Cyclograms Based on Principal Components for Assessing the Gait

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Abstract**—Objective measure of the gait quality is essential for evaluating the therapeutic protocol's effects on stroke patients' rehabilitation. We present a new proposal for assessing the gait, which uses the principal component analysis (PCA) of feet kinematics and ground reaction forces (GRF) data. The data have been acquired by the Gait Master comprising five GRF sensors and 6D inertial measurement units (IMU) per insole. The PCA reduces the 22-time series output from two insoles and generates cyclograms, allowing qualitative analysis of the pathologic and healthy gait differences. We suggest that cyclograms in the space with principal components on the axis provide useful information to the clinician about the gait performance. Five volunteers with no known motor impairment participated in the determination of the regular pattern. We tested the method in a small series of patients after stroke using the pattern of healthy as a standard. The results suggest that the PCA analysis provides a good measure of gait quality.**

Index Terms**—Gait; Stroke; Cyclograms; Principal component analysis (PCA); Inertial measurement unit (IMU); Ground reaction force (GRF).**

I. Introduction

THE characterization of gait in persons with motor disabilities is instrumental in selecting the most effective therapeutic protocol. The characterization can be performed based on data acquired during the gait. The data of interest are the ground reaction forces (GRF) and leg segments' kinematics since they fully define the biomechanics.

The precise measurement of leg segments' ground reaction forces and kinematics can be done in the specialized laboratories instrumented with camera systems and force plates [1, 2]. The difficulty is that the recording process requires a specialist's participation with the experience in acquiring motion data and setting the markers on the appropriate places at the body. The gait laboratory setup is designed for only straight-line walking, and GRF is acquired for one or two steps. The alternative to the recordings in the gait laboratories is to implement a wearable system [3-7]. Wearable systems combine sensors integrated into shoe insoles and inertial measurement units (IMU) that measure the acceleration and angular rates of body segments. Information from all sensors must be synchronized, which is not the most trivial task because of the time delays and lost packages when wireless technology is used. The difficulty is that sensors integrated into insoles, although being much improved (availability of new materials and miniaturization of electronics and wireless communication) measure only total ground reaction forces and have hysteresis, delay, and insufficient robustness when the temperature and humidity change. The recently introduced Gait Master system [8] with several industrial quality GRF sensors and IMU provides versatility comparable with the force plates in the gait laboratories. The data from the insoles is stored in a time-stamped format for off-line analysis. The set of data comprises the 22-time series. This data is sufficient to determine gait parameters [1, 2]. Table I shows the typical collection of data that can be estimated from a wearable system.

TABLE 1: FEATURES IN GAIT ANALYSIS

Gait Feature	Definition
Walking Speed	The average speed while the subject is walking
Cadence	Average steps per minute while walking
Swing Time	The transition time of the foot from lift to landing
Stance Time	The transition time of the foot from landing to lift
Stride Length	The distance between the heel contacts of the ipsilateral foot and contralateral foot
Step length	The distance between two consecutive heel contacts of the same foot
Ground reaction force	The distribution of the GRF over the sole
Symmetries	Differences between the same events in ipsilateral and contralateral legs

The reason for the quantification of the gait is the objective assessment of the performance. However, there is no golden standard what is the normal performance. Young people have different gait patterns than persons of older age. Females have different gait patterns influenced by the type of shoes used, etc. [9].

Methods used in clinical studies compare the measured features between before and after the therapy, or between different therapeutic protocols. The comparison is statistically analyzed, and significant differences are used as measures.

Another method to use gait data is to form cyclograms. Cyclograms are a spatial presentation where two or more recorded signals (e.g., hip and knee angles; hip, knee, and ankle angles) are the coordinate system axes. The cyclograms can be used to analyze the different gait modalities and compare healthy vs. pathologic gait [10].

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We introduce here the method which uses cyclograms generated in the space of principal components calculated from data recorded during gait. The principal components analysis (PCA) reduces the 22-time series recordings to a set of orthogonal values that can be used for the creation of a two-dimensional cyclogram. In principle, the analysis can look into three or more dimensional cyclograms.

The method that we present, PCA, was applied to sets of data separately for the left and right legs. Data recorded were considered as sequences of stochastic events. The reason for developing this method for representing the gait performance follows the previous research in applying PCA to analyze kinematic data [11].

We illustrate the method by using data recorded in healthy and patients with stroke. Besides, we associate a numerical measure calculated from the cyclograms to be a classifier of difference between the healthy and pathologic gaits.

II. Methods and Instrumentation

A. Instrumentation

We used Gait Master insoles [8] with five GRF sensors and the one 6D IMU per insole. The insoles use the hardware built around MPU-6050 (16-bit conversion). Each insole includes a wireless communication circuit allowing real-time data transfer at 100 Hz (11 signals per insole) to the host computer at distances up to 30 m. The LabView environment's proprietary acquisition software provides online data with the delay of 50ms and stores data in a time-stamped format for off-line analysis. The program has a graphical user interface (GUI), allowing the clinician to intuitively operate the system.

1) Subjects

Six healthy volunteers participated in this study. They were considered healthy since no known sensory-motor impairment was reported or known from their health record. Four patients with stroke were recruited. The measurements were performed in the Clinic for rehabilitation "Dr. Miroslav Zotović“, Belgrade, Serbia. All patients signed an informed consent approved by the board of the Institute. Patients participated in testing the efficiency of the functional electrical stimulation assisted pedaling.

B. Procedure

Subjects were asked to walk at their normal walking pace. They repeated walking over a 5m flat surface two times. If necessary, they would rest between the trials.

C. Signal processing

Steps extraction and the stance and swing detections were done based on the threshold method for detecting heel strike and toe-off events. The threshold was set to be 5% of the maximum value from the GRF signal from the heel and the toes' lateral side. The first and last steps were excluded from further analysis. The singles used in the principal component analysis were the angular velocity in the sagittal plane (GyroY), the acceleration in the direction of sole (AccX), and the direction orthogonal to the sole (AccZ), and the all five ground reaction forces individually (GRF). The signals were selected based on the heuristic analysis of all 11 signals measured by each insole. We normalized the signals to make them have the unit variance.

The PCA allowed the mapping of the original data into orthogonal space, where the principal axis is the direction of the data's maximal deviation [12]. The analysis includes calculating the correlation matrix, extraction of the application of the principal component of the varimax rotation, and calculation of factor scores. The number of principal components we used in this study was chosen based on Kaiser's proposed method [13]. We retained only elements in which the eigenvalues were more significant than one. The Bartlett's test of sphericity showed that data was suitable for PCA.

The proposed method uses 2D cyclograms in the space of the first two principal components. Cyclograms were compared for consecutive steps for different gait categories. These cyclograms are the image representation for the gait performance assessment.

We defined the quantitative parameter d, as shown in Eq. 1:

$$d = {d_{PC1_{stance}}}\big/{d_{PC2_{stance}}} * {d_{PC2_{swing}}}\big/{d_{PC1_{swing}}} \quad (1)$$

where $d_{PC1_{stance}}$ is the maximal distance on the PC1 axis between points on cyclograms for the stance phase. Similarly, $d_{PC1_{swing}}$ is the distance for the swing phase, while PC1 and PC2 subscripts represent the distance on the PC1 and PC2 axis, respectively (Fig 1).

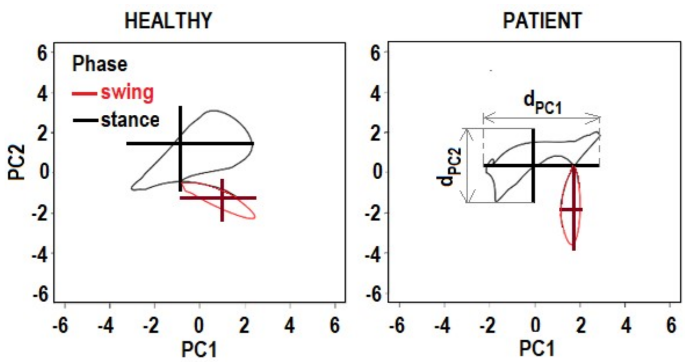

Fig.1. Sketch of the parameters defining the cyclogram that can be automatically calculated. The left panel shows a characteristic pattern for one leg during healthy gait. The right panel shows an example of the non-paretic limb during the gait of a patient.

III. Results

Fig. 2 shows the processed data and a characteristic single step for a person's left leg with no known sensory-motor impairment.

Fig. 2 shows the processed data for about eight seconds (left panel) and extracted data for a single step for a person's left leg with no known sensory-motor impairment (right panel).

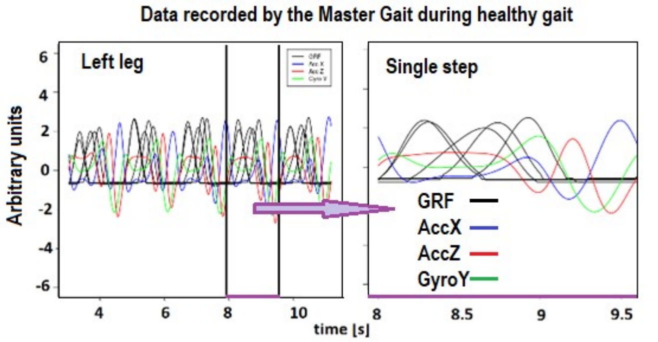

Fig.2. An example of the eight signals extracted from the 22-time series was recorded with the insole in the left shoe during a healthy person (left panel). The right panel shows the processed and standardized data for a single step. Acronyms AccX (blue) and AccZ (red) are used to the accelerations in the direction of the sole, and the direction orthogonal to the sole, GyroY (green) is denoting the angular rate of the foot in the sagittal plane, and GRF (five black lines) are five signals from the GRF sensors.

Left panels in Fig. 3 show the first two principal components (PC 1 and PC 2) vs. time. The right panels in Fig. 3 are cyclograms in the two-dimensional PCA space (PC1 and PC2, the horizontal and vertical axis). The black color shows the stance phase, while the red color indicates the swing phase.

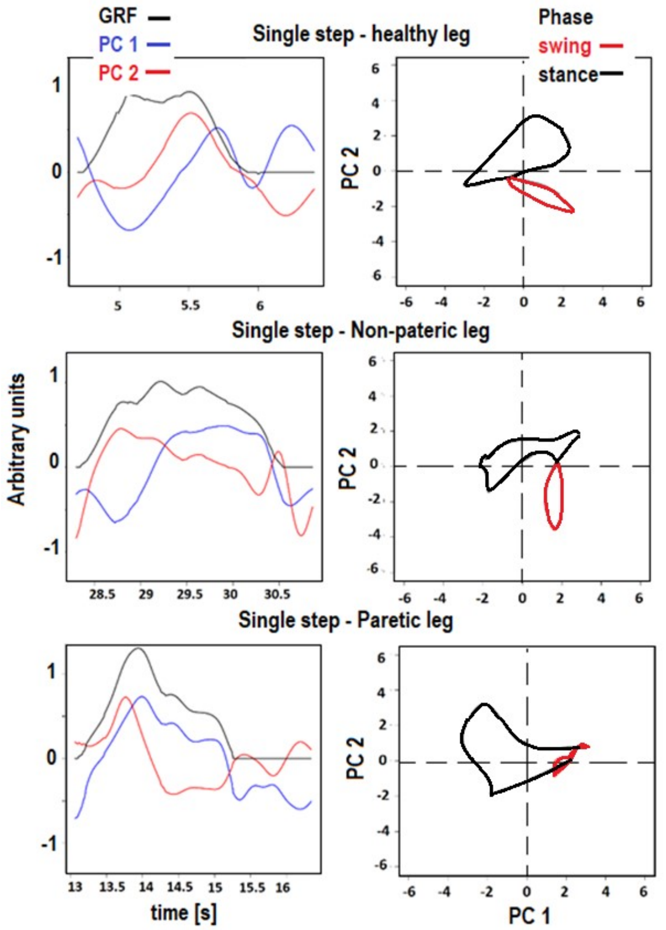

Fig.3. Left panels show the first two principal components (PC 1, PC 2) and the sum of all five sensors (GRF). The right panels show PCA cyclograms for a single gait cycle

and use two colors for distinguishing between the swing and stance phases. The upper row uses data from the left leg of a healthy subject. There is a distinct difference in the cyclograms for both paretic and non-paretic legs compared with the cyclogram for healthy gait patterns.

Fig. 4 shows the variability of cyclograms for four consecutive steps.

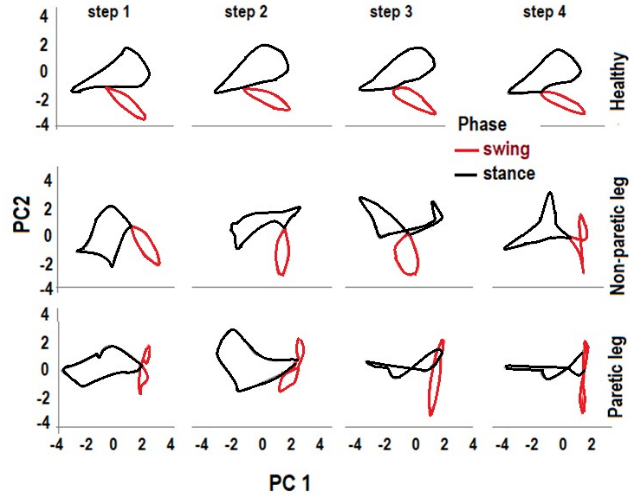

Fig.4. Cyclograms for four consecutive steps. The first row shows cyclograms for the left leg of a person with no known sensory-motor impairment. The second and third rows are cyclograms for a patient's non-paretic and paretic leg after stroke. Red lines are used to the swing phases and the black lines for the stance phases.

The top panels show a healthy pattern, the second row shows the non-paretic leg, and the bottom panels represent the paretic limb. The red color indicates the swing phases, while the black lines show each step's stance phases.

Fig. 4 indicates that there is a small variability from step to step in a healthy gait. There are significant differences between cyclogram in patients for the paretic and non-paretic legs. There is a high variability from step to step, especially noticeable in the cyclograms for the paretic limb.

In conclusion, the pathological gait patterns have different cyclogram shapes than healthy gait patterns, and they have more substantial shape variability from step to step.

TABLE II. THE VALUES OF THE RATIO OF LENGTHS d_{PC1} AND d_{PC2} FOR FOUR CONSECUTIVE STEPS OF A HEALTHY AND PATIENT N^{o}1 FOR THE STANCE AND THE SWING PHASES

	Healthy – left leg		non-paretic		Paretic	
	stance	swing	stance	swing	stance	Swing
Step 1	1.4	1.1	1.2	0.6	1.8	0.2
Step 2	1.2	1.7	0.9	0.3	1.2	0.7
Step3	1.3	2	1.3	0.8	2.3	0.2
Step 4	1.3	1.9	1.1	0.5	2.2	0.3
Mean±SD	1.3±0.1	1.7±0.4	1.1±0.2	0.5±0.2	1.9±0.4	0.3±0.3
d ± SD	0.8±0.2		2.3±0.6*		7.8±5.6*	

Data for four steps for the healthy gait and one patient are in Table I. The columns are the values of the d_{PC1} and d_{PC2}. The data for one leg of a healthy gait and non-paretic and paretic sided of one patient with stroke. The asterisks annotate the significant difference.

TABLE III. THE MEAN AND STANDARD DEVIATIONS OF d (RATIO OF d_{PC1} AND d_{PC2}) FOR ALL CONSECUTIVE STEPS FOR A HEALTHY AND FOUR PATIENTS.

	d ± SD	
Healthy (left leg)	0.9±0.2	
	Non paretic leg	Paretic leg
Patient Nº 1	2.3±0.6	7.8±5.6
Patient Nº 2	3.2±.1.2	6.9±4.5
Patient Nº 3	1±0.9	7.9±6.3
Patient Nº 4	0.7±0.6	1.5±1.2

Table III shows the values of the parameter d for the healthy gait and the gait of four patients.

IV. DISCUSSION AND CONCLUSION

The cyclograms reflect the gait performance reduced to two principal components. The parameter d is a quantitative measure of the cyclograms, which we suggest to be used as the gait measure. The new standard is a simple means for evaluating a therapy [14, 15].

The shapes of cyclograms in patients show a discrepancy in patients' gait compared with healthy persons (Fig. 6). The cyclograms are a catching eye measure to the gait performance. The software we developed allows the clinician to superimpose the cyclogram of a patient over the cyclogram of a healthy gait.

The cyclograms can be used as a simple gait event visualization method. The characteristic points of transition between swing and stance phase of the first two principal components are shown as one point on cyclograms.

Data presented for patients show a significant difference compared with the healthy (Fig. 4, Tables I and II). The high variability between steps is noticeable in patients after stroke compared with the repeatability in persons with no known sensory or motor impairment.

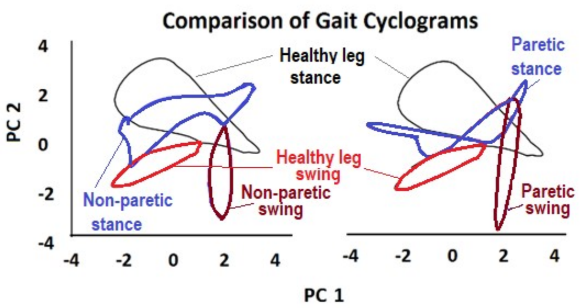

Fig.5. The superimposed cyclogram of a healthy leg over the cyclogram of the non-paretic leg (left panel) and the same cyclogram of a healthy superimposed over the cyclogram of the paretic limb for one gait cycle (right panel).

The orientation of the axis is not essential, since if the sign of a component is changed, the variance contained in that component is not changed. More precisely, these components are given by PCA component scores. Each original variable is a linear combination of the weighted components. The cyclograms are not fully closed curves; some overlap since we observe consecutive steps, but this does not limit the estimation of the parameter d.

The cyclograms shape for the non-paretic leg is more similar to the one presenting healthy gait (Fig. 5). This can be explained by the fact that the neural system still has not developed compensation strategies for this leg. Thus, we can conclude that this image representation is an effective and simple way to follow the therapy's progress.

We suggest that the PCA distinguishes between healthy gait and gait of a person after a stroke.

The Gait Master system also provides data that can be used to study the gait in more detail. More extensive clinical studies for the method's validation started, but the current Covid-19 pandemic slowed down the data collection.

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