Evaluating perceptual maps of asymmetries for gait symmetry quantification and pathology detection

Antoine Moevus, Max Mignotte, J.A. de Guise, and Jean Meunier

Abstract— **The gait movement is a complex and essential process of the human activity. Yet, many types of diseases (neurological, muscular, orthopedic, etc.) can be diagnosed from the gait analysis. This paper introduces a novel method to quickly visualize the different body parts related to an (temporally shift-invariant) asymmetric movement in the human gait of a patient for daily clinical usage. The goal is to provide a cheap and easy-to-use method that measures the gait asymmetry and display results in a perceptual and intuitive way. This method relies on an affordable consumer depth sensor, the Kinect, which is very suitable for small room and fast diagnostic, since it is easy to setup and marker-less.**

I. Introduction

Scientists and medical communities have been interested in the analysis of gait movement for a long time, because, as mentioned in [1], [2], [3] symmetrical gait is expected in the case of healthy people, whereas asymmetrical gait is a common feature of subjects with loco-motor disorders.

Abnormal or atypical gait can be caused by different factors, either orthopedic (hip injuries [4], bone malformations, etc.), muscular, or neurological (Parkinson's disease, stroke, etc.). Consequently, different parts of the body can be involved or affected, which make gait analysis a complex procedure. Nevertheless, gait analysis remains a powerful early clinical diagnostic tool that is easy to perform and non-invasive, and has been used until now for detection and tracking of disease progression, joint deficiencies, pre-surgery planning, as well as recovery from post-operative surgery or accident.

But nowadays, with the aging population, clinical diagnostics have to be cheaper, faster and more convenient, while remaining accurate. However, analyzing a gait video sequence is often difficult, requires time, and subtle anomalies can be omitted. Also, videos are not easy to annotate, store and share. The goal of the proposed diagnostic tool is to evaluate a perceptual color map of asymmetries from a video, acquired by a depth sensor (Kinect), and recorded in the coronal (front) plane of a patient walking on a treadmill. A perceptual color map of asymmetries is the compression of a patient's video mapped into a color image in such manner that asymmetries of the body parts related to an (temporally shift-invariant) asymmetric movement in the human gait cycle may be clearly visible and immediately quantifiable.

II. Previous work

One popular method for gait analysis is motion capture [11] which consists in tracking infrared (IR) reflective markers with multiple IR cameras. This method is effective but requires a lot of space to be set up along with lots of expertise and time and effort to be installed and used.

In [6], the authors proposed to also use a treadmill and a Kinect depth sensor to quantify the gait asymmetry with a low-cost gait analysis system. More precisely, the authors compute an index for quantifying possible asymmetries between the two legs by first dividing each gait cycle in two sub-cycles (relative to the left and right step sub-cycle), and by comparing these two sub-cycles, in term of an asymmetry index (proportional to the difference of depth, over a gait cycle, between the two legs) after a rough spatial and temporal registration procedure. Although, the system is able to distinguish whether the patient has a symmetric walk or not, no visualization or information on the location of the asymmetries is provided, unlike our method.

In [10], the Kinect camera is placed at the back of a treadmill and is used to record a video sequence of the patient walk. The authors then simply compute 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 one image which is finally called a depth energy image (DEI). Their results were conclusive since they were able to distinguish both visually and quantitatively asymmetries (a symmetric walk generating a DEI exhibiting a symmetric silhouette, in terms of mean depth and conversely). Nevertheless, this latter strategy is inherently inaccurate since taking the average (mean) depth over a gait cycle does not allow to detect all asymmetric body movements; indeed, movement variation of some parts of the body can clearly be different and asymmetric while keeping the same mean (in term of mean depth).

In our work, the depth image sequence of the gait, containing a number of gait cycles (and wherein each pixel of the video corresponds to a depth signal, as a function of time) is reduced to three dimensions with a Multi-Dimensional Scaling (MDS) mapping [12] using a temporally shift invariant Euclidean distance. This allows us to quickly display the gait image cube into an informative color image (with red, green and blue channels) allowing to visualize the asymmetric body

This work was supported by the Fonds Qubcois de la Recherche sur la Nature et les Technologies (FQRNT). Ethical approbation was obtained from the research ethics board of our university for this project.

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parts of the gait cycle of a patient with a color difference, in a perceptual color space, which is even greater than the asymmetry is large in magnitude.

III. Data description

The dataset consists of multiple sequences of people walking on a treadmill, facing a cheap depth sensor (Kinect). The Kinect sensor outputs 30 depth maps per second (30 fps), with a resolution of 640 per 480 pixels. The dataset contains 51 sequences acquired from 17 subjects walking with or without simulated length leg discrepancy (LLD). Every patient had to walk normally (group A), then with a 5 cm sole under the left foot (group B), then with the sole under the right foot (group C). Sequences are approximately 5 minutes long and contains around 180 gait cycles. For all sequences, the same relative position between the treadmill and the sensor is kept in order for the subject to be within the same area of images.

IV. Method

In addition to a prerequisite setup step, the method can be divided into three steps: pre-processing, MDS-based dimensionality reduction and color space conversion.

A. Setup Phase

Since the scene took place in a non-cluttered room where the treadmill is in the same position relatively to the camera, a 3D bounding box around the subjects can be set. Hence, by retrieving 3D information, such as the position of the treadmill or the patient, we can convert this information back in the 2D image space and segment the patient's silhouette directly from a depth map.

Therefore, the setup step is to, first, determine the 3D position of the treadmill and the patient by converting a depth map in a 3D point cloud. To do so, the depth sensor is reasonably considered as a pinhole camera model with intrinsic parameters, K, (see [5, p. 30]) defined as:

$$K = \begin{bmatrix} f & 0 & c_u \\ 0 & f & c_v \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 575.82 & 0 & 240 \\ 0 & 575.82 & 320 \\ 0 & 0 & 1 \end{bmatrix} \quad (1)$$

where f is the focal length in pixels and (c_u, c_v) is the image center in pixels (values given by the manufacturer). From a depth map, a pixel at position $(u, v)^T$ with depth value, d is projected in 3D space, $(X, Y, Z)^T$, using:

$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = dK^{-1} \begin{pmatrix} u \\ v \\ 1 \end{pmatrix} = d \begin{pmatrix} 1/f * (u - c_u) \\ 1/f * (v - c_v) \\ 1 \end{pmatrix} \quad (2)$$

First, the positions of the points around the patient, approximated by a 3D bounding box, is first estimated. Second, the minimal and maximal depth, Z_{min} and Z_{max}, of the 8 points (of the bounding box) are then retrieved. Third, the 8 points were projected back in the 2D image space (see [5, p. 30]) where the minimal and maximal vertical and horizontal 2D position value (u_{min}, u_{max}, v_{min}, and v_{max}) are finally estimated.

The necessity of working in 3D space is because of the spatial coherence of objects in the scene. For instance, in 3D space the treadmill is always beneath the subject whereas in an image it overlaps the patient, as shown in Fig. 1b. Once this step is done, it is no more necessary to project the depth maps in the 3D space as long as the camera and the treadmill stay at the same relative position. In our case, some small adjustments on the enclosing parameters, u_{min}, u_{max}, v_{min}, v_{max}, Z_{min} and Z_{max}, were needed to encompass all sequences.

B. Silhouette Segmentation

Now, with, the required information, the patient can be segmented in each frame of the original gait depth sequence (of N frames).

1) Background removal: Background removal is trivial since the subject is in the middle of the image in a non-cluttered room. Therefore, every pixel outside the range of the enclosing parameters around the subject are clipped to a default value.

2) Treadmill removal: After background removal, the only objects remaining in the image are the treadmill and the patient. Because the treadmill is below the patient, it can be removed by selecting pixel with coordinates superior to a threshold (Y axis is going from top to bottom) and clip them. An equation in the 2D-space can be derived from Eq. (2) in order to work directly on the image:

$$Y < T_y \quad (3)$$

$$\frac{d}{f}(v - c_v) < T_y \quad (4)$$

$$v < \frac{fT_y}{d} + c_v, \quad \text{since } d > 0 \text{ and } f > 0 \quad (5)$$

where T_y is the threshold value measured during the setup phase and d is the depth.

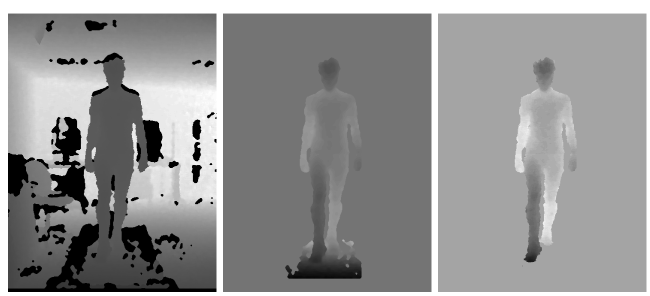

Fig. 1: Setup and pre-processing steps. (a) Original depth map. (b) After clipping. (c) After treadmill removal.

Fig. 1 visually shows the different steps of the setup and pre-processing stage.

3) Filtering: Finally, the whole sequence is filtered with a 3D (5×5) median filter to remove some aberrations on the contours or on top of the treadmill.

C. Dimensionality Reduction

The MDS dimensionality reduction-based mapping technique [12] aims at visualizing the (temporally shift-invariant) asymmetric body parts of the gait cycle of a patient with a perceptual color difference which is even greater than the asymmetry is large in magnitude. This mapping is achieved by considering each pair of pixels (i.e., pair of N-dimensional depth signals) in the original gait video sequence and by quantifying their (temporally shift-invariant) degree of asymmetry with a temporally shift-invariant pairwise Euclidean distance d_{tsi} between each pair $(\mathbf{s}_1(t), \mathbf{s}_2(t))$ of depth signals:

$$d_{\text{tsi}}(\mathbf{s}_1, \mathbf{s}_2) = \min_{\forall \tau} \Big\{ \sum_{t=0}^{N} \mathbf{s}_1(t+\tau), \mathbf{s}_2(t)) \Big\} \qquad (6)$$

where the maximal value of τ corresponds approximately to the number of frames in a gait cycle.

In addition, four points are important to consider in this step:

• First, it is important to understand that the use of the shift-invariant pairwise Euclidean distance is crucial in this MDS-based mapping step. Indeed, two pixels in the gait video cube, i.e., two depth signals (as a function of the time) with a perfect similar movement but in phase opposition (phase difference of half a gait cycle) like the legs and arms will have to be considered as symmetric with the same (perceptual) color in the final asymmetry map.

• Second, in order to finally provide a final perceptual color asymmetry visualization map, the MDS mapping is achieved in a perceptual color space, namely the classical CIE 1976 L^*, a^*, b^* (LAB) color space which is approximately perceptually uniform. In this color space, a color difference shall (perceptually) appear twice as large for a measured (temporally shift-invariant) asymmetry value which is twice bigger.

• Third, as already said, MDS is a dimensionality reduction technique that maps objects lying in an original high N dimensional space to a lower dimensional space (3 in our application), but does so in an attempt that the between-object distances are preserved as well as possible. The original MDS algorithm is not appropriate in our application and more generally for all large scale applications because it requires an entire $N \times N$ distance matrix to be stored in memory (with a $O(N^3)$ complexity). Instead, the FastMap [7] is a fast alternative to the MDS that we have adopted herein with a linear complexity $O(pN)$ (with $p = 3$, the dimensionality of the target space)[1].

• The above-mentioned FastMap-based mapping method, which exploits an algebraic procedure[1], has the main advantage of being very fast (for large scale applications) but slightly less accurate than a (gradient descent or local stochastic search-based) optimization procedure [8]. For this reason, we decide to refine the estimated asymmetry map given by the FastMap as being the initial starting solution of a stochastic local search (using a local exploration around the current solution and the Metropolis criteria) as proposed in [8].

[1]In FastMap, the axis of target space are then constructed dimension by dimension. More precisely, it implicitly assumes that the objects are points in a p-dimensional Euclidean space and selects a sequence of $p \leq N$ orthogonal axes defined by distant pairs of points (called pivots) and computes the projection of the points onto the orthogonal axes.

TABLE I: Average and SD (σ) of the ASI for the 17 patients

	Normal gait	Left LLD	Right LLD
Average	0.045374	0.053549*	0.055936*
σ	0.008080	0.006274	0.009451

*Paired difference t test is statistically significant ($p << 0.01$)

D. Color Space Conversion

It is important to mention that, at this stage, we are not assured that the LAB color values of the 3D asymmetry map are not saturated in the RGB space. In order to fix this problem, we use a simple linear stretching of the L, A, B color values such as $L \in [0:100]$, and A, B have a maximal amplitude of 100 with a zero mean in order to ensure that a very small number of pixels are outside the RGB color space [8].

V. Experimental Results

This section presents the asymmetry maps obtained for patients with or without (simulated) pathologies. Sequences of 300 frames have been used (longer sequences did not yield better results). This corresponds approximately to 5 or 8 gait cycles depending on the subject's speed and step size. On average for all images, the correlation score [8] for the compression of 300 frames to 3 channels is $93.5\% \pm 2\%$ which shows us that the FastMap-based MDS procedure is able to preserve, due to its non-linearity property, a large quantity of information of the original image sequence.

Asymmetries can be easily detected visually, as shown by Fig. 2, 3, and 4, but also quantitatively. To do so, the mean of biggest mirrored differences[2] is computed for each line of the map, which yields a vertical curve[3]. Then, by taking the mean value of the curve, a a global asymmetry index (ASI) is computed.

Table I shows the average and standard deviation of the ASI for the three groups of patient. The statistical difference for the paired t test were highly significant for both left and right legs LLD group ($p << 0.01$). This demonstrates that this method can efficiently detect gait symmetry. In practice, three patients had a higher ASI for their normal gait than with the sole (Fig. 4). By looking at their videos, the authors have noticed that those patients already had a visible gait asymmetry (one arm swinging more than the other, tilted shoulders, etc.).

[2]For a line $\mathbf{k}$ of width w, the set of mirrored differences is: $\{\|p_{i,\mathbf{k}} - p_{w-i,\mathbf{k}}\|_2^2, \forall_{i \in [0,w/2]}\}$ where $p_{i,j}$ is a pixel at position (i, j).

[3]To estimate this curve, images are centered a first time based on the position of the neck, then more accurately by seeking the minimum area of the curve around the axis of symmetry.

VI. Conclusion

In this paper, we have presented a new gait analysis system, based on a depth sensor, which estimates a perceptual color map providing a quick overview of existing asymmetry existing in the gait cycle of a patient and an index (ASI), that was proved statistically significant ($p << 0.01$). While being cheap, markerless, non-invasive, easy to set up and suitable for small room and fast diagnostic, this new gait analysis system offers a readable and flexible tool for clinicians to analyze gait characteristics which can be easily exploited for disease progression, recovery cues from post-operative surgery or might be used for other pathologies where gait asymmetry might be a symptom.

VII. Acknowledgments

Authors would like to thank E. Auvinet for the usage of his dataset [6].

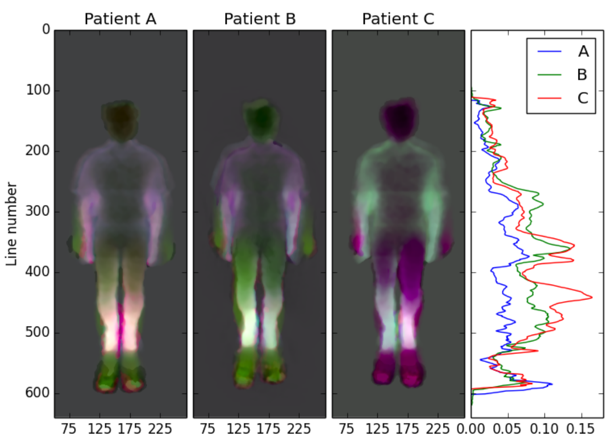

Fig. 2: Asymmetry map for subject #15, one of the best result of the dataset. ASI is 0.03082 for normal gait, 0.04740 for left asymmetry, and 0.05266 for right asymmetry.

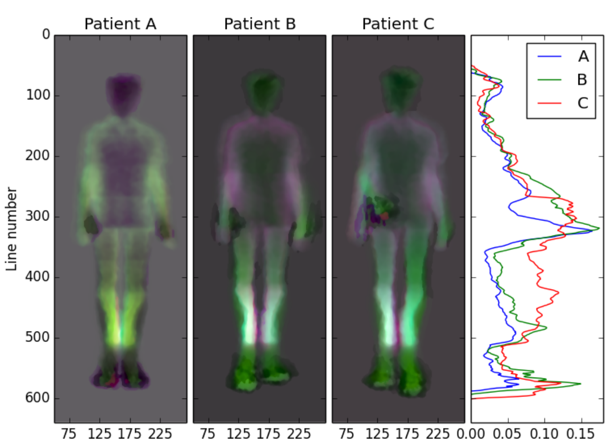

Fig. 3: Asymmetry map for subject #05, one of the best result of the dataset. ASI is 0.04164 for normal gait, 0.05858 for left LLD, and 0.06824 for right LLD. With the right LLD (case C), the asymmetry of arm swing is clearly noticeable.

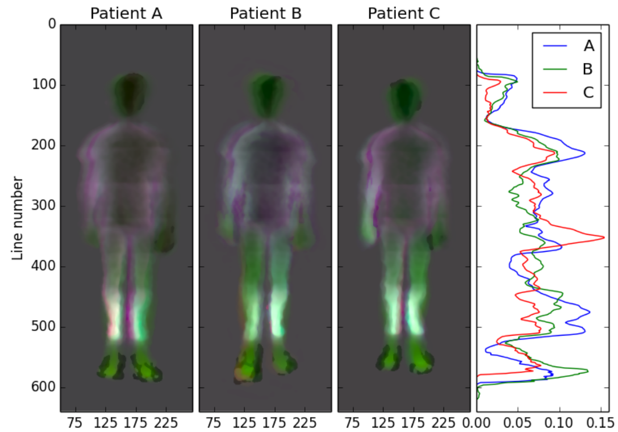

Fig. 4: Asymmetry map for subject #09, the worst result of the dataset. The corresponding ASI are 0.05672 for normal gait, 0.05166 for left LLD, and 0.04625 for right LLD. The patient had naturally a strong arm swing but a sole on the left foot seems to help rectifying it.

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