Determination of Directional Influences of Kinematic Data in the Stance Period During Running

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Abstract: The study of the interactions among elements of a system is decisive to understanding their behavior patterns. The knowledge of the details of human motion allows physiotherapists to propose prevention and rehabilitation programs, as well as to identify movements that could lead to an injury. This work examines Partial Directed Coherence measures to determine the direction of the influences, throughout the stance phase only, among kinematic joints data acquired during the running activity. Five channels of the ankle, knee, hip, pelvis and trunk kinematic data were processed in each of the three anatomical planes, sagittal, frontal and transverse. These analysis suggested that the ankle joint receives a intense proximal to distal influence, whereas the knee, hip, pelvis and trunk joints presents a predominance of distal to proximal interaction.

1 INTRODUCTION

In many biomedical systems, the knowledge of the interactions among the structural elements plays a key role to understand their connectivity architecture. In this way, the direction of the information flow is an aspect of great interest, since it could improve the interpretation of the dynamics present (Blinowska, 2011).

Physical therapists deal with human motion and are especially concerned with movement disorders that could lead to injuries. This study focused on running, a commom physical activity which involves more than 38 million Americans (NSGA, 2011). This sport presents potential risk to injury that comes with the exponential growth. It is estimated an incidence higher than 70% of musculoskeletal injury each year among runners (Ferber et al., 2009). The knee is the most affected site (Ferber et al., 2009).

The interactions of the joint kinematic during running are complex and not yet fully understood (Pandy and Andriacchi, 2010). There is a hypothesis that proximal segments (i.e, trunk, pelvis and hip) could influence the distal's ones (i.e knee) and vice-versa (Powers, 2003); (Hewett and Myer, 2011). A better comprehension of the interjoint movement coordination could improve knee injury treatment and prevention programs.

In this study, multi-joints recordings of 3D joint kinematics generated a huge amount of biomedical data of thirty subjects. Although (Nakashima et al., 2014) analyzed kinematic data with Partial Directed Coherence (PDC) covering all the running trial, including stance and swing phases, most running injuries occurs during the ground contact when the locomotor system must dissipate the ground reaction force (Cavanagh and Lafortune, 1980). The impact peak during each step is equivalent to 2-3 times of the body weight (Lieberman et al., 2010). So our aim was to examine directional influences of the 3D joint kinematics data of the trunk, pelvis, hip, knee and ankle acquired during a usual running, with the PDC approach considering only the stance phase events, that is, the target of the analysis are the parts of the signal when ground contact occurred.

PDC is a frequency domain approach of the Granger-Geweke Causality (GGC) method (Jo-

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vanović et al., 2013). PDC determines the direct connection strength between two distinct signals (Fasoula et al., 2013). According to (Baccala et al., 2016), PDC proposes a direct path of influence, indicating the structures that are adjacents. Many of the PDC studies is in neural structures, where the aim is to determine the brain connectivity patterns (Gürkan et al., 2014); (Jovanović et al., 2013); (Varotto et al., 2012).

This work follows this description. The Theory Section introduces the framework of pairwise PDC approach. The Material and Methods Section describes the participants of the study, 3D joint kinematic data acquisition process details and their processing procedures. In Result Section, three distinct graphs present the PDC values computed, one for each of the three anatomical planes: sagittal, frontal and transverse. The Discussion and Conclusion Section compares the results with interpretations of the literature.

2 THEORY

Granger Causality (GC) method applies the linear regression model in a pairwise analysis of two stationary stochastic processes. The main idea of GC is that if the prediction of a time series x_1 could be improved by including the past terms of a time series x_2, then x_2 is said to cause x_1 (Blinowska, 2011). Specifically, x_1 is estimated using only previous values of the series x_1, and then x_1 is estimated including previous values of the series x_2. In both estimations, two matrices are computed: the autoregressive (AR) coefficients matrix and the covariance matrix of the noise terms. Thus, comparing the variances of the AR prediction error of x_1 before and after including the series x_2, the improvement of the prediction is determined by the decrease of the variance with past values of x_2 (Blinowska, 2011).

Multivariate formulation and spectral form of GC were stated by GGC (Jovanović et al., 2013), where the multivariate autoregressive (MVAR) model is estimated and the causal influence between two channels is computed from the spectral density matrix (Fasoula et al., 2013).

As an adaptation of GGC, Directed Transfer Function (DTF) is a causality measure in frequency domain (Jovanović et al., 2013) that describes direct and cascade influences (Blinowska, 2011), that is, DTF describes the influence direction including indirect propagation, when the interaction flows through intermediate elements (Baccala et al., 2016). Thus, if there is a propagation from 1 to 2 and from 2 to 3, DTF presents influence from 1 to 3 (Blinowska, 2011).

PDC was introduced by (Baccalá and Sameshima, 2001) as a normalized measure (Jovanović et al., 2013) and sets a pairwise analysis of directional interactions in an n-dimensional random process $X(t) = [x_1(t), x_2(t), ..., x_n(t)]^T$ (T denotes matrix transposition). Assume that the Eq. 1 is the MVAR representation of the process $X(t)$, where p is the model order, $A(r)$ are the MVAR estimative coefficient matrices and $E(t) = [e_1(t), e_2(t), ..., e_n(t)]^T$ is a zero mean white noise vector.

$$X(t) = \sum_{r=1}^{p} A(r)X(t-r) + E(t) \tag{1}$$

Each $A(r)$ matrix is formed by $a_{ij}(r)$ elements that represent the lagged effect of the $j-th$ on the $i-th$ series.

Applying Fourier transform in Eq. 1,

$$A'(f)X(f) = E(f) \tag{2}$$

where $A'(f)$ (Eq. 4) is calculated from $A(f)$, the frequency domain representation of $A(r)$, given by

$$A(f) = \sum_{r=1}^{p} A(r)e^{-ir2\pi f} \tag{3}$$

$$A'(f) = I - A(f) \tag{4}$$

(Baccalá and Sameshima, 2001) denotes PDC, direct influence from x_j to x_i at frequency f as in the Eq. 5, where $\mathbf{a}'_k(f)$ is the k_{th} column of $A'(f)$. In the Eq. 4, I is the identity matrix and in Eq. 5, H denotes Hermitian matrix.

$$\pi_{ij}(f) = \frac{A'_{ij}(f)}{\sqrt{\mathbf{a}'^{H}_j(f)\mathbf{a}'_j(f)}} \tag{5}$$

3 MATERIAL AND METHODS

3.1 Subjects

In this study, thirty recreational runners participated (mean (SD); age 27.67 (5.43) years, mass 72.05 (13.61) kg, height 1.73 (0.09) m, average running distance 35.70 (18.25) km/week and running experience 4.13 (4.02) years). They were familiar with treadmill running and ran a minimum of 20km/week at least 3 months prior to study enrollment. The presence of bone, joint, and ligament injury for at least 3 months prior the assessment, lower limb surgery, pain in the ankle, knee, hip or trunk while running or wearing orthotics that could interfere with their running pattern were the exclusion criteria. The subjects were evaluated by a licensed physical therapist to screen for the inclusion and exclusion criteria. The testing protocol was approved by the Federal University of São Carlos Ethics Committee for Human Investigations, and the subjects signed a written informed consent form to participate in this study.

3.2 Data Acquisition Procedure

The session started with a 5-minute warm-up on a treadmill (model LX 160 GIII, Movement, Manaus, Brazil) at 1.38 m/s. Next, the subjects were instructed to start running at a comfortable speed, determined by the volunteer and adjusted by the assessor for 2 minutes. A neutral running shoe (Asics Gel-Equation 5, ASICS, Kobe, Japan) was provided for all the runners.

The kinematic data of the dominant lower limb and trunk were recorded at 240 Hz during running with a six-camera Qualisys motion analysis system (Qualisys Inc., Gothenburg, Sweden). Twenty reflective markers located on anatomical landmarks and five cluster tracking markers were placed on each subject. Each running trial was performed for 1 minute and 30-s and samplings of data were collected without informing subjects about the exact moment of sampling or the variables studied.

The Cardan angles were calculated using the joint coordinate system definitions recommended by the International Society of Biomechanics (Wu et al., 2002) relative to the static standing trial using the Visual 3D software (C-Motion Inc, Rockville, MD). The kinematic data were filtered with the Visual 3D software using a fourth order, zero lag, low-pass Butterworth filter at 12 Hz. For each plane (X - sagittal, Y - frontal and Z - transverse), five joints were collected: ankle, knee, hip, pelvis and trunk.

3.3 Data Processing

As the first step, data from all the 30 volunteers were processed in order to separate their stance phases, and, from these periods, PDC values were computed.

3.3.1 Stance Phases

Stance phases of the kinematic data were defined based on heel strike and toe-off. Heel strike was identified as the velocity inversion (positive to negative) of heel marker in frontal plane (Y) (Zeni et al., 2008). Toe-off was determined by the second peak knee extension (sagittal plane) (Fellin et al., 2010). Thus, for each stance phase, there were two points identified, one for the beginning (heel strike) and another for the ending (toe-off) of the period.

3.3.2 PDC

The kinematic data were processed by an app developed in Python 2.7.4 (Python Software Foundation, USA), running on Intel Core i5 (Intel Corporation, USA) CPU at 1.70GHz, 4 GB RAM and Ubuntu 13.04 operating system (Canonical Ltd., UK). As a preprocessing step, each data channel was normalized by its root mean square (RMS).

The estimation of the AR coefficients matrix used the periods of stance already established as different observations of the system. Thus, from the heel strike point until the toe-off point of one stance event, a time window was set. The values of the 15 channels in that time window was included to determine the best Bayesian Information Criterion (BIC) value and then the AR model estimative. A visual selection by regularity in data was done to analyze the stationarity of the signals.

The function developed to identifying the best BIC value took into account values from 1 to the minimum number of points of the stance phases of the individual running trial. Therefore the number of order tests was diversified among the subjects, because each one had different points number.

PDC values were computed taking the channels in pairs. The highest one was used to represent the interaction between two channels of a subject. The influence of the thirty subjects was evaluated by the mean value of the group. Distal to proximal and proximal to distal influences were analyzed by anatomical plane between each pair of joints. To determine whether the influence was distal to proximal or proximal to distal, the T-Test was applied with 5% of significance under the null hypothesis that the means of that two types of influences were equal.

At each relevant step, intermediate files were saved, such as the stance phases, the orders analyzed to determinate the best BIC value, the PDC values themselves, including the resumed ones and the directed graphs.

4 RESULTS

The process of dividing the entire running trial in stance phases generated 35 periods and 73 points per period, on average, both for the entire group. Therefore, an average of more than 30 observations were used to compute the PDC values.

The best BIC order accepted was between 1 and 5, depending on the number of points of the stance phases of the subject, since the procedure tested values from 1 to the minimum of that number of points.

In average, the routine for determining the best BIC order computed the AR estimative up to order 77, the mean of the minimum number of points.

The resumed PDC values were presented in three directed graphs, for each anatomical plane. Thus, in one graph, there are five nodes, representing the kinematic joints in that plane. The interactions are being illustrated by edges where thicker stubs are the arrows. Moreover, the thickness of the edges denotes the strength of the influence. Therefore, in Fig. 1, the edge between nodes ”Ankle” and ”Trunk” shows an influence from ”Trunk” to ”Ankle”, and its PDC value is higher than between ”Hip” to ”Pelvis”. There is only one direction between two nodes, the higher value chosen from the distal to proximal or proximal to distal influences mean values, when there was a statistical difference indicated by the T-Test.

In the sagittal plane, ankle received the strongest influences. Also, Fig. 1 shows that pelvis and trunk are highly influenced too. Instead, knee and hip are sources of influences.

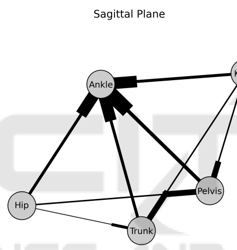

Figure 1: Directional influences of the 3D kinematic data during running, in sagittal plane. Nodes are the kinematic joints (ankle, knee, hip, pelvis and trunk). Each edge represents the mean value from the thirty subjects computed from the individual maximum PDC, and its thickness is the strength of the influence. Thicker stubs represent arrows.

In frontal plane, ankle remains as the most influenced channel. As Fig. 2 presents, pelvis still receives a substantial influence from hip and less strong interactions from knee and trunk. Hip stays as a source of influences.

Transverse plane (Fig. 3) presents ankle and trunk as the receivers with the highest PDC. Pelvis is destination of intermediate influence, and hip persists as an essential source of interactions.

5 DISCUSSION AND CONCLUSION

The aim of this work was the analysis of the direction of influence of the kinematic data, considering only the stance phase, during running, by the PDC approach.

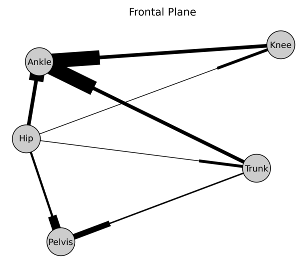

Figure 2: Mean values computed from individual maximum PDC, in frontal plane, during running. As in Fig. 1, nodes are the kinematic joints of ankle, knee, hip, pelvis and trunk. Thicker stubs represent arrows.

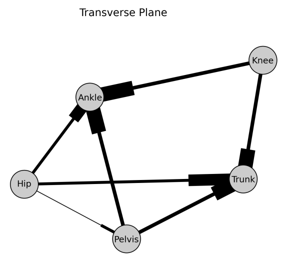

Figure 3: Mean values computed from individual maximum PDC, during running, in transverse plane. Also, nodes are the kinematic joints of ankle, knee, hip, pelvis and trunk. Thicker stubs represent arrows.

To the best of the authors knowledge, no study assessed the direction of interaction flow of 3D kinematics of the ankle, knee, hip, pelvis and trunk covering stance phases during running. In (Nakashima et al., 2014), the kinematic channels of one subject were analyzed during the entire running cycle, without any stance phase separation.

In fact, the hypothesis that there was a marked proximal to distal influence to ankle motion indicated in (Nakashima et al., 2014) was confirmed in this study with a larger sample size, even analyzing specifically the stance phase. Our data is also supported by (Mackinnon and Winter, 1993) that hypothesized that the trunk and hip motion could influence the ankle motion during walking.

Interestingly, the hip influenced the most proximal (pelvis and trunk) and distal joints (ankle and knee), supporting the importance of the core stability to control de movements of the extremities (Peters and Tyson, 2013); (Noehren et al., 2013). The trunk joint was especially influenced in the sagittal and the transverse planes. The pelvis joint received important influences in sagittal and frontal planes. In frontal plane, (Mackinnon and Winter, 1993) indicated an influence from the hip and (Powers, 2003) suggested an effect from the knee.

The next step is to analyze results from generalized PDC (gPDC), a variation of PDC that deal with time series with different variances (Taxidis et al., 2010).

These analyses can expose the directional influence patterns that may help physiotherapists to distinguish normal movements from altered ones during running and to propose treatment running techniques, prevention and rehabilitation programs.

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