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Inertia Measurement Techniques for Human Joints' Movement Analysis

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Abstract. Development and assessment of techniques that allow inertia measurement units consisting of an accelerometer and a gyroscope to be used for monitoring human joints' movements are presented. A new wavelet packet decomposition technique was developed that denoised the accelerometer signals. Investigations on the use of accelerometers to analyse legs' movements are described.

Keywords. joints' movement analysis, accelerometry, wavelet analysis, gait analysis

1. Introduction

Assessment of human joints' movements has been of great interest to many researchers and medical practitioners due to its importance for diagnosing and monitoring several medical conditions [1][2]. Movement analysis is important in assessing disabilities such as those affecting balance that increase the likelihood of fall and associated injuries. Many of these conditions are directly related to mobility-impaired or mobility reducing disorders such as arthritis, obesity, stroke, chronic pulmonary disease, multiple sclerosis and Parkinson's disease [2].

The gold standard for movement analysis utilises a complex camera (vision) based aparatus. Although the method can be accurate, it has shortcomings that include its high cost, its restriction to being available primarily at some specialised gait laboratories and its complex procedures for data recording and analysis [3]. Recent technological developments in areas of nano and microprocessor technologies, computing and digital signal processing have resulted in major technological advances for measuring, monitoring and quantifying human movements [4] using Microelectromechanical Systems (MEMS) based on powerful integrated circuits called Inertia Measurement Units (IMUs). A typical IMU consists of a three-axis accelerometer, a three-axis gyroscope and a three-axis magnetometer and can be used to measure acceleration, angular rate of rotation and magnetic field vector respectively in their three-dimensional local coordinate systems [5].

In theory, the movements' measurements obtained using IMUs once processed using suitably designed algorithms can estimate important information such as rotation, acceleration, orientation and distance. There are however some challenges in deploying IMUs for measuring and analysing patterns of human movements in practical scenarios. The data obtained from the IMUs are prone to various errors that reduce their accuracy

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of analysis. Also, interpreting and relating the outputs from an IMU (accelerometer, gyroscope and magnetometer) to actual movement patterns require carefully designed models. In some studies, to improve the IMUs' effectiveness, the movement related information is estimated by combining (for fusing) the signals from an accelerometer and a gyroscope using a variety of algorithms such as the Kalman and complementary filters so that they complement each other's abilities [6].

Accelerometers have been reported to be very effective in posture and motion analysis, for detecting cyclical movements and conditions of daily living [7]. Accelerometer data were used to develop an efficient system for assessing static and dynamic balance and postural sway [8]. Mayagoitia *et al.* [9] used a tri-axial accelerometer to measure and monitor human balance. Luinge and Veltink [10] attached 3D accelerometers to the back of the trunk at the T4/T5 level and the pelvis to estimate the inclination of the body segments for monitoring daily life tasks, focusing on lifting and stacking objects. Kavanagh and Menz [11] reviewed the literature that used this technique for quantifying human movement and concluded that accelerometry techniques are accurate and reliable for providing information related to walking and gait patterns.

A gyroscope indicates the rate a body's rotation and so to obtain the actual angle of rotation, the gyroscope's signal needs to be integrated. Therefore an initial offset in the gyroscope's output results in a gradually increasing amplitude drift that obscures the movement information. An accelerometer on the other hand suffers from noise during a movement's initiation or when there is a sudden change in the movement's direction. By combining the outputs from the gyroscope and accelerometer, these two shortcomings can to an extent be resolved. A number of approaches for combining the gyroscope and accelerometer signals were reported. Hong [12] developed a fuzzy logic based complementary filter for determining attitude reference. Shen *et al.* [13] took this research further and designed an SPSA (simultaneous stochastic approximation algorithm) based on fuzzy complementary filter. Calusdian *et al.* [14] designed an adaptive-gain quaternion-based complementary filter algorithm that could accurately track orientation during dynamic and slow motion for tracking foot orientation during standing and swing phase. Tseng *et.al* [15] proposed a method to combine passive complementary filter and observer estimation methods to improve attitude estimation. Tian *et al.* [16] proposed an adaptive-gain complementary filter.

However, despite extensive progress in utlising IMUs for movement analysis, there remain significant challenges in applying them for practical problem solving situations. For example in real-time clinical assessments and monitoring activities of daily living, problems such as heavy computational demands need careful consideration. Hence, there is a need for further research and development to enhance ways IMUs are employed and their data are processed and interpreted.

In this study, a novel wavelet packet decomposition based technique to denoise accelerometer signals using the gyroscope as a guide was developed and its effectiveness was compared with the well-known complementary filter method. The study also includes an investigation of accelerometer based techniques to measure the legs' movement angle, velocity, acceleration and displacement to assist in clinical diagnosis and rehabilitation purposes.

2. Methods

In this section initially a method devised to denoise accelerometer signals is described then accelerometer based experiments to analyse legs' movements are explained.

2.1. Wavelet packet based method to denoise accelerometer signals

A technique based on wavelet packet decomposition (a generalisation of wavelet decomposition) was developed to denoise accelerometer signal using the gyroscope signal as a guide. This part of the study was based on simulated accelerometer and gyroscope signals (Figure 1) to facilitate an evaluation of the effectiveness of the methods. The simulated accelerometer signal shown in Figure 1 (top figure) represents a leg's movements in a simplified form. Gaussian noise was added to this signal to represent the effect of measurement noise (shown in Figure 1, middle). The simulated gyroscope signal (shown in Figure 1, bottom) had an amplitude drift that increases with time.

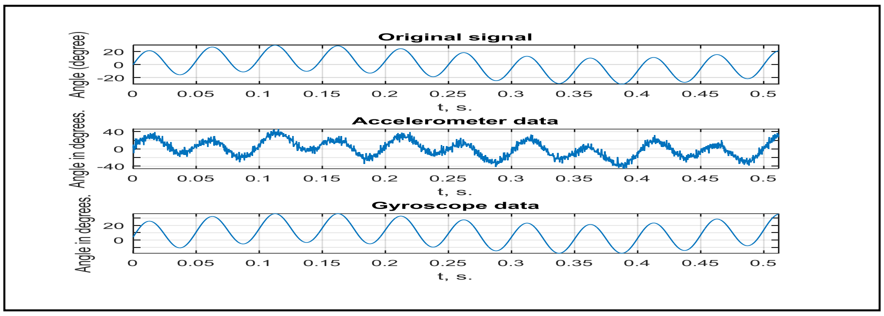


Figure 1. Simulated accelerometer signal (top), noisy accelerometer signal (middle) and gyroscope signal with drift (bottom).

In wavelet packet, a signal is successively decomposed by suitably chosen lowpass and highpass filters and at each stage of decomposition, the resulting signals are down sampled by a factor of 2. The outputs of the lowpass filter and highpass filters represent the coarse and detail information of the signal respectively. The decomposition is successively repeated in the similar manner for the required number of stages (called levels). The noisy accelerometer and drifting gyroscope signals were both decomposed separately using Matlab© to 8 levels using the Daubechies 20 wavelet family (filter). The coefficients of the terminal nodes were expressed as nodes 255 to 510. The values of these nodes for both the decomposed noisy accelerometer and drifting gyroscope signals were compared for similarity by performing correlation. Two nodes with the largest correlation magnitude (i.e. closest similarity) were chosen and the values of the nodes that were not selected were set to zero. The accelerometer signal was then reconstructed based on the new wavelet packet coefficients for the noisy accelerometer.

The reconstructed accelerometer signal obtained using the above method was compared with the complementary filter approach for combining the noisy accelerometer and drifting gyroscope signals. The movement angle from the complementary filter was obtained from Eq. (1) as

$$\theta_{current} = \alpha\left(\theta_{previous} + \Delta_t \theta_g\right) + (1 - \alpha)\theta_a \quad (1)$$

The complementary filter algorithm was designed using the filter parameter α= 0.98, making the design rely more heavily on the gyroscope's based angle (θ_g) than the accelerometer angle (θ_a). The sampling interval Δ_t= 0.018 seconds (corresponding to sample rate of 55 samples per second).

2.2. Accelerometry techniques for measuring legs' movements

In this part of the study, four tri-axial accelerometer boards (ADXL335 from Sparkfun) with dimensions 4 mm × 4 mm × 1.45 mm were used for the experiments. The ADXL335 measures a minimum full-scale range of ±3 g [17] [18]. These boards were connected to an Arduino Mega 2560 microcontroller board, that in turn was connected up to a computer via a USB cable. The microcontroller board digitised the analogue *x*, *y* and *z* accelerometer signals for display, storage and processing by the computer. The data recording sample rate was 244 samples/second [18], which was sufficient to avoid aliasing. The accelerometers were attached to the left and right thighs and shanks of a healthy adult subject as he performed the following movements:

- Sleeping on his back on the floor and fully stretched one of his legs to touch the floor and then bent it fully toward his chest, repeating 30 times. This was repeated for the other leg.
- Walking normally the length of a long (about 20 m) corridor.

The movement angles were calculated from the accelerometer signals using [18]

$$\alpha_{thigh} = tan^{-1}\frac{a_{x1}}{a_{z1}} \quad (2)$$

$$\beta_{shank} = tan^{-1}\frac{a_{x2}}{a_{z2}} \quad (3)$$

$$\emptyset_{joint} = \alpha_{thigh} + \beta_{shank} \quad (4)$$

Where α_{thigh}, β_{shank} and $\emptyset_{joint}$ are the tilt angles of the thigh and shank, and the relative joint angle respectively; α_{x1} and α_{z1} are the acceleration measures for the *x* and *z* axes of the accelerometer attached to the thigh and α_{x2} and α_{z2} are the acceleration measures for the *x* and *z* axes of the accelerometer attached to the shank. Once the legs' joint angle was determined, the angular velocity (*v*), angular acceleration (*a*) total angular displacement (*d*) were obtained from it using [18]

$$v(t) = \frac{d(\phi)}{dt} \quad (5)$$

$$a(t) = \frac{d(v)}{dt} \quad (6)$$

$$d = \int_{t=0}^{t=T} v(t) \quad (7)$$

where *T* is the signal recording duration.

3. Results and discussion

3.1. Wavelet packet based method to denoise accelerometer signal

The correlation between the terminal nodes of the wavelet packet for the noisy accelerometer and time drifting gyroscope signals indicated that the nodes with the two highest similarities were nodes 255 and 258 (Figure 2). These nodes were then selected with the values of the remaining nodes set to zero to re-construct the accelerometer signal as shown in Figure 3.

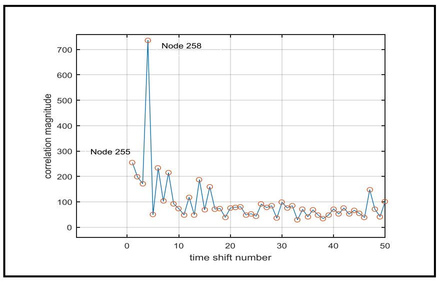


Figure 2. Wavelet packet correlation plot.

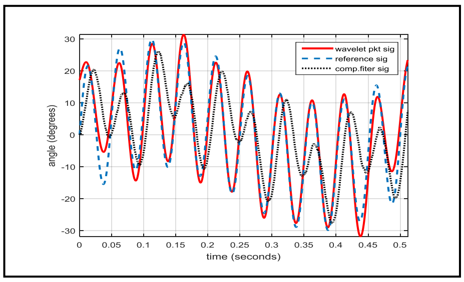


Figure 3. The original accelerometer signal (blue), those from the complementary filter (black) and the wavelet packet (red).

Figure 3 shows the original simulated accelerometer signal, the denoised accelerometer signal obtained using the wavelet packet decomposition technique and the signal obtained from the complementary filter. The denoised accelerometer signal obtained using the wavelet packet method is significantly more similar to the original signal as compared with the signal obtained using the complementary filter. Wavelet packet processes a signal at different frequency bands and thus can be more effective in representing the characteristics of the signal and noise than the complementary filter. The method is thus valuable in denoising accelerometer signals.

3.2. Accelerometry techniques for measuring legs' movements

The accelerometer derived information data obtained from the legs while the subject slept on his back and moved his legs in turn from fully stretched on the ground to fully bent close to the chest are shown in Figures 4 and 5 and the related data are summarised in Table 1. Table 2 shows the angular velocity, acceleration and total displacement results for the legs' movements when the subject slept on his back. The results indicate that the right leg moved faster than the left leg and had a total displacement of 89.2 radians (over the duration of the recording) as compared with the left leg that had total a total displacement of 79.2 radians.

In the walking scenario shown (results summarized in Tables 3 and 4 and shown in Figures 6 and 7), the angular range of movement was wider for the left leg than the right leg. The angular velocity, acceleration and total displacement values were also higher for the left than the right leg. The largest peaks present in the magnitude frequency spectrum of the legs' angular movements were at 0.77 Hz, 1.55 Hz and 2.33 Hz with the dominant frequency appearing at 1.55Hz.

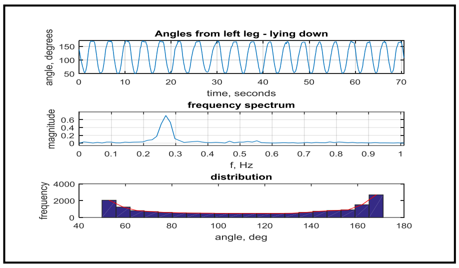


Figure 4. Angle measurement for the left leg while subject slept on his back.

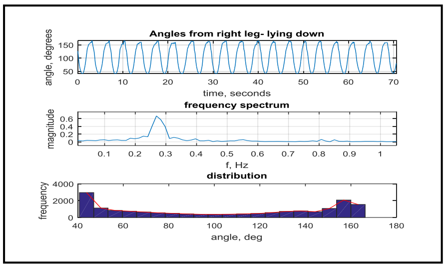


Figure 5. Angle measurement for the right leg while subject slept on his back.

Table 1. Legs' movement range and frequency when subject slept on his back

Leg	Movement Range (degrees)	Movement Frequency (Hz)
Left	52.9 - 167.9	0.26
Right	43.9 - 163.1	0.26

Table 2. Legs' movement angular velocity, acceleration and total displacement when subject slept on his back

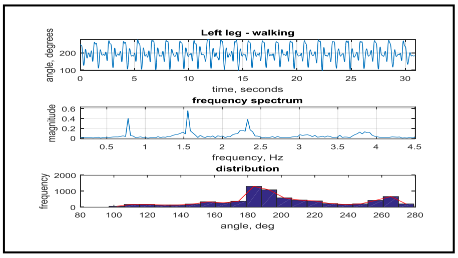
Leg	Angular Velocity (rad/s)	Acceleration (rad/s^2)	Total Displacement (rad)
Left	2.85	27.09	79.15
Right	3.50	38.34	85.19

Table 3. Legs' movement range and frequency when the subject walked

Legs	Movement Range(degree)	Frequency (Hz) associated with the three largest peaks in the magnitude spectrum
Left leg	101.7 - 274.5	0.77, 1.55, 2.33
Right leg	115.2 - 284.1	0.77, 1.55, 2.33

Table 4. Velocity, acceleration and total displacement when the subject walked

Leg	Angular Velocity (rad/s)	Acceleration (rad/s^2)	Total Displacement (radians)
Left	24.63	436	216.4
Right	23.75	411	196.3



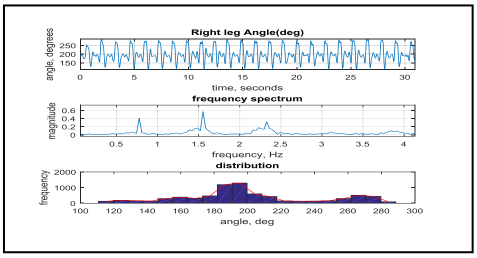
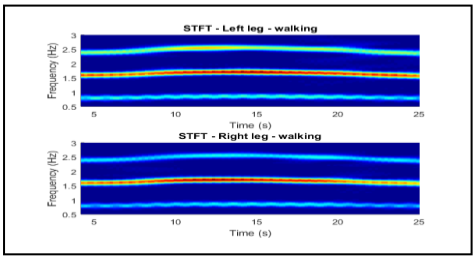


Figure 6. Angle measurements for left leg when the subject walked.

Figure 7. Angle measurements for the right leg when the subject walked.

The short-time Fourier transforms plots of the legs' angular rotation angular when the subject walked and slept on his back are displayed in Figures 8 and 9 respectively. Figure 8 shows three main frequency components that slightly vary in their values over time. Figure 9 indicates that the main frequency of the movement for both legs was 0.26 Hz (i.e. 3.8 seconds per cycle) that also varies slightly over time during walking. Short-time Fourier transform is valuable in visualising consistency in movement and in associating time and frequency of the movement.



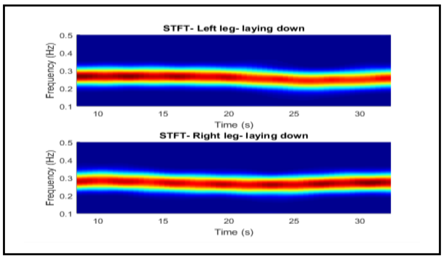


Figure 8. Short-time Fourier transform of the legs' angular rotation signal when the subject walked.

Figure 9. Short-time Fourier transform of legs' angular rotation when the subject slept on his back.

The findings of this study highlight some of the technological challenges and opportunities that inertia measurement units (accelerometers and gyroscope) can provide in health care. More research and developments are needed to deal with these challenges and explore the opportunities they provide. Medical conditions involving movement dysfunctions such balance problems will be obvious application areas for IMUs. We are also currently exploring IMUs to help monitoring and diagnosis arthrosis by quantifying joint movement information.

4. Conclusions

A wavelet packet decomposition technique for denoising a simulated accelerometer signal was developed and its performance was compared with that for the complementary filter. The wavelet packet approach was more effective in representing the original reference accelerometer signal than the complementary filter.

A system to measure the legs' movement using two pairs of accelerometers was also developed. Accelerometer signals recorded from the legs of a healthy adult subject who slept on his back and moved his legs in turn from fully stretched on the ground to fully bent close to his chest and while he walked were analysed. The results obtained indicated differences between angular rotation, angular velocity, angular velocity and total angular displacement for the legs for the related scenarios. The approaches can be valuable for investigating movement related disorders.

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