ANALYSIS OF KINEMATIC PATTERNS IN RUNNERS. AN APPROACH BASED ON INERTIAL SENSORS AND FUNCTIONAL DATA ANALYSIS

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The aim of this study was to define a methodology able to analyse the foot motion using an inertial measurement unit (IMU) integrated in the midsole of the running shoe. Nineteen subjects performed two tests: an incremental running test in order to determine their individual anaerobic threshold (IAT) and, 2-7 days later, a constant-speed test according to their speed at IAT. The foot motion at the sagittal plane was analysed using Functional Data Analysis (FDA) techniques. This methodology enables to determine the variations in the runners´ steps comparing two fatigue states.

KEY WORDS: foot motion, functional data analysis, fatigue, running.

INTRODUCTION: Running is one of the most popular leisure sports activities. However, many people start practicing running and then stop. 38% of the European runners have, or have suffered a running injury and between 37 and 56% of recreational runners become injured at least once each year. Overuse injuries contribute to 50-75% of all running injuries (van Mechelen, 1992). A major contributor to running injuries is inadequately designed training programs which lead to training errors (Pujalte & Silvis, 2014). Training errors include running too far, increasing the distance or time too quickly, high intensity, hill work, poor technique and fatigue. There are specific studies about the effect of fatigue and relationship with biomechanical variables; however the results are not always consistent (Zadpoor & Nikooyan, 2012).
The classic analysis in biomechanics includes the acquisition of kinematic and kinetic patterns by expensive recording systems and the analysis of discrete variables. This approach has the drawbacks concerning the implementation and processing of data. Biomechanical instrumentation is very useful in the field of research but their cost and complexity hinders its use in other areas. Parametrization also implies a loss of information with respect to the continuous variables recorded over time (Medina et al., 2013).
The goal of this study was to define a methodology, using a low cost measuring system integrated into the running shoe, able to analyse the foot motion using Functional Data Analysis (FDA). This procedure is focused on the identification of changes in the biomechanical variables along time and their relationship with the fatigue state of the runner.

METHODS: The study sample consisted on 19 subjects, recreational runners (6 females, 13 males; mean age: 38.9±6.4 years; mass: 69.7±11.5 kg; height: 171.54±8.31 cm) volunteered to participate in this study. All participants competed regularly in 10-km running races at regional levels, and their best performances in 10-km competitions ranged from 45 to 60 minutes. None of the participants had received any pharmacological treatments the last six months or had any type of neuromuscular disorder or cardiovascular, respiratory or circulatory dysfunction. The participants received a verbal explanation about the possible benefits, risks and discomfort associated with the study and signed a written informed consent before participating in the study.
The subjects performed two tests on two different days with at least 48 hours and a maximum of seven days between sessions. In the first session, all subjects completed a maximal incremental running test on a treadmill to determine maximal physiological variables and speed corresponding to individual anaerobic threshold (IAT). The procedure is described by Niess et al., (2003). In the second session, according to their IAT speed, the runners performed a constant-speed test in order to find possible changes in biomechanical parameters while running.

The subjects adjusted their running speed according to auditory signals timed to match 20-m intervals delineated by marker cones around a 400-m long outdoor athletics track. At the end of each lap, the subjects were asked about their perceived exertion through Borg scale (Borg, 1982). The test was concluded once the subjects failed to reach the next cone in three consecutive times in the period stipulated or the grade of exertion stated by the subjects reached the maximum value in the Borg scale.
The foot motion at the sagittal plane was recorded by using an inertial measurement unit (IMU) integrated in the midsole of the running shoe (Figure 1). The angle of foot motion was calculated using the algorithm described by Favre et al., (2006). The sensor was validated by the procedure described by Parrilla et al., (2013), obtaining +/-0,7º error.

Figure 1: Runner during a constant-speed test (left) and IMU integrated in the midsole (right).

The time scale of each step recorded was linearly adjusted in order to express the evolution of the movement as a percentage of the gait cycle. For each lap, the average step was calculated. For each subject, only the first and the last five laps were considered. This provided 95 foot motion waveforms, which were analysed using FDA techniques. FDA is a statistical data analysis approach that works with the whole waveform or function as a single data, instead of discretizating and extracting scalar parameters from the curves, which is the classical approach in biomechanical studies. Functional principal component analysis (FPCA) was applied to the signals obtained using the whole set of 95 observations. This technique defines a base of independent functions that can be combined to explain all the observed variability. Thus, for the observed i-th function fi(t),

$$f_i(t) = F(t) + a_{i1}\,PC_1\,(t) + a_{i2}\,PC_2(t) + \dots \dots a_{im}PC_m(t) \qquad (1)$$

where F(t) is the functional average of $f_i(t)$ for all observations, $PC_j(t)$ are the functional principal components, and a_{ij} are the scores of the i-th observation for component $PC_j(t)$. The full calculation procedure is described by Epifanio et al., (2008).
The a_{ij} scores characterize the biomechanical pattern of the subject. With the aim of identifying differences at the beginning and at the end of the test, a_{ij} scores were analysed using paired difference test. FDA was performed in MATLAB and the statistical analysis in SPSS.

RESULTS and DISCUSSION: Figure 2 shows the results of the FDA. The average curves are shown in solid line, whereas the dash lines (--) and the plus line (++) represent the average minus or plus two times the standard deviation of each factor. This representation allows assigning an intuitive meaning to each component. The first four principal components (PC1 to PC4) explained 90,13% of the observed variance.
PC1 is related to the total foot motion range; high scores are related to smaller ranges whereas low scores are related to larger ranges. PC2 is related to the velocity of the movement; high scores are associated to higher stance time. PC3 indicates differences in the foot motion range during the stance phase. Finally, PC4 is related to the take off.

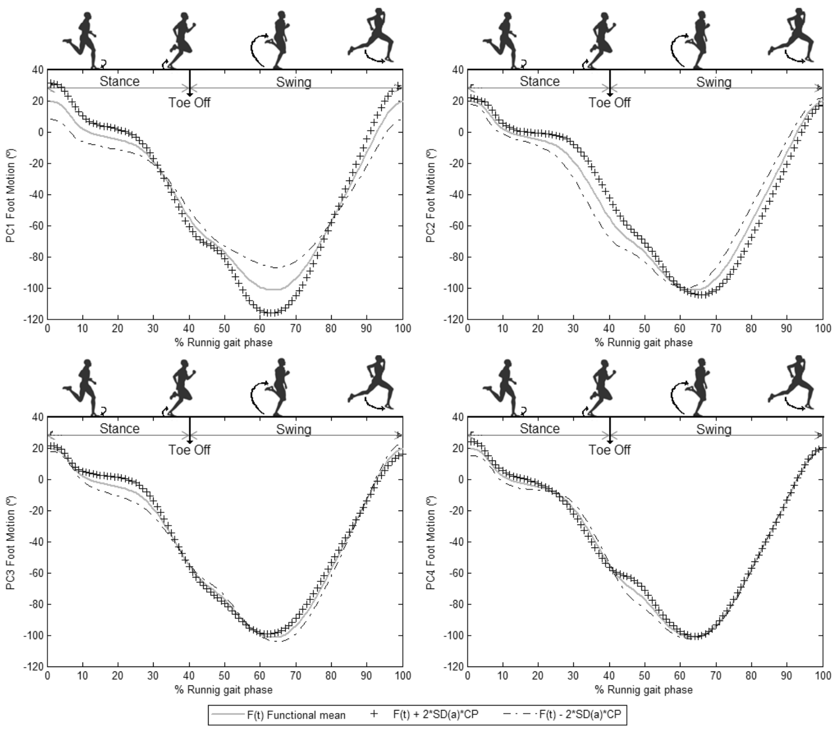

Figure 2: Principal Components of Foot Motion.

Table 1 shows the results of the paired difference analysis comparing each functional PC score that characterize the foot motion between the two states studied: the start of the test (first 5 laps) and the end of the test (the last 5 laps).

Table 1:
Results of paired differences analysis.

	Mean	SD	Standard error of measurement	95% CI		t-value	2-Tail Sig
				Lower	Upper		
Score_PC1	2,554	25,841	2,651	-2,710	7,818	,963	,338
Score_PC2	-4,919	27,303	2,801	-10,481	,643	-1,756	,082
Score_PC3	3,500	8,765	,899	1,714	5,285	3,892	,000*
Score_PC4	-1,830	8,035	,824	-3,467	-,193	-2,220	,029*

Results show that no statistical differences ($p<0,05$) were found in the first two scores: foot motion range (PC1, p=0,338) and stance time (PC2, p=0,082) although it seems that there is a trend in the increase of stance time.

On the other hand, the third score (PC3, p=0,000), related to the stance phase, was found statistically significant. The motion range in the first phase of stance and in the swing phase was higher in the last laps. This result is in line with those obtained by Kellis & Liassou, (2009). Finally, scores of the fourth principal component (PC4, p=0,029), related to the take-off phase, were also found statistically significant. In this case, high scores on this factor indicate an alteration in the morphology of the curve. This alteration may be due to less muscle control associated to fatigue state (Mizrahi et al., 2000).

CONCLUSION: The present study has demonstrated the technical feasibility to characterize the biomechanical patterns of running through the measures obtained by the sensor system developed and the methodology of analysis proposed.

Using functional data is advantageous for the statistical treatment of time functions. In particular, FPCA allows reducing the information of a family of curves to a small set of scalar variables minimising the loss of the original information that is contained in the raw signals.

This technique has been applied to the study of the relationship between biomechanics and fatigue. The scores of the principal components allowed to distinguish between the two states.
This technique has clear advantages for the extraction of scalar variables form waveforms: it does not require a pre-processing of the function, and it allows using curves of different morphologies, since that information is already included in the principal components. The results found about the relationship between the biomechanical parameters recorded and the state of fatigue are consistent with the literature. However, it would be interesting to study the evolution of these parameters when the runner speed is not constant, under more realistic conditions. These results could be used in the future to monitor the runners and follow-up their training plans.

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