A PROCEDURE FOR QUANTITATIVE ANALYSIS OF THE INTRA/INTER-INDIVIDUAL VARIABILITY

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Multifactorial movement analysis has been largely adopted, both in sport and clinical applications, for the evaluation of various motor performances such as walking, running, jumping, and so on. A number of very sophisticated motion analyzers are, in fact, able to provide automatically a complete set of data for three-dimensional (3D) representation of any complex motor performance (Woltring, 1984; Ferrigno, Borghese, & Pedotti, 1990).

However, the discussion of the obtained results and the comparison among the trials of a given type of performance, either from a single subject or from different groups of subjects, are generally supported by a purely visual interpretation of the pattern morphology or, at least, by taking into account just a limited number of parameters for each variable (Winter, 1987).

The purpose of this work was to describe the crucial steps of an analytical procedure which has been specially developed for a point to point comparison between different groups of movement data. A practical example of the final results provided by such a procedure will be presented as simply synthesized through an Index of Estimated Differences (IED) and will concern the objective comparison of trials obtained from a group of differently trained runners.

METHODOWGY

The crucial steps of the proposed procedure will be discussed in the following sub-headings. From a general point of view, the acquired data were:

a) the three orthogonal components of the ground reaction force generated by a force platform during the ground contact phase;
b) and the three dimensional coordinates of a number of markers, placed on suitable anatomical landmarks, which are detected by means of a motion analyzer.

It is quite obvious that the quality of the acquired data (depending on the adopted sensors, sampling rate, filtering method, accuracy of 3-D reconstruction, and so on) can

strongly affect the reliability of the comparison process. Therefore the content of the **acquired data** shall be supposed as being **adequate and** consistent. After data **acquisition,** a **"pre-treatment"** phase included all those procedures dedicated to the computation of derived variables such as: the two components on the horizontal plane of the **displacement** of the ground reaction force application point, the course of **suitable** angles between the sticks joining markers, the three components of the velocity and acceleration of each marker. as well as the angular velocities **and** accelerations.

Check of Steady-State

A constant experimental uniformity of the various trials is mandatory in order to perform a reliable comparison. The criteria for evaluating such uniformity depend in general on the movement to be analyzed. For the purpose of this work, where only cyclic running at constant speed is considered, the steady state criterion is used. Such a criterion **requires** that the analyzed **performance** can reasonably be supposed in a range defined as stationary condition (Santambrogio. 1989). This is accomplished by integrating in time, over a complete step cycle, the horizontal component in the advancing direction of both the ground reaction force and the acceleration of a close barycenmc marker (for example the marker at the hip). Because steady-state (S) criterion implies that such integrals must be practically nil, the acceptance of the **trial** was based on verification of the following **formula:**

$$S = \{\Sigma_j \beta_j^+\} / \{\Sigma_j |\beta_j^-|\} \qquad 1-p < S < 1+p$$

where β represents either the horizontal ground reaction force or the acceleration, the summations are extended over the step cycle, symbols $^+$ and $^-$ indicate the positive and negative values of b respectively and p is a suitable accepting threshold.

Normalization

Normalization procedure, both in time and amplitude, is necessary in order to compare data sets that are relative to different subjects performing the same movement or different trials of the same subject analyzed in different conditions. Time normalization consists of an interpolation/approximation procedure that is necessary to obtain the same number of samples **from** different data aquisitions, such as two different **running** cycles. Amplitude normalization is involved when various data sets, featured by the same sampling rate and by different bias values, have to be compared. In order **to** perform both the two kinds of normalization on the whole set of movement data and to prevent magnification of noise due to differentiating process, a new filtering and interpolating/approximating procedure, called LAMBDA (**D'Amico & Ferrigno,** 1990). has been used.

LAMBDA (Linear-phase Autoregressive Model-Based Derivative Assessment) is an automatic filtering algorithm that. by fitting an **Autoregressive** (AR) model to the noisy measures. **determines** for each data set the parameters of a suitable Finite Impulse Response (FIR) filter. For the aim of this study. two main blocks can be identified in the proposed procedure: the filter and the **Continuous** Inverse Fourier Transform **(CIFT)** interpolator/approximator. **CIFT acted** as an interpolator if no **pre-processing** is performed by filter block; **CIFT** worked as **approximator** if the whole algorithm is applied. The filter block input is the time series of the data to be processed while its output is the related filtered Discrete Fourier **Transform** (DFT).

A standard inverse **DFT** would give a filtered data set sampled at the same time instants as the input data were. By using a **CIFT** sampled at absolutely arbitrary time instants, the data can be **expanded** or compressed (Virtual Sampling) to a whatever number of points. The data flow scheme of the algorithm is shown in Figure 1.

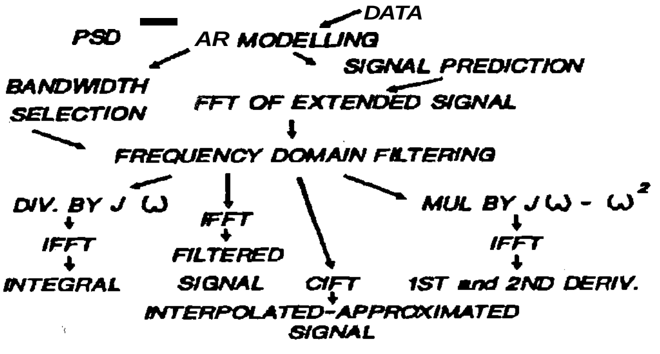

Figure 1. Algorithm block scheme

An AR model was **fitted** to the measured data in order to estimate the signal **PSD** and to extrapolate the signal before and after the record to avoid edge distortions. The AR model parameters were computed by the forward backward prediction Modified Covariance algorithm. This algorithm allowed for **obtaining** of sharp **PSDs** without bias or **spectral** line splitting **(Marple,** 1987). By analyzing the PSD, the cut-off **frequency** was selected as the bequency at which the Signal to Noise Ratio (SNR) falls below a pre-set threshold. The noise is estimated as the average of the PSD in the high kequency region of it, under the assumption that the signal is 'reasonably' band-limited. The extrapolated data were then Fourier transformed in the frequency domain and filtered by a low-pass FIR filter at the cut-off frequency previously determined. The **interpolation** between data samples was performed during **CIFT**:

$$x(n)=\mathrm{Re}[X(1)]+X(M/2+1)e^{j\pi(N/N1+Ex)n}+2\sum_{k=1}^{(M/2)-1}X(k)e^{jk\pi(N/N1+Ex)n/(M/2)}$$

where $x(n)$ is the time-domain output of the CIFT interpolator/approximator, $X(k)$ is the k-th DFT coefficient, M is the number of DFT samples, Ex is the length of the data extension (namely the extrapolation performed with the AR model parameters), N is the number of samples of the original signal, N1 is the number of samples of the interpolated signal. N and N1 can stand in whatever ratio between them.

Data stratification and testing

Called m and q the number of markers placed on the athlete's anatomical landmarks and the number of computed angles respectively, the normalization procedure leads to $n=9m+9q+5$ series of N1 values; the series refer to the following variables: the three trajectories of each marker and the related first and second derivatives, the three time-courses of each angle and the related first and second derivatives. and the time-courses of the three ground reaction force components plus the displacement on the ground plane of the force application points. By denoting: $j=1,2,3$ the generic axis (x,y,z) of movement, $K(k)$ $(k=1,2,...,8)$ the generic kinematic/force variable, $l=0,1,2,...,m+q$ the generic marker/angle, a set of typical series where the i-th element is formed by the stratified averaging identified as cross-mean value and related standard deviation of the original data:

$$\mu\{K_{k,j,l}(i)\}_r \quad \sigma\{K_{k,j,l}(i)\}_r \text{ where } r=1,2,...,u.$$

u is the number of mals performed by a subject; the limits imposed to the indexes k, j and l are: $l=0$ when k represents a force or an application point component while j skips z axis when k refers to an application point component.

It is important to note that in practice the value u cannot be arbitrarily imposed but it has to satisfy suitable expressions [Santambrogio. 19891 checking the stability of standard deviations; such stability provides, in fact, a smoothing in the single mal features and enhances the individual trend. Under such conditions all the samples forming the i-th normalized instantaneous value of a typical series referred to mals from either a single or a suitably arranged homogeneous group of athletes are approximately normally distributed around their own mean value and can then be easily treated through statistics. The arrangement of each new set formed by the single athlete's typical series into the most proper homogeneous group creates/up-dates the statistical content of that group; the set of all the groups forms the basal data collection that is used for comparison. Each homogeneous group contains all those typical series provided by individuals with similar anthropomemc features and associating, from a statistical point of view, with a given motor performance. The differences occurring between two homogeneous groups of data can be estimated by applying a two-tailed t-test to each element of the related typical series. The t-test results are synthesized by the IED value defined as:

$$IED = (n\ N1)^{-1} \sum_{I}^{N1} \delta i \qquad \text{where} \qquad \delta i = \sum_{k}^{n} \tau\{K_{k,j,l}(i)\}_k$$

each on-off addend being set equal to zero or one corresponding to verification or non-verification, respectively, of the null hypothesis. IED can then assume n multiplied by N1 discrete values between zero (when no differences occur) and one.

RESULTS AND DISCUSSION

In order to provide an example of application, a group of six differently trained runners were considered to arrange the basal data collection. For each athlete the kinematics of 11 running trials, performed on a treadmill at a constant speed of 15 Km/h, was acquired by using the ELITE motion analyzer. The athlete's anatomical landmarks, previously marked by means of suitable passive markers, were: head, shoulder, elbow, wrist, hip, knee, ankle and 5th metatarsal head. For simplicity, only the results concerning the trajectories of such markers will be considered here. Table 1 reports the resulting IED values (computed at a level of significance of 1 % and associated with each marker, each axis of movement and the global one) pointing out the differences found between the reference data and those from another runner not included in the group forming the basic statistics.

Table 1

IED(head) =	1.82%	IED(shoulder) =	26.56%	IED(elbow) =	6514	E D =	42.71%
IED(hip) =	9.11%	IED(knee) =	32.81%	IED(ankle) =	9.894	IED(foot) =	28.644
IED(x) =	21.87%	IED(y) =	12.30%	IED(z) =	25.10%	IED(global) =	19.76%

As it can be clearly seen, the global IED value proved a significant kinematic similarity involving about the 80% of an entire run stride. Referring to the 3-D coordinates of each marker, the major difference occurred at the wrist and the knee joints. Taking into consideration the results along the axes of motion, the largest differences involved lateral displacement (z axis).

CONCLUSION

The proposed statistical analysis, which can include a combined evaluation of kinematic and ground reactions, provides a powerful multidimensional description of the motor performance. In the future, the addition of parameters extracted from the EMGs will further complete the general picture of the motor performance of a subject under study. The general procedure described here represents a further step toward an automatic multifactorial movement analysis to provide an objective and quantitative comparison among different subjects and the distinctive parameters of statistical classes of normality and pathologies.

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