



HAL
open science

Gait deviation change prediction for patients with gait disorders using artificial intelligence

Nawel Ben Chaabane, Pierre-Henri Conze, Mathieu Lempereur, Olivier Rémy-Néris, Sylvain Brochard, Béatrice Cochener, Mathieu Lamard

► **To cite this version:**

Nawel Ben Chaabane, Pierre-Henri Conze, Mathieu Lempereur, Olivier Rémy-Néris, Sylvain Brochard, et al.. Gait deviation change prediction for patients with gait disorders using artificial intelligence. IEEE Engineering in Medicine and Biology Conference, Jul 2023, Sydney, Australia. hal-04065712

HAL Id: hal-04065712

<https://imt-atlantique.hal.science/hal-04065712v1>

Submitted on 30 Oct 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Gait deviation change prediction for patients with gait disorders using artificial intelligence

Nawel Ben Chaabane*, Pierre-Henri Conze[◊], Mathieu Lempereur[◄], Gwenolé Quéllec[▷],
Olivier Rémy-Néris[◊], Sylvain Brochard[◊], Béatrice Cochener[◊], Mathieu Lamard*

Abstract—This paper addresses gait deviation change prediction for patients with gait disorders. Two cases are predicted and referred to as two classes: the patient’s gait improves (gait deviation from normative data is reduced) within the next clinical gait analysis (CGA) session (class 1) or not (class 0). To cope with available kinematic data obtained from CGA, a two-dimensional fast Fourier transform (2D FFT) is used to build 2D frequency images. After that, fine-tuned VGG16, ResNet34 and EfficientNet_b0 are applied to these images separately. These pre-trained models showed an over-fitting behaviour. To overcome this issue, a 2D convolutional neural network (2D CNN), trained from strach and with low computational footprint, is proposed. Our model attains an area under the curve (AUC) above 0.69, which is promising for such a complex task. The achieved results demonstrate the efficiency of deep learning models and are the first of their kind regarding the state-of-the-art.

I. INTRODUCTION

Gait disorders, also referred to as gait disturbances, deal with abnormalities in the gait cycle that can cause varying compensations at the trunk, hip, knee, or ankle joint. Many types of gait disorders exist, including propulsive gait and scissors gait [1]. These disorders may significantly impact the quality of life [2] since the personal independence of patients is usually restricted. Additionally, issues with balance and gait can be precursors of falls, which are the most frequent cause of severe injuries in the elderly [3]. However, most of the time, gait disorders and falls are inefficiently evaluated, which leads to misdiagnoses [1]. Due to increased age or various diseases, gait disorders can be classified by etiology:

- neurological conditions (e.g., Parkinson’s disease patients have a propulsive gait [4])
- orthopedic problems (e.g., osteoarthritis, skeletal deformities)
- medical conditions (e.g., heart failure, respiratory insufficiency, obesity)

Diagnosing gait disorders is a challenging task. This is usually done by physical therapists using different qualitative strategies, such as observing walking patterns. Qualitative analysis is useful in clinical practice since it is fast and does not require any or a minimum amount of equipment [5].

* Nawel Ben Chaabane and Mathieu Lamard are with LaTIM UMR 1101, Université de Bretagne Occidentale, Brest, France. [◊] Pierre-Henri Conze is with IMT Atlantique and LaTIM UMR 1101, Brest, France. [▷] Gwenolé Quéllec is with Inserm, LaTIM UMR 1101, Brest, France. [◄] Mathieu Lempereur is with LaTIM UMR 1101 and CHRU de Brest, Brest, France. [◊] Olivier Rémy-Néris, Sylvain Brochard and Béatrice Cochener are with LaTIM UMR 1101, Université de Bretagne Occidentale and CHRU de Brest, Brest, France. nawel.ben-chaabane@inserm.fr.

Its reliance on a strong clinical expertise, which makes it prone to bias and limited precision, is one of its main shortcomings. To overcome this limitation, Clinical Gait Analysis (CGA) is increasingly employed. It exploits instrumentation to quantify the gait cycle by precisely and extensively recording spatio-temporal, kinematic and kinetic data. Such data enables statistical and three-dimensional analysis and comparisons between various conditions (e.g. pre-surgery versus post-surgery or treatment) and normative outcomes. In [20], a correlation was found between CGA results and accurate locomotor disorders diagnosis. Nevertheless, many challenges are raised with CGA. Clinicians are confronted with many intricate information that should be carefully exploited to make relevant personalized recommendations regarding the therapeutic strategies. This clinical information is a mixture of illness trajectories, medical interventions, and disease complications [8]. In this direction, our goal is to use artificial intelligence to help clinicians analyze the large amount of clinical information arising from CGA.

In this study, we go beyond objectively quantifying the gait’s quality by rather predicting the future gait evolution. The underlying aim is to enable clinicians selecting the best treatment plan with the aid of these predictions. Although the analysis of gait signals has already benefited from learning-based approaches (e.g., gait event detection [6]), our study is, to the best of our knowledge, the first to use deep learning to forecast how gait quality will evolve in the future. Pre-trained deep learning models, especially Convolutional Neural Network (CNN), have achieved outstanding results in computer vision and medical image analysis tasks. This motivated us to map the time representation of 1D gait signals to a 2D frequency representation. We thus propose to represent time series of kinematic data as images using two-dimensional Fast Fourier Transforms (2D FFT) [7]. In the same spirit as in [9] where a 2D CNN extracts features of FFT images computed from electrocardiogram signals towards arrhythmia classification, our approach trains a deep classification network on the resulting FFT images to automatically predict the upcoming gait deviation change. The effectiveness of the proposed approach is evaluated on a gait dataset collected from more than 700 patients.

II. MATERIALS AND METHODS

A. Data acquisition and mathematical formalism

CGA involves sophisticated instrumentation to capture full-body motion. After initial calibration in the standing position, the patient was asked to walk naturally throughout

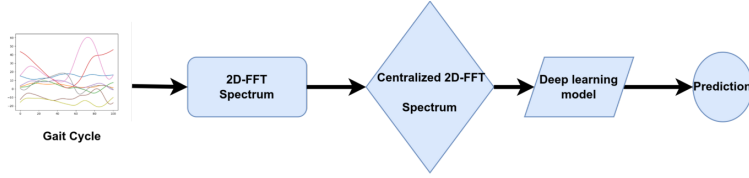


Fig. 1. Proposed gait deviation change prediction pipeline for patients with gait disorders.

the motion laboratory. The system involved in our study consisted of 16 reflective surface markers attached to the skin at the joints and several infrared cameras. These cameras estimated the 3D positions of surface markers to calculate joint angles over time [15]. Nine different joint angles (i.e., kinematic variables) were calculated with great precision. This includes pelvic anteversion/retroversion, tilt and rotation, hip flexion/extension, abduction/adduction and internal/external rotation, knee flexion/extension, ankle plantar/dorsiflexion and the foot's angle of progression [10]. For each gait cycle, 101 temporal steps per joint angle were collected. Hence, a gait cycle provided 101×9 values. A gait session is defined as a set of gait cycles. Let $E_{p,d}$ denote the gait session of patient p on date time d :

$$E_{p,d} = \{C_{E_{p,d}}^1, C_{E_{p,d}}^2, \dots, C_{E_{p,d}}^K\} \quad (1)$$

where $C_{E_{p,d}}^k$ is the k -th gait cycle from session $E_{p,d}$ and K is its total number of gait cycles. Let $c_{t,n}^{E_{p,d}^k}$ denote the gait cycle $C_{E_{p,d}}^k$ value at time t and joint angle n , respectively. To keep notations simple, $c_{t,n}^{E_{p,d}^k}$ is referred to as $c_{t,n}$ in what follows. A Gait Profile Score (GPS) was assigned to each gait cycle. The GPS was developed by Baker et al. [10] in 2009 as a walking behavior score [11]. It is a global raw score [10] of the distance between the subject and the average of healthy subjects [12] over all gait cycles [12]. Mathematically, it is a summary measure that represents the root mean square difference between the pathological kinematic data and the physiological normative data [11]. The GPS is divided into 9 Gait Variable Score (GVS) sub-scores, one per joint angle. Eq.2 gives GVS_n , the GVS of the kinematic variable n [10], [12].

$$GVS_n = \sqrt{\frac{1}{T} \sum_{t=1}^T (c_{t,n} - c_{t,n}^{-ref})^2} \quad (2)$$

where T is the total number of points of the gait cycle (101 in our database) and $c_{t,n}^{-ref}$ the mean of the kinematic variable n in the reference population at point t of the gait cycle. The GPS is obtained from the GVS scores [10]:

$$GPS = \sqrt{\frac{1}{N} \sum_{i=1}^N GVS_n^2} \quad (3)$$

where N is the total number of kinematic variables and is equal to 9. Let $(E_{p,d}, E_{p,d+\Delta d})$ be a couple of gait sessions separated by Δd . We assign a GPS variation ΔGPS to each gait cycle $C_{E_{p,d}}^k$ of the current examination $E_{p,d}$ as follows:

$$\Delta GPS(C_{E_{p,d}}^k) = GPS_{average}(E_{p,d+\Delta d}) - GPS(C_{E_{p,d}}^k) \quad (4)$$

where $GPS_{average}(E_{p,d+\Delta d})$ is the average GPS per cycle of $E_{p,d+\Delta d}$ and $GPS(C_{E_{p,d}}^k)$, the GPS of the current gait cycle $C_{E_{p,d}}^k$. An examination's average GPS per cycle $GPS_{average}(E_{p,d})$ is simply equal to:

$$GPS_{average}(E_{p,d}) = \frac{\sum_{k=1}^K GPS(C_{E_{p,d}}^k)}{K} \quad (5)$$

B. Gait database

734 patients (115 adults) were involved in our study. The average patient age within the first gait session is equal to 14 years, with a standard deviation of 16 years. Neurological conditions, notably cerebral palsy, are the most frequent etiologies. 53693 gait cycles were collected in total. Their average number per gait session is equal to 18 with a standard deviation of 6. The average number of sessions per patient was 1.988 (with a standard deviation of 1.515). The average time delay between two consecutive sessions was approximately equal to 740 days, with a standard deviation of 577 days. The shortest (resp. longest) Δd was equal to 4 (resp. 4438) days. In our dataset, we had 1384 pairs of consecutive examinations belonging to 319 patients (the remaining patients had only one session and were therefore excluded). To make the ΔGPS prediction possible, it was necessary to consider the same gait conditions (e.g., without any equipment, with a cane, with a rollator, with an orthosis, with prosthesis) for both CGA. Thus, we selected pairs of examinations acquired without any equipment (79% of all available pairs, i.e. 1152). For our prediction task, we exploited 21167 gait cycles from the first sessions of available pairs. ΔGPS was ranked in a binary fashion. Either it is negative, in which case the patient's gait improves (class 1), or positive when the patient's gait worsens (class 0).

C. Proposed method

The full proposed pipeline is shown in Fig.1. By converting temporal kinematic data into 2D images, CNN models are allowed to extract distinctive features that are not achievable when exploiting 1D temporal data [16]. On the other hand, pre-trained networks have recently generated interest for use in a variety of applications outside their initial domain [17]. These highly accurate networks are applicable to time series with a little variation. To achieve this goal, it is necessary to produce informative images from signals [17]. Besides, encoding time series as images enables the use of efficient data augmentation techniques [13]. In our study,

TABLE I

PATIENT DISTRIBUTION AMONG THE GAIT DATABASE.

Train	Validation	Test
224 patients	48 patients	47 patients
15509 cycles	2678 cycles	2980 cycles
844 pairs	142 pairs	166 pairs
54.39 % of class 1	54.11 % of class 1	55.60 % of class 1

2D FFT images were used in order to extract new patterns from the frequency representation of the kinematic data. The distribution of patients between training, validation, and test subsets is provided in Tab.I.

1) Two-dimensional Fast Fourier Transform (2D FFT):

2D FFT is a common approach for mapping signals into the frequency representation. Due to its time shift invariance, 2D FFT is regarded as the best transformation between the time and frequency domains among spectrum analysis approaches [13]. It simply involves several one-dimensional Fourier transforms. Each value in the signal is assigned to a single pixel [14]. The 2D FFT is performed following:

$$F(u, v) = \frac{1}{T \cdot N} \sum_{t=0}^T \sum_{n=0}^N c_{t,n} \exp(-j2\pi(\frac{ut}{T} + \frac{vn}{N})) \quad (6)$$

where $F(u, v)$ is the direct Fourier transform of the image. It is a complex function that shows the phase and magnitude of the signal in the frequency domain. u, v are the frequency space coordinates. $c_{t,n}$ is the initial pixel value of the image in the spatial domain. The spectrum, or magnitude, of the 2D FFT $|F(u, v)|$ is a two-dimensional signal that carries frequency information. It can be seen as an image. Centralized spectra are obtained by shifting the zero-frequency component to the center. This can be done without any information loss since the 2D FFT has translation and rotation attributes. A centralized spectrum image is more visible than a standard FFT spectrum since white region displays high energy in the low frequency range. For our prediction task, centralized FFT spectra were employed. First, we considered our gait cycles, with their 101×9 representation in the time domain. Then, a 2D FFT was performed on them, as well as the magnitude of the 2D FFT, yielding a 101×9 frequency domain representation. This representation can be considered as a 2D image that we shifted to the center in order to have the centralized FFT spectra. A centralized FFT spectrum for a given gait cycle is represented in Fig.2.

2) Proposed deep learning models:

a) *Timm pre-trained models:* The Timm library’s [18] pre-trained VGG16, ResNet34, and EfficientNet_b0 were considered. They support any number of input channels, so we did not need to reshape our 2D grayscale image into an RGB image. For VGG16, the required minimum input size of the model is 32×32 . The width dimension of the image (N) is equal to 9, which is less than 32. Image were therefore repeated 4 times in this width dimension to

TABLE II

QUANTITATIVE RESULTS. BEST RESULTS IN BOLD.

Architecture	Number of parameters	val AUC	test AUC
VGG16	134,263,489	0.650	0.642
ResNet34	21,278,913	0.653	0.679
EfficientNet_b0	4,008,253	0.637	0.628
CNN	35,505	0.726	0.693

match the minimum required size. Transfer learning with fine-tuning techniques was used for our prediction task. The last fully connected layer of one neuron was utilized as the output layer for the prediction task. All convolutional blocks were trainable, as it is the case with top layers.

b) *Two-dimensional 2D CNN:* The pre-trained Timm models showed an overfitting behaviour with fast convergence, as we can see in Fig.3 for EfficientNet_b0. Therefore we decided to test a CNN model that we have developed from scratch. A certain number of two-dimensional convolutional layers was used. This was a hyper-parameter to optimize in a set of finite values $\{1, 2, 3, 4, 5\}$. The convolutional layers were followed by a dropout function. After that, two-dimensional max-pooling (MaxPooling2D) and batch normalization were applied. Then, the output of the batch normalization was flattened and sent to a dense layer of a certain number of neurons to tune. The output layer of our model is a dense one with a single neuron in order to predict the ΔGPS . In total, the architecture hyper-parameters to tune are as follows: the number of convolutional layers (referred to as num_layers), the number of filters of each convolution layer (num_filters), the kernel size of each convolution layer (kernel_size), the dropout rate (dropout), the pooling size of the 2D max pooling operations (pool_size), the number of neurons in the dense layer (units) and the learning rate (lr). We tested five models with a varying number of convolutional layers (from 1 to 5). For each of these five architectures, we tuned the rest of the hyper-parameters using KerasTuner [19] to maximize the validation AUC.

III. RESULTS AND DISCUSSIONS

In this section, we present the results for our prediction task. Area Under the curve (AUC) scores obtained on the validation set and on the test set are referred to as val AUC and test AUC, respectively. Tab.II presents the results obtained with the proposed architectures.

Not surprisingly, results on the test set are almost the same as those obtained on the validation set. The tested Timm models give similar results, all of them achieved a val AUC above 0.63. The CNN trained from scratch is the most efficient model, with a val AUC equal to 0.726. It has two convolutional layers and the following values of hyper-parameters: num_filters = 4, kernel_size = 32, dropout = 0, pool_size = 8, units = 300 and lr = $4,127 \times 10^{-4}$. The overfitting issue persists, AUC on train set is significantly higher than val AUC. This is due to the lack of kinematic data, although we have drastically reduced the number of parameters. We strongly believe that the CNN outperforms the pre-trained Timm models for two reasons. First, our

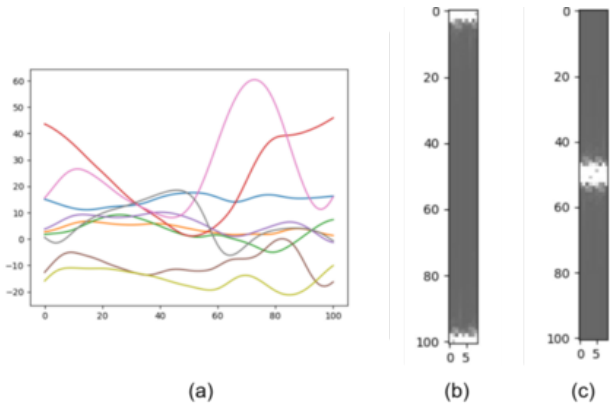


Fig. 2. 2D FFT for a given gait cycle. (a) The gait cycle; (b) FFT spectrum of the gait cycle; (c) Centralized FFT spectrum of the gait cycle.

dataset is relatively small. Second, Timm models were pre-trained on a classification task involving a set of images totally different from our synthetic 2D FFT images.

IV. CONCLUSION

Obtained results are interesting for a prediction task on data with numerous sources of disparity and randomness. The forecasting of future medical outcomes may be considerably harder than the traditional classification of items into categories, given its inherent uncertainty in unseen interleaved events [8]. To the best of our knowledge, our study is the first to use artificial intelligence algorithms in order to predict gait deviation evolution. Other time series imaging techniques, with less information loss, could be considered as well. In addition, it is crucial to note the impact of age on the prediction task. This constitutes a potential limitation of our study. In future work, we will intend to model all the historical sessions in order to provide more precise predictions.

ACKNOWLEDGMENTS

This study received funding from the Brittany region, as part of the ARED program and from the French government via the national research agency (Agence Nationale de la Recherche) as part of the investment program for the future (programme Investissement d’Avenir), under the reference ANR-17-RHUS-0005 (FollowKnee project).

REFERENCES

- [1] Walter Pirker and Regina Katzenschlager. Gait disorders in adults and the elderly. *Wiener Klinische Wochenschrift*, 129(3):81–95, 2017.
- [2] Philipp Mahlknecht, Stefan Kiechl, Bastiaan R Bloem, Johann Willeit, Christoph Scherfler, Arno Gasperi, Gregorio Rungger, Werner Poewe, and Klaus Seppi. Prevalence and burden of gait disorders in elderly men and women aged 60–97 years: a population-based study. *PLoS one*, 8(7):e69627, 2013.
- [3] Lewis Sudarsky. Gait disorders: prevalence, morbidity, and etiology. *Advances in neurology*, 87:111–117, 2001.
- [4] Cecilia Raccagni, Jorik Nonnekes, Bastiaan R Bloem, Marina Peball, Christian Boehme, Klaus Seppi, and Gregor K Wenning. Gait and postural disorders in parkinsonism: a clinical approach. *Journal of Neurology*, 267(11):3169–3176, 2020.

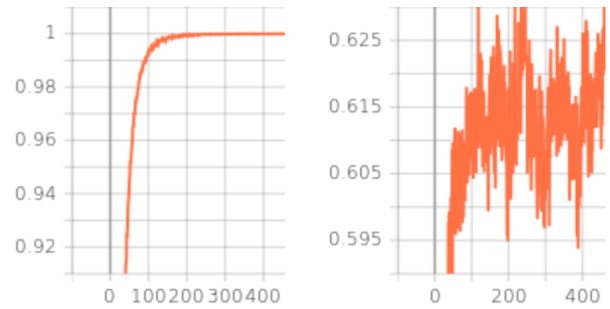


Fig. 3. AUC curves for 400 epochs on both train and validation sets (from left to right) using EfficientNet_b0.

- [5] Florent Moissenet and Stéphane Armand. Qualitative and quantitative methods of assessing gait disorders. *Orthopedic management of children with cerebral palsy: a comprehensive approach*, pages 215–239, 2015.
- [6] Mathieu Lempereur, François Rousseau, Olivier Rémy-Néris, Christelle Pons, Laetitia Houx, Gwenolé Quellec and Sylvain Brochard. A new deep learning-based method for the detection of gait events in children with gait disorders: Proof-of-concept and concurrent validity. *Journal of Biomechanics*, 98:109490, 2020.
- [7] Richard Tolimieri, Myoung An and Cha Lu. Mathematics of multi-dimensional Fourier transform algorithms. 2012.
- [8] Trang Pham, Truyen Tran, Dinh Phung, and Svetha Venkatesh. Deepcare: A deep dynamic memory model for predictive medicine. In *Pacific-Asia conference on knowledge discovery and data mining*, pages 30–41. Springer, 2016.
- [9] Sudipta Singha Roy, Mahtab Ahmed, and Muhammad Aminul Haque Akhand. Noisy image classification using hybrid deep learning methods. *Journal of Information and Communication Technology*, 17(2):233–269, 2018.
- [10] Richard Baker, Jennifer L McGinley, Michael H Schwartz, Sarah Beynon, Adam Rozumalski, H Kerr Graham, and Oren Tirosh. The gait profile score and movement analysis profile. *Gait & posture*, 30(3):265–269, 2009.
- [11] Josef Christian, Josef Kröll, and Hermann Schwameder. Comparison of the classifier oriented gait score and the gait profile score based on imitated gait impairments. *Gait & Posture*, 55:49–54, 2017.
- [12] Gabor J Barton, Malcolm B Hawken, Mark A Scott, and Michael H Schwartz. Movement deviation profile: A measure of distance from normality using a self-organizing neural network. *Human movement science*, 31(2):284–294, 2012.
- [13] Zhiguang Wang and Tim Oates. Imaging time-series to improve classification and imputation. In *Twenty-Fourth International Joint Conference on Artificial Intelligence*, 2015.
- [14] E Oran Brigham. *The fast Fourier transform and its applications*. Prentice-Hall, Inc., 1988.
- [15] Ge Wu, Peter R Cavanagh, et al. Isb recommendations for standardization in the reporting of kinematic data. *Journal of biomechanics*, 28(10):1257–1262, 1995.
- [16] Zeeshan Ahmad and Naimul Mefraz Khan. Multidomain multimodal fusion for human action recognition using inertial sensors. In *2019 IEEE Fifth International Conference on Multimedia Big Data (BigMM)*, pages 429–434. IEEE, 2019.
- [17] Saeedeh Zebhi. Human activity recognition using wearable sensors based on image classification. *IEEE Sensors Journal*, 2022.
- [18] Ross Wightman. Pytorch image models. <https://github.com/rwightman/pytorch-image-models>, 2019.
- [19] Tom O’Malley, Elie Bursztein, James Long, François Chollet, Haifeng Jin, Luca Invernizzi, et al. Kerastuner. <https://github.com/keras-team/keras-tuner>, 2019.
- [20] Soo Chan Kim, Joo Yeon Kim, Hwan Nyeong Lee, Hwan Ho Lee, Jae Hwan Kwon, Mi Joo Kim, Jong Hyun Hwang, Gyu Cheol Han, et al. A quantitative analysis of gait patterns in vestibular neuritis patients using gyroscope sensor and a continuous walking protocol. *Journal of neuroengineering and rehabilitation*, 11(1):1–9, 2014.