

# High-Frequency Spectral Energy Map Estimation Based Gait Analysis System Using a Depth Camera for Pathology Detection

Didier Ndayikengurukiye and Max Mignotte<sup>(✉)</sup>

Département d'Informatique et de Recherche Opérationnelle (DIRO),  
Université de Montréal, Montréal, QC, Canada  
{ndayiked,mignotte}@iro.umontreal.ca

**Abstract.** This paper presents a new and simple gait analysis system, from a depth camera placed in front of a subject walking on a treadmill, capable of detecting a healthy gait from an impaired one. Our system relies on the fact that a normal or healthy walk typically exhibits a smooth motion (depth) signal, at each pixel with less high-frequency spectral energy content than an impaired or abnormal walk. Thus, the estimation of a map showing the location and the amplitude of the high-frequency spectral energy (HFSE), for each subject, allows clinicians to visually quantify and localize the different impaired body parts of the patient and to quickly detect a possible disease. Even if the HFSE maps obtained are clearly intuitive for a rapid clinical diagnosis, the proposed system makes an automatic classification between normal gaits and those who are not with success rates ranging from 88.23 % to 92.15 %.

**Keywords:** Gait analysis · Spectral energy · Map estimation · Pathology detection · Kinect

## 1 Introduction

The human gait movement is an essential and complex process of the human activity and also a remarkable example of collaborative interactions between the neurological, articular and musculoskeletal systems working effectively together. When everything is working properly, the healthy locomotor system produces a stable gait and a highly consistent, symmetric (nice) walking pattern [7, 11].

This is why human gait impairment is often an important (and sometimes the first) clinical manifestation and indication of various medical disorders. In fact, abnormal or atypical gait can be caused by different factors, either orthopedic (hip injuries, bone malformations, etc.), muscular (weakness, dystrophy, fiber degeneration, etc.), neurological (Parkinson's disease, stroke [2], spinal stenosis, etc.) or neuropsychiatric (autism, schizophrenia, etc.). As a consequence, gait analysis is important (because possibly highly informative) and increasingly used nowadays for the diagnosis of many different types (and degrees) of diseases.

In addition, it also exploited as a reliable and accurate indicator for early detection (and follow-up) of a wide range of pathologies.

In this field, the value of sophisticated, marker-based, video-based gait analysis is well established and have also proved their efficiency. Nevertheless, in order to be used, as an early (and fast) diagnostic tool, it is now important to design a reliable and accurate imaging system that is also inexpensive, non-invasive, fast, easy to set up and suitable for small room and daily clinical [3, 4, 15] (or home [6]) usage. This has now become possible thanks to the recent technological progress in depth sensor technology. In this paper, we focus on this kind of approach and introduce a new gait analysis system with the above mentioned advantages and characteristics over more sophisticated approaches. This new gait analysis system aims at distinguishing the healthy (human) gait from the impaired ones. In addition, our system localizes the affected body side of the patient and quantify the patients' gait pattern abnormality or alterations of a human subject. We hope this approach will be exploited, for example, as a good indicator or as a first interesting screening for a possible (orthopedic, muscular or neurological) disease, prior to a more thorough examination by a specialist doctor.

## 2 Previous Work

Current gait analysis systems can be performed with or without markers. Among the marker-based, gait analysis approaches, we can mention the sophisticated Vicon motion-tracking and capture system [1] which offers millimeter resolution of 3D spatial displacements. On one hand, this system is very accurate. On the other hand, the high cost of this system (which consists in real-time tracking multiple infrared red (IR) reflective markers with multiple IR cameras [14]), inhibits its widespread usage for routine clinical practices (since it requires lots of space, time, and expertise to be installed and used).

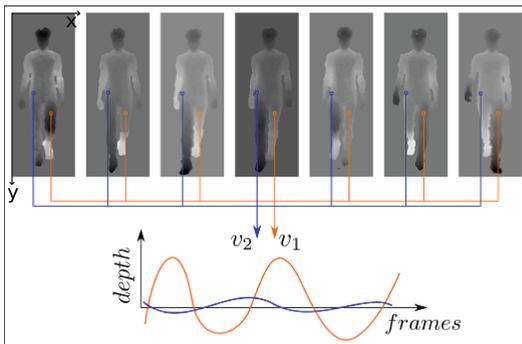
Therefore, marker-less systems are a promising alternative for clinical environments and are often regarded as easy-to-set-up, easy-to-use, and non-invasive. They are either based on stereo-vision [9], structured light [16], or time-of-flight (TOF) [8] technologies. Although low-cost, the setup and calibration procedure of these systems remain complex. Besides, stereo vision-based systems [10] are not guaranteed to work well if the patient's outfit lacks texture.

An interesting alternative is to use the recent Kinect<sup>TM</sup> sensor which is based on structured light combined with machine learning technology and two other computer vision techniques; depth from focus and depth from stereo. The Kinect<sup>TM</sup> is robust to texture-less surfaces, accurate and remains also compact and very affordable. This new sensor is able to real-time provide an image sequence where the value of each pixel is proportional to the inverse of the depth at each pixel location with a good accuracy. As interesting feature, the Kinect<sup>TM</sup> camera is also capable to offer (*via* a machine learning subsystem) a real-time estimation of a set (of 20) 3D points representing the different joints of the human body (by selecting the skeleton *mode* of this sensor). This rough skeleton model was exploited by some authors [5, 6] in order to measure spatial-temporal

gait variability (such as the stride duration, speed, etc.) and are compared to those obtained with the high-end Vicon MX system. They found that the Kinect was capable of providing accurate and robust results for some gait parameters, but further research is under way to see if these parameters can be subsequently used for a reliable gait analysis and classification system.

Amongst the existing gait analysis system which are based on a direct analysis of a depth map (related to a human walking session on a treadmill), and recorded by a Kinect<sup>TM</sup>, as the system proposed in this work (see Fig. 1), we can cite the feasibility study proposed in [15] and tested on 6 subjects. In this work, the authors simply computed the mean of the obtained depth image sequence (over a gait cycle or a longer period) in order to compress the gait image sequence into a single image which was finally called a depth energy image (DEI). Through this DEI image, the authors were able to distinguish both visually and quantitatively (through the measurement of asymmetry indexes) an abnormal gait and more precisely possible asymmetries in the gait pattern (a symmetric walk generating a DEI exhibiting a symmetric silhouette, in terms of mean depth and conversely). In the same spirit, the authors in [3] propose to quantify the possible asymmetries between the two depth signals of the legs by first dividing each gait cycle in two sub-cycles (left and right steps), and by comparing these two sub-cycles, in terms of depth difference, after a rough spatial and temporal registration procedure. In fact, the two above-mentioned studies use (with many other studies) the notion of possible asymmetry between the depth signals of the legs or, more precisely, the amplitude difference between the right and left legs obtained by the two phases of the gait cycle, as main and relevant measure, for an abnormal or impaired human gait.

Nevertheless, this asymmetry measure should rather be computed, not directly on the pixel-wise depth signals (recorded by the depth sensor) but rather on some interesting features of this depth signal. In the case of an abnormal or impaired human gait, the depth signal exhibits, in time (and for some pixels, often located at the lower limbs), a continuous but (possibly locally) rugged, unsmooth depth signal or function describing in fact, an irregular leg motion (chaotic, unstable with



**Fig. 1.** Example of two depth signals for a gait cycle of an human subject: pixel on the hip (blue curve) and pixel on the thigh (orange curve). (Color figure online)

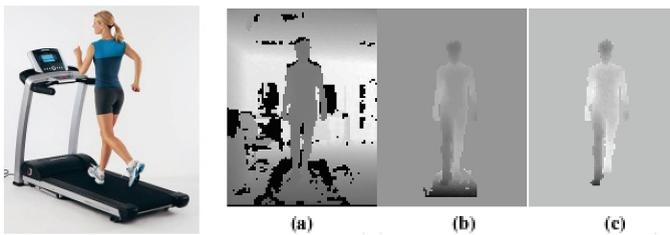
possible sharp transitions with even singularities in time like shock waves or discontinuities eventually sometimes caused by pain due to physical damage or without pain caused by neurological damage. In this case, the unsmooth behavior of the depth signal comprises some high-frequency harmonics that we can detect and eventually on which we can then compute some asymmetry indexes.

More precisely, in our application we have decided to quantify the atypical gait by exploiting asymmetry measures computed on a map exhibiting the high-frequency spectral (energy) content of the depth signal of each pixel as interesting and spectral more informative feature of the raw depth signal.

### 3 Data Description and Pre-processing

For the experiments, 17 (healthy) subjects (young male adults,  $26.7 \pm 3.8$  years old,  $179.1 \pm 11.5$  cm height and  $75.5 \pm 13.6$  kg with no reported gait issues) were asked to walk normally on a treadmill (Life Fitness F3) with or without simulated length leg discrepancy (LLD). Every subject had to walk normally (group A), then with a 5 cm sole, impairing the normal walk, under the left foot (group B), then with the sole under the right foot (group C). After a habituation period of about 2 min, their normal speed was determined and their gait movement was simultaneously recorded using an inexpensive commercial Kinect<sup>TM</sup> depth camera placed in front of the subject. The Kinect sensor outputs 30 depth maps per second (30 *fps*), with a resolution of 640 per 480 pixels and for all sequences, the same relative position and distance between the treadmill and the sensor were kept constant in order for the human subject to be located within the same image area. Therefore, the dataset contains 51 different video sequences of a human walk (of approximately 5 min long and containing around 180 gait cycles) with or without a simulated length leg discrepancy (LLD) issue which will be analyzed by our automatic gait analysis system. The institutional ethics review board approved the study.

Since the scene took place in a non-cluttered room where the treadmill is in the same position relatively to the camera, a silhouette extraction strategy (background and treadmill removal) can be easily defined as proposed in [12]. Finally, each sequence is filtered with ( $3 \times 3 \times 3$ ) median filter to reduce the noise level, while preserving the important image (sequence) features, i.e., spatial or depth discontinuities (see Fig. 2).



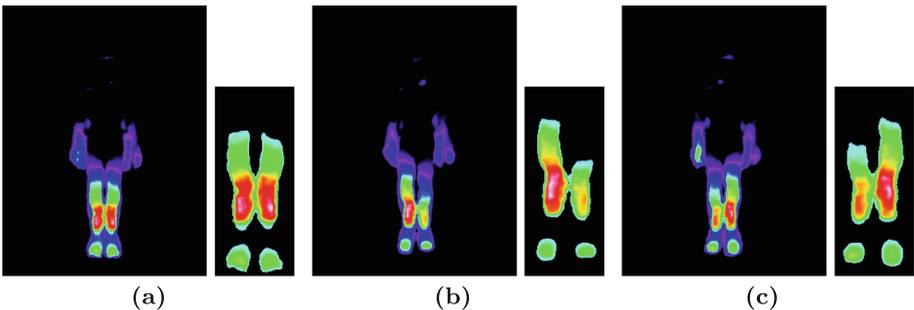
**Fig. 2.** Setup and pre-processing steps: (a) Original depth map, (b) After the background removal, (c) After the treadmill removal and contrast adjustment.

## 4 Proposed Model

Our model is based on the idea that, for a normal gait, the depth signal of each pixel of a human subject is smooth with little discontinuity. Conversely for a pathological gait (*i.e.*, associated to a possible pathology), the (pixel-wise) depth signal is not so smooth and exhibits some discontinuities which are in fact expressed by a greater amplitude of its high-frequency spectral energy.

Formally, let  $s_p(t)$  be the depth signal of the pixel  $p$ . We compute the energy of the Fourier Transform of each pixel's depth signal to obtain  $|S_p(\nu)|^2$ . This energy spectrum is then high-pass filtered (by setting to zero all the energy values associated with frequencies that are less than a threshold  $\tau$ ,  $\tau = 8$  obtained by trial and error in our case) in order to estimate the high-frequency spectral energy (HFSE) content at each location of the gait movement. In order to highlight some relevant features on this HFSE map, this one is then thresholded (by setting to zero all energy value below  $\rho = 85$ ) in order to better localize the areas with a HFSE content (in terms of size, shape and difference between the left and right legs). In the case of a pathological gait, the unsmooth behavior of a depth signal comprises some high-frequency harmonics showing areas of high energy values that we can easily detect especially when this map is shown in pseudo colors (see Fig. 3). In addition, this allows the clinician to visually quantify and localize the different impaired body parts of the patient.

In order to now automatically classify a healthy gait from an impaired one, we extract three relevant features on this map at the lower limb level (between  $1/2H$  and  $1/4H$  with  $H$  the image height). These features are mainly based on the difference of the HFSE content between the left and right legs since visually, we can differentiate a healthy gait from an impaired one from the asymmetry between these two areas. To this end, we first calculate the axis of symmetry of the map (see the algorithm in Appendix) and let  $L$  and  $R$  be respectively the area occupied by the pixels whose energy values are non-zero and are located to the left (and right) of the axis of symmetry of the image of HFSE. The first



**Fig. 3.** HFSE maps for the S15 subject: (a) Without heel (and thresholded HFSE map at lower limbs) (b) Heel under left foot (and thresholded HFSE map at lower limbs) (c) Heel under right foot (and thresholded HFSE map at lower limbs).

considered feature is  $\frac{L}{L+R}$ , the second feature is  $\frac{R}{L+R}$  and the third is  $2 \times \frac{L}{R}$ . We have normalized the first two features because the silhouettes of the subjects are usually not the same size. In addition, we have doubled the ratio to strengthen small differences between some ratio. These three features are used to train and test the Gaussian Naive Bayes (GNB), the k-Nearest Neighbors (k-NN), the Logistic Regression (LR) and the Support Vector Machine (SVM) classifiers.

## 5 Experimental Results

We performed experimentations on all 17 subjects and obtained 3 HFSE maps for each one. We treated these maps as it is shown by Fig. 3 for subject S15. As we can see, the classification of the maps in two categories (pathological or not) or in three categories (without heel, heel under left foot or heel under right foot) is easy for a human operator. Table 1 shows the value of the three features computed on the S15 thresholded HFSE map at lower limbs.

Finally, we did the classification using the Gaussian Naive Bayes (GNB), the k-Nearest Neighbors (k-NN), the Logistic Regression (LR) and Support Vector Machine (SVM) (with linear, polynomial[degree = 3], radial basis function[RBF] and sigmoid function as kernel function respectively) classifiers. We use the library from Pedregosa et al. [13] for all the four classifiers. Because we have a relatively small number of maps, we ordered the 51 maps randomly and we take one as a test set and the rest as training set. We repeat the process for all the maps and at the end we average the results (leave one cross-validation). Other experiments are made by dividing the 51 maps into k parts. Each of the k parts is taken as a test set and the k-1 others as training set. We also made the average of the results (k-fold cross-validation). The classification results are shown in Table 2 for the logistic regression and SVM models because we kept the classifiers giving the best performance (SVM best kernel: cubic polynomial).

**Table 1.** Features for the S15 subject

	Normalized left area $\frac{L}{L+R}$	Normalized right area $\frac{R}{L+R}$	Double ratio $2 \times \frac{L}{R}$
Without heel: A	0.52	0.48	2.16
Heel under left foot: B	0.62	0.38	3.29
Heel under right foot: C	0.42	0.58	1.44

**Table 2.** Classification success rate of 51 HFSE maps of 17 subjects in two classes (normal or not) and in three classes (A, B, C) for logistic regression (left) and support vector machine (right) (LOOCV: Leave one out cross-validation, k: k-fold cross-validation)

	2 classes 3 classes			2 classes 3 classes	
LOOCV	90.20%	88.24%	LOOCV	92.16%	88.24%
$k = 5$	86.36%	88.36%	$k = 5$	88.36%	88.36%
$k = 4$	86.06%	88.46%	$k = 4$	84.62%	88.46%
$k = 3$	86.28%	88.24%	$k = 3$	66.67%	88.24%

## 6 Conclusion

In this paper, we have presented a new gait analysis system that is low cost, marker-less, non-invasive, simple to install and requiring a small room. The estimation of a map showing the location and the amplitude of the high-frequency spectral energy, obtained from each subject, allows the clinician to visually quantify and localize the different impaired body parts of the patient. We hope this approach will be exploited, for example, as a good indicator or as a first interesting screening for a possible (orthopedic, muscular or neurological) disease, prior to a more thorough examination by a specialist doctor. The proposed system is also capable to automatically classify between healthy patients and those who are not and to automatically localize the impaired body parts of the patient (right or left) with success rates ranging from 88.23% to 92.15% for SVM and 88.23% to 90.19% for logistic regression on test data.

## A Appendix: Algorithm

**Estimation of the Asymmetry Indexes**

---

$I$  Thresholded high frequency spectral energy map (size:  $height \times width$ ) of the depth signal of each pixel at lower limb (Input)

$AI_j$  Asymmetry indexes of  $I$  ( $j \in \{1, 2, 3\}$ ) (Output)

$r$  Size of the search interval

$G_I$  Gradient magnitude map of  $I$

Vct Vector of floats of size  $height$

$x_{sym}$  Column coordinate estimation of the longitudinal axis

**Initialization** :  $G_I \leftarrow$  gradient magnitude map of  $I$

**1. Longitudinal Axis Estimation**

▷ for each  $i \in [0, \dots, height]$  do

- grdMax  $\leftarrow$  0
- for each  $j \in [(width/2) - r, \dots, (width/2) + r]$  do
  - for each  $m \in [0, \dots, width/2]$  do
    - grd  $\leftarrow G_I[i][j - m] + G_I[i][j + m]$
    - if (grd > grdMax) { pos  $\leftarrow$   $j$  grdMax  $\leftarrow$  grd }
- Vct[ $i$ ]  $\leftarrow$  pos

▷  $x_{sym} \leftarrow$  median value of the vector elements Vct[]

**2. Estimation of the Asymmetry Indexes**

- $L, R \leftarrow$  Number of pixels located to the left (for L) and to the right (for R) of  $x_{sym}$  with a non-zero value

▷  $AI_1 \leftarrow L/L + R$     $AI_2 \leftarrow R/L + R$     $AI_3 \leftarrow 2L/R$

## References

1. Motion capture systems from vicon. <http://www.vicon.com/>
2. Alexander, L.D., Black, S.E., Patterson, K.K., Gao, F., Danells, C.J., Mclroy, W.E.: Association between gait asymmetry and brain lesion location in stroke patients. *Stroke* **40**(2), 537–544 (2009)
3. Auvinet, E., Multon, F., Meunier, J.: Lower limb movement asymmetry measurement with a depth camera. In: 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 6793–6796, August 2012
4. Carse, B., Meadows, B., Bowers, R., Rowe, P.: Affordable clinical gait analysis: an assessment of the marker tracking accuracy of a new low-cost optical 3d motion analysis system. *Physiotherapy* **99**(4), 347–351 (2013). <http://www.science-direct.com/science/article/pii/S0031940613000266>
5. Clark, R.A., Bower, K.J., Mentiplay, B.F., Paterson, K., Pua, Y.H.: Concurrent validity of the microsoft kinect for assessment of spatiotemporal gait variables. *J. Biomech.* **46**(15), 2722–2725 (2013)
6. Gabel, M., Gilad-Bachrach, R., Renshaw, E., Schuster, A.: Full body gait analysis with kinect. In: 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 1964–1967. IEEE (2012)
7. Hamill, J., Bates, B., Knutzen, K.: Ground reaction force symmetry during walking and running. *Res. Q. Exerc. Sport* **55**(3), 289–293 (1984)
8. Hansard, M., Lee, S., Choi, O., Horaud, R.: *Time-of-Flight Cameras*. Springer, Heidelberg (2013)
9. Lazaros, N., Sirakoulis, G.C., Gasteratos, A.: Review of stereo vision algorithms: from software to hardware. *Int. J. Optomechatronics* **2**(4), 435–462 (2008)
10. Leu, A., Ristic-Durrant, D., Graser, A.: A robust markerless vision-based human gait analysis system. In: 2011 6th IEEE International Symposium on Applied Computational Intelligence and Informatics (SACI), pp. 415–420 (May 2011)
11. Loizeau, J., Allard, P., Duhaime, M., Landjerit, B.: Bilateral gait patterns in subjects fitted with a total hip prosthesis. *Arch. Phys. Med. Rehab.* **76**(6), 552–557 (1995)
12. Moevus, A., Mignotte, M., de Guise, J., Meunier, J.: Evaluating perceptual maps of asymmetries for gait symmetry quantification and pathology detection. In: 36th International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC 2014, Chicago, Illinois, USA, August 2014
13. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, É.: Scikit-learn: machine learning in python. *J. Mach. Learn. Res.* **12**, 2825–2830 (2011)
14. Potdevin, F., Gillet, C., Barbier, F., Coello, Y., Moretto, P.: The study of asymmetry in able-bodied gait with the concept of propulsion and brake. In: 9th Symposium on 3D Analysis of Human Movement, Valenciennes, France (2006)
15. Rougier, C., Auvinet, E., Meunier, J., Mignotte, M., de Guise, J.A.: Depth energy image for gait symmetry quantification. In: 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC, pp. 5136–5139. IEEE (2011)
16. Salvi, J., Pages, J., Batlle, J.: Pattern codification strategies in structured light systems. *Pattern Recogn.* **37**(4), 827–849 (2004)