

STATISTICAL INDICATOR FOR THE EVALUATION OF HUMAN GAIT ANALYSIS BY GROUND REACTION FORCES

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ABSTRACT

In this paper multivariate analysis is adopted to evaluate the gait of subjects submitted to surgical reconstruction with complex traumas of the foot (loss of skin, crushing) due to car crashes or accidents on the job.

The analysis of gait parameters are a significant barrier to the clinical application of gait analysis. Principal component modeling of gait kinetic parameters reduces the data to measures of distance from normal and these measures are shown to be sensitive to change in gait pattern associated with traumas at the foot dorsum, or at the calcaneal area or at the forefoot area and their surgical reconstruction treatment.

Principal component model is developed for twelve kinetic gait parameters of a group of 27 normal elderly subjects. The loading vectors revealed the structure of the model. Scores and the residuals are used as distance measures about which confidence intervals are defined.

Pathological gait data from 21 patients are characterized with respect to a control group. This method allows to find out a subset of parameters of the recorded data, important in sense of detecting deviation from gait considered to be normal.

Mahalanobis distance is used to summarize the consistency of pathological sample with the gait presumed to be normal. Results are shown to agree with the clinical status. The differences in gait pattern obtained by the principal component models are clinical relevant.

Keywords: Principal component analysis, Mahalanobis distance, Ground reaction forces.

INTRODUCTION

The clinical evaluation of the gait is usually based on a visual inspection. This kind of analysis could be extremely subjective. The perception and/or the deviation by the “normal trend” of the movement result strictly connected with the experience and the knowledge of the clinician. For this purpose the evaluation process has to be reliable and reproducible [1],[2].

Therefore instrumental methods for the analysis of the movement [3], [4], are associated to the clinical examination for the individualisation and/or quantification of the “disability signs” not perceived by visual inspection. This kind of analysis provides report not easily interpretable by the clinician. The knowledge in this domain is often badly structured and accessible by a strictly and specialised staff [5], [6]. Multivariate analysis allows to extract relevant information to evaluate human gait.

This work characterizes the gait of pathological subjects quantitatively with respect to subjects whose gait is considered to be normal.

Principal Component Analysis (PCA) [8], [9] is adopted to characterize the gait of subjects with complex traumas of the foot (loss of skin, crushing) due to car crashes or accidents on the job submitted to surgical reconstruction.

The surgical treatment following this kind of traumas is focused on the morphological reconstruction and on the foot functional recovery. The reconstructive surgery main objective is to restore the anatomical shape, the weight bearing capability and the ambulation dynamics. The substitution of specific skin and muscles with coverage tissues often allows to rescue the injured foot and to recover ambulation [10]. After a rehabilitation program, patients recover their walking ability but some of them frequently claim gait disturbances (pain, fatigue and reduced functionality) over time. These problems are not easily justified by the clinical examination.

This study is aimed at to characterise the functional ability of the subjects after reconstructive surgery by means of a 3D bilateral gait analysis. In particular Ground Reaction Forces (GRF) are recorded and analysed to reveal process hidden to the clinical eye.

PATIENTS/MATERIALS AND METHODS

The study population is composed by 21 patients, all belong to the second group of Hidalgo [11]. In fact they have injuries limited to the tegument or complex traumas of the foot without significant fractures. According to the type of injury the subjects are classified in three groups:

1) if the injury is localized under the foot from the plantar area under the metatarsal heads up to the fingers the subjects are classified to the *forefoot group* (5 subjects);

2) if the injury is localized under the foot in the region from the posterior part of the heel up to the plantar arch the subjects are classified to the *rearfoot group* (10 subjects);

3) if the injury is localized at the forefoot in the region of the dorsum the subjects are classified to the *dorsum group* (6 subjects).

The control group consists of 27 subjects matched for age and sex.

Each subject is asked to walk freely, wearing his/her shoes, in order to become familiar with the environment and to chose his/her preferred cadence. Shod condition is adopted to guarantee a familiar and comfortable situation to the subjects: in fact some of them cannot walk barefoot. These initial gait trials allow to the examiner to determine the starting position. No information about the platform position (*BERTEC*® force platforms, $f_{acq}=500\text{Hz}$) is given to the subject to avoid influence in the cadence. Data are collected for three trials in the moment each foot had its stance on the related platform.

GRF are examined to study the foot behaviour during the phase of weight acceptance, rolling and raising of the toe. The presence of some altered stance mechanisms are investigated [4], [12].

The parameters of interest are extracted by GRF trajectories as described in [13]: the forces parameters (F_1, F_2, \dots, F_6) and the corresponding time instants (T_1, T_2, \dots, T_6).

To define the “normal gait model”, PCA is applied to the data of the control group subjects. Most data sets contain one or a few unusual observations that do not seem to belong to the pattern of variability produced by other observation. When an observation is different from the majority of data or is sufficiently unlikely under assumed probability model of the data, it is considered an outlier.

Initially the set is cleared from outliers. In fact is important that all samples represent “not pathological” gait. Multivariate outliers are found using “leave one out” Hotelling’s T^2 -Test [14]. This method consists on compute the distance between each point (x_i) and the mean (\bar{x}) of the training set in the original variable space, using (1):

$$D_i = (x_i - \bar{x})C_x^{-1}(x_i - \bar{x})^T \quad (1)$$

where C_x is the variance-covariance matrix of the data matrix. D_i values are compared with a critical value obtained by:

$$H \cong \frac{(n-1)^2}{n} \beta_{(\alpha; p/2; (n-p-1)/2)} \quad (2)$$

where β the beta-distribution, n is the number of samples and p is the dimension. Due to the fact that an outlier found with this control limit has influenced by the estimation of the mean (\bar{x}) and the covariance matrix (C_x), these estimations and the D_i s have to be recalculated after the elimination of the outlier (*leave-one-out*) and again all D_i s are compared to the new border. This is repeat until no outlier is found anymore.

Principal component analysis as a classification and data structure detection method is than applied to the data from 2/3 of the whole control group without outliers. PCA is applied to identify the main structure of the data through describing the variation in the data [15-18].

Four steps are involved in the application of the PCA. The first step consists of finding the covariance matrix of the GRF parameters. A matrix is created from parameters extracted by the trajectories. It consists of 138 rows, each row representing a single trial of a subject, and 12 columns which contain the parameters. The purpose of applying PCA is to extract the maximum variance from the data by means of a few orthogonal components called principal components (PCs).

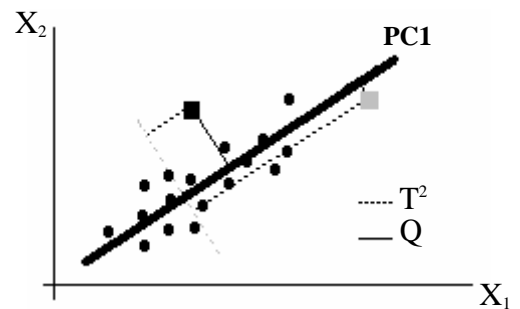


Fig.1 Two variables (x_1 and x_2) which produce a model with 1 Principal Component (the bold line). The grey square represents an observation with a large T^2 but a small Q whereas the black square represents an observation with a large Q but a small T^2 [15].

The second step is to choose the number of PCs which should be retained for further analysis. The eigenvalues or factors loading of each PC indicate how many components are important in conveying most of the major information. Based on the Kaiser criteria [19], the

eigenvalues that accounted for more than 1% of the variance could be applied for further data interpretation. However, in reality, the first few PCs accounted for most of the data variations suggested for analysis.

As the PC model is to be used to assess future patients data, cross validation is chosen as it is suited to apply the model to future observations not included in the construction of the model. Cross validation measures the predictive power of the model using a summary of the predicted residual calculated by deleting and predicting each observation in turn from the model. The predicted residuals are compared as one adds PC until the overall prediction is no longer significantly improved by the addition of extra PC [20] [21]. So we use 1/3 of the whole control group to cross validate the model and the first eleven representative curves are retained as important factors.

The third step is to choose and perform an appropriate type of rotation on the PCs to maximise the variation leading to more physiologically interpretable information. Varimax rotation is used to achieve the basic structure in a set of data by rotating the PC axes.

The last step is to give a physical meaning to each PC. To get a first impression of the differences between the groups, PCs are calculated also for the pathologic groups. The interpretation of the first PCs is made by a simplification. Factors loading are marked with “+” or “-” if the value is greater than half of the maximum coefficient (again in absolute value) for the relevant

principal component [7] (fig. 2).

In order to assess the samples in the “normal gait” PC model, the difference distances T^2 and Q [15] are calculated for pathologic and control group. T^2 is the Mahalanobis distance between each observation and the centre of the hyper plane defined by the PC model. It demonstrates the sample accordance with the model (fig.1): higher the T^2 value, higher is the probability of the sample not belonging to the control population. Q is the residual, the perpendicular distance between the sample and the hyper-plane represented by the chosen PCs.

To understand better how and how much changes in certain variables change the distance of the subject to the control group, we create twelve “test sample” which have mean values for all variables but one. This analysis allows to infer the parameters that cause T^2 and Q values faraway from the reference (non pathological values).

In order to obtain a numerical description that summarizes the consistency of the sample with the gait presumed to be normal and than considered as reference, the Mahalanobis distance between each sample and the training set in the T^2 - Q plane is used. This quantity is obtained for all subjects forming the normal model and the distribution can be used to derive a confidence interval (bootstrap [22]), to which the patient gait data are then compared.

		<i>F1</i>	<i>F2</i>	<i>F3</i>	<i>F4</i>	<i>F5</i>	<i>F6</i>	<i>T1</i>	<i>T2</i>	<i>T3</i>	<i>T4</i>	<i>T5</i>	<i>T6</i>
Control group													
	mean	11,41	8,03	11,85	0,43	-1,96	2,03	0,24	0,46	0,79	0,01	0,18	0,87
	sd	0,85	0,99	0,77	0,28	0,36	0,35	0,03	0,05	0,01	0,01	0,03	0,01
Forefoot group													
<i>controlateral</i>	mean	10,92	8,56	11,05	0,45	-1,40	1,67	0,21	0,41	0,76	0,02	0,14	0,87
	sd	0,88	0,54	0,78	0,23	0,46	0,36	0,06	0,06	0,03	0,01	0,04	0,02
<i>treated</i>	mean	10,51	8,40	10,56	0,46	-1,59	1,36	0,26	0,45	0,73	0,02	0,19	0,82
	sd	0,32	0,40	0,87	0,18	0,39	0,40	0,06	0,03	0,04	0,01	0,05	0,05
Rearfoot group													
<i>controlateral</i>	mean	11,09	7,99	11,07	0,37	-1,58	1,61	0,23	0,44	0,77	0,02	0,17	0,86
	sd	0,93	0,92	0,88	0,16	0,29	0,43	0,04	0,08	0,03	0,01	0,03	0,02
<i>treated</i>	mean	11,05	7,95	11,02	0,37	-1,62	1,46	0,25	0,46	0,73	0,02	0,19	0,83
	sd	0,54	0,89	0,88	0,23	0,42	0,45	0,03	0,05	0,06	0,01	0,03	0,06
Dorsum group													
<i>controlateral</i>	mean	11,33	8,12	11,65	0,46	-1,85	1,90	0,22	0,45	0,78	0,02	0,16	0,87
	sd	0,95	0,57	1,06	0,24	0,46	0,39	0,05	0,07	0,02	0,01	0,04	0,03
<i>treated</i>	mean	11,34	7,92	11,32	0,46	-1,76	1,74	0,24	0,45	0,78	0,02	0,16	0,87
	sd	1,00	0,64	0,99	0,25	0,40	0,26	0,02	0,06	0,02	0,01	0,04	0,03

Table.1 Mean values and related standard deviation of kinetics parameters.

RESULTS

The average and the standard deviation of $F_1, F_2, \dots, F_6, T_1, T_2, \dots, T_6$ are presented in table 1. Our control group data are in good agreement with previous reported studies [13] [23] showing that our control group subjects' gait performance is within the range of able-bodied gait reported in literature.

The PCs are calculated for 2/3 of the subjects from the control group cleared from the eight outliers. The number of PCs model is chosen through cross-validation.

PCs simplifications and factors loading analysis allow to point out the different structure and the meaning of pathological and not pathological PCs.

	Control Group	Dorsum Group	Forefoot Group	Rearfoot Group
F1	+	+		
F2	-	-		
F3	+	+		
F4	+			
F5	-	-		
F6	+	+		
T1	-	-	-	
T2				
T3			+	+
T4	+	+		
T5		-		
T6			+	+

Fig.2 First simplified [3] principal components of control and pathological groups.

In fact the sign (+/-) is important for the PC that is considered to see that the values of the variables are high respectively low together if they have the same sign or that the values contrast if they have different signs. The interpretation of the components is quite difficult because the structure is complicated for most of them. Nevertheless for some of the PCs illustrative relations to the trajectories can be drawn (fig.2). The first component of the “normal gait model”, for example, has a rather interesting structure: it contrasts the corresponding vertical and fore-aft forces at loading response (F1 and F4) and at terminal stance (F3 and F6) with the forces at mid stance (F2 and F5). I.e. when the values of F1, F4, F3 and F6 are high, the values of F2 and F5 are low and vice versa. Added to this T1 and T4 are contrasted.

This structure differs to some extent very much from the pathological group. The PCs' composition of the rear foot and the forefoot group is simpler; the first component represents the time instants T3 and T6. Only

the dorsum group shows a strong similarity to the control group.

T^2 and Q are calculated for pathologic and control group and each sample are represented in T^2 -Q plane. The application of the model to the pathologic groups reveals that most of the rearfoot subjects are distinguished from “normal model” by their T^2 value, while the Q values are similar to those of the control group. Many forefoot subjects differ in both T^2 and Q values (fig. 3). The dorsum subjects have Q and T^2 values inside the “normal model” confidence interval. This is the group of which most samples are close to the control group (fig. 4).

The Mahalanobis distance (MD) between each sample is calculated to have a numerical description that summarizes the consistency of each subject with the control group gait. No conclusion about its distribution can be drawn. Thus a non parametric method, the Bootstrap (with 2000 re-samples), is applied and the confidence interval for the control group are calculated: MD=5,07. This kind of distance is visualised in the T^2 -Q plane with an ellipse (grey in the figures 3-4).

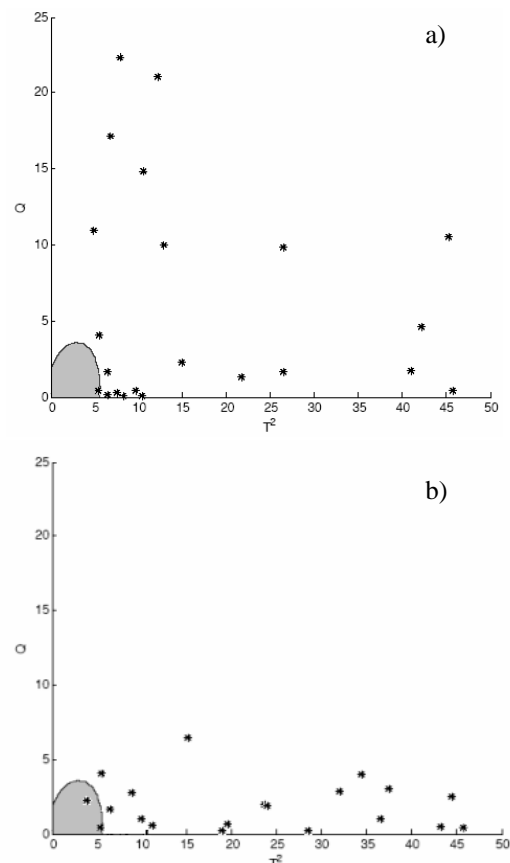


Fig.3 Samples of the forefoot (a) and rearfoot (b) group in the T^2 -Q plane. The gray ellipse is the CI for the 95% of the control population.

The analysis of model structure allows to infer the parameters that cause T^2 and Q values faraway from the values of the control group. Interestingly some

parameters have almost no influence, whereas high/low values in T2, T3 and T6 result in rather extreme values in T^2 and Q ($T^2 > 20$ and $Q > 17$), and consequently in a position in the T^2 -Q plane far away from the samples of the control group.

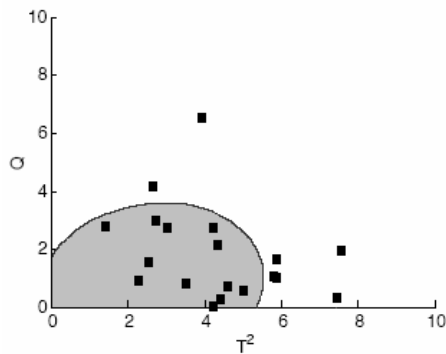


Fig.4 Samples of the dorsum (squares) group in the T^2 -Q plane. The gray ellipse is the CI for the 95% of the control population.

Indeed for the dorsum group T2, T3 and T6 are comparable to those obtained for the control group, while differences can be noticed for the other pathological group.

DISCUSSION

Principal analysis modeling is a promising technique for the successful reduction and analysis of gait kinematic parameters. It fulfils two objectives of gait analysis: detection and characterizations. The first represents the ability to classify a subject as different from what is often a “normal” population and the second represents the ability to characterize pathological gait with respect to a control group.

Using PCA kinetic parameters are represent as a set of scores and residuals that are reduced to one statistical distance measures: Mahalanobis distance. Confidence interval about it derived from normal subjects provides limits to which patient gait is compared. This distance can be used as a statistical indicator to characterize the kinematic of different subjects in respect to their accordance with the model. The structure of the model provides the interpretation of the difference by identifying the portion of the stance responsible for the differences. In fact PCA allows also to find out which variables (T2, T3 and T6) associated to the recorded data are relevant in detecting deviation from the behavior considered to be normal.

The work presented here demonstrates that the difference detected by principal component models are correlated with clinical status.

Results of this study confirm that subjects operated at the dorsum have a gait rather similar to that considered to be normal. In fact the information are structured in such a manner to allow the correlate the movement analysis deviations with physiological causes. Injuries at the plantar area induce severe alterations revealed by this statistical approach but not recognized by subjective clinical evaluation.

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