentioned in Table 1. Each activity was performed two to three times. Recording time for each activity is around 7 to 10 seconds. Number of Recorded activities = [(3 non-fall x 2 trial) + (5 fall x 3 trial)] x 2 subject = 42.

Table 1. Types of Non-fall & Fall Activities performed

Sr. No.	Activity	Type
1	Standing idle	Non-fall
2	Sitting idle	Non-fall
3	Stand then walk	Non-fall
4	Stand then Back-fall	Fall
5	Stand then Front-fall	Fall
6	Stand then Right-side fall	Fall
7	Stand then Left-side fall	Fall
8	Walking & Front-fall by obstacle	Fall

Preprocessing of EEG signal

The recorded EEG signal contains motion artifacts, eye blinking, and other noises. Unwanted noise from the EEG signal must be removed to extract the features from EEG data. To remove such noises, a 16th-order low-pass Butterworth filter with a cutoff frequency of 2 Hz and an 8th-order high-pass Butterworth filter with a cutoff frequency of 40 Hz was used.

EEG feature Extraction

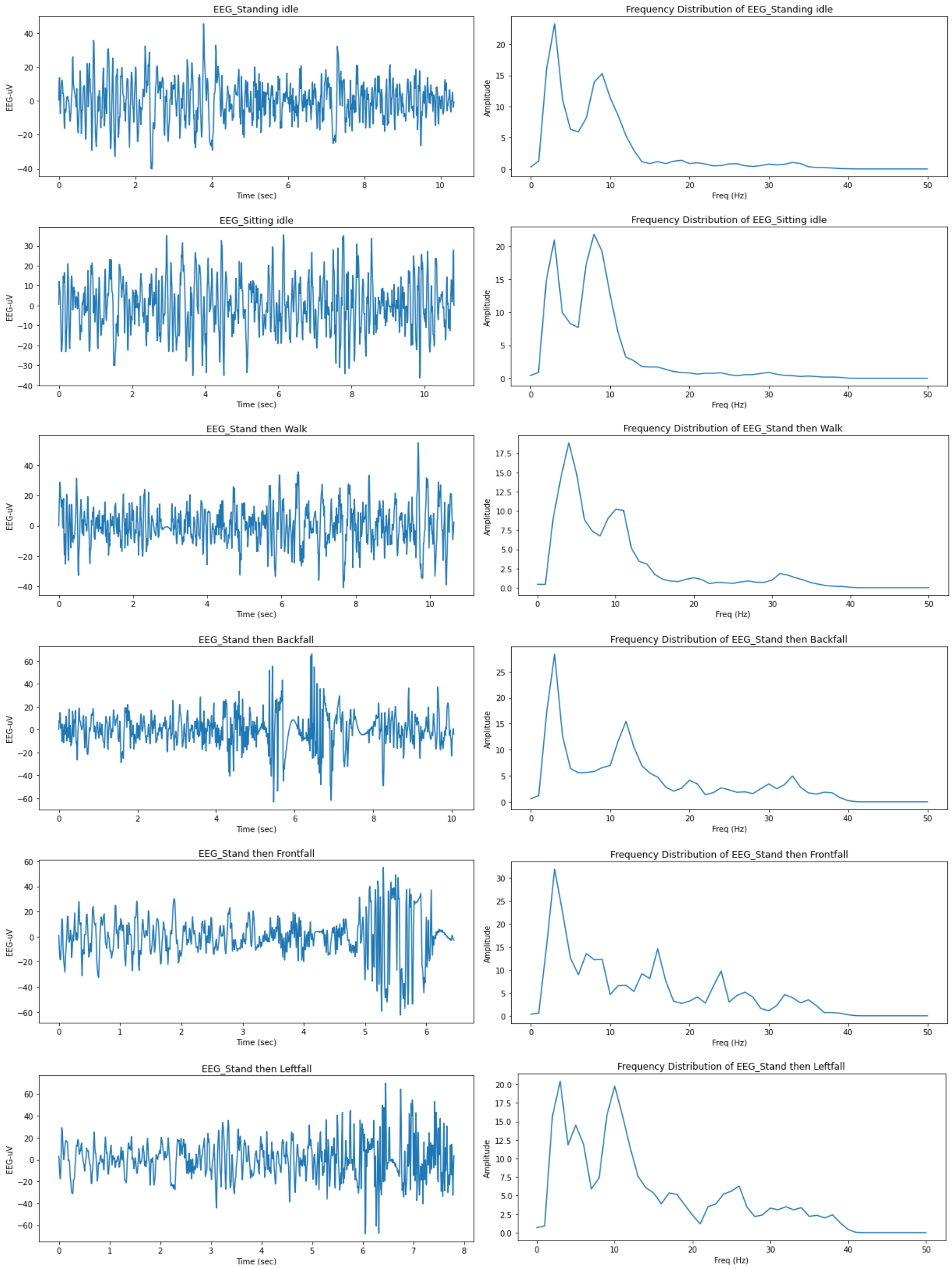
Feature extraction is an important step for the preliminary analysis of EEG signals for various non-fall and fall activities. Appropriate feature selection is important as it should indicate variation between non-fall & fall activities. After preprocessing of the EEG signal, the following time-domain & frequency-domain EEG features of non-fall and fall activities were extracted for further analysis: Min, Max, Mean, Med, P2P, Var, STD, RMS, RSS, Totpow, Avgpow.

Table 2. List of Extracted EEG Features

Feature	Description	Formula
Min	Minimum of EEG signal	*Min*
Max	Maximum of EEG signal	*Max*
Mean	Mean of EEG signal	$Mean = \frac{\sum X_i}{N}$
Med	Median of EEG signal	$Med = \left(\frac{N+1}{2}\right)^{th} term, N = Odd$ $Med = \frac{\left(\frac{N}{2}\right)^{th} term + \left(\frac{N}{2}+1\right)^{th} term}{2}, N = Even$
P2P	Peak-to-peak of EEG signal	$P2P = \lvert Max - Min \rvert$
Var	Variance of EEG signal	$Var = \frac{\sum (X_i - Mean)^2}{N}$
STD	Standard Deviation of EEG signal	$STD = \sqrt{\frac{\sum (X_i - Mean)^2}{N}}$
RMS	Root mean square of EEG signal	$RMS = \sqrt{\frac{1}{N}\sum X_i^2}$
RSS	Root sum square of EEG signal	$RSS = \sqrt{\sum \lvert X_i \rvert^2}$
Totpow	Total Power of EEG signal	$Totpow = \sum_{k=1}^{K} I_k(f_n)$ $I_k(f_n)$ *is periodogram of k segments of Xi.*
Avgpow	Average Power of EEG signal	$Avgpow = \frac{1}{K}\sum_{k=1}^{K} I_k(f_n)$

RESULTS & DISCUSSION

For primary analysis of EEG signals, we have to perform morphological, time-domain, and frequency-domain analysis. Figure 2 shows the EEG signal with power spectrum for one set of non-fall and fall activities listed in the experimental protocol.


EEG_Standing idle
Frequency Distribution of EEG_Standing idle
EEG_Sitting idle
Frequency Distribution of EEG_Sitting idle
EEG_Stand then Walk
Frequency Distribution of EEG_Stand then Walk
EEG_Stand then Backfall
Frequency Distribution of EEG_Stand then Backfall
EEG_Stand then Frontfall
Frequency Distribution of EEG_Stand then Frontfall
EEG_Stand then Leftfall
Frequency Distribution of EEG_Stand then Leftfall
EEG-uV
Time (sec)
Amplitude
Freq (Hz)

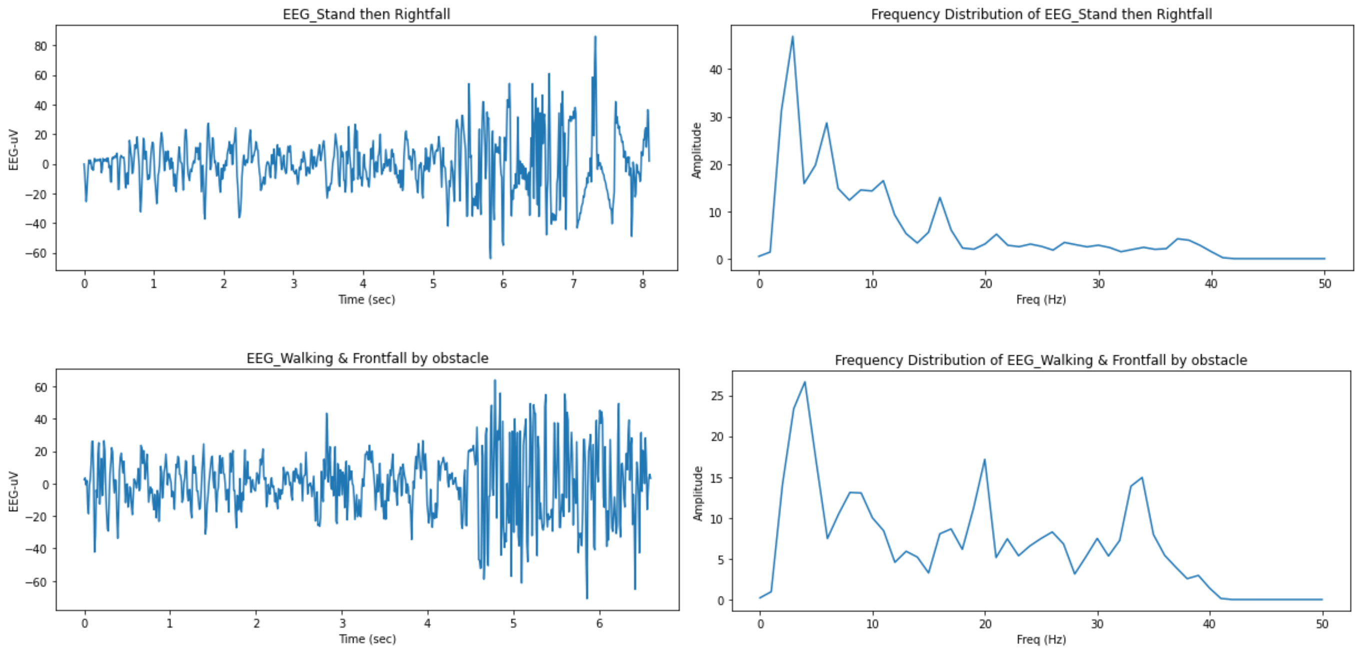


Figure 2. EEG Signal and Power spectrum during Non-fall & Fall activities

Table 3. Extracted Features for one set of Non-fall & Fall activities

Activity	Min	Max	Mean	Med	STD	P2P	Var	RMS	RSS	Totpow	Avgpow
Standing idle	-40.174	45.465	0.040	0.642	11.847	85.638	140.362	11.848	381.151	148.601	2.914
Sitting idle	-36.422	35.561	0.033	-0.133	12.876	71.984	165.791	12.876	423.149	166.392	3.263
Stand then walk	-40.960	55.109	0.147	-0.266	12.688	96.069	160.977	12.689	414.082	143.617	2.816
Stand then Backfall	-63.277	66.298	0.005	0.360	14.204	129.576	201.766	14.204	450.305	207.463	4.068
Stand then Front fall	-62.519	55.049	-0.118	0.524	16.708	117.568	279.141	16.708	424.329	265.787	5.212
Stand then Right fall	-67.925	69.977	-0.090	-0.437	16.991	137.902	288.693	16.991	474.539	252.272	4.947
Stand then Left fall	-64.017	86.080	0.050	0.156	17.619	150.097	310.425	17.619	501.444	320.982	6.294
Walking & Front-fall by obstacle	-71.038	63.976	0.041	0.298	19.833	135.015	393.364	19.833	509.531	343.443	6.734

Using morphological analysis of EEG signals, we observe that for three non-fall activities, overall amplitude & positive-negative peak values are lower than five fall activities. By observing the power spectrum of non-fall activities for standing & sitting idle states, we found that most of the signal power is concentrated at lower frequencies below 10Hz, and higher frequency content is negligible. For the non-fall activity of stand then walk, the power spectrum indicates that the majority of the signal power is concentrated at lower frequencies below 12Hz, and small power is concentrated at higher frequencies. The EEG signal of five fall activities indicates that overall amplitude and positive-negative peak values are larger than non-fall activities. For fall activities, the EEG power spectrum has a higher peak amplitude at lower frequencies compared to non-fall activities. By observing the power spectrum of fall activities, we found that signal power is distributed over lower frequencies below 10Hz and higher frequencies above 10Hz. During fall activities, we get higher EEG signal power at lower & higher frequencies and multiple peaks at higher frequencies in the power spectrum compared to non-fall activities.

We have extracted time-domain and frequency-domain EEG features for various non-fall & fall activities to analyze the EEG signal further, as indicated in Table 3 and Figure 3. Table 3 shows the EEG features for one set of activities, while Figure 3 shows the range of feature values of all recorded activities. The statistical analysis indicates that min-max values of EEG for fall activities are higher than non-fall activities. The mean and median value of EEG for non-fall & fall activities has no significant difference. The standard deviation of the EEG signal is comparatively higher in the case of fall activities than in non-fall activities. The peak-to-peak values of fall activities are significantly higher than that of non-fall activities. The variance of fall activities is higher than that of non-fall activities. The Root mean square & Root sum square of the EEG signal are higher in the case of fall activities compared to non-fall activities. Frequency domain features like EEG Total power & Average power are higher for fall activities than non-fall activities. There is a notable difference in most of the time & frequency-domain features of EEG for non-fall and fall activities.

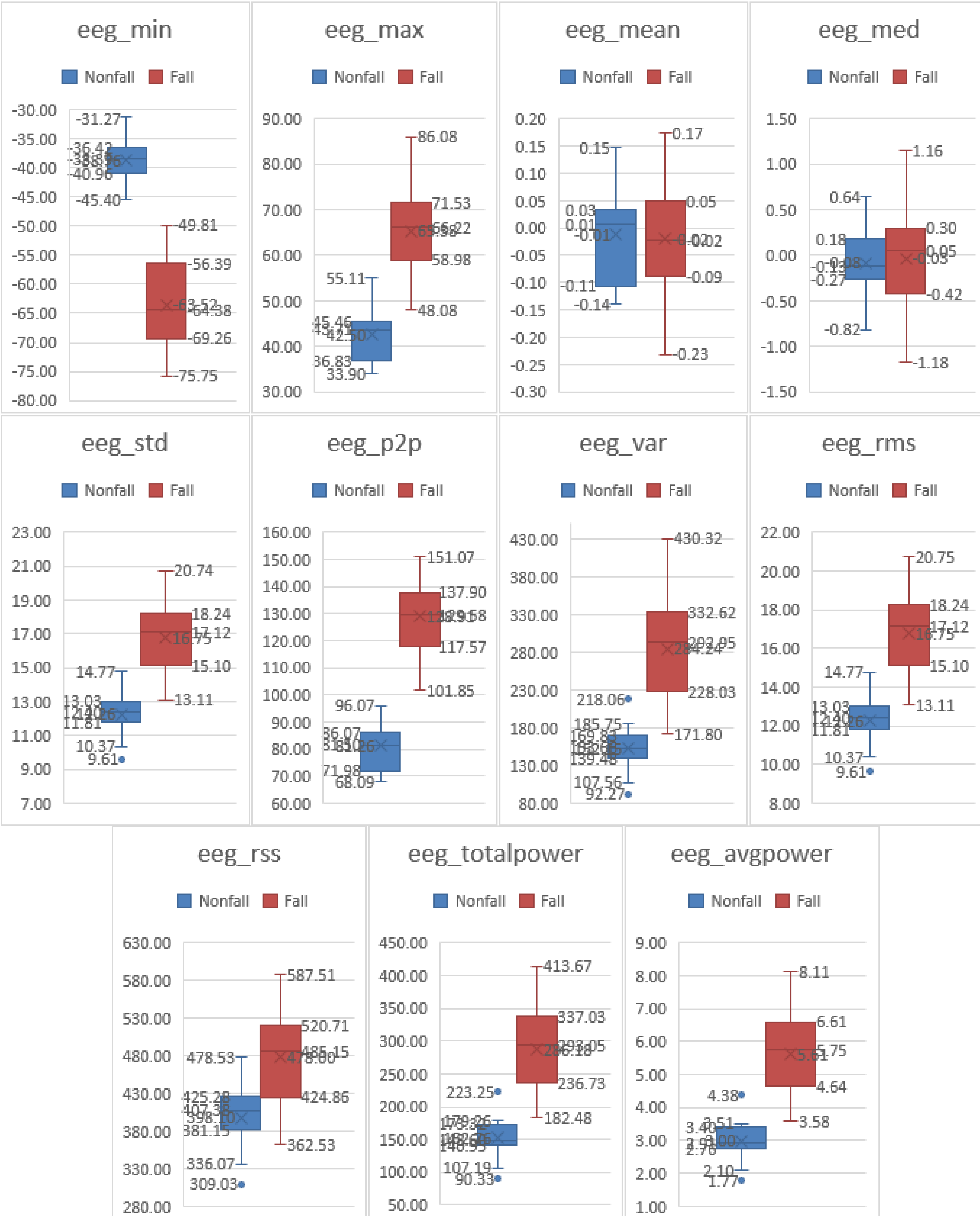


Figure 3. Range of Extracted Features for Non-fall & Fall Activities

Conclusion & Future Work

A little research is being done on bioelectric signals for fall detection among different types of fall detection techniques. Our study evaluated the feasibility of fall detection using morphological, statistical, and spectral analysis of single channel-EEG signals during fall and non-fall activities. In our research, we have acquired single-channel EEG from the primary motor cortex area and reference at the right mastoid for three non-fall & five fall activities. The acquired EEG signal is bandpass filtered from 2Hz to 40Hz for feature extraction using a Butterworth filter. Nine time-domain features and two frequency-domain features are extracted to analyze EEG signals during non-fall & fall activities. From morphological analysis, we conclude that there are significant differences in amplitude, waveform & frequency distribution of EEG for non-fall & fall activities. From statistical analysis, we found that values of time-domain & frequency-domain features of EEG are significantly higher for fall activities than non-fall activities. Our study concludes the use of Single-channel EEG for fall detection due to significant differences in morphology, time-domain & frequency-domain features of single-channel EEG between non-fall and fall activities.

In future work, we will include more subjects for detailed EEG analysis and extract more features for non-fall and fall activities.

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Conflict of Interest Statement

The authors do not have any conflict of interest for the publication of this work.

References

1. World Health Organization. WHO Global Report on Falls Prevention in Older Age.; **2007**.
2. Falls https://www.who.int/news-room/fact-sheets/detail/falls (accessed Apr 2, 2024).
3. C.G. Swift, S. Iliffe. Assessment and prevention of falls in older people – concise guidance. *Clinical Medicine* **2014**, 14 (6), 658–662.
4. G. Bergen, M.R. Stevens, E.R. Burns. Falls and Fall Injuries Among Adults Aged ≥65 Years — United States, 2014. *MMWR Morb Mortal Wkly Rep* **2016**, 65 (37), 993–998.
5. J. Jagnoor, W. Suraweera, L. Keay, et al. Childhood and adult mortality from unintentional falls in India. *Bull World Health Organ* **2011**, 89 (10), 733–740.
6. Ageing and health https://www.who.int/news-room/fact-sheets/detail/ageing-and-health (accessed Apr 2, 2024).
7. H. Patel, M. Patel. Sensors for Falls and Fall Detection Techniques: From the past to the future. *J. Integr. Sci. Technol.* **2023**, 11 (4), 575.
8. M. Jahanshahi, M. Hallett. The Bereitschafts potential: Movement-Related Cortical Potentials; Springer US, **2003**.
9. L. Deecke, B. Grözinger, H.H. Kornhuber. Voluntary finger movement in man: Cerebral potentials and theory. *Biol Cybern* **1976**, 23 (2), 99–119.
10. D.J. McFarland, L.M. McCane, S. V. David, J.R. Wolpaw. Spatial filter selection for EEG-based communication. *Electroencephalogr Clin Neurophysiol* **1997**, 103 (3), 386–394.
11. S.-H. Choi, M. Lee. Estimation of Motor Imaginary Using fMRI Experiment Based EEG Sensor Location. *Int. J. Computational Intelligence Research* **2007**, 3 (1).
12. A.L. Adkin, S. Quant, B.E. Maki, W.E. McIlroy. Cortical responses associated with predictable and unpredictable compensatory balance reactions. *Exp Brain Res* **2006**, 172 (1), 85–93.
13. Y. Wang, B. Hong, X. Gao, S. Gao. Design of electrode layout for motor imagery based brain-computer interface. *Electron Lett* **2007**, 43 (10), 557–558.
14. R. Li, R. Gao, L. Yuan, et al. An enhanced ensemble deep random vector functional link network for driver fatigue recognition. *Eng Appl Artif Intell* **2023**, 123, 106237.
15. J.J. Bird, A. Lotfi. Fall compensation detection from EEG using neuroevolution and genetic hyperparameter optimization. *Genet Program Evolvable Mach* **2023**, 24 (1), 1–26.
16. F. Ziying, D. Neo, W. Jue, Z. Yicheng, Y.Y.H. Lam. An Integrated Fall Prevention System with Single-Channel EEG and EMG Sensor. *2021 4th Int. Conf. Circuits, Systems and Simulation, ICCSS 2021* **2021**, 183–189.
17. R. Rading. Fall detection and prevention among elderly persons using wearable technologies. *TechRxiv* **2020**.
18. K. Zarei, G. Shinozaki. Prediction of Delirium, Mortality, and Fall Risk in inpatients using Bispectral EEG. *Am. J. Geriatric Psychiatry* **2019**, 27 (3), S212–S213.
19. D. De Venuto, G. Mezzina. Multisensing architecture for the balance losses during gait via physiologic signals recognition. *IEEE Sens J* **2020**, 20 (23), 13959–13968.
20. S.R. Dhole, A. Kashyap, A.N. Dangwal, R. Mohan. A novel helmet design and implementation for drowsiness and fall detection of workers on-site using EEG and Random-Forest Classifier. *Procedia Comput Sci* **2019**, 151, 947–952.
21. H. Li, G. Huang, Q. Lin, et al. Combining movement-related cortical potentials and event-related desynchronization to study movement preparation and execution. *Front Neurol* **2018**, 9 (OCT), 363335.
22. H. Wöhrle, M. Tabie, S.K. Kim, F. Kirchner, E.A. Kirchner. A Hybrid FPGA-Based System for EEG- and EMG-Based Online Movement Prediction. *Sensors* **2017**, 17 (7), 1552.
23. A. Reyes-Muñoz, M.C. Domingo, M.A. López-Trinidad, J.L. Delgado. Integration of Body Sensor Networks and Vehicular Ad-hoc Networks for Traffic Safety. *Sensors* **2016**, 16 (1), 107.
24. D. De Venuto, V.F. Annese, M. Ruta, E. Di Sciascio, A.L. Sangiovanni Vincentelli. Designing a Cyber-Physical System for Fall Prevention by Cortico-Muscular Coupling Detection. *IEEE Des Test* **2016**, 33 (3), 66–76.
25. D. De Venuto, V.F. Annese, M. de Tommaso, E. Vecchio, A.L. Sangiovanni Vincentelli. Combining EEG and EMG Signals in a Wireless System for Preventing Fall in Neurodegenerative Diseases. *Biosystems and Biorobotics* **2015**, 11, 317–327.
26. Y.C. Fang, R.J. Dzeng. A Smartphone-based Detection of Fall Portents for Construction Workers. *Procedia Eng* **2014**, 85, 147–156.
27. I.K. Niazi, N. Mrachacz-Kersting, N. Jiang, K. Dremstrup, D. Farina. Peripheral electrical stimulation triggered by self-paced detection of motor intention enhances motor evoked potentials. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **2012**, 20 (4), 595–604.
28. B. Mehta, V. Dave. Detection of Cardiovascular Autonomic Neuropathy using Machine Learning Algorithms. *J. Integr. Sci. Technol.* **2023**, 11 (4), 562–562.
29. Y.S. Rao, B. Mehta, A. Kathiriya, et al. Smart Stethoscope for Remote Healthcare Monitoring Using IoT: A Cost-Effective Solution. *3rd Asian Conference on Innovation in Technology, ASIANCON 2023* **2023**.
30. B. Mehta, H. Patel, M. Nanavati, N. Limbad, P. Gohel. Implementation and comparative analysis of various Pyramid-based Image Fusion techniques for Multimodal MRI images of brain. *J. Integr. Sci. Technol.* **2025**, 13 (2), 1031.