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Spatiotemporal analysis of human gait, based on feet trajectories estimated by means of depth sensors

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ABSTRACT
This paper addresses a methodology for the analysis of human gait, based on the data acquired by means of depth sensors. This methodology is dedicated to healthcare-related applications and involves the identification of the phases of the gait cycle by thresholding estimates of velocities of the examined person's feet. In order to assess its performance, a series of experiments was carried out using a reference gait-analysis system based on a pressure-distribution-measurement platform. An original method for quantifying gait asymmetry, based on a quasi-correlation between the feet trajectories, was also proposed and tested experimentally. The results of the reported experiments seem to promise a high applicability potential of the considered methodology.

Section: RESEARCH PAPER

Keywords: Gait analysis; gait asymmetry; healthcare; depth sensor; measurement data processing

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1. INTRODUCTION

The analysis of human gait is a fertile research field with various applications related to healthcare, in particular – to monitoring of elderly persons. Gait analysis can be used, *e.g.*, for estimating the risk of falling [1], diagnosing cognitive impairments [2] and optimising the rehabilitation after a stroke [3]. Such analysis may involve the estimation of [4]

– angles between body segments,
– ground-reaction forces,
– electromyographic signals,
– spatiotemporal gait parameters.

This paper is focused on the estimation of the latter, and in particular of [5]:

– length and duration of steps and strides,
– walking speed,
– cadence (or the number of steps per minute),
– duration of the phases of a gait cycle.

The gait cycle is the time interval encompassing the repeatable pattern of movement performed during walking, *i.e.* a single stride or two steps (one by each foot). Within the gait cycle, the so-called *swing phase* and *stance phase* can be identified. These phases correspond to the time intervals when a given foot is moving or resting on the floor, respectively. The duration of the so-called *double-support phase*, during which both feet contact the floor, is also of interest for healthcare practitioners [2].

Important information, useful from the healthcare perspective, can be extracted from the average values of the aforementioned parameters and from some indicators characterising their variability [6]. Estimates of those parameters can also be used for obtaining information about gait asymmetry, which is considered particularly useful in the treatment of stroke-induced hemiplegia [7]. The gait asymmetry is typically quantified by comparing the values of some parameters, characterising the left and right sides of the body, *e.g.* by computing the ratio between the duration of the stance phases of the two feet [3].

The spatiotemporal gait parameters can be estimated by a trained clinician using a stopwatch; the simplicity and low cost of such an examination method are behind its prevalence, although its accuracy and repeatability are quite limited [8]. A technological solution that allows for more reliable analysis of gait, relatively widespread in research laboratories and clinical facilities, involves the use of platforms or treadmills equipped with pressure sensors. Even more detailed and useful information can be obtained by means of optoelectronic systems based on multiple video cameras, tracking the motion of special markers attached to the person's body; however, such systems are quite expensive and need to be installed in a large room. The last decade has brought about the development of other gait-analysis techniques based on various types of sensors, including wearable sensors, which seem to be applied most frequently. This paper is devoted to a technique whose applicability potential has not yet been fully explored, *viz.* a technique based on depth sensors.

In the last decade, the possibility of using depth sensors for the analysis of human gait has attracted considerable interest of the scientific community. This interest seems to be justified by the facts that 1) such sensors are relatively inexpensive and commercially available, and 2) the acquisition of data representative of human movement can be quite fast and convenient, *viz.* it can be performed in the natural conditions of overground walking, without requiring the person to wear any devices or markers on the body or clothes. Moreover, the data acquired by means of such sensors convey quite detailed and rich information about human movement, allowing for both its spatiotemporal and kinematic analysis. Such sensors do not seem, however, as reliable – in terms of the attainable measurement uncertainty – as marker-based optoelectronic systems or pressure-measuring platforms. Furthermore, unlike wearable sensors, depth sensors have a limited field of view to which the examination must be confined, and their reliability depends – to some extent – on the angle at which the examined person is observed. Given their advantages and disadvantages with respect to other technologies applicable for gait analysis, the depth sensors are often considered potentially useful for rapid screening of patients prior to more detailed diagnostic procedures. The gait-analysis systems based on depth sensors may, therefore, become quite common in clinical practice and in-home monitoring; the development of suitable data-processing methods and research aimed at assessing the validity of those methods is thus necessary [9]. A recent review of issues related to the development of gait-analysis systems based on depth sensors and other techniques can be found in [10], Chapter 8.

A depth sensor typically consists of a projector and a camera, both operating in the infrared range of electromagnetic radiation. The data acquired by means of such a sensor represent its distance to the objects present in its field of view. Those data are organised in sequences of so-called *depth images*. In a depth image, each pixel represents the three-dimensional position of a point belonging to a surface reflecting infrared radiation. An exemplary depth image is shown in Figure 1a.

What makes the depth sensors particularly promising for gait analysis is the existence of algorithms for automatic identification of human silhouettes and for the localisation of various anatomical landmarks, such as the head, the feet, selected joints *etc.* Such an algorithm is implemented in one of the most popular devices comprising depth sensors, *viz.* the Microsoft Kinect device [11], including its Kinect v2 model which has been used in the experiments reported in this paper. Similar algorithms, which can be used for processing data from other depth sensors, are available commercially. An exemplary human silhouette, identified using the algorithm implemented in the Kinect v2 device, is shown in Figure 1b.

Various approaches to the application of depth sensors in the systems for gait analysis have been reported in the last decade. The difficulties in developing such systems are mainly related to

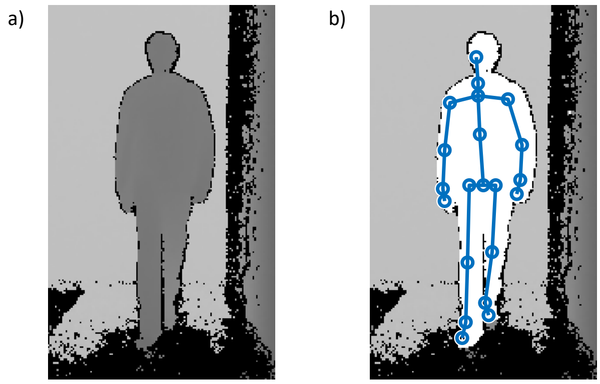

Figure 1. A depth image in which brighter pixels represent larger distance from the sensor (a); a human silhouette, identified in that image by means of the Kinect device (b).

the uncertainty of localisation of feet and other anatomical landmarks, and from the limitations of the depth sensors' field of view. The techniques proposed so far differ in terms of the examination setup (which may involve the use of one or more depth sensors, a treadmill, wearable devices *etc.*), the data-processing methods used for the identification of the gait-cycle phases, and other aspects [12]–[14].

The methodology for spatiotemporal gait analysis considered in this work consists in obtaining some estimates of feet positions using a depth sensor, followed by processing them by means of a procedure which comprises the following operations:

- estimation of feet velocities;
- identification of the swing and stance phases by thresholding feet velocities;
- estimation of selected spatiotemporal gait parameters; and
- computation of indicators of gait asymmetry.

The above-listed operations are described in more detail in Section 2. Section 3 is devoted to the description of the experiments that were carried out in order to assess the applicability potential of the considered methodology for gait analysis. The results of these experiments are presented in Section 4 and discussed in Section 5 where conclusions are drawn.

The following acronyms appear in the rest of this paper:

- TVR – total variation regularisation;
- STR – stance time ratio;
- GCT – gait cycle time;
- SPM – steps per minute.

2. DATA PROCESSING PROCEDURE

2.1. Estimation of feet velocities

The estimates of the positions of feet, obtained by means of a Kinect v2 device, are subject to non-negligible measurement uncertainty. Among the 25 anatomical landmarks, whose positions can be estimated using the algorithm implemented in that device, the feet and ankles are usually localised with the least accuracy [15]. That algorithm performs poorly in distinguishing a foot from the ground when the foot is resting; hence, the estimates of feet positions are more accurate at the moments when the feet are off the ground [16]. The antero-posterior component of those estimates (*i.e.* the one corresponding to the walking direction) is more accurate than the vertical one and the medio-lateral one; furthermore, those estimates are more accurate if the person is walking rather than when the range of movement of the feet is small (*e.g.* in sit-to-stand tests) [15].

When compared with the reference data acquired by means of marker-based optoelectronic movement-analysis systems, the foot position estimates obtained by means of Kinect v2 devices have turned out to be somewhat biased [17]. This is, however, of lesser practical importance for the gait-analysis methodology proposed here, because this methodology refers to the differences among the estimates of the positions of feet rather than to their absolute values. On the other hand, those estimates are subject to random errors. The mean Euclidean distance between those estimates and the corresponding reference values has been reported to be *ca.* 8.0 cm [18]. Although such distance may be considered negligible in various applications, in the case of the proposed methodology it could – if not remedied – significantly distort the results of data processing; that is because this methodology involves the numerical differentiation of sequences of foot position estimates, and differentiation is numerically ill-conditioned, which means that small errors can be very significantly amplified in its course. An exemplary foot trajectory and the results of its differentiation by means of the central-difference method, without any prior denoising, are shown in Figure 2. As discussed in the following subsections, the visible abrupt changes in the estimates of foot velocity would hinder the identification of the stance and swing phases according to the proposed methodology. In order to prevent this effect, the foot position estimates were denoised prior to their numerical differentiation.

In the context of the analysis of human movement, the technique most commonly used for denoising depth-sensor-based estimates of positions of anatomical landmarks is low-pass filtering by means of a Butterworth filter of order 2, 3 or 4 with a cut-off frequency from the range [2, 10] Hz (*cf.*, *e.g.*, [13], [18], [19]). In this study, this denoising technique was compared with two other techniques, less frequently considered in this context: the Savitzky-Golay filter and the total-variation regularisation technique (the TVR technique).

Filtering by means of a Savitzky-Golay filter is equivalent to approximating the data – within a moving window – by means of a fixed-degree polynomial [20]; both the length of the moving window and the degree of the approximating polynomial need to be optimised empirically. This technique is particularly useful for denoising data representative of a smooth signal – *i.e.* a signal adequately modelled by a mathematical function which has some continuous derivatives – while, at the same time, preserving the width and height of the peaks present in that signal [21].

The Savitzky-Golay filter is a low-pass filter whose cut-off frequency increases with the increasing polynomial degree and with the decreasing window length. Unlike the Butterworth filter, the Savitzky-Golay filter is characterised by a linear phase response. It has similarly flat passband but less attenuation in the stopband than the Butterworth filter [22]. The frequency characteristics of exemplary filters of both kinds are presented in Figure 3, their impulse responses – in Figure 4.

The TVR technique is well-suited for processing piecewise-linear rather than smooth signals [23]. It seems potentially useful for denoising the estimates of the antero-posterior position of a foot during walking, because that position is constant during the stance phase and changing approximately linearly during the swing phase. This technique is characterised by a single scalar regularisation parameter whose value needs to be optimised empirically.

If the Savitzky-Golay filter or the TVR technique is applied, the estimates of the derivative can be obtained directly, without

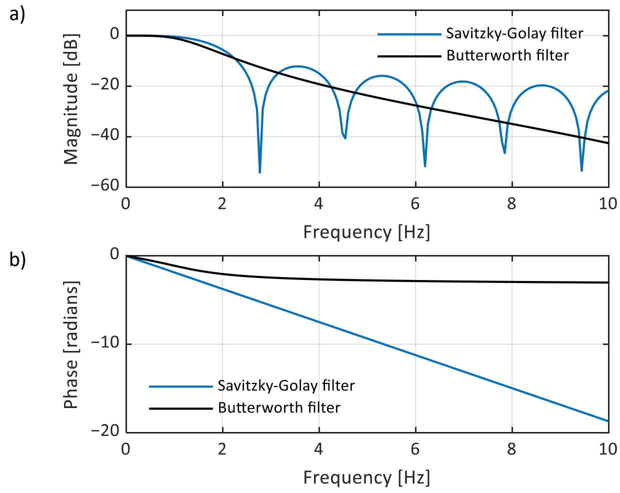

Figure 3. The frequency characteristics of the Savitzky-Golay filter with 19-sample window and 2-degree approximating polynomial, and of the Butterworth filter of order 2 with the cut-off frequency 1.4 Hz.

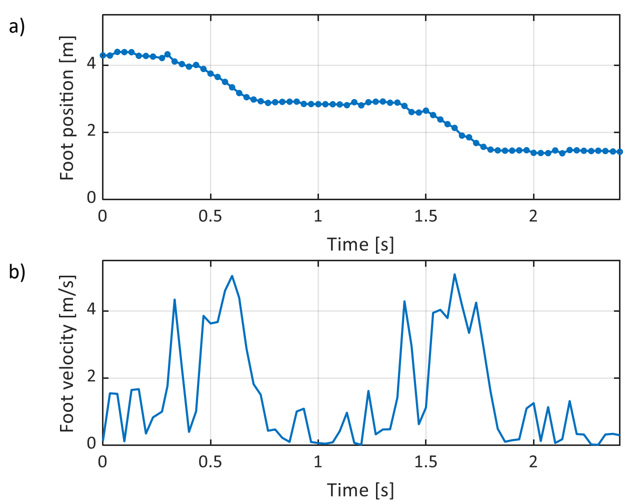

Figure 2. An exemplary sequence of data acquired by means of a Kinect v2 device, representative of the antero-posterior position of the left foot of a person who was walking toward that device (a), and the results of numerical differentiation of that sequence using the central-difference method (b).

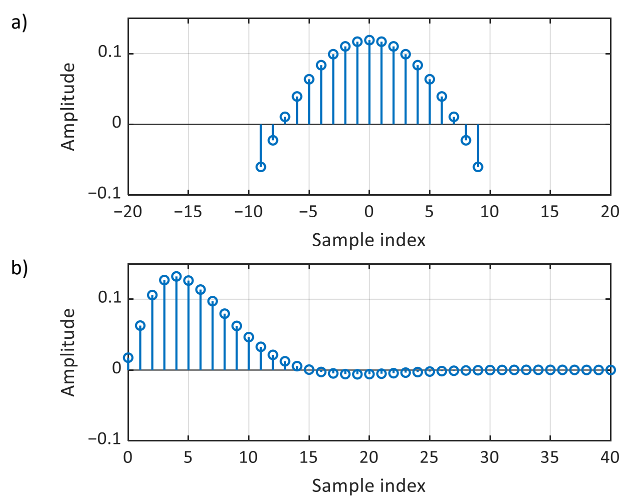

Figure 4. The impulse response of the Savitzky-Golay filter with 19-sample window and 2-degree approximating polynomial (a), and of the Butterworth filter of order 2 with the cut-off frequency 1.4 Hz (b).

computing the denoised sequence of data. However, in the experiments reported herein, better results were obtained by computing the velocity estimates using the central-difference method on the basis of the denoised position estimates. A recent review of methods of numerical differentiation, which can be used in this context, can be found in [10], Chapter 5.

Exemplary estimates of feet velocities, obtained by means of the three above-described denoising techniques, are shown in Figure 5.

2.2. Identification of gait-cycle phases

The swing phase and the stance phase were identified as the time intervals in which the velocity of the examined foot is above or below – respectively – an empirically selected threshold. Two variants of threshold values were considered here:

- a fixed absolute value;
- a value relative to the maximum velocity estimate present in the set of data under analysis.

Exemplary results of this operation are shown in Figure 6.

2.3. Estimation of spatiotemporal gait parameters

The length and duration of the steps were estimated according to the definitions provided in the documentation of the Zebris FDM gait analysis system [24]. The estimates of the duration of the left and right stance phase and the double-support phase were divided by the duration of the gait cycle. The average walking speed was estimated by dividing the total distance, travelled during the experiment, by the total walking time. The cadence was estimated by computing the inverse of the duration of the steps, averaged over all observed left and right steps. The estimates of each spatiotemporal gait parameter, differing from their median value by more than an empirically selected threshold value, were identified as outliers and removed from the set of results.

For brevity, some spatiotemporal gait parameters whose values can be inferred from the values of the parameters

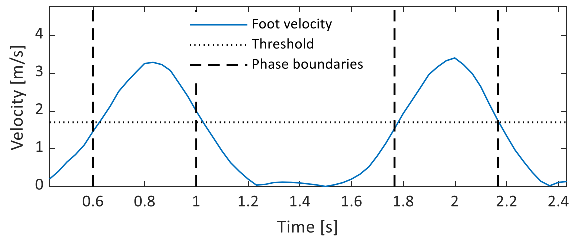

Figure 6. The exemplary results of the identification of the gait-cycle phases by thresholding the estimates of the foot velocity.

mentioned above – such as the stride length or the duration of the swing phase – are omitted here.

2.4. Quantification of gait asymmetry

The following indicator – which, to the best authors' knowledge, has not been considered in any previous studies – can be used for quantifying gait asymmetry:

$$r_{\mathrm{LR}} \equiv \max_{\tau} \left\{ \frac{\int_0^T v_{\mathrm{L}}(t)\, v_{\mathrm{R}}(t+\tau)\, dt}{\sqrt{\int_0^T v_{\mathrm{L}}^2(t)\, dt \int_0^T v_{\mathrm{R}}^2(t+\tau)\, dt}} \right\} \in [-1,+1] , \qquad (1)$$

where $v_{\mathrm{L}}(t)$ and $v_{\mathrm{R}}(t)$ denote the horizontal speed of the left and right foot – respectively – at a time instant t belonging to the time interval under analysis $[0, T]$. This indicator can be interpreted as the maximum of a quasi-correlation between the trajectories of both feet; its values close to 1 indicate near-perfect symmetry, and smaller values – lesser symmetry. The stance time ratio (STR), defined as follows:

$$STR \equiv \begin{cases} ST_{\mathrm{L}} / ST_{\mathrm{R}} & \text{if } ST_{\mathrm{L}} > ST_{\mathrm{R}} \\ ST_{\mathrm{R}} / ST_{\mathrm{L}} & \text{otherwise} \end{cases} \in [0,1] \qquad (2)$$

– where ST_{L} and ST_{R} denote the stance time of the left and right foot, respectively – was used as a reference indicator of gait asymmetry [3].

3. EXPERIMENTATION PROGRAMME

A set of experiments was completed in order to assess the applicabilitiy potential of the considered methodology for spatiotemporal gait analysis. The data representative of the human gait were acquired by means of a Kinect v2 device and a Zebris FDM pressure-measurement platform simultaneously. Three persons walked over the platform 33 times in total. The depth sensor's line of sight coincided with the walking direction. The sketch of the experimental setup is shown in Figure 7.

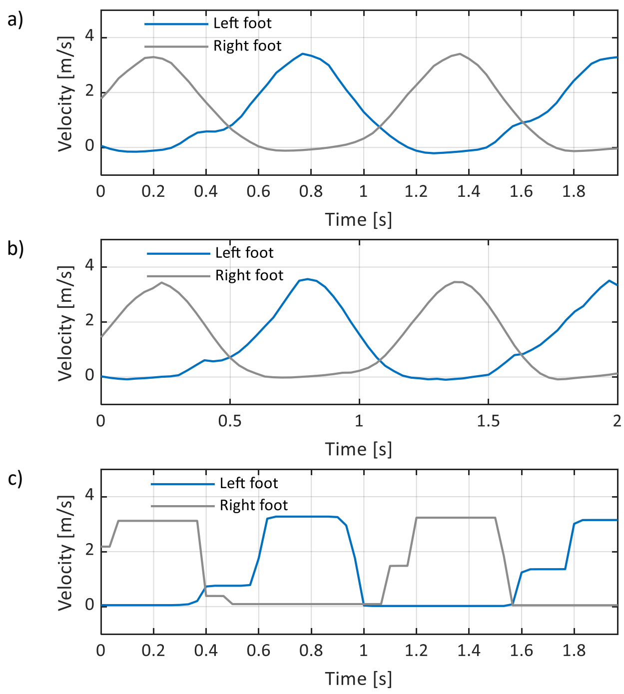

Figure 5. The estimates of the feet velocities, obtained by means of numerical differentiation of some exemplary feet trajectories denoised using the Butterworth filter (a), the Savitzky-Golay filter (b) and the TVR technique (c).

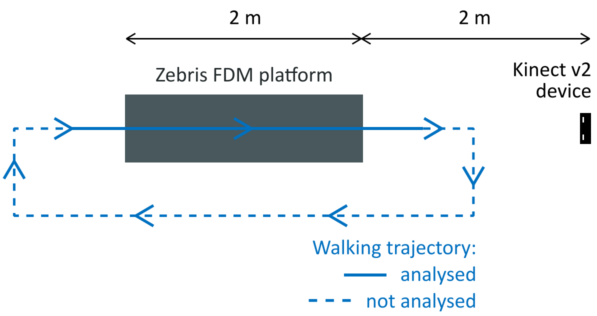

Figure 7. Sketch of the experimental setup.

Subsets of data from the depth sensor, representative of the 2.8 m displacement which comprised the space covered by the platform – with a certain margin – were extracted. According to the examination procedure associated with the Zebris platform, the examined persons' passages across the platform were grouped into triplets and the results corresponding to each triplet of passages were averaged; thus, 11 pairs of the estimates of each parameter were obtained (*i.e.* the pairs comprising one depth-sensor-based estimate and one Zebris-platform-based estimate). The mean error and the standard deviation of errors of the depth-sensor-based estimates were evaluated by treating the Zebris-platform-based estimates as the reference. The data-processing software associated with the Zebris platform was used for evaluating the standard deviation of the Zebris-platform-based estimates of spatiotemporal gait parameters.

The cycle of data processing was repeated six times, according to six variants of the procedure described in Section 2 – the variants being the combinations of the three denoising techniques (the Butterworth filter, the Savitzky-Golay filter and the TVR technique) and two options of velocity threshold values (absolute or relative to the maximum velocity estimate).

4. RESULTS

The values of the parameters of data-processing methods, optimised empirically in such a way as to minimise the differences between the depth-sensor-based and Zebris-platform-based estimates of the spatiotemporal gait parameters, are presented in Table 1. The selected values of the parameters of the Savitzky-Golay filter correspond to the cut-off frequency of 1.53 Hz.

The mean errors and standard deviations of the estimates of spatiotemporal gait parameters are presented in Table 2. The use of the absolute velocity threshold consistently yielded better results than the use of the relative threshold in all cases; hence, for brevity, only the results obtained using the absolute threshold are presented in Table 2.

The values of the indicators of gait asymmetry r_{LR} and STR, determined for all the recorded passages (the latter – on the basis of the data from both the depth sensor and the Zebris platform), are shown in Figure 8. The reported experiments involved only healthy persons whose gait was quite symmetric; thus, all these values are close to 1. To further assess the informative value of the proposed indicator r_{LR}, another experiment, including emulation of asymmetric gait, was performed. During this experiment, a single healthy person walked first naturally and next – making fast steps with the right foot and slow steps with the left foot. The values r_{LR} = 1.00 and STR = 0.99 were obtained for natural gait, whereas r_{LR} = 0.86 and STR = 0.77 – for emulated asymmetric gait. The results of this experiment are illustrated in Figure 9.

Table 1. Empirically selected values of the parameters of data-processing methods in six variants of the procedure for estimation of spatiotemporal gait parameters.

Butterworth filter		
	Absolute threshold	*Relative threshold*
Order	2	4
Cut-off frequency	1.4 Hz	3.6 Hz
Velocity threshold	1.7 m/s	40 %
Savitzky-Golay filter		
	Absolute threshold	*Relative threshold*
Window length	19 samples	19 samples
Polynomial degree	2	2
Velocity threshold	1.7 m/s	42 %
TVR technique		
	Absolute threshold	*Relative threshold*
Regularisation parameter	$8 \cdot 10^{-4}$	$1 \cdot 10^{-3}$
Velocity threshold	1.6 m/s	50 %

5. DISCUSSION AND CONCLUSION

All three denoising techniques, introduced in Section 2.1, allowed for obtaining estimates of spatiotemporal gait parameters subject to quite similar uncertainty. In the case of the step times, the TVR technique yielded more biased estimates but less dispersed than the low-pass filters. In the cases of other parameters, differences in the uncertainty indicators could be noticed among the different denoising techniques, but the reported results do not justify the indication of any of them as capable of providing the most reliable results.

The absolute (rather than the relative) value of the velocity threshold can be recommended for further study.

Table 2. Mean values and the standard deviations of the errors corrupting the estimates of spatiotemporal gait parameters, obtained by means of the depth sensor, and the standard deviations of the corresponding reference estimates obtained by means of the Zebris platform; the symbols *L* and *R* indicate the left and right side of the body; GCT is the acronym of gait-cycle time; SPM – of steps per minute.

	Depth-sensor-based estimates						**Zebris-platform-based estimates**
	Mean error			***Standard deviation of errors***			***Standard deviation of estimates***
	Butterworth filter	*Savitzky-Golay filter*	*TVR technique*	*Butterworth filter*	*Savitzky-Golay filter*	*TVR technique*	
Step time (L)	–0.004 s	–0.004 s	–0.009 s	0.019 s	0.022 s	0.016 s	0.009 s
Step time (R)	0.000 s	0.001 s	0.008 s	0.020 s	0.023 s	0.021 s	0.013 s
Step length (L)	–1.4 cm	–0.8 cm	–2.1 cm	1.8 cm	3.4 cm	3.2 cm	1.4 cm
Step length (R)	–0.4 cm	–0.9 cm	0.1 cm	3.8 cm	3.6 cm	4.1 cm	1.5 cm
Stance time (L)	0.1 % GCT	0.9 % GCT	–0.5 % GCT	2.5 % GCT	2.1 % GCT	2.3 % GCT	0.5 % GCT
Stance time (R)	–0.2 % GCT	–0.3 % GCT	–2.1 % GCT	1.0 % GCT	1.1 % GCT	2.1 % GCT	0.8 % GCT
Double-support time	0.6 % GCT	0.9 % GCT	–1.9 % GCT	4.1 % GCT	2.6 % GCT	3.6 % GCT	0.8 % GCT
Walking speed	–1.4 cm/s	–1.4 cm/s	–1.4 cm/s	2.9 cm/s	2.9 cm/s	2.9 cm/s	5.1 cm/s
Cadence	0.70 SPM	0.54 SPM	0.31 SPM	2.25 SPM	2.37 SPM	2.12 SPM	2.46 SPM

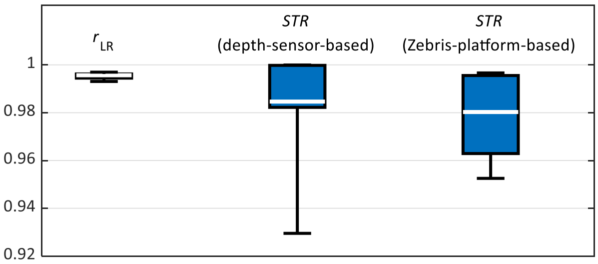

Figure 8. The values of the indicators of gait asymmetry, obtained in the experiment on only healthy persons whose gait is quite symmetric; the white horizontal lines indicate the median values; the boundaries of the blue rectangles indicate the first and third quartiles; the black whiskers indicate the minimum and maximum values.

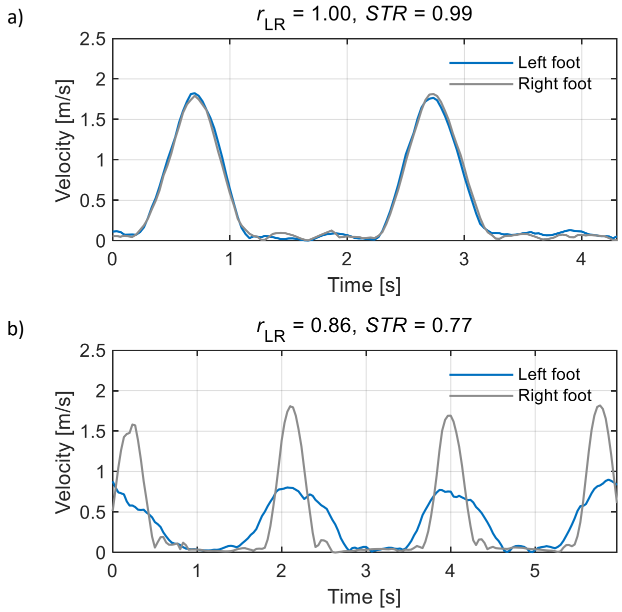

Figure 9. The estimates of the speed of feet, shifted in time so as to maximise the quasi-correlation defined by Equation (1), obtained for quite symmetric gait (a) and quite asymmetric gait (b), and the corresponding values of the indicators of gait asymmetry.

The mean differences between the depth-sensor-based estimates of spatiotemporal gait parameters and the corresponding reference values were quite small, whereas the standard deviations of the depth-sensor-based estimates were somewhat larger than those of the reference values but within the same order of magnitude. These results indicate a high applicability potential of the considered methodology for gait analysis: the somewhat larger uncertainty of the estimates may be justified by the considerably smaller cost and complexity of the examination setup and procedure, if compared to the use of the Zebris platform.

Moreover, the considered methodology enables one to quantify gait asymmetry. In the experiments involving healthy persons, the values of all considered indicators of gait asymmetry – presented in Figure 8 – are, as expected, close to 1; the dispersion of the values of the proposed indicator r_{LR}, defined by Equation (1), is the smallest. In the experiment including the emulation of asymmetric gait – whose results are presented in Figure 9 – significantly different values of the indicators were obtained for symmetric and asymmetric gait. The aforementioned experimental results suggest that the proposed indicator may become quite useful in clinical practice; however, more experimental work is needed to reliably assess its capability to properly characterise the degree of gait asymmetry.

The following practical considerations can be made based on the experiments:

– The value of the foot velocity threshold has a significant impact on the uncertainty of the estimates of spatiotemporal gait parameters; in most experiments, the values 1.6–1.7 m/s have yielded the best results. The choice of the type of the low-pass filter used for denoising the foot position estimates does not seem to significantly affect the results, but the values of that filter's parameters need to be selected carefully.
– The best results can be obtained if the examined person walks towards the depth sensor along its line of sight; if the walking direction does not parallel that line, the feet occlude each other from time to time and, consequently, the reliability of the obtained results is significantly reduced.
– Certain kinds of examined person's clothing, such as skirts or wide trousers, significantly hinder the localisation of the feet on the basis of depth-sensor data, making it impossible to obtain reliable estimates of spatiotemporal gait parameters.

The authors' plans for future work include:

– the implementation and testing of other data-processing methods aimed at identifying gait-cycle phases, including the methods based on the distances between the examined person's knees [13] and on the vertical oscillations of that person's centre of mass [14];
– the experiments aimed at assessing the uncertainty of identification of gait-cycle phases, involving the use of a reference optoelectronic gait-analysis system (which, in contrast to the Zebris platform, is capable of providing not only the reference values of spatiotemporal gait parameters, but also the reference three-dimensional trajectories of the feet);
– the experiments involving persons whose ability to walk is impaired, in particular – whose gait is significantly asymmetrical.

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