Identification of Pronation-supination Patterns on Runners
An Aplication of Functional Principal Component Analysis

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Abstract: The correct classification of runners according to their gait patterns is a relevant issue for the design of sports footwear. Specifically, the classification of runners as neutral, pronators, and supinators is a problem that is not yet fully solved, and requires expert observation, since current models based on the automatic processing of kinematic measures are very limited. This work proposes a method based on Functional Data Analysis (FDA) for automatically describing the morphology of the curves that represent ankle movement patterns. By Functional Analysis of Principal Components, the information contained in each data stream is reduced to a small set of variables, that allows an efficient classification of subjects.

1 INTRODUCTION

In recent years, there has been an increment in the practice of running. In spite of the evident advantages of sports practice, running has some health risks, as any other physical activity. One of the risk factors is the inadequacy of footwear to the runner's characteristics. Specifically, the excess of pronation or supination has been described as one of the most frequent causes of injury in urban races (Hintermann and Nigg, 1998; Nester et al, 2003; Branthwaite et al., 2004).

Classifying a runner as normal, pronator, or supinator , currently requires the expert judgment of a professional, and it is not easy to do automatically. Most specialists use qualitative methods based on observing the orientation of body parts during the support stance (Kapandji, 1987; Stell and Buckley, 1998). Many research studies use video-photogrammetry in order to measure pronation and supination as the maximal inversion-eversion angle during the support phase (Perry and Lafortune, 1995; McClay, 1998).

However, the attempts to develop automatic systems for such a classification have not led to good results. First, inversion-eversion measures show a relevant dispersion, and it is difficult to establish clear limits (Stacoff et al., 2000). Besides, multivariate classification requires using many variables, and such systems usually have robustness issues (Stefanyshyn et al., 2003). Moreover, defining the variables that characterize the gesture is not a trivial task, since it is highly dependent on the shape of the motion curves, which do not always show easily identifiable patterns. Finally, the parameterization of the curves implies a loss of information, since any limited set of parameters cannot convey the whole continuous information of a function recorded over time.

One possibility to overcome those limitations is Functional Data Analysis (FDA). Instead of extracting scalar parameters from a curve (such as maxima, minima, phase durations, etc.), this statistical technique works with time functions that consider each curve as a single datum (Ramsay and Silverman, 2005). FDA has been used to generalize many classic statistical techniques, such as principal component analysis (FPCA) (Ramsay and Dalzell, 1991). FPCA allows describing the variability associated to a set of curves, in order to reduce continuous information into a small set of independent variables, while maintaining all the information of original curves (Epifanio et al., 2008).

The goal of this study was to define a procedure for classifying runners in three groups: neutral,

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pronators and supinators by using video-photogrammetry three-dimensional records of continuous motion. The method uses Functional Principal Component Analysis (FPCA) to obtain a reduced set of principal factors as data, which are used for characterizing the subject groups and for defining a classification model of individuals.

2 METHODS

2.1 Sample of Study

The study sample consisted on 14 assiduous male runners aged from 21 to 50. The runners were selected from the competitors of the 32nd Valencia marathon, and a Sports Society in Valencia called 'Correcaminos' (Road Runner), specialized in athletics and trekking. These were all heel strikers, and did not suffer any current injury.

2.2 Clinical Assessment

A footcare specialist performed a clinical evaluation of the users' lower limb, carrying out an anamnesis, as well as a static assessment of the characteristics and morphology of their legs, including ankles and feet, using exploration techniques and a podoscope for recording the shape of the foot's plant. This information was used to classify the runners into three groups: normal, pronator and supinator runners.

2.3 Biomechanical Analysis

Each runner performed four trials with two footwear models, so that there were 112 observations in total. During the study, subjects were asked to run at a fixed and controlled speed of 5 minutes/km, that is, 12 km/h. In addition, the testing order of the footwear models was randomized, so learning effects were eliminated.

Motion of lower limb and footwear were recorded by using videophotogrammetry (Kinescan/IBV, Page et al 2009). A set of reflective markers were placed at anatomical places according to the protocol described in (Wu et al., 2002). The gestures were recorded at 250 fps. The movement of markers was analyzed to measure flexion-extension, axial rotation, and inversion-eversion angles, using the algorithm of kinematical analysis described in Page et al. (2009). Three curves were taken for each record, corresponding to the time functions of those angles.

2.4 Data Processing and Statistical Analysis

The support phase of each record was extracted by trimming the original signal. The data streams were smoothed by a base of B-splines, as described in Ramsay et al. (2005), and time scales were linearly adjusted in order to express the evolution of the movement as a percentage of the support time.

FPCA was applied separately to the three angles (flexion, rotation and inversion-eversion) using the whole set of 112 observations for each angle. This technique defines a base of independent functions that can be combined some way to explain all the observed variability. Thus, for the observed i-th function $f_i(t)$,

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

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).

These data were used to define a classification model by linear discriminant analysis. The independent variables were the a_{ij} scores, whereas the model was trained by the classification in three levels (neutral, pronator, or supinator) of the participants, according to the opinion of an expert. All calculations were performed in MATLAB.

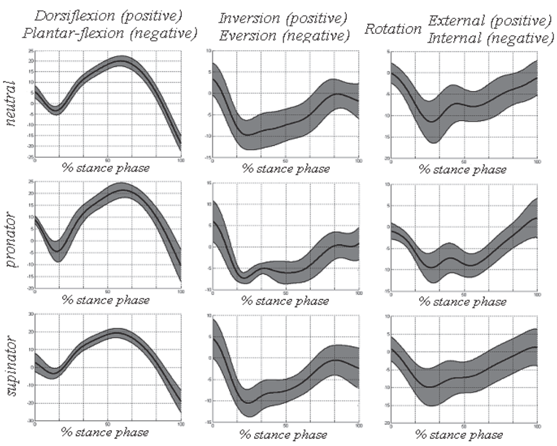

Figure 1: Movement patterns for each group.

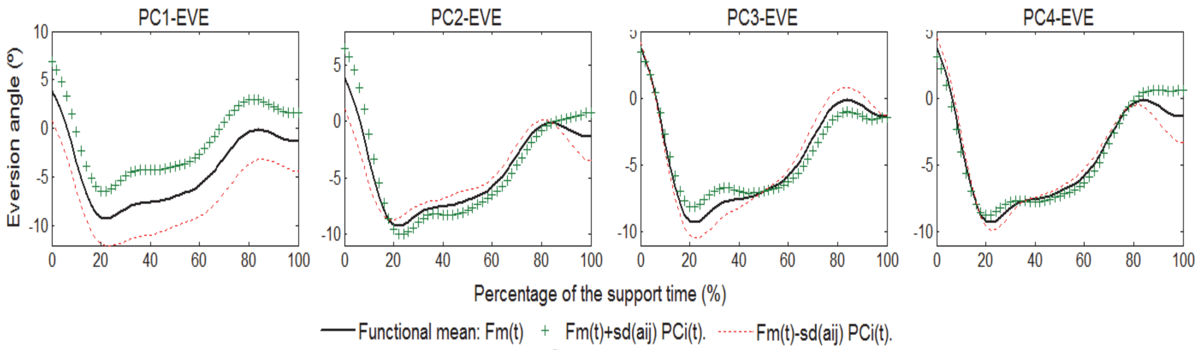

Figure 2: Results of FPCA for the eversion angle. Each graphics represents the functional mean (solid black line) and the mean plus or minus the $sd(a_{ij}) \times PC_j(t)$.

3 RESULTS AND DISCUSSION

Figure 1 show the averages and standard deviations of the three angles measured for each group. As can be seen in the graphs, there are qualitative differences between groups, although it is not easy to quantify them, since each group has a different number of local maxima and minima.

Figure 2 shows the results of the FPCA for the eversion angle (EVE). This analysis was also applied to the other angles, rotation (ROT) and flexion (FE) but only the case of eversion is shown because it is the most relevant one for the attempted classification. Each plot represents the functional mean (solid black line) and the mean plus or minus the $sd(a_{ij}) \times PC_j(t)$. This representation allows assigning an intuitive meaning to each component.

Thus, PC1-EVE is an "offset" factor, related to the general position of the whole curve in the Y-axis. PC2-EVE is related to the range of the first support phase, and the moment where maximal eversion is seen. PC3-EVE indicates the differences in the signal shape, so that high scores are associated to lower ranges and two local minima, whereas negative scores are related to broader ranges and just one minimum. Finally, PC4-EVE is mainly related to the final value of eversion before taking off.

The first four principal components explained 97.3% of the observed variance. Likewise, 4 factors explained 97.5% of variance in flexion-extension angles, and further 4 factors explained 96.2% of axial rotation variance. Thus, FPCA allows representing the whole information contained in the curves with just 4 variables. This is an important improvement with respect to classical methods, which require identifying specific landmarks and use many variables (Stacoff et al, 2000; Cheung and Ng, 2007)

Table 1 shows the coefficients of the two discriminant functions (LD1, LD2) that were obtained in the discriminant analysis, using PCj. as independent variables. Figure 3 shows a scatter plot of these functions for the observed values.

Table 1: Classification results.

	PC_{1FE}	PC_{3EVE}	PC_{2ROT}	PC_{2FE}	PC_{1EVE}	PC_{3FE}	PC_{4ROT}
LD1	0.61	0.60	-0.37	-0.41	0.24	0.10	-0.12
LD2	-0.13	0.013	-0.48	0.09	0.07	-0.53	0.61

As can be seen in Figure 3, LD1 clearly separates between pronators (high values) from the rest of subjects; and this function specially depends on the first and third components of eversion, (PC1-EVE, PC3-EVE) the first component of flexion-extension (PC1-FE), and the second component of axial rotation (PC2-ROT) (see Table 1).

The distinction between supinators and neutrals is less clear, and it depends on a combination of LD1 and LD2. This function is associated to the fourth and second component of axial rotation angle, and to the third component of flexion-extension.

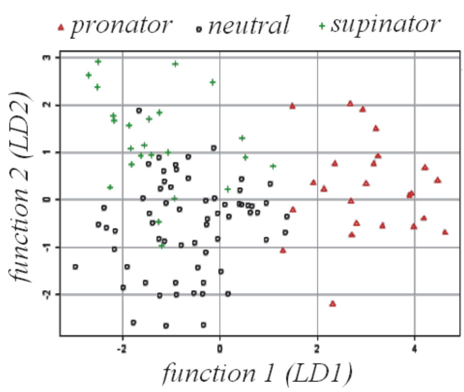

Figure 3: Scatterplot of observations for discriminant function coefficients.

Finally, Table 2 shows the results of the classification obtained by a "leave-one-out" cross-validation. The classification is fairly good for pronators, who are clearly discriminated from the rest, but not that good for the supinators.

These results show that it is possible to classify runners from kinematical variables by means of FDA, in contrast with the lack of correspondence between clinical and biomechanical criteria that has been reported in previous works (Stefanyshyn, 2003).

Table 2: Classification results.

	Prediction			
Group	P	N	S	Success
P (24)	21	2	1	88%
N (64)	1	57	6	89%
S (24)	0	9	15	63%

4 CONCLUSIONS

Using functional data is advantageous for the statistical treatment of time functions. FPCA in particular allows reducing the information of a family of curves to a small set of scalar variables, automatically and without loss of the original information that is contained in the raw signals.

This technique has been applied to the classification of runners as neutral, pronators, or supinators. The scores of the principal components allowed to distinguish clearly between pronators and the result of population, whereas the separation between neutrals and supinators will require further data processing, like analyzing the movement of the distal part of the foot.

This technique has clear advantages for the extraction of scalar variables form curve characteristics: 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.

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