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Depth Energy Image for Gait Symmetry Quantification

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Abstract— **This paper introduces a new quantification method for gait symmetry based on depth information acquired from a structured light system. First, the new concept of Depth Energy Image is introduced to better visualize gait asymmetry problems. Then a simple index is computed from this map to quantify motion symmetry. Results are presented for six subjects with and without gait problems. Since the method is markerless and cheap, it could be a very promising solution in the future for gait clinics.**

I. INTRODUCTION

Gait analysis systems are important for helping diagnostic of abnormal gait patterns. For simplicity, gait symmetry has been often used to characterize gait problems [5]. Indeed, the lower limbs are supposed to evolve symmetrically for a normal walker. This statement is controversial for some researchers as the gait can be influenced for example by limb dominance [6]. However, a quantification tool for gait symmetry could be useful for clinicians to evaluate walking dysfunctions, for example for stroke and amputee patients, or to analyze the recovery after a knee surgery.

One commonly used method for gait analysis is motion capture (MOCAP) [8], [10] which consists in tracking infrared (IR) reflective markers using multiple IR cameras. Such systems have been used to analyze gait symmetry [8], [10], as well as acceleration signals [9], with walkway systems [3] or laterally placed cameras [5]. In this paper, a new gait analysis system is proposed based on a treadmill associated with a cheap depth sensor placed at the back of the treadmill. The advantages of our system compared with MOCAP systems are that no markers are needed and its low cost price, which makes the system well adapted for clinical use.

For our experiments, six young male adults were asked to walk on a treadmill (Life Fitness F3). After a period of habituation of $5min$, their normal walk speeds were determined and used for further testing. Three tests were done:

- **Normal walk** which served as a reference.
- **Right leg problem** which was simulated with a heel cup (height of $2.5cm$) placed inside the right shoe.
- **Left leg problem** which was simulated with a heel cup (height of $2.5cm$) placed inside the left shoe.

The heel cup is used here to generate a limping walk which will produce an unbalanced gait with asymmetric characteristics. For each test, after another period of habituation on the treadmill (2-3 min), a three-minute video was recorded with the depth camera (see Section II) placed at the back of the treadmill (back view of the person). Ethical approbation was obtained from the research ethics board (REB) of our university for this project.

II. DEPTH SENSORS

Depth maps, which show the different depths of a scene, can be obtained in several ways:

- **Stereo vision** [13] The 3D view of a scene can be reconstructed with a calibrated binocular system. However, to obtain precise depth maps, such systems require to be well calibrated and to have a textured scene. Moreover, stereo reconstruction algorithms are often computationally expensive.
- **Time-of-Flight (TOF) camera** [14] Accurate depth images can be obtained with a TOF camera, but this technology is very expensive and currently limited to low image resolution (e.g. image size of 176x144 pixels in [7], [14]).
- **Structured light** With a known artificial texture projected on the scene, a depth map can be obtain from a monocular system. The Kinect sensor [11] is based on this method with an infrared structured light (IR dots) projected in the scene and observed with an infrared camera. Such systems can acquire bigger images than a TOF camera at a lower price (e.g. image size of 640x480 pixels at 30 fps for the Kinect sensor which is currently fifty times cheaper than a TOF camera).

For clinical gait analysis, a low-cost and easy-to-install system is more suitable, which encouraged us to choose the Kinect sensor [11] to acquire depth images. The resulting images are disparity maps where far objects are represented with higher Kinect disparity values (within the depth range used in our study). The disparity values can be converted in depth values after a calibration step, which consists in moving a plane along a rail at known depths and acquiring corresponding disparity values. Then, a set of disparity-depth pairs is obtained and used to compute the relation between disparity and depth:

$$Depth = 1/(-0.0032936\ Disparity + 3.5463) \quad (1)$$

An attempt to use depth images for gait analysis has previously been done using a TOF camera [7]. However,

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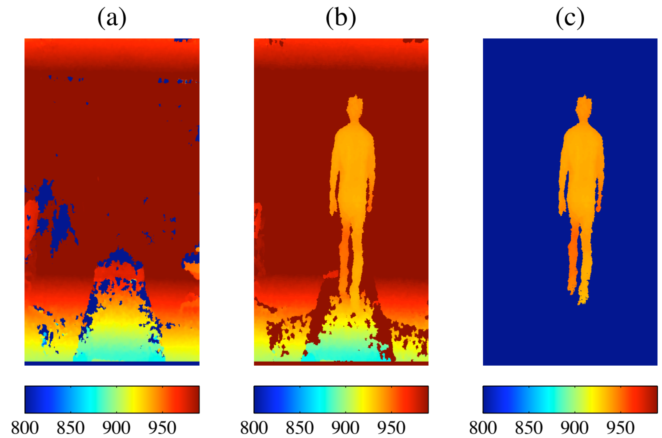


Fig. 1. The disparity human silhouette (c) is obtained from (a) the background disparity image B and (b) the current disparity image I. The color-bars represent the disparity values.

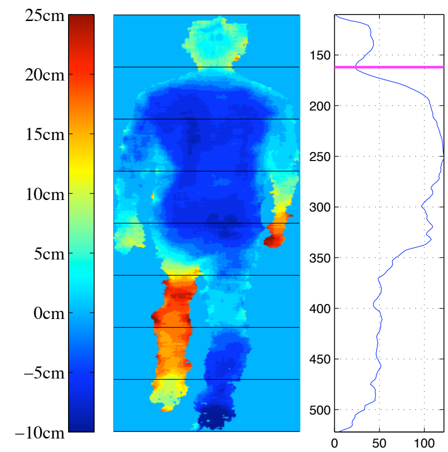


Fig. 2. On the left, the centered depth silhouette with depth values from $-10cm$ to $15cm$. On the right, the vertical projection of the silhouette with the detected localization of the neck in magenta.

the TOF camera was placed sideways to use depth to discriminate the two legs. In this work, the depth sensor is placed at the back of the treadmill to clearly have the two legs entirely visible in the image (no occlusion). Moreover, with this configuration, the depth of each leg is directly readable with the depth image.

III. DEPTH ENERGY IMAGE (DEI)

Gait Energy Image (GEI) [1], which has been widely used for gait recognition, consists in computing the mean body silhouette over gait cycles in the sagittal plane, the body silhouette being extracted with a background subtraction method. Based on this idea, we introduce a new spatio-temporal gait representation, called Depth Energy Image (DEI), which uses depth silhouette images in the coronal plane instead of binary silhouette images in the saggital plane.

A. Depth silhouette image

The human silhouette image is extracted with a classical background subtraction method [2] applied to disparity values instead of gray level values. From N_{train} background images ($N_{train} = 200$ in our experiments), the mean disparity background image B is computed and used for segmentation. For each pixel (i, j) of the current image I, if $|I(i, j) - B(i, j)| \geq T(i, j)$ then the pixel is considered as foreground, with the threshold $T(i, j)$ equals to 10 times the pixel standard deviation (computed during the training phase). The binary silhouette is then cleaned with morphological filtering. An example of disparity silhouette, obtained by combining the binary silhouette with the current image, is shown in Fig. 1.

The disparity silhouette is then converted to depth values using (1) and centered with the mean silhouette depth at each instant t (to avoid depth differences due to different localizations of the person on the treadmill). An example of the final depth silhouette which will be used thereafter is shown in Fig. 2.

As some of our subjects did not keep their heads always straight, the silhouette are recomputed from the neck to the feet using the vertical projection of the silhouette (number of silhouette pixels for each line). We assumed that the neck localization corresponds to the local minimum of the vertical projection which is the closest to one eighth of the human height from the top of the head as shown in Fig. 2.

B. Depth Energy Image

The Depth Energy Image (DEI) is simply the mean depth silhouette over a gait cycle. A symmetric walk should generate equal mean depth legs over a gait cycle, which can be used later to compute a symmetry index.

To compute the DEI over a gait cycle, each depth silhouette is vertically normalized and reshaped to 300x200 pixels to be summed:

$$I_{DEI} = \frac{1}{N} \sum_{t=1}^{N} I_{HD}^{(t)} \qquad (2)$$

where N is the number of images for one gait cycle and $I_{HD}^{(t)}$ is the centered human depth silhouette at time t.

For better precision, the DEI is computed on 1800 images which correspond to a one minute walk at 30 fps. An example of DEI obtained for a symmetric normal walk is shown in Fig. 3. This figure shows also the absolute value of DEI which will be used for gait analysis.

IV. GAIT ANALYSIS

A symmetry leg motion index is computed with the absolute value of DEI, separated in two sub-images corresponding to the left and the right legs. For each sub-image, the maximum value for each row is computed to obtain two curves, one for each side of the body, as shown in Fig. 4. For symmetric walk, the left side curve in red must be similar to the right side curve in blue for the lower limbs. Therefore, we used as a symmetry index, the mean absolute distance value D_{leg} between these two curves for the leg section (between $\frac{1}{2}H_{image}$ and $\frac{3}{4}H_{image}$ with H_{image} the image height). For

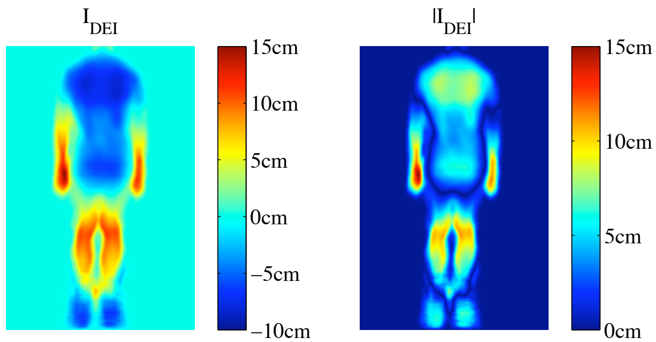


Fig. 3. On the left, an example of DEI obtained for a symmetrical normal walker, and the corresponding absolute value of DEI on the right.

example in Fig. 4(a), this distance D_{leg} is smaller than $0.6cm$ for a symmetric walk.

V. EXPERIMENTAL RESULTS

The data acquisition from the Kinect was done with libfreenect [12]. The video sequences were acquired with a frame rate of 30 Hz for an image size of 640x480 pixels. The image processing analysis was done with Matlab®.

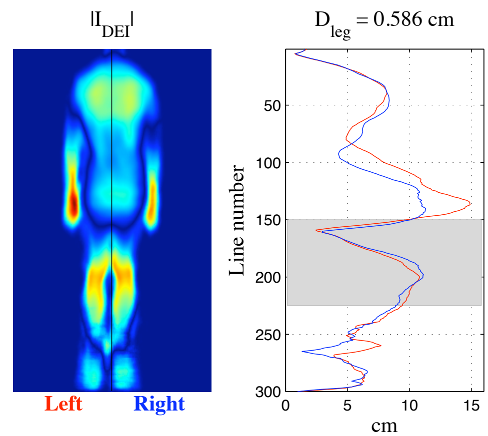
Our method has been tested on six subjects:

- 3 subjects had a symmetric normal walk as the one shown in Fig. 4. For these normal walks, the curves were similar for the two legs. With the right leg problem generated with a heel cup, the right leg curve (blue curve) was higher than the left one (red curve), which means that the right leg was on average in front of the left. As expected, the inverse occurred with the left leg problem where the left leg is on average in front of the right. The distance D_{leg} was higher than $1cm$ for symmetric problems.
- 3 subjects had a little asymmetric normal walk as the one shown in Fig. 5. Similar results were observed with these subjects for left and right leg problems with a distance D_{leg} higher than $1cm$.

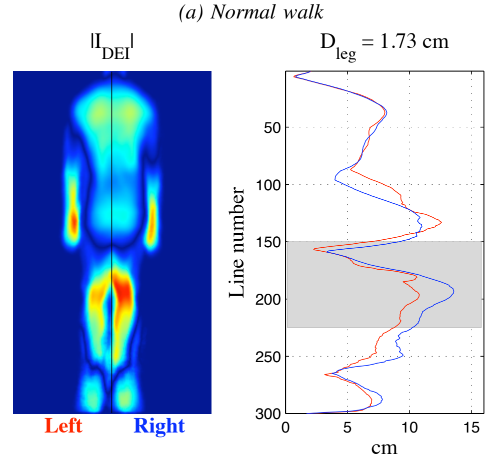
The heel cup used here to simulate a leg problem generates a leg length discrepancy (LLD). Research works on LLD [4] have shown that stance time and step length decrease for the shorter leg. This can explain the fact that the leg without the heel cup (shorter leg) was on average behind the other leg.

Table I summarizes the distances obtained for the different subjects. For symmetric normal walkers, the distance D_{leg} for normal walk was smaller than $0.6cm$, and increased in case of leg problems. The distance D_{leg} was higher for normal walk of asymmetric normal walkers, but the heel cup effect was still visible increasing the asymmetry as shown in Fig. 5.

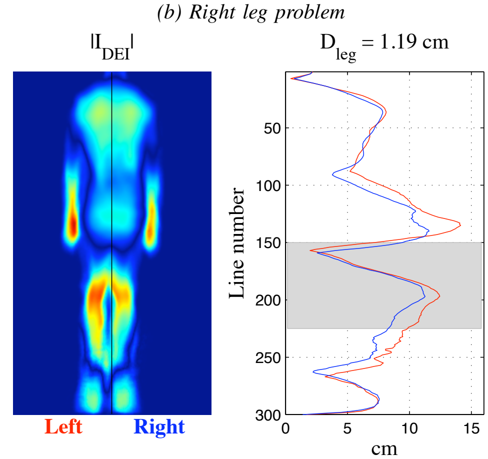
DEI has proven its efficiency in detecting an asymmetric gait. This image is even more informative as the upper limbs can also be analyzed. All of our subjects had an asymmetry of arm swing for normal walk, which has been previously described by [10] with a MOCAP system. This arm swing asymmetry can be clearly seen with the DEI (see Fig. 4-5) and confirmed with a measure index D_{arm} computed



(a) Normal walk



(b) Right leg problem



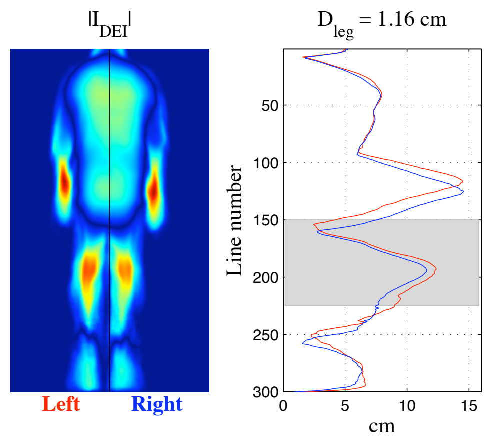
(c) Left leg problem

Fig. 4. Example of subject S2 with symmetric normal walk (a) and gait problems generated with a heel cup (b-c). The left leg is shown in red and the right leg in blue.

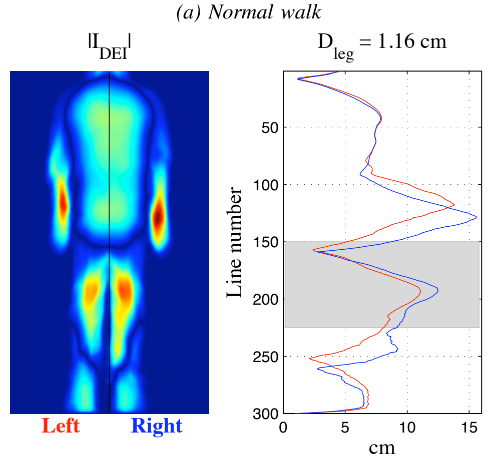
for the arm portion (between $\frac{1}{4}H_{image}$ and $\frac{1}{2}H_{image}$ with H_{image} the image height). The distance D_{arm} is also shown in Table I.

VI. CONCLUSIONS AND FUTURE WORKS

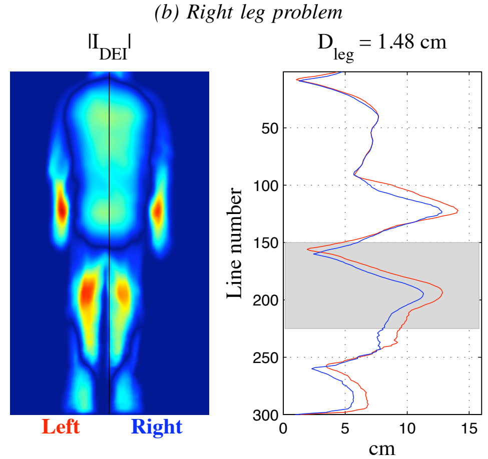
A new gait analysis system, based on depth information acquired from a structured light system, is proposed in this paper and tested with this preliminary study on



(a) Normal walk



(b) Right leg problem



(c) Left leg problem

Fig. 5. Example of subject S6 with an asymmetric normal walk. The left leg is shown in red and the right leg in blue.

gait symmetry. Our results show that gait asymmetry can be efficiently detected from back-viewed depth images. A new type of image, the Depth Energy Image (DEI) which corresponds to the mean silhouette depth over a long period, offers a directly readable tool for clinician to analyze gait characteristics. A measure has been proposed to quantify leg (and arm) motion asymmetry. This gait analysis system is much less expensive than a MOCAP system and does not require wearable markers. Therefore it offers a new

- Subjects with normal walk -

Subject	S1	S2	S3
Normal walk D_{leg} (cm)	0.549	0.586	0.566
Right leg problem D_{leg} (cm)	1.72	1.73	1.56
Left leg problem D_{leg} (cm)	1.21	1.19	1.81
Normal walk D_{arm} (cm)	1.16	2.14	3.3
Right leg problem D_{arm} (cm)	1.06	1.36	3.48
Left leg problem D_{arm} (cm)	0.697	1.53	3.27

- Subjects with slightly asymmetric normal walk -

Subject	S4	S5	S6
Normal walk D_{leg} (cm)	1.52	0.744	1.16
Right leg problem D_{leg} (cm)	1.17	0.707	1.16
Left leg problem D_{leg} (cm)	2.31	2.18	1.48
Normal walk D_{arm} (cm)	1.79	2.74	1.64
Right leg problem D_{arm} (cm)	1.4	2.42	2.4
Left leg problem D_{arm} (cm)	1.48	2.15	0.829

TABLE I
DISTANCES OBTAINED FOR THE DIFFERENT SUBJECTS.

promising solution for clinical diagnostic. For future works, this method will be further evaluated and improved with more subjects, different gait measurements or indexes, and other depth camera positioning (e.g. side view).

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