A Modified Filtering Model of VGRF Gait Signals

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***Abstract*—In order to understand the movement ecology of species, preprocessing is considered a fundamental step to in treating any signal contaminated with noise. Thus it is performed on data to remove undesirable characteristics that were introduced during acquisition. A modified filtering model of gait vertical ground reaction force signals is highlighted in this work in the light of the commonly applied fixed filters on the signals from various sources. This common practice is pointed out to harm the signal's content. The alternative technique is based on Empirical Mode Decomposition.**

Keywords—Vertical Ground Reaction Force Signal (VGRF), Filtering, Empirical Mode Decomposition (EMD).

I. Introduction

Understanding the way we move has been a topic of research for several decades. The complication raised with the fact that different body parts have to travel with the body at the time of asserting and transmitting forces from ground to body. Understanding human locomotion will inspire us in developing a Prosthetics leg exoskeleton robot, building robotic passively walking toys, improving athletic performance, identification of people for security purposes, diagnose specific pathologies, researching new rehabilitative tools in the treatment of mobility-limiting conditions, motion planning and control problems for under actuated robots and many more.

To achieve this mission, filtering is used to remove any unwanted disturbance in the vertical ground reaction force (VGRF) data. For instance, the presence of noise can totally mask the true information in data. In addition, it's significant to eliminate sources of variation on the measured VGRF like the influence of mediolateral and anterior-posterior variations.

GRF are being filtered with low pass Butterworth filter with the following cut-off frequencies of:

- 20 Hz (second order) during walking on treadmill as white noise existed due to vibrations and motion artifact [1].

- 100 Hz (fourth-order)[2].

- 50 Hz (second order)[3].

- 6 Hz (second order)[8].

- 25 Hz (fourth order, nonrecursive filter)[8].

- 20 Hz (fourth-order, zero-lag)[39].

The vertical GRF is also being low passed filtered with a cut-off frequency 15 Hz to reduce measurement noise according to another article [4]. While other studies consider the reservation GRF data as being filtered using a 7 point moving average [5], GRF data were also filtered with a cutoff frequency of 75 Hz [3]. In a further study, GRF data were filtered using a low-pass filter with 50 Hz cutoff frequency [6]. Moreover, 13-point moving average low-pass filter with a cut-off frequency of 33.3Hz was used to filter the GRF data [7]. Such kind of filtering without relying on a given basis may remove components of the actual movements [9].

Antonsson's database composed of two categories, runners and walkers. He studied 30 foot contacts from 12 subjects. By applying FFT spectral power analysis of these force records, 99% of the integrated power content of VGRF signals below 9 Hz. For running, 99% of the integrated power content of the VGRF signals was at frequencies less than 10 Hz [1, 5]. Furthermore, the amplitudes above 10 Hz are recorded to be less than 5 % of the fundamental frequency. 2 % above 20 Hz and all amplitudes more than 1 % are delimited below 50 Hz. 99.5 % frequency in VGRF is recorded to be 6.39±2.31 Hz in Parkinson Diseased (PD) subjects. The median frequency is found 0.45±0.09 Hz and the bandwidth is said to be 1.23±0.29 Hz. A difference is found in frequency content when compared to healthy subjects [10]. After averaging the VGRF signals of PD subjects, the power of high frequency is lower and the first and second peak's amplitude are lower than normal subjects with a delayed occurrence of the first peak. The average power is between 0.5 Hz and 1.5 Hz is logged in PD [11]. These results helped in the process of selecting the appropriate filter that is the fourth order Butterworth filter with a 25Hz cutoff frequency. This filter appeared to eliminate 99% of the noise while retaining all of the important components of the signal [5]. However, in this paper we will examine this kind of filter and show a pertinent part of the signal being lost. As a solution, decomposing the signal into different frequency components and then eliminating certain bands gives better filtering and adaptable way to various and different VGRF sources.

II. Methodology

A. Theoratical Background

Empirical Mode Decomposition (EMD) is a self-adaptive method applied for non-stationary and nonlinear signal-processing proposed by Haung et al [11]. It is empirical because it is unlike other transforms which relies on theory,

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EMD derived from observation or experiment in time domain. Mode stands for a particular form or variety. Decomposition because it generates a set of finite time series basic parts called Intrinsic Mode Functions (IMF) resulted from the separation of the original signal. Those IMFs include different frequency bands, with different frequency component, ranging from high to low. It's intrinsic because they naturally derived from the raw signal itself based upon the local time scale of the signal. That's why EMD is adaptive. The technique can be summarized as follows [12]:

1- Identify all local extreme (maxima and minima) then interpolate between minima (maxima) ending up with upper and lower envelops curve [$X_{min}(t)$, $X_{max}(t)$] that encompasses the whole data set.

2- Subtract the mean of the two envelops from the raw signal to obtain new function:

$$h_{11}(t) = X(t) - \frac{X_{\min}(t) + X_{\max}(t)}{2} \tag{1}$$

3- Use the above sifting techniques frequently to minimize the mean to approach zero. The stopping criterion is given by:

$$SD_k = \frac{\sum_{t=0}^{T} \left| h_{k-1}(t) - h_k(t) \right|^2}{\sum_{t=0}^{T} h_{k-1}^2(t)} \tag{2}$$

Where, T is the whole time period

4- The number of extrema and zero crossing are equal or differ at most by one.

5- The original signal X(t) can be reconstructed using the following equation

$$X(t) = \sum_{j=1}^{n} c_j(t) + R_n(t) \tag{3}$$

This results on a set of IMFs with a certain frequency range and the last IMF is the residue $R_n(t)$. The IMFs are arranged from higher frequency components into lower one. The residue represents the trend (i.e. the time-varying mean) of the raw signal which is characterized by being monotonic or having one extreme i.e. with no periodic behavior.

B. Database

Eight sensors (Ultraflex Computer Duyno Graphy, Infotronic Inc.) were placed underneath each of the subject's feet to collect VGRF in Newton as a function of time. Prior to performing the experiment, subjects provided written informed consent. Each subject walked at his/her usual back and forth for two minutes at their self-selected pace level ground without any secondary task in a well-lit, obstacle free, 25-m long, 2-m wide corridor. 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 located between the legs and the person is facing towards the positive side of the Y axis. The sampling rate is 100 Hz. This database has been drawn from physionet gait database [13].

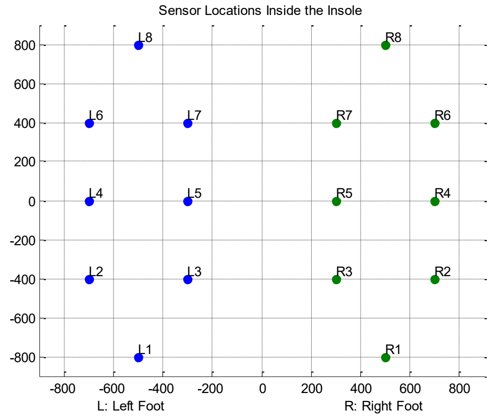

Fig. 1: Sensor's position as distributed underneath both feet.

C. Analysis

Filtering can put the data under certain limitations, namely this would force the gait data after filtering to be stable and linear. However, most of the experimental data certainly gait data should be criticized to be non-stationary and nonlinear. This will avoid us from handling the data in artificial way by going into linear analysis of these nonlinear and non-stationary signals. Merely, methods of non-stationary can be employed to emphasize the real changes in the gait time series data signals.

While standing at rest, VGRF is the only force that do exist. However, at the time of heel-strike that separates the swing phase from the stance phase following the toe-off of the other foot, the vertical force is no longer vertical, it tilts over to produce shear force. When the foot hits the ground as termed heel strike, the VGRF associated with tangential forces slanted from GRF vector component parallel to the ground acting backwards. It is formed by an exchanging of frictional forces with ground that leads to a brake impulse and therefore the body slow down. This prevent foot sliding forward along the ground. However, the dynamic characteristics of gait reaction forces are usually exploited by filtering as shown in Fig.3. Filtering at 25 Hz is useful for certain data while it is not applicable for another subjects as in Fig.3. Given that the foot will act also as a shock absorber to disperse the force during landing. The GRF vector is illustrated by a black arrow on Fig.2 during contact, midstance and propulsive phase.

Fig. 2. VGRF vector during the stance phase of Gait Cycle

Likewise, during toe-off there will be an appearance of propulsive impulse to stimulate motion due to tilting of the force over forwards. This helps accelerating the body.

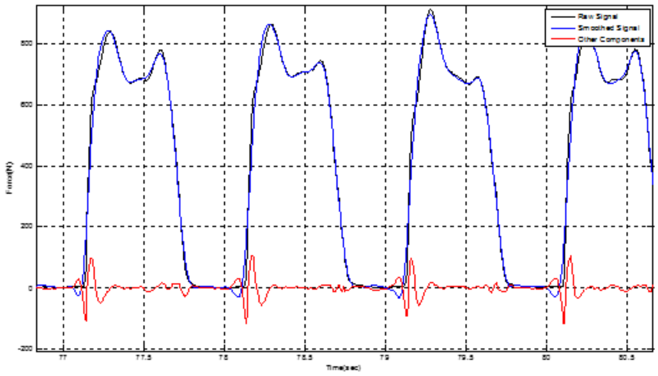

Fig. 3. VGRF filtering by second order Butterworth filter of 25 Hz shows a vital part being attenuated colored in red

Knowing that, when the concavity upward in the horizontal and normal forces exist, this indicates a brake impulse which is followed by deceleration motion. In contrary, when concavity is downward, this signifies propulsive impulse followed by an acceleration motion. This specify an important coefficient to consider which named static friction. Static friction is defined as the ratio of the magnitude of the horizontal frictional force to the normal force. This coefficient could yield when slippage could occurs. Knowing that, part of this noise reflect the horizontal speed of the foot during the touchdown of the heel with ground.

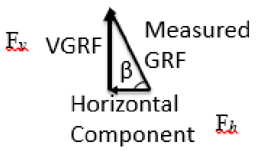

Fig. 4. During Heel strike, the measured VGRF consist of horizontal frictional component

Referring to Fig.4 and by applying Pythagoras theorem, the measured ground reaction force can be derived by equation (3):

$$F_m^2 = F_v^2 + F_h^2 \tag{3}$$

Then

$$\tan\beta = \frac{F_v}{F_m} \tag{4}$$

Where

F_m : The measured ground reaction force

F_v : The vertical component of ground reaction force, load

F_h: The horizontal frictional component exerted by each surface on the other.

β: The angle indicating the direction of the measured GRF

The horizontal friction is considered as non-fundamental force as a result from intermolecular and interatomic kinetic dry friction between ground and foot. This would complicate its calculation and is considered to be highly stochastic. This energy that examined as frictional forces by subject is lost as heat. An empirical law termed as Coulomb's Law of Friction can approximate this model by equation (5):

$$F_h \leq \mu F_v \tag{5}$$

Where, μ is the dimensionless coefficient of friction. It can be defined from equation (5) as the ratio of the force of friction between foot and ground and the pressing normal force.

III. RESULTS AND DISCUSSION

By Newton's law the force is given by: F=ma where "m" is the mass of the parts contributed to this force, and "a" is the acceleration. Since a frictional backward force exist, this suggest definitely the existence of backward acceleration as a braking action on the body, slowing it down.

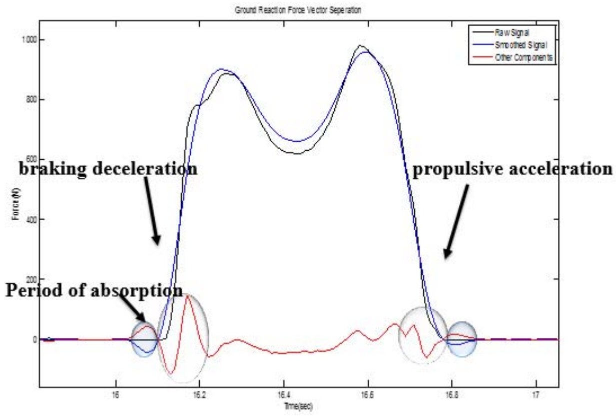

Fig. 5. Loading response and the push-off are circled.

From Fig.5, at instant just prior to the collision of the heel with ground i.e. as it start to touches the ground the normal force is in negative due to the fact that a forward directed force termed as "claw back" exists due to initial parameters [2]. During this phase, the skeletal system act as a shock absorber. At those moments slippage is occurring and shown by the small red peak and this indicate the existence of force with direction of motion. However, this pronation activate information record by the lower central nervous system through sensory neurons that registered in central nervous system which in turns activate the muscles contraction to prevent the forefoot from slapping down and therefore generate forces and moments at synovial joints to invoke the movement regulated by rigid links. Fig.5 can be used for illustration. The last exert ground reaction force which followed by a decreasing in magnitude of the horizontal component as shown in Fig.4 to serve a friction in the opposite direction of motion preventing the subject from slipping and therefore falling. As a result, at the period of absorption shown in Fig.5 indicates that the horizontal and frictional force are equal in magnitude but in opposite directions where still there is no movement. This can be verified by newton's third law that states that for every action i.e. force there is an equal and opposite reaction i.e. counter force.As a summary, this work emphasize the use of an adaptive way of filtering using the EMD technique as shown in Fig. 6 instead of using a fixed filtering bandwidth of frequencies over all gait VGRF signals (x[n]).

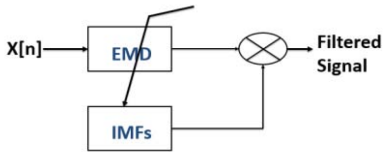

Fig. 6. Proposed filter

At this stage, we choose to remove certain intrinsic mode functions (example is shown in Table I) according to their weighted energy and preferred number of intrinsic mode function.

TABLE I. INTRINSIC MODE FUNCTION CHARACTERISTICS

Channel	Zero Crossings	Extrema Counts	Mean Freq. [Hz]	Power (%)
IMF_h1	7050	4056	29.09068	0.045846
IMF_h2	2506	1676	10.34326	0.354629
IMF_h3	736	472	3.04068	9.128521
IMF_h4	494	316	2.042248	4.668593
IMF_h5	229	114	0.948923	84.29544
IMF_h6	158	86	0.655995	1.052419
IMF_h7	75	40	0.313557	0.241007
IMF_h8	35	18	0.148527	0.089646
IMF_h9	18	10	0.078389	0.041991
IMF_h10	10	6	0.045383	0.008957
IMF_h11	2	4	0.012377	0.031212
IMF_h12	3	1	0.016503	0.041738
IMF_residual	0	1	0.004126	

An example of EMD applied to a data from a control subject is shown in Fig.7. The first subplot represents the raw signal. Fig.7 illustrates the idea that the first IMF captures the largest frequency components. The second IMF has a lower oscillation and so on to reach a trend with the lowest component as shown in the last row of Fig.7. Therefore EMD acts as an adaptive filter to extract the components present in the signal. It's worthy therefore to mention that the first IMF extracts most of noise present in signal.

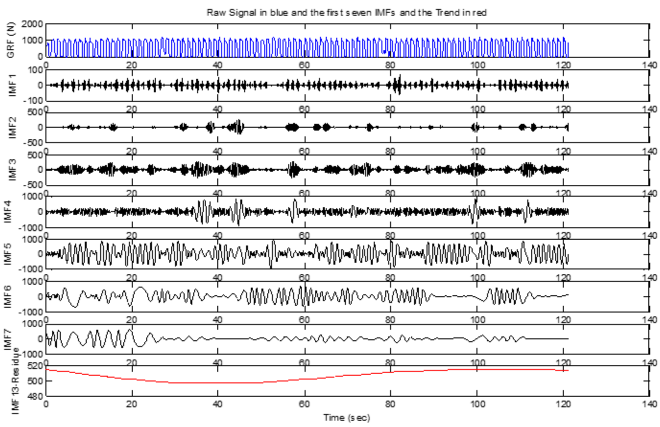

Fig.7.The first raw is the original signal. Seven IMFs plus the trend are plotted

As a result, it is better to filter the signal at a mean frequency of 29.09 Hz instead of filtering it by 25 Hz second order Butterworth filter and losing crucial part of the signal. This filtering could be at 28 Hz on another gait if it represents the mean frequency of the highest oscillations. This is because we have assumed in this case that noise exist in the IMF1. Fig. 6 therefore indicates that EMD is applied to the signal then a choice of the number of intrinsic mode functions that must be removed from signal must be made. This would remove same number of oscillations between different gait subjects but not necessary the same frequency content.

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