Sensors' Ground Reaction Force Behavior for Both Normal and Parkinson Subjects - A Qualitative study

Alkhatib R., Corbier C., El Badaoui M., Moslem B., Diab. M.O.

Abstract* - Characterization of normal and abnormal Gait has been a major research field for decades, whether in fall prevention, sports biomechanics or even disease indication. In this paper, we assess time domain statistical properties of the Vertical Ground Reaction Force (VGRF) during moderate-pace walking, aiming eventually to create a reliable mathematical model of VGRF for normal and abnormal cases. For that endeavor, first order statistical analysis was performed upon signal segmentation in order to determine the degree of stationarity and base the model upon it. Furthermore, we performed curve fitting of the VGRF time series between present and past values, which led us to model the waveform with linear regression via Autoregressive Model for both Normal Walking Signals and Parkinson diseased patients' walking signals. However this is done only for one chosen sensor. However, it would be crucial to take the advantage of the array of sensors. Evaluating the cross-covariance between multi-sensor data of a given subject at different time lags capture the most important information. The seasonality in the values give a quite important indications of the behavior of data. The objective behind this analysis is to recommend a preliminary basis to create reliable mathematical model of normal walking signals versus pathological walking signals, that we will emphasize in a complementary work, in the simplest way available and creating fall prevention indicators for old patients.

I. Introduction

Walking gait is defined as sequences of repetitive cyclic gestures consisting of periodic movement of each foot from one position of support to the next. For that purpose, various sensory network architectures were designed to capture the most of the biomechanics of walking and running in subjects. In fact, sensor distribution in such designs is crucial and should be delicately treated, knowing that we have continuously varying centers of pressure (COP). That being said, one of our previous studies showed that the sensor located at the inner arch of the sole of the foot (i.e. at mid foot) holds the most relevant information needed for better classification between balanced and unbalanced gait in comparison to other sensor positions [1]. This bipedal locomotion is an evoked response sensitive to the initial conditions of the nonlinear dynamical stimuli signals or perturbations which make them very difficult to predict within short intervals of time into future [1]. In consequence, its identification relies upon the understanding of the components of the stimulus environment. However, gait signals themselves are of a stochastic nature [5]. This contradiction introduces the chaotic nature of gait signals.

In this study, analysis of vertical ground reaction force (VGRF) time series signals for both normal and Parkinson is conducted. For instance the incidence of a stochastic deterministic level function is shown by the non-stationarity in mean and variance. In other words heteroskedasticity appeared in the walking gait VGRF signals. In addition, the crosscorrelation between sensors suggest a model as the sum of certain deterministic (stationary and non-stationarity) [7] and stochastic (fluctuation) signals. Furthermore, the rate of decay of the autocorrelation part forms an indicator of the memory type (range of dependence) that forms an indicator to whether the gait is normal or abnormal.

II. Database and Preprocessing

A. Database Description

VGRF in Newton as a function of time are extracted from 8 sensors (Ultraflex Computer Duyno Graphy, Infotronic Inc.) underneath each of the right and left foot. 18 normal persons, and 29 subjects with Parkinson walked for two minutes at their own natural pace and with acquisition sampling rate of 100Hz. The database is obtained from PhysioNet [2]. Subjects provided written informed consent prior to performing the experiment.

The sensors location inside the insole as lying approximately at the following (X, Y) coordinates measured as a person is comfortably standing with both legs parallel to each other are shown in Fig.1. The origin (0, 0) is just between the legs and the person is facing towards the positive side of the Y axis.

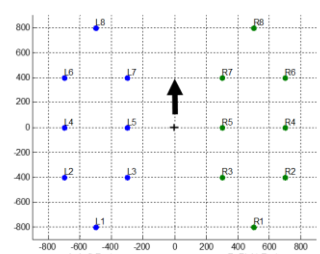

Figure 1. Sensors location in both right and left insoles.

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B. *Conditioning the Data*

The VGRF time series are divided into short segments as shown in Fig.2. Some disturbed parts are eliminated. Mainly their statistical properties, in particular the mean and standard deviation, form outliers compared to the vast of segmented step signal statistics. Then the average is taken for the segments of the signal to represent one usual step.

When performing comparative study between subjects, all data are normalized by the norm-2. In this study, no filtering is used as this is not required to perform the upcoming analysis. Knowing that traditional filtering could omit important part of the signal needed [6].

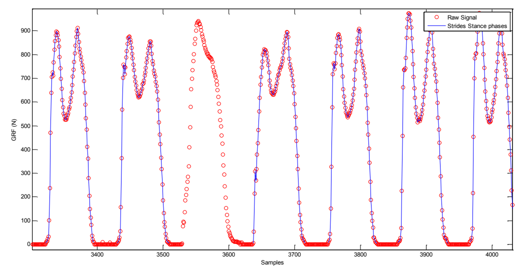

Figure 2. The signal is being divided as shown in the solid blue line.

III. MODEL

Once time series shows a constant mean and variance besides to when autocorrelation only depends on time lag, the signal is supposed to be stationary. However, VGRF is said to be non-stationary signal [1] and cyclostationary as in reference [3]. In this paper, the approach monitored from wide point of view by assuming VGRF data to be non-stationary. This is verified by taking the mean and the standard deviation of segments that corresponds to a given step. Fig.3 presents those statistics to vary from one step into another. The mean ranges from 32 to 77 and standard deviation ranges from 70 to 135.

Figure 3. Standard deviation versus mean for an abnormal subject upon mid-sensor located in the right foot.

This forms a good indicator that the signal is non-stationarity in the variance and in the mean specifically. However, this is not to contradict for the moment the cylostationarity hypothesis of the signal that is a form of non-stationarity [3]. In our case the mean and standard deviation are highly correlated. In consequence, a lognormal model is greatest to be used later to acquire better analysis of the entire signal. This would help in modeling steps and the percentage of error is anticipated to decrease.

A. *VGRF Analysis for Normal Subject*

The autocorrelation (ACF) of VGRF for a normal subject gait articulates a slow decay as revealed from Fig.4. This indicates a long memory [4]. In addition, plotting the partial autocorrelation function (PACF) demonstrates the non-stationarity phenomena of the signal. This non-stationarity is of integration order 2 because the PACF value at lag two recorded to be one in absolute value. This proposes the existence of stochastic trend of order 2.

However, this range of dependence is not fixed throughout the different steps of the same signal. It would be interesting to investigate more on its range of variation.

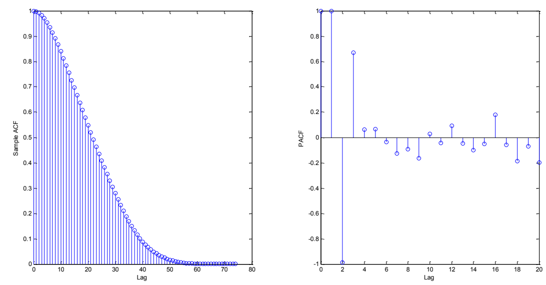

Figure 4. Sample and Partial Autocorrelation for a Normal subject.

B. *VGRF Analysis for Parkinson Subject*

Strong autocorrelation exposed in the ACF for Parkinson subjects don't die quickly over long range of observations compared to normal subjects. This is a good indicator of the non-stationarity of the signals in general. In particular, ACF recognized a longer memory in the gait signals of Parkinson subjects given the autocorrelation value in its minimum around 60 time lag as shown in Fig.5. Whereas it is documented to be in the range of 50 lag corresponding to normal gait as obtained in Fig.4. The PACF also indicates the non-stationarity of integration order 2.

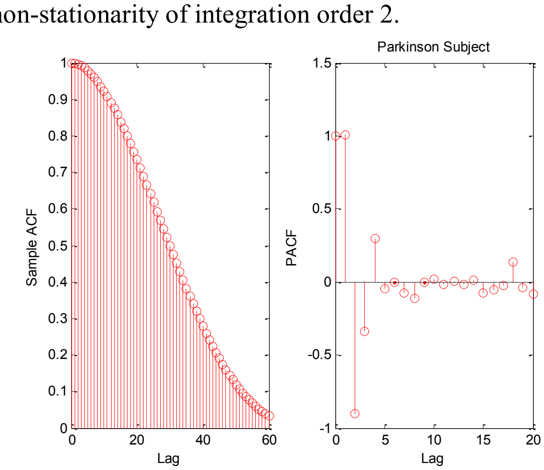

Figure 5. Sample and Partial Autocorrelation for a Parkinson subject.

Knowing that performing the difference transformation over the original data signals two consecutive times, no longer memory is then will be available as shown in Fig.6. However the non-stationarity of integration of order 1 will be available at the first difference.

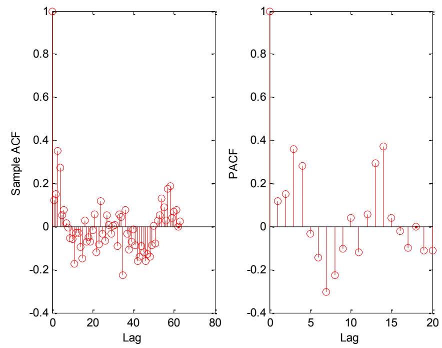

Figure 6. Sample and Partial Autocorrelation for VGRF signal differenced two times.

C. Univariate Time Series Model

In this section, the mid sensor is taken into consideration in reference to [1], but this is not to say to omit other sensors. Fig.7 and Fig.8 displays an interesting linear relationship between y_{t-1} and y_t. Knowing that the degree of linearity decreases as the time lag (τ) to the future values increases ($y_{t+\tau}$). In addition, the slope of the regressor starts to diverge from one in both increasing and decreasing phases of the foot step, where the slope from the "heel strike" to the moment where the foot becomes flat starts to decrease and the slope for "foot flat to toe off" starts to increase. This leads to elliptical shape in the whole data.

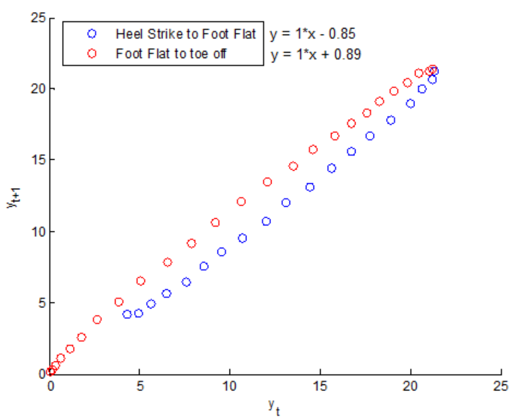

Figure 7. Linearity in the plot of current values versus past values in VGRF's data for midsensor on a single step. In this case the difference is one time lag. Given ($y = y_t$) and ($x = y_{t-1}$) in equations.

In this model, a deterministic trend can be obtained as a function of time. The model is given by the simplest first order autoregressive (AR (p=1)) model as in (1) where the future value is regressed on the current value:

$$y_t = \beta y_{t-1} + \alpha + \varepsilon_t. \tag{1}$$

Where $0 \le y_t \le y_{max}$ and y_{max} is the maximum value that can be reached. It is related to the weight [8] in addition to the way a person walks (step starts by heel contact, toe contact or shuffling). This can be easily determined from a previous step and forms a parameter to the model. The slope is shown to be ($\beta = 1$) for both increasing and decreasing phases of the step. However, the intercept α can be obtained either from a trained previous step or from the first few values i.e. local model is obtained as recent observations are used. The error term is important and forms the residual and its model is purely indeterministic as to be handled later. From Fig.6 the model for both phases are given as in (2)

$$\begin{cases} y_t = 1y_{t-1} - 0.85 + \varepsilon_{1t} \\ y_t = 1y_{t-1} + 0.89 + \varepsilon_{2t} \end{cases} \quad 0 \le y_t \le 22 \tag{2}$$

It's important to mention that modeling over both parts of the step signal, the AR (p=2) model yields a 99.1% fit to estimation data as this will be elaborated more on a complementary work. This is 91.9% with AR of order one.

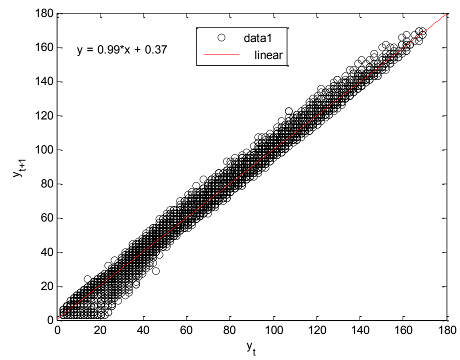

Figure 8 Linearity in the plot of current values versus past values in VGRF's data for midsensor given the 2 min signal.

IV. Sensor's Behavior

As the dataset is made up of 8 electrodes underneath each foot, it's hard to visualize and then analyze them in the absence of theoretical background.

Dimensionality reduction is the key. A hypercube is made up of matrices like the one in (3) at different time lags.

$$M(\tau) = \begin{bmatrix} C[L_1R_1]_\tau & C[L_1R_2]_\tau & \cdots & C[L_1R_8]_\tau \\ C[L_2R_1]_\tau & & & \\ \vdots & & \ddots & \vdots \\ C[L_8R_1]_\tau & & \cdots & C[L_8R_8]_\tau \end{bmatrix}$$

(3)

- L_i is i-th left signal and R_j is the j-th right foot signal
- τ is the time shift or lag between signals ; $0 \le \tau \le N-1$
- "C_{LR}" :the covariance sequence given as the mean-removed cross-correlation sequence
  $C_{LR}(\tau) = R_{LR}(\tau) - \mu_L \mu_R$
  $K_{LR}(\tau) = E\{L_t R_{t-\tau}\}$
- μ is the mean and E is the expectation and K is cross-correlation and therefore cross-covariance can be computed using (4):

$$C[L_iR_j]_\tau = \frac{1}{N-1}\sum_{t=1}^{N} L_i(t)R_j(t-\tau) - \overline{L_i}\,\overline{R_j} \tag{4}$$
$$0 \le \tau \le N-1 \quad i,j \in [1 \quad 8]$$

A. Procedure

Each covariance matrix allows us to characterize the direction of the greatest variance in our data. This is so called principal component analysis (PCA) used to reduce the dimensionality of the data by selecting directions along which our data has the largest variance. Finding such eigenvectors have the property of not rotating when multiplied by the covariance matrix as in (5). Then eigenvectors (e) having largest eigenvalues ($\boldsymbol{\lambda}$) corresponds to our principal components that will give a new dimensions of our data.

$$M_c(\tau).e = \lambda.e \tag{5}$$

B. Eigenvalue Analysis

The eigenvalues are obtained by solving equation (6). Fig.9 shows eigenvalues of the 8 principal components for normal subject.

$$[\det(M_c(\tau) - \lambda.e) = 0] \qquad at\ a\ given\ \tau \tag{6}$$

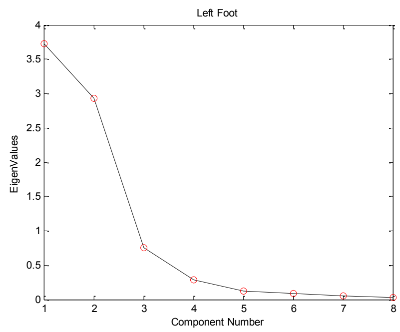

Figure 9: Eigenvalue versus its component number for Left foot sensors in a normal subject

The first principal component has variance (eigenvalue) 6.6677 as shown in Fig.7. The first three principal components accounts for 84.46 % of the total variance. The first four counts for 94%. This is a good indicator that most of the data structure can be captured in three or four underlying dimensions. The remaining principal components account for a very small proportion of the variability and are probably unimportant.

The same analysis is performed to obtain the eigenvalues for all 16 sensors. Then the maximum eigenvalues is plotted against different time lags as shown in Fig.8. The smooth decrease that forms the trend forms a non-stationarity relation among sensor's data.

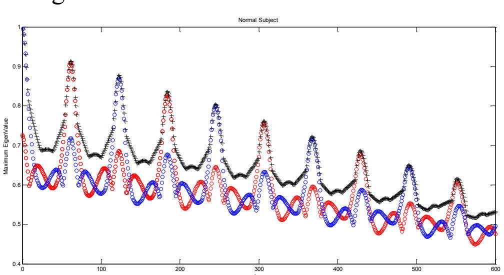

Figure 8: Maximum Eigenvalues being computed at different time lags for left sensor to right foot sensors (Red), left sensor to Left foot sensors (Blue), and black indicates when computed for all sensors as one matrix.

However, a seasonality that described by the repeated patterns are observed after certain period lags around 60 points (100 Hz sampling frequency). Knowing that when the covariance didn't attain zero value, this specify the randomness situation no longer available. In consequence, the VGRF signal are a mixture of stationary and non-stationarity sources. They are stationary from macroscopic point of view but microscopically they are non-stationary. The latter is of lower power component as Fig.8 illustrates.

V. Conclusion

Analyzing the behavior by either taking each sensor separately or the bunch of sensors all together could represent a signature to differentiate between pathological (Parkinson) and normal gait. As a consequence of what is mentioned, a methodology is needed to classify the signals as a sum of stationary and non-stationarity parts in order to handle them in a correct way. This could be attained by modeling the signals using ARIMA (autoregressive integrated moving average). Moreover, it may be better to try to predict the change that occurs from one period to the next.

In the presence of set of 16 sensors, and the reason their summation is not a good practice [1], a model to develop relation between them is correlated to the patterns observed in the maximum eigenvalues observed over the covariance matrices. This is to end up with models termed vector Autoregressive integrated moving average (VARIMA).

As a future work, we will focus on those non-stationary signals by starting with stochastic trend stationary processes as assumed model, wherein the process has stationary behavior around such trend. This time series modeling will yield the advantage of Generalized Autoregressive Conditional Heteroskedasticity (GARCH).

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