We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

5,000
Open access books available

125,000
International authors and editors

140M
Downloads

Our authors are among the

154
Countries delivered to

TOP 1%
most cited scientists

12.2%
Contributors from top 500 universities

WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com

Chapter

Correlations of Gait Phase Kinematics and Cortical EEG: Modelling Human Gait with Data from Sensors

Chaitanya Nutakki, Sandeep Bodda and Shyam Diwakar

Abstract

Neural coding of gait intent and continuous gait kinematics have advanced brain computer interface (BCI) technology for detection and predicting human upright walking movement. However, the dynamics of cortical involvement in upright walking and upright standing has not been clearly understood especially with the focus of off-laboratory assessments. In this study, wearable low-cost mobile phone accelerometers were used to extract position and velocity at 12 joints during walking and the cortical changes involved during gait phases of walking were explored using non-invasive electroencephalogram (EEG). Extracted gait data included, accelerometer values proximal to brachium of arm, antecubitis, carpus, coxal, femur and tarsus by considering physical parameters including height, weight and stride length. Including EEG data as features, the spectral and temporal features were used to classify and predict the swing and stance instances for healthy subjects. While focusing on stance and swing classification in healthy subjects, this chapter relates to gait features that help discriminate walking movement and its neurophysiological counterparts. With promising initial results, further exploration of gait may help change detection of movement neurological conditions in regions where specialists and clinical facilities may not be at par.

Keywords: human gait, cortical activation, electroencephalography, stance, swing, accelerometer sensors

1. Introduction

Upright gait has been used as a peculiar biometric characteristic and can offer clues to help develop detection mechanisms for walking-related neurological disorders, if detected can help reduce cost and help propose diagnostic approaches [1]. Gait and locomotion are complex sequential processes involving timed coordination between central nervous system, muscles and bones [2]. The action of numerous muscles and the variability in joint kinematics, leads to changes between different phases in gait, mainly swing and stance [3]. Human gait analysis involves the measurement and assessment of kinematic and inverse dynamic parameters that characterize the different phases of gait and quantifies the musculoskeletal functions [4, 5]. Within the context of gait measurement, sensors used in assessing

GAIT include floor based sensors (FS), wearable sensors (WS) and non-wearable sensors (NWS) techniques [6]. In techniques involving NWS, gait has been captured using cameras with video and image processing allowing features to attribute to gait patterns [7]. FS based techniques use force plates located on the ground to extract the walking parameters through pressure estimates and ground reaction forces [8]. In WS based techniques, sensors like accelerometers [9–11], gyroscopes, goniometers, etc. attached to the different biomechanical parts of the human body frame measure gait patterns during walking [12]. Peak detection methods in algorithms allow gauging gait events like heel strike, swing and stance from accelerometer and gyroscope data [13–16].

Aiming towards potential applications in medicine, it has been noted that gait and posture control in patients with neurodegenerative disorders become irregular due to weakening of motor neurons that controls the muscles [17]. Neurodegenerative diseases including the Parkinson's and Huntington disease result in progressive degeneration of neurons causes changes in neuromuscular control [18]. In clinical analysis, in order to understand the patient's walking capability and movement tracking usually require expensive (cost, effort and time) methodologies and structured laboratories [19, 20]. A study by Hausdorff et al. [21] had demonstrated the differences between gait cycles and subphases duration in Parkinson's patients compared to normal subjects. Also, magnitude difference between gait stride intervals of human subjects with neurodegenerative conditions have been analysed by using (DFAT) detrended fluctuation analysis techniques [22].

Research progress in understanding the brain function during gait intent, but the information on movement-related cortical activity, neural circuit mechanisms and computations underlying the control of upright walking in humans are yet to be understood completely [23, 24]. Studies have shown rhythmic foot and leg movements recruit primary motor cortex [25, 26], while fNIRS has shown involvement of frontal, premotor and supplementary motor areas during walking [27, 28]. Recent literature have indicated augmented beta oscillations during double support phases of the gait cycle (event-related synchronization, ERS) and to be suppressed during the swing and single support phases (event-related desynchronization, ERD) [29–35]. Other studies have shown enhanced gamma oscillations during early and mid-swing phases of gait cycle and suppressed gamma rhythms towards the end of the swing phase and during the double support [36–40].

Studies involving other techniques such as single-photon emission computed tomography (SPECT) have reported neural characteristics during voluntary walking; studies [41, 42] using SPECT evaluated changes in the brain activity as a result of walking, and identified the SMA, S1, M1, cerebellum, and basal ganglia functioning as the control mechanisms of bipedal gait. Another SPECT study [43], investigated cortical activation during treadmill walking and found network activation in the premotor cortex, somatosensory association cortex, cingulate cortex and brain stem apart from the structures reported [41]. In both tomography SPECT studies, walking tasks were carried out prior to image acquisition.

Additionally, neurodegenerative diseases that relate to gait effects can be classified using machine learning tools as a decision support to clinicians for better prediction [44] of patient conditions. Gait disorder related to amyotrophic lateral sclerosis (ALS) have been classified by using wavelet-based scheme and features reflect regularity and gait coherence between both limbs as seen from the approximation part of the raw gait signal [45].

Identification and classification of human gait using low cost experimental techniques are crucial and necessary for the developing countries like India. Current diagnosing techniques for gait related disorders are more expensive and inaccessible to the common people. The main purpose of this study was to

develop a low-cost model that can be employed in the future as an off-laboratory diagnosing tool for identifying gait abnormalities and classify human gait phases and pathological disorders. With machine learning jointly with inverse dynamic analysis using triaxial accelerometer sensors in today's mobile phones, it may be reliable to analyse the each joint kinematic and behaviour during swing and stance phases that can further be used for the development of control strategies to set up brain machine interfaces (BMI), human-machine interfaces (HMI) and prostheses. Gait kinematic movement in terms of EEG allowed to understand the cortical regions that are active during gait phases helps in diagnosing the gait neurological disorders.

In this chapter, we address the usage of low-cost mobile phone-based accelerometer sensors in order to extract and analyse human gait patterns. Average torque and the gait kinematic parameters of the lower body during stance and swing phases were analysed to understand how gait can be attained. In this study, we compared neural spectral representations from scalp EEG signals during active walking. Simultaneous recording of EEG with gait and their analysis was done to interpret cortical activity during the stance and swing phases of a gait cycle.

2. Methods

2.1 Low cost sensor-based gait recording and assessment

Gait data was extracted from 20 healthy volunteers using 12 smartphone-based accelerometers and a software application that allowed synchronous collection of data from the devices and mapped to additional parameters, including weight and age. The data collection and methods were approved by the institutional ethical review board and an open consent was collected from the participants prior to gait and EEG recordings. A total of 40 trails and 120 gait cycle accelerometer data were extracted from brachium of arm (shoulder), antecubitis (elbow), carpus (wrist), coxal (hip), femur (knee) and tarsus (ankle) were taken for further analysis. The extracted data was then normalized and sixth order Butterworth filter with a cut-off frequency of 10 Hz was used for noise reduction. Data processing was based on the time noted by the observer during each gait phase (**Figure 1A**).

2.2 Estimating torque amplitude for each joint

This method employed 12 joint related positions to collect data from subjects. Joint torques (Eq. (1)) were calculated by providing joint length, force and angle to compute muscle force that attributed to joint rotation at different gait phases.

$$T_{j..n} = Fi * R * \sin\theta \tag{1}$$

$$F_{i..n} = m_{i..n} * a_{i..n} \tag{2}$$

Here, '$F_i...n$' was the force (Eq. (2)) of each joint (i) derived from mass and acceleration of each joint, where the acceleration and angle were directly retrieved from the accelerometer sensor, 'R' was taken as length of joint measured before the experiment was done.

Average torque amplitude was computed as A, the average torque amplitude for each joint (Eq. (3)).

$$\mathrm{A_j} = \frac{1}{\mathrm{T}}\sum_{\mathrm{t=1}}^{\mathrm{T}} \mathrm{A_j(t)} \tag{3}$$

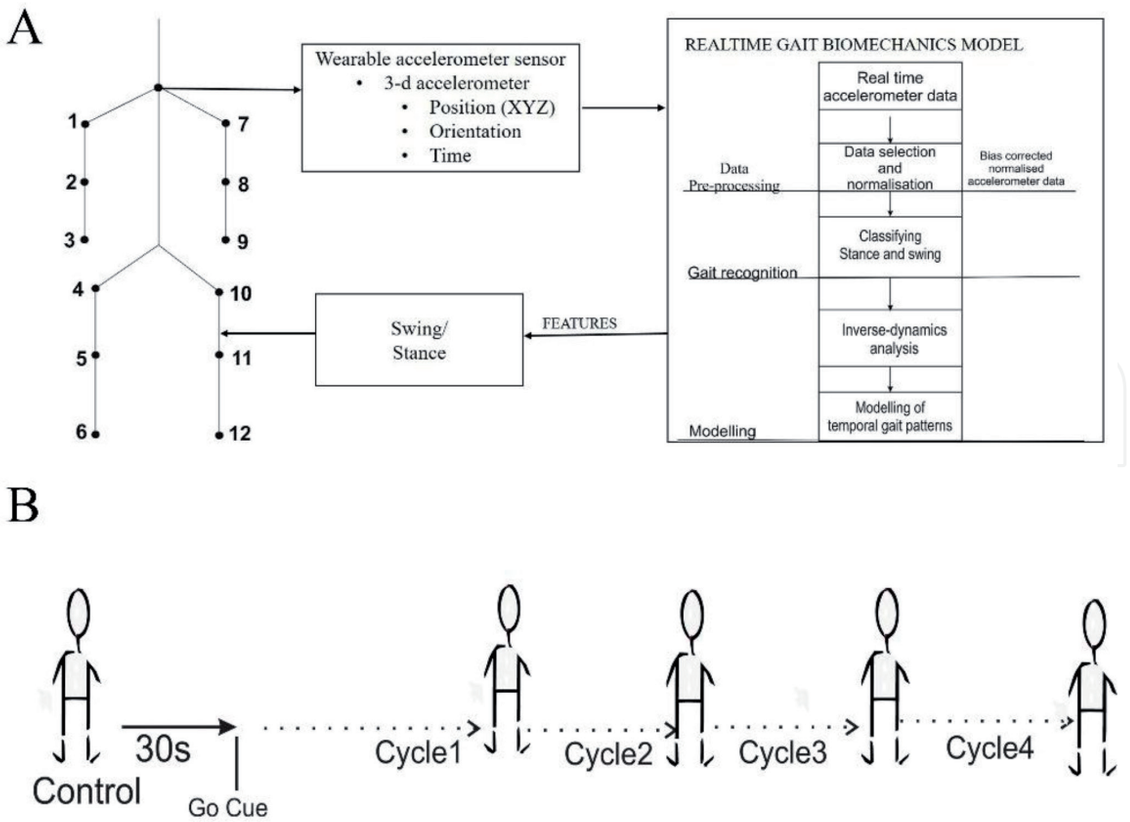

Figure 1.
(A) Classifying swing stance from gait data. (B) Schematic representation of EEG recording protocol for gait.

2.3 Experimental recording of gait using EEG

EEG was measured from four healthy subjects with four cycles per trial and two trials were recorded per subject. All subjects had provided their informed consent and were approved by the institutional ethical review board. Subjects were without any known medical conditions and had normal or corrected-to-normal vision. All subjects were explained the aim of the study before participating in the recordings. Contiguous EEG was recorded (**Figure 1B**) from 14 Ag/AgCl electrodes positioned on a commercial scalp cap based on the 10–20 placement system at a sampling rate of 128 Hz using electrode (see **Figure 1B** for protocol).

All trials began with a relaxation phase (blank screen), considered as reference or baseline signal for the analysis; 30 seconds of the relaxation phase was followed by upright active walking after the audio cue 'START'. Subject performed four cycles with each cycle including a swing and a stance phases starting with right leg followed by left leg.

Signal processing and data analysis on raw EEG signal were performed using custom scripts MATLAB R2017b (MathWorks, Massachusetts, USA) and EEGLAB toolbox [46] The reference channel (mean) was subtracted, detrended and band-pass filtered using a FIR filter of order 20 within the range, 0.1–60 Hz and notch filter applied to remove line noise of 50 Hz. Based on the marker points for various tasks (relax, step1, step 2,..., step 8, stop), data was extracted for each task and the power spectrum was estimated for the relative bands α/μ, β and γ in the EEG signals. Spectral bands were estimated for each stance and swing phases of gait cycle and averaged across all the trials of the four healthy subjects. From the pre-processed epochs, estimated bands were quantified and significant regions were identified.

3. Results

3.1 Torque variations across the subjects define swing and stance gait phases

Joint torques during stance and swing phases were measured using inverse dynamic analysis to understand how gait can be attained [47] at different phases. Subjects were divided into groups with respect to weights. Group I was categorized in to subjects with 60–70 kg, Group II was categorized in to subject with 70–80 kg, Group III was categorized into subjects with 80–90 kg. Average torque amplitude of subjects was analysed and compared during swing (**Figure 2A**) and stance (**Figure 2B**) phases.

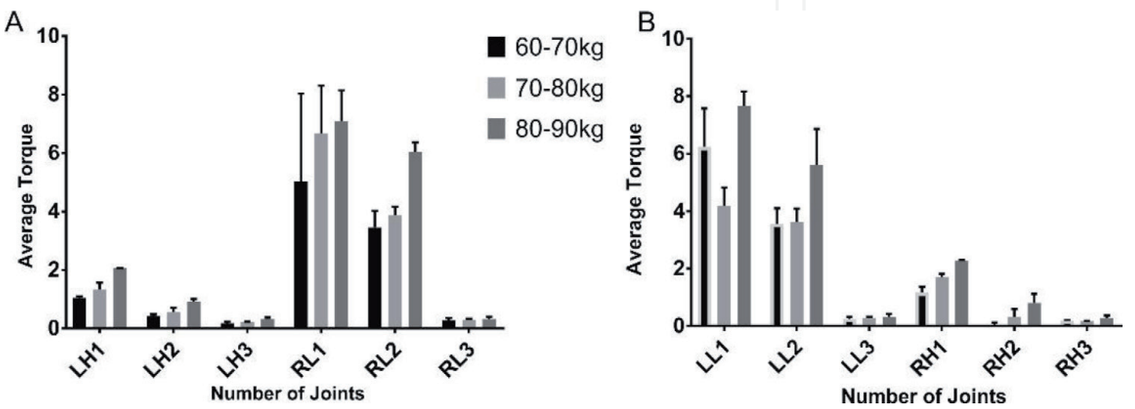

Figure 2.
Torque variations during gait. (A) Average torque amplitude of joints with different weight groups during swing. (B) Average torque amplitude of joints with different weight groups during stance. RH, right hip; RK, right knee; RA, right ankle; LS, left shoulder; LE, left elbow; LW, left wrist; LH, left hip; LK, left knee; RS, right shoulder; RE, right elbow; RW, right wrist and 1–3 are joint positions.

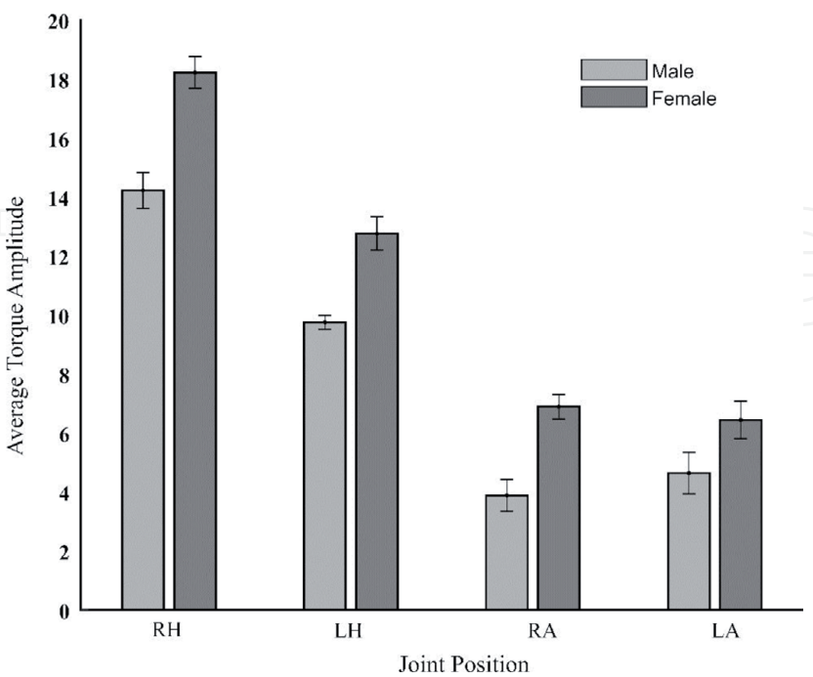

Figure 3.
Torque amplitude changes across hip and ankle of male and female subjects. Hip and ankle joints show significant changes allowing classification of male and female subjects. RH, right hip; LH, left hip; RA, right ankle; LA, left ankle.

3.2 Variations in torque allow to differentiate male and female gait

Lower body torque amplitude of male and female were analysed and compared during swing and stance from frontal plane. Torque amplitude of hip and ankle of female joints in the frontal plane showed more activity than the male in frontal plane (**Figure 3**).

3.3 Temporal and spectral EEG features of gait

Gait-related cortical potentials include the positive and negative motor potentials at the onset of movement for swing and stance. Positive amplitude of motor potential has observed for swing phase of the gait cycle in the frontal electrodes (F3) whereas negative amplitude of motor potential has observed for stance phase of the gait cycle in the frontal electrodes (F3). The clear distinction of motor potential has shown (**Figure 4A** and **B**).

From the spectral maps over the comparison of swing (**Figure 5C**) and stance (**Figure 5D**) and we have observed higher activity in parietal and frontal regions over the low frequency band regions delta and theta bands. Also, decreased alpha and beta band in frontal and central cortical regions were observed during swing than during stance phase. However, only right swing and left stance were explored in this study.

3.4 Classifying gait sensorial data using different machine learning algorithms

Since gait cadence has nonlinear and complex behaviours, extracted gait data was classified using different machine learning algorithms with validations using percentage split (60 and 70%) methods. Training accuracies suggest most algorithms had similar Among all the tested algorithms [48], Naïve Bayes and SVM with linear kernel showed highest training accuracies as in other studies [44, 49, 50] across different splits with gait accelerometer data (see **Figure 6**). We also tried leave-one-out-cross-validation but had similar results (data not shown). The data suggests that machine learning methods may help predict normal gait phases with torque features. Although recorded simultaneously, since EEG classification using machine learning was not done in this study, we may need to explore a potential technique for identifying gait phases in terms of spectral compositions. Errors were attributed to variability in data from accelerometer time and frequency fluctuations due to different models used (data not shown).

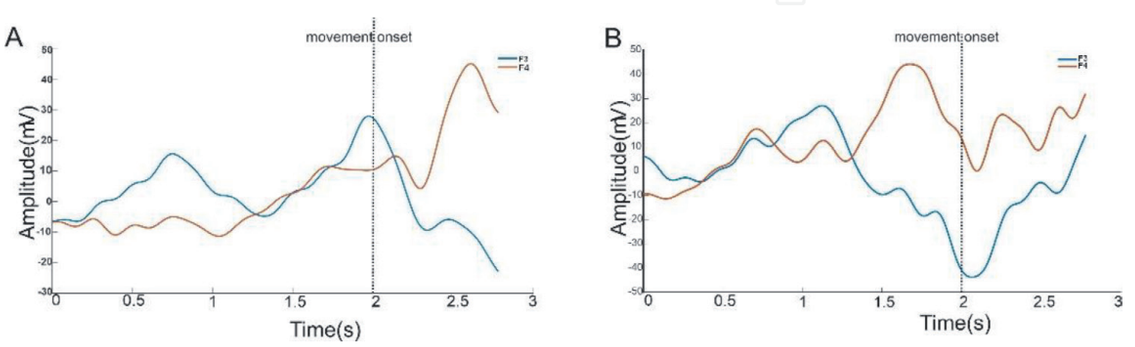

Figure 4.
Gait related cortical potentials: evoked average response for swing and stance phase of gait cycle (A) time course of F3 (blue) F4 (red) response of swing phase of gait cycle showing positive amplitude at the movement onset (B) time course of F3 (blue), F4 (red) response of stance phase of gait cycle shows negative amplitude at the movement onset.

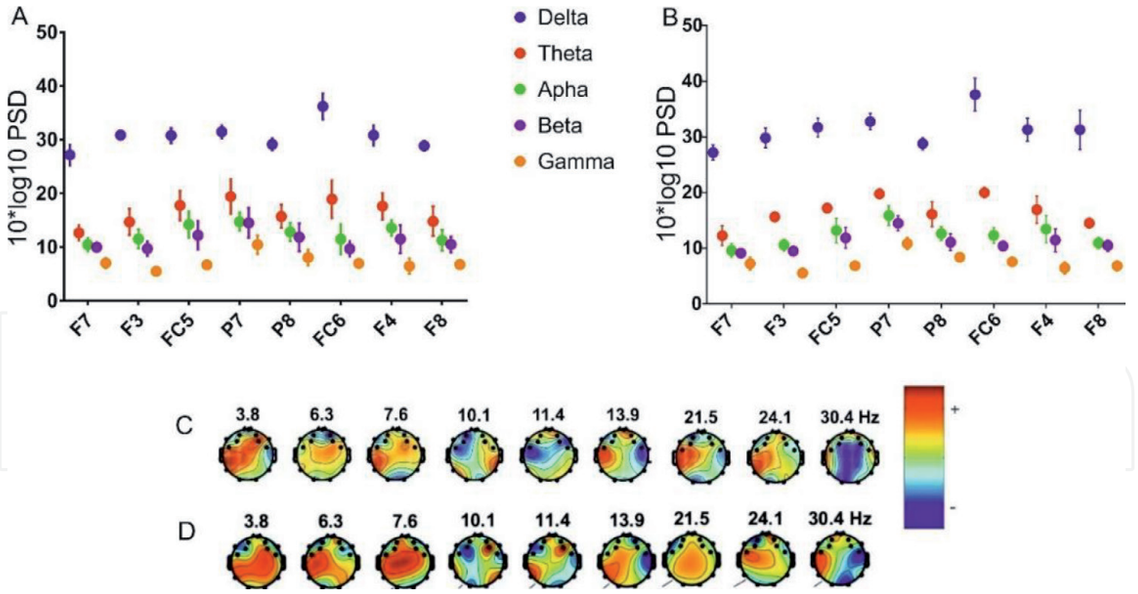

Figure 5.
Spectral changes for swing and stance phases of a gait cycle. (A) Swing phase of gait cycle showing higher delta and theta bands in frontal regions (F8, F3 and F7) electrodes. (B) Stance phase of gait cycle showing higher delta band parietal regions (P7 and P8). (C and D) Scalp maps for frequency ranges during swing (C) and stance gait phases (D).

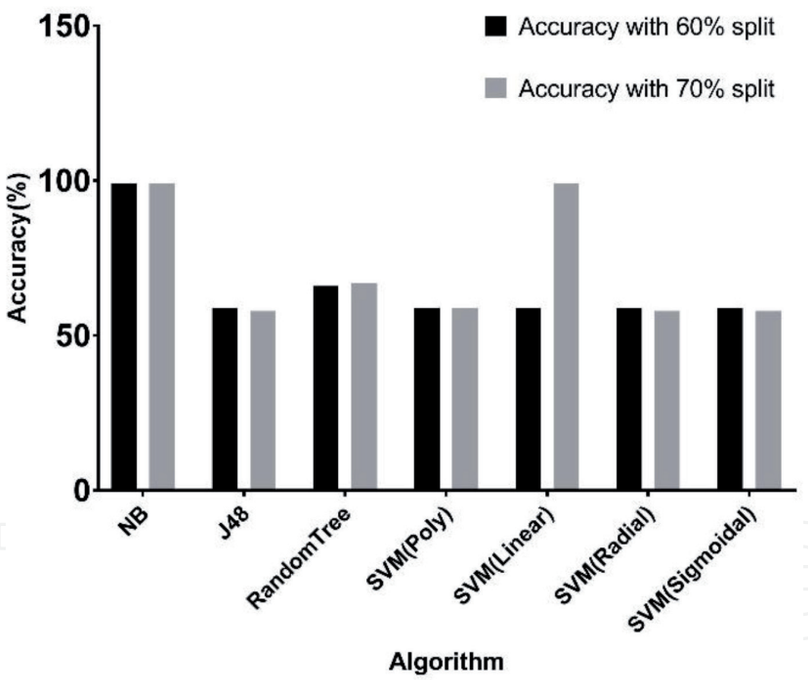

Figure 6.
Classification of gait data using machine learning algorithms. Naïve Bayes (NB), J48 decision tree, random tree, support vector machine algorithms with polynomial, linear, radial and sigmoidal and radial basis functions allowed classifying gait data.

Support vector machines had 58–59% training accuracies and so did J48 algorithm. Random tree had 67% while Naïve Bayes and linear SVM showed more than 98% accuracy perhaps attributed to complex decision boundaries.

4. Discussion

Torque-based reconstructions of gait from mobile phone triaxial accelerometer data may help identifying swing and stance phases in gait in addition to allowing

specific joint based data for discriminating male and female characteristics in gait. Reliably using EEG to predict swing and stance will include comparisons of temporal and spectral components although the resolutions and accuracies are not so reliable beyond basic gait changes, we find the positive and negative amplitudes of the MRCPs can serve as good discriminators.

Gait data was classified using machine learning algorithms with percentage split cross-validations. As with many datasets, with increase in training data samples, a consequential increase in the accuracy was observed. Among the algorithms Naïve Bayes, SVM and tree-based algorithms showed high accuracy across the data with validations based on different percentage splits of training data. The data from accelerometers may be used in the BCI-related predictive algorithms for gait phase estimates.

The study computed joint torques in order to understand relationship of joint rotations during gait phases. As indicated, generated torque amplitude was sufficient to test classification algorithms on accelerometer-based gait data. We analysed the data grouped based on the subject weight since average torque amplitude of each subject was dependent on the weight of the subject. As the weight of the subject increased, increments in the joint torques were observed across the subjects. The torques and forces within subjects during different gait cycles showed little difference.

In terms of gait data from accelerometers, male subjects showed variations in the frontal and sagittal axes and estimates suggested higher joint movement correlated to higher torque amplitude changes with respect to motion. Hip and ankle joints served as strong discriminators in classification of subject gender based on data. Rather than acceleration, torques classified variations of gait across male and female subjects.

EEG-gait methodology allowed to map cortical organization relationships and between the contralateral and ipsilateral joints during gait. During stance when compared to swing, there was higher activity in the delta and theta bands in the frontal and parietal regions, whereas decreased activity in beta band in the parietal regions. Using delta and beta rhythms in the fronto-parietal cortical microzones, it may be possible to classify swing and stance. Additionally, gait-based assessments need to rely on motor related cortical potentials and their amplitudes. Temporal analysis of gait related potentials has shown positive and negative motor potentials for stance and swing and their significant variety could be related as a marker discriminating stance and swing.

The significance of such assessments is many; with gait categorization using torque, it may now be possible to employ mobile phone accelerometers to estimate swing and stance variations as a preclinical step for estimating medical disorders. The variations could also allow gait as a biometric information especially in validating male and female subjects and their upright walking capabilities. Although EEG data is far from assessing gait intent, initialization, swing and stance phases may be explored for correlations related to neurophysiological changes attributing such data for classifying neurological disorders in the future.

5. Conclusions

Spatio-temporal reconstruction of swing and stance from triaxial accelerometers allow an understanding of how multi-position accelerometer data accounts for healthy gait before developing optimizations and methods to assess dysfunctional gait. The study suggests quantifying specific torque patterns during gait may facilitate cheaply and easily detecting gait phase changes. Although a more detailed

and multi-configuration data relating gait and EEG may be needed, this step helps to propose a pre-clinical assessment tool for rural communities, especially when multi-specialty hospitals may consider outreach or where specialists may need more time to understand movement related conditions prior to an actual diagnosis. With useful preliminary results that supports gait as a BCI technology, it further warrants the need to investigate the utility of mobile phone sensors for extracting accelerometer-based data and its use in a patient population.

Acknowledgements

This work derives direction and ideas from the Chancellor of Amrita University, Sri Mata Amritanandamayi Devi. This work was partially supported by Grants DST/CSRI/2017/31 of Department of Science and Technology, Visvesvaraya Fellowship, Ministry of Electronics and IT, Government of India and by Embracing The World, Research-for-a-Cause-Initiative.

Conflict of interest

The authors declare no conflict of interest.

Author details

Chaitanya Nutakki, Sandeep Bodda and Shyam Diwakar*
Amrita School of Biotechnology, Amrita Vishwa Vidyapeetham, Amritapuri Campus, Kollam, Kerala, India

*Address all correspondence to: shyam@amrita.edu

References

[1] Nonnekes J, Goselink RJM, Růžička E, Fasano A, Nutt JG, Bloem BR. Neurological disorders of gait, balance and posture: A sign-based approach. Nature Reviews Neurology. 2018;**14**:183-189

[2] Pedotti A. A study of motor coordination and neuromuscular activities in human locomotion. Biological Cybernetics. 1977;**26**:53-62

[3] Stickford ASL, Stickford JL. Ventilation and locomotion in humans: Mechanisms, implications, and perturbations to the coupling of these two rhythms. Springer Science Reviews. 2014;**2**:95-118

[4] Novacheck TF. The biomechanics of running. Gait & Posture. 1998;**7**:77-95

[5] Cappellini G, Ivanenko YP, Poppele RE, Lacquaniti F. Motor patterns in human walking and running. Journal of Neurophysiology. 2006;**95**:3426-3437

[6] Gafurov D. A Survey of Biometric Gait Recognition: Approaches, Security and Challenges. Proceedings of the Norwegian Informatics Conference; 2007. pp. 19-21

[7] Baratin E, Sugavaneswaran L, Umapathy K, Ioana C, Krishnan S. Wavelet-based characterization of gait signal for neurological abnormalities. Gait & Posture. 2015;**41**:634-639

[8] Mostayed A, Kim S, Mazumder MMG, Park SJ. Foot step based person identification using histogram similarity and wavelet decomposition. In: 2008 Int. Conf. Inf. Secur. Assur. (isa 2008); IEEE; 2008. pp. 307-311

[9] Godfrey A, Del Din S, Barry G, Mathers JC, Rochester L. Instrumenting gait with an accelerometer: A system and algorithm examination. Medical Engineering & Physics. 2015;**37**:400-407

[10] Patterson M, Caulfield B. A novel approach for assessing gait using foot mounted accelerometers. In: Proc 5th Int ICST Conf Pervasive Comput Technol Healthc; 2011. DOI: 10.4108/icst.pervasivehealth.2011.246061

[11] Del Din S, Hickey A, Hurwitz N, Mathers JC, Rochester L, Godfrey A. Measuring gait with an accelerometer-based wearable: Influence of device location, testing protocol and age. Physiological Measurement. 2016;**37**:1785-1797

[12] Mantyjarvi J, Lindholm M, Vildjiounaite E, Makela S, Ailisto H. Identifying users of portable devices from gait pattern with accelerometers. In: Proceedings. (ICASSP '05). IEEE Int. Conf. Acoust. Speech, Signal Process. IEEE; 2005. pp. 973-976

[13] Selles RW, Formanoy MAG, Bussmann JBJ, Janssens PJ, Stam HJ. Automated estimation of initial and terminal contact timing using accelerometers; development and validation in transtibial amputees and controls. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2005;**13**:81-88

[14] Derawi MO, Bours P, Holien K. Improved cycle detection for accelerometer based gait authentication. In: 2010 Sixth Int. Conf. Intell. Inf. Hiding Multimed. Signal Process. IEEE; 2010. pp. 312-317

[15] Casamassima F, Ferrari A, Milosevic B, Ginis P, Farella E, Rocchi L. A wearable system for gait training in subjects with Parkinson's disease. Sensors. 2014;**14**:6229-6246

[16] Rebula JR, Ojeda LV, Adamczyk PG, Kuo AD. Measurement of foot placement and its variability with inertial sensors. Gait & Posture. 2013;**38**:974-980

[17] Wu Y, Krishnan S. Computer-aided analysis of gait rhythm fluctuations in amyotrophic lateral sclerosis. Medical & Biological Engineering & Computing. 2009;**47**:1165-1171

[18] Schlachetzki JCM, Barth J, Marxreiter F, et al. Wearable sensors objectively measure gait parameters in Parkinson's disease. PLoS ONE. 2017;**12**:e0183989

[19] Komaris D-S, Govind C, Murphy A, Ewen A, Riches P. Identification of movement strategies during the sit-to-walk movement in patients with knee osteoarthritis. Journal of Applied Biomechanics. 2018;**34**:96-103

[20] Barth J, Klucken J, Kugler P, Kammerer T, Steidl R, Winkler J, et al. Biometric and mobile gait analysis for early diagnosis and therapy monitoring in Parkinson's disease. In: 2011 Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE; 2011. pp. 868-871

[21] Hausdorff JM, Lertratanakul A, Cudkowicz ME, Peterson AL, Kaliton D, Goldberger AL. Dynamic markers of altered gait rhythm in amyotrophic lateral sclerosis. Journal of Applied Physiology. 2000;**88**:2045-2053

[22] Hausdorff JM, Cudkowicz ME, Firtion R, Wei JY, Goldberger AL. Gait variability and basal ganglia disorders: Stride-to-stride variations of gait cycle timing in parkinson's disease and huntington's disease. Movement Disorders. 1998;**13**:428-437

[23] Presacco A, Goodman R, Forrester L, Contreras-Vidal JL. Neural decoding of treadmill walking from noninvasive electroencephalographic signals. Journal of Neurophysiology. 2011;**106**:1875-1887

[24] Choi JT, Bastian AJ. Adaptation reveals independent control networks for human walking. Nature Neuroscience. 2007;**10**:1055-1062

[25] Sburlea AI, Montesano L, Cano-De La Cuerda R, Alguacil Diego IM, Miangolarra-Page JC, Minguez J. Detecting intention to walk in stroke patients from pre-movement EEG correlates. Journal of Neuroengineering and Rehabilitation. 2015;**12**:1-12

[26] Hortal E, Úbeda A, Iáñez E, Fernández E, Azorín JM. Using EEG Signals to Detect the Intention of Walking Initiation and Stop. Cham: Springer; 2015. pp. 278-287

[27] Perrey S. Possibilities for examining the neural control of gait in humans with fNIRS. Frontiers in Physiology. 2014;**5**:204

[28] Jin H, Li C, Xu J. Pilot study on gait classification using fNIRS signals. Computational Intelligence and Neuroscience. 2018;**2018**:1-9

[29] Artoni F, Fanciullacci C, Bertolucci F, Panarese A, Makeig S, Micera S, et al. Unidirectional brain to muscle connectivity reveals motor cortex control of leg muscles during stereotyped walking. NeuroImage. 2017;**159**:403-416

[30] Bradford JC, Lukos JR, Ferris DP. Electrocortical activity distinguishes between uphill and level walking in humans. Journal of Neurophysiology. 2016;**115**:958-966

[31] Bruijn SM, Van Dieën JH, Daffertshofer A. Beta activity in the premotor cortex is increased during stabilized as compared to normal walking. Frontiers in Human Neuroscience. 2015;**9**:593

[32] Bulea TC, Kim J, Damiano DL, Stanley CJ, Park H-S. Prefrontal, posterior parietal and sensorimotor network activity underlying speed control during walking. Frontiers in Human Neuroscience. 2015;**9**:247

[33] Cheron G, Duvinage M, De Saedeleer C, et al. From spinal central pattern generators to cortical network: Integrated BCI for walking rehabilitation. Neural Plasticity. 2012;**2012**:375148

[34] Gwin JT, Gramann K, Makeig S, Ferris DP. Electrocortical activity is coupled to gait cycle phase during treadmill walking. NeuroImage. 2011;**54**:1289-1296

[35] Knaepen K, Mierau A, Swinnen E, Fernandez Tellez H, Michielsen M, Kerckhofs E, et al. Human-robot interaction: Does robotic guidance force affect gait-related brain dynamics during robot-assisted treadmill walking? PLoS ONE. 2015;**10**:e0140626

[36] Seeber M, Scherer R, Wagner J, Solis-Escalante T, Müller-Putz GR. EEG beta suppression and low gamma modulation are different elements of human upright walking. Frontiers in Human Neuroscience. 2014;**8**:485

[37] Seeber M, Scherer R, Wagner J, Solis-Escalante T, Müller-Putz GR. High and low gamma EEG oscillations in central sensorimotor areas are conversely modulated during the human gait cycle. NeuroImage. 2015;**112**:318-326

[38] Storzer L, Butz M, Hirschmann J, Abbasi O, Gratkowski M, Saupe D, et al. Bicycling and walking are associated with different cortical oscillatory dynamics. Frontiers in Human Neuroscience. 2016;**10**:61

[39] Wagner J, Solis-Escalante T, Grieshofer P, Neuper C, Müller-Putz G, Scherer R. Level of participation in robotic-assisted treadmill walking modulates midline sensorimotor EEG rhythms in able-bodied subjects. NeuroImage. 2012;**63**:1203-1211

[40] Wagner J, Solis-Escalante T, Scherer R, Neuper C, Müller-Putz G. It's how you get there: Walking down a virtual alley activates premotor and parietal areas. Frontiers in Human Neuroscience. 2014;**8**:93

[41] Fukuyama H, Ouchi Y, Matsuzaki S, Nagahama Y, Yamauchi H, Ogawa M, et al. Brain functional activity during gait in normal subjects: A SPECT study. Neuroscience Letters. 1997;**228**:183-186

[42] Wieser M, Haefeli J, Bütler L, Jäncke L, Riener R, Koeneke S. Temporal and spatial patterns of cortical activation during assisted lower limb movement. Experimental Brain Research. 2010;**203**:181-191

[43] Hanakawa T, Katsumi Y, Fukuyama H, Honda M, Hayashi T, Kimura J, et al. Mechanisms underlying gait disturbance in Parkinson's disease. Brain. 1999;**122**:1271-1282

[44] Nutakki C, Narayanan J, Anchuthengil AA, Nair B, Diwakar S. Classifying gait features for stance and swing using machine learning. In: 2017 Int Conf Adv Comput Commun Informatics, ICACCI 2017; 2017. DOI: 10.1109/ICACCI.2017.8125896

[45] Wu Y, Shi L. Analysis of altered gait cycle duration in amyotrophic lateral sclerosis based on nonparametric probability density function estimation. Medical Engineering & Physics. 2011;**33**:347-355

[46] Delorme A, Makeig S. EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis.

Journal of Neuroscience Methods. 2004;**134**:9-21

[47] Vaughan CL. Are joint torques the Holy Grail of human gait analysis? Human Movement Science. 1996;**15**:423-443

[48] Hall M, Frank E, Holmes G, Pfahringer B, Reutemann P, Witten IH. The WEKA data mining software. ACM SIGKDD Explorations Newsletter. 2009;**11**:10-18

[49] Mannini A, Trojaniello D, Cereatti A, Sabatini A. A machine learning framework for gait classification using inertial sensors: Application to elderly, post-stroke and Huntington's disease patients. Sensors (Basel). 2016;**16**, **134**:1-14

[50] Ye Q, Xia Y, Yao Z. Classification of gait patterns in patients with neurodegenerative disease using adaptive neuro-fuzzy inference system. Computational and Mathematical Methods in Medicine. 2018;**2018**:9831252