Real-time Gait Pattern Classification Using Artificial Neural Networks

Conference Paper · May 2022

DOI: 10.1109/MetroLivEnv54405.2022.9826927

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***Abstract*—The expression of human gait associated with neurological disorders is difficult to describe and is characterized by fluctuating predominance in the presence of complex movement patterns. The analysis of human gait patterns can provide significant information related to the physical and neurological functions of individuals, and may contribute to the diagnosis of human motor disorders in pathological conditions.**

The present study seeks to determine the classification capacity of different types of simulated abnormal gait patterns by recording the accelerations of the center of mass, the extraction of characteristics in the time and frequency domain and the classification based on the use of artificial neural networks in real time.

***Index Terms*—gait pattern, neural network**

I. Introduction

Human gait refers to the repetitive locomotion pattern of how a person walks. Although, the process appears automatic and easy, gait is actually a complex and high-level motor function [1]. The human body in a bipedal position is propelled forward, its weight being supported alternately by both lower limbs [2] [3]. This anterior displacement is directly related to the anticipatory postural activity, which establishes the dynamic conditions through specific motor activation [4]. Normal gait requires precise control of limb movements, posture, and muscle tone, an extraordinarily complex process that involves the entire nervous system [5]. When any of these components is compromised, it can generate functional gait disorders, which are both common and disabling [6]. These characteristic patterns determine that the type of gait is a first-order semiological date in the differential diagnosis of neurological disorders that affect the musculoskeletal system [2] and it is relevant to consider that it corresponds to a multi-factorial system, which means that it is influenced by variables such as body mass, gender and even other factors such as depression [7] [8], [9] which explains its high complexity, making it susceptible to a variety of underlying neurological abnormalities [5].

There are established methods using various sensors for gait analysis, of which accelerometers are one of the most often employed [10] being a reliable method for the study of bipedal balance and gait in general [11]. This bio-instrument has become a reference sensor for activity classification systems, whether on smartphones or portable recording systems [12] allowing to apply a variety of approaches or classification algorithms on the extracted acceleration signals [13].

In the present investigation, simulated normal and pathological gait patterns were classified in real time that represent balance alterations, this by extracting characteristics of the acceleration signals of the center of mass together with the use of Artificial Neural Networks with the purpose to improve the ability to identify movement disorders associated with gait.

II. Related Work

Gait analysis involves a large number of interdependent variables that are difficult to interpret. Machine learning (ML) has made it easier to assess and understand gait patterns [14]. Numerous studies have used different data classification techniques for gait analysis [15], [16]. Among the most used are: Support Vector Machines (SVM) [17] [18] [19];

Nearest Neighbor Classifier (NNC) [20] [21]; Artificial Neural Networks (ANN) [22] [23] [24]. The reported results show that supervised ML techniques achieve accuracy greater than 90% in the identification of gait patterns [14]. However, efforts to recognize gait patterns in real time are still

III. METHODS

A. Experimental protocol

The test consisted of walking on a flat surface a distance of 10 meters in a previously marked straight line. A smartphone was used as an accelerometer fixed firmly at the lumbar level by means of a velcro belt. Each subject was instructed by a clinician specialized in the area of neurorehabilitation, ensuring the quality of the gesture performed (See figure 1).

B. Dataset

A total of 10 subjects between 21 and 32 years of age, 2 female and 8 male (See table I) were evaluated. Each of them simulated different gait conditions and dynamic balance disturbances in a controlled environment supervised by an expert clinician in gait disorders. The subjects simulated each gait pattern in 10 consecutive events with a duration of 10 seconds for each recording, obtaining a total of 100 recordings for each gait pattern. Being a total of 400 records.

At the time of the evaluation, the subjects had to have no musculoskeletal or neurological alterations that would prevent functional movement. Prior to the measurements, they were asked to sign the informed consent on the evaluation to be carried out, which had been approved by the Ethics Committee of the faculty of medicine from Universidad Diego Portales (register number 40-2021).

The abnormal gaits studied correspond to Normal, Parkinsonian, Cerebellar and Hemiplegic patterns (See figure 1).

Parkinsonian gait is the characteristic gait of Parkinson's disease, characterized by presenting bradykinesia (delayed movement) with short, slow steps and problems when taking off the forefoot [25]. The parkinsonian gait is among the most common gait disorders in the elderly [5]. In the gait pattern caused by Cerebellar Ataxia, an uncoordinated progression can be observed that manifests itself with balance problems, which develops a gait with significant instability; to compensate for this, the subjects walk with a wide base of support, shorter steps, increased support phase, sacrificing the swing phase and causing a lower cadence [26]. Hemiplegic gait is the result of poor control of the flexor muscles during swing phase and spasticity of the extensor muscles acting to lengthen the affected leg. The knee is stiff, hyperextends during stance, and does not flex normally during swing [27].

C. Signal processing

The center-of-mass acceleration signals were filtered using a sixth-order Butterworth low-pass filter with a cutoff frequency of 30 Hz. For feature extraction, a 100-ms window with an 80-ms increment was used. 33 time-domain features along with 5 spectral power features were extracted (for power edges see table II).

Characteristic	Male	Female
Subject (n)	8	2
Age (years)	24.5 ± 3.51	25.5 ± 2.12
Weight (kg)	78.62 ± 7.11	74 ± 2.70
Size (m)	1.78 ± 0,05	1.635 ± 0.09
Imc (kg/m^2)	24.56 ± 1.23	27.75 ± 7.28

TABLE I
DESCRIPTION OF SAMPLE.

Features extraction by each plane
acc RMS
acc Peak 1 Height
acc Peak 2 Freq
acc Peak 2 Height
acc Peak 3 Freq
acc Peak 3 Height
acc Spectral Power 0.1 - 0.5
acc Spectral Power 0.5 - 1.0
acc Spectral Power 1.0 - 2.0
acc Spectral Power 2.0 - 5.0

TABLE II
FEATURES EXTRACTED BY EACH PLANE.

For the implementation of the model, we worked with the Edge Impulse, Inc. software. This software allows recording the movements, processing the signals, generating the classification through a neural network and exporting the model to a microcontroller or smartphone, allowing real time classification .

D. Model

The already presented features was used in order to train the model. These data were divided into a training percentage (80%) and a validation percentage (20%) in order to train and test the model. In total, 100 records were divided for each gait pattern, 80 to train and 20 to validate. A neural network with 33 inputs was implemented, 20 neurons in the first dense layer, 10 neurons in the second dense layer and four neurons in the second dense layer. output layer. A number of cycles of 30 was considered together with a learning rate of 0.0005; the cycles number was limited to 30 after the study of model loss (See Figure 3 and 4).

IV. RESULTS

The confusion matrix of the implemented model is reported, specifying the performance for each type of gait evaluated. A high sensitivity was obtained for each of the gait types. In the Cerebellar gait it was 97.0%, Hemiplegic 90.3%, Normal 99.8% and Parkinsonian 98.1% (See Figure 2). We observe that Hemiplegic is confused with cerebellar because the accelerometers signals has same type (impulse sequence).

A total precision of 96.3% was obtained along with a loss function of 0.10 for the validation stage of the study after 30 iterations (See Figure 3 and 4).

V. CONCLUSIONS

The presented model was executed and exported to a smartphone, allowing real-time evaluation of the different gait patterns. For the real-time assessment, the trained subjects were asked to execute each of the gait patterns for 10 seconds and then change the pattern for another 10 seconds until all the movement patterns included in this study had been evaluated, showing a high sensitivity.

This methodology can be used to identify characteristic gait patterns, which is why the clinical use of this model can be an additional tool to identify movement disorders. Software such as Edge Impulse allows the implementation of classification methodologies quickly, easily and at low cost.

Based on the results obtained in this research, it is necessary to incorporate different abnormal gait patterns to know the identification and classification capacity based on methodologies such as those implemented in this research. Efforts should aim to include people diagnosed with this type of pathology in these models.

VI. ACKNOWLEDGEMENTS

This collaboration was made possible thanks to a grant from the Escuela de Ingeniería Informática, Universidad de Valparaíso, Chile (grant No. 01.016/2020) and FONDECYT Regular 1201787-Multimodal Machine Learning approach for detecting pathological activity patterns in elderly and ANID MileniumScience Initiative Program NCS2021-013 and STIC-AmSud code 20-STIC- 07 and ECOS– CONICYT ECOS180054.

Finally, we want to thank the kinesiology students of Universidad Diego Portales of Chile Sebastián Parada, Gabriel Araya, María Bau and Fernanda Neira for their collaboration in this project.

REFERENCES

[1] Mansfield, P. Neumann, D. Essentials of kinesiology for the physical therapist assistant e-book. (Elsevier Health Sciences,2018)

[2] Kharb, A., Saini, V., Jain, Y. Dhiman, S. A review of gait cycle and its parameters. *Ijcem International Journal Of Computational Engineering & Management*. **13** pp. 78–83 (2011)

[3] Davis, R. Reflections on clinical gait analysis. *Journal Of Electromyography And Kinesiology*. **7**, 251–257 (1997)

[4] Massot, C., Simoneau-buessinger, E., Agnani, O., Donze, C. Leteneur, S. Anticipatory postural adjustment during gait initiation in multiple sclerosis patients: A systematic review. *Gait & Posture*. **73** pp. 180–188 (2019)

[5] Jessica m. baker. Gait Disorders. *The American Journal Of Medicine*. **131**, 602–607 (2018)

[6] Jorik nonnekes and evžen růžička and tereza serranová and stephen g. reich and bastiaan r. bloem and mark hallett. Functional gait disorders. *Neurology*. **94**, 1093–1099 (2020)

[7] Deschamps, T., Thomas-ollivier, V., Sauvaget, A., Bulteau, S., Fortes-bourbousson, M. Vachon, H. Balance characteristics in patients with major depression after a two-month walking exercise program: A pilot study. *Gait & Posture*. **42**, 590–593 (2015)

[8] Aguiar, L., Santos-rocha, R., Vieira, F., Branco, M., Andrade, C. Veloso, A. Comparison between overweight due to pregnancy and due to added weight to simulate body mass distribution in pregnancy. *Gait & Posture*. **42**, 511–517 (2015)

[9] Julien, D., Gauvin, L., Richard, L., Kestens, Y. Payette, H. Associations between walking and depressive symptoms among older adults: Do purposes and amounts of walking matter? Results from the VoisiNuAge Study. *Mental Health And Physical Activity*. **8** pp. 37–43 (2015)

[10] Delaram jarchi and james pope and tracey k. m. lee and larisa tamjidi and amirhosein mirzaei and saeid sanei., A Review on Accelerometry-Based Gait Analysis and Emerging Clinical Applications. *ieee Reviews In Biomedical Engineering*. **11** pp. 177–194 (2018)

[11] Moe-nilssen, R. Helbostad, J. Interstride trunk acceleration variability but not step width variability can differentiate between fit and frail older adults. *Gait & Posture*. **21**, 164–170 (2005)

[12] Godfrey, A., Conway, R., Meagher, D. ólaighin, G. Direct measurement of human movement by accelerometry. *Medical Engineering & Physics*. **30**, 1364–1386 (2008)

[13] Clements, C., Buller, M., Welles, A., Clements, cynthia m and buller, mark j and welles, alexander p and tharion, william j. Tharion, W. Real time gait pattern classification from chest worn accelerometry during a loaded road march. (2012)

[14] Preeti khera and neelesh kumar. Preeti khera and neelesh kumar. Role of machine learning in gait analysis: a review. *Journal Of Medical Engineering & Technology*. **44**, 441–467 (2020)

[15] Alaqtash, M., Sarkodie-gyan, T., Yu, H., Fuentes, O., Brower, R. Abdelgawad, A. Automatic classification of pathological gait patterns using ground reaction forces and machine learning algorithms. (2011)

[16] Mu, T., Pataky, T., Findlow, A., Aung, M. Goulermas, J. Automated nonlinear feature generation and classification of foot pressure lesions. *Ieee Transactions On Information Technology In Biomedicine*. **14**, 418–424 (2009)

[17] Lai, D., Levinger, P., Begg, R., Gilleard, W. Palaniswami, M. Automatic recognition of gait patterns exhibiting patellofemoral pain syndrome using a support vector machine approach. *Ieee Transactions On Information Technology In Biomedicine*. **13**, 810–817 (2009)

[18] Begg, R., Palaniswami, M. Owen, B. Support vector machines for automated gait classification. *Ieee Transactions On Biomedical Engineering*. **52**, 828–838 (2005)

[19] Begg, R. Kamruzzaman, J. A machine learning approach for automated recognition of movement patterns using basic, kinetic and kinematic gait data. *Journal Of Biomechanics*. **38**, 401–408 (2005)

[20] Mezghani, N., Husse, S., Boivin, K., Turcot, K., Aissaoui, R., Hagemeister, N. Deguise, J. Automatic classification of asymptomatic and osteoarthritis knee gait patterns using kinematic data features and the nearest neighbor classifier. *Ieee Transactions On Biomedical Engineering*. **55**, 1230–1232 (2008)

[21] Wang, L., Tan, T., Hu, W. Ning, H. Automatic gait recognition based on statistical shape analysis. *IEE Transactions On Image Processing*. **12**, 1120–1131 (2003)

[22] Köhle, M. Merkl, D. Analyzing human gait patterns for malfunction detection. (2000)

[23] Hanson, M., Powelljr, H., Barth, A., Lach, J., Hanson, mark a and powell jr, harry c and barth, adam t and lach, john and brandt-pearce, maïté. T-pearce, M. Neural network gait classification for on-body inertial sensors. (2009)

[24] Wu, W., Su, F., Cheng, Y. Chou, Y. Potential of the genetic algorithm neural network in the assessment of gait patterns in ankle arthrodesis. *Annals Of Biomedical Engineering*. **29**, 83–91 (2001)

[25] Mcmichael, G. The genetic determinants of cerebral palsy. (2016)

[26] Buckley, E., Mazzà, C. Mcneill, A. A systematic review of the gait characteristics associated with Cerebellar Ataxia. *Gait & Posture*. **60** pp. 154–163 (2018)

[27] Mcgee, S. Evidence-based physical diagnosis e-book. (Elsevier Health Sciences,2021)

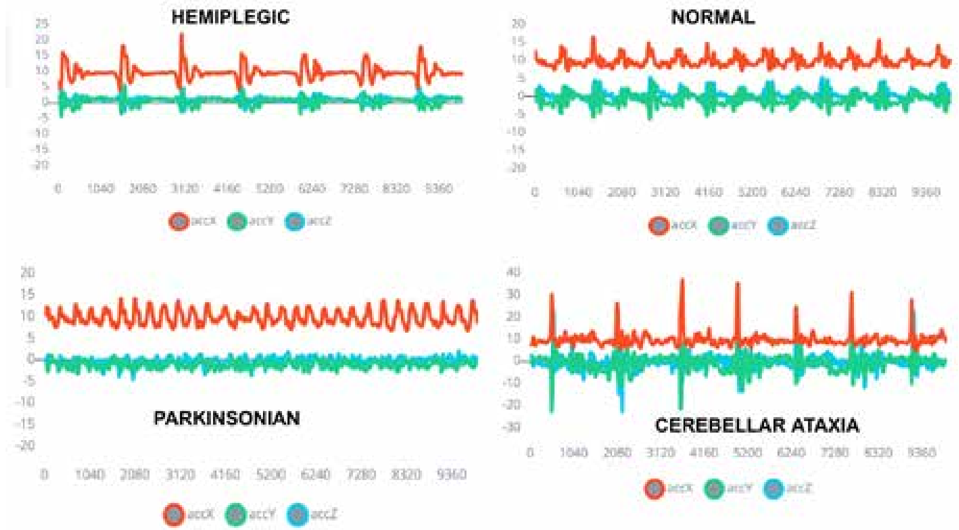

Fig. 1. Acceleration patterns in the three planes of movement of the different types of gait.

	CAREBELLAR ATAXIA	HEMIPLEGIC	NORMAL	PARKINSONIAN
CAREBELLAR ATAXIA	97.0%	2.6%	0.3%	0.1%
HEMIPLEGIC	7.2%	90.3%	2.4%	0.1%
NORMAL	0%	0.2%	99.8%	0%
PARKINSONIAN	1.0%	0.8%	0.2%	98.1%
F1 SCORE	0.95	0.93	0.98	0.99

Fig. 2. Confusion matrix for multi-class classification

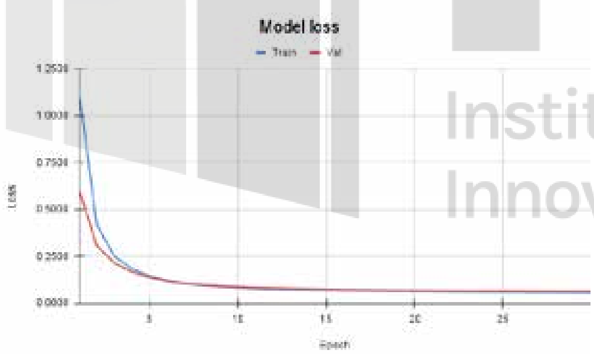

Fig. 3. Training and validation set loss function for multi-class classification.

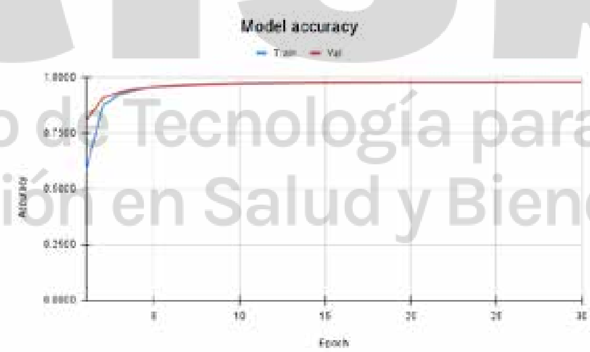

Fig. 4. Accuracy for the training and validation set for multi-class classification.