



High-frequency spectral energy map estimation based gait analysis system using a depth camera for pathology detection **Didier Ndayikengurukiye & Max Mignotte**

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Abstract We present 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%.



Classification

We did the classification using the Gaussian Naive Bayes (GNB), the k-Nearest Neighbors (k-NN), the Logistic Regres-

Introduction

The human gait movement is an essential and complex process, and is 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 [1], [2]. 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 highfrequency spectral energy.

Data Description and Pre-Processing

17 (healthy) subjects (young male adults, 26.7 ± 3.8 years old, 179.1 ± 11.5 cm height and 75.5 ± 13.6 kg with no reported gait issues) were asked to walk on a treadmill (Life Fitness F3) with or without simulated length leg discrepancy (LLD). After a habituation period of about 2 min, their normal speed was determined and their gait movement was simultaneously recorded using an inexpensive commercial KinectTM placed in front of the subject (see Figure 1). 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)[3].

Figure 2: 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).

Experimental Results

Maps estimation

We performed experimentations on all 17 subjects and obtained 3 HFSE maps for each one. We treated these maps as it is shown by Figure 3 for subject S15.



sion (LR) and Support Vector Machine (SVM), radial basis function[RBF] and sigmoid function as kernel function respectively) classifiers. We use the library from Pedregosa et al. [4] 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 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 crossvalidation, 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%

Conclusion

• New gait analysis system that is low cost, marker-less, non-

Method

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 $\tau = 8$) in order to estimate the highfrequency 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 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: this allows the clinician to visually quantify and localize the different impaired body parts of the patient.



Figure 3: HFSE map for the S15 subject: (a) Without heel (b) Heel under left foot (c) Heel under right foot.

(c)

Features Extraction

(a)

We extract three relevant features on this map at the lower limb level (between $\frac{1}{2}H$ and $\frac{1}{4}H$ with H the image height). We first calculate the axis of symmetry of the map. 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 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.



Figure 4: Thresholded HFSE map at lower limbs for the S15 subject: (a) Without heel (b) Heel under left foot (c) Heel under right foot.

invasive, simple to install and requiring a small room.

- Map showing the location and the amplitude of the highfrequency spectral energy, obtained from each subject, allows the clinician to visually quantify and localize the different impaired body parts of the patient.
- Approach that can 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.
- System 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.

References

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Figure 1: Setup and pre-processing steps:(I)Acquisition of depth frames, (II) (a) Original depth frame, (b) After the background removal, (c) After the treadmill removal and contrast adjustment.

Table 1: Features for the S15 subject						
	left	right	double ratio			
	area $\frac{L}{L+R}$	area $\frac{R}{L+R}$	$2 \times \frac{L}{R}$			
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			

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