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A study on band-pass filtering for calculating foot displacements from accelerometer and gyroscope sensors

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***Abstract*— As a promising alternative to laboratory-constrained video capture systems in studies of human movement, inertial sensors (accelerometers and gyroscopes) are recently gaining popularity. Secondary quantities such as velocity, displacement and joint angles can be calculated through integration of acceleration and angular velocities. It is broadly accepted that this procedure is significantly influenced by accumulative errors due to integration, arising from sensor noise, non-linearities and asymmetrical sensitivity/offset signals and bias drifts. In this paper, we assess the effectiveness of applying band-pass filtering to raw inertial sensor data under the assumption that sensor drift errors occur in the low frequency spectrum. The normalized correlation coefficient ρ of the Fast Fourier Transform (FFT) spectra corresponding to vertical toe acceleration from inertial sensors and from a video capture system as a function of digital band-pass filter parameters is compared. The Root Mean Square Error (RMSE) of the vertical toe displacement for 30 second walking windows is calculated for 2 healthy subjects over a range of walking speeds. The lowest RMSE and highest cross correlation achieved for the slowest walking speed of 2.5Km/h was 3.06cm and 0.871 respectively, and 2.96cm and 0.952 for the fastest speed of 5.5Km/h.**

I. INTRODUCTION

Microelectrical-mechanical systems (MEMS) provide the possibility to measure physical quantities such as accelerations and angular velocities using smaller and cheaper inertial sensors. These inertial measurement units (IMUs) generally consist of accelerometers and gyroscopes. In gait analysis, reduced sensor sizes promise better portability and opens avenues to research of gait in natural environments.

Recent studies have begun applying inertial sensor technologies to monitoring gait, in particular foot motion. Morris et al. [1] had designed a gait shoe to monitor several quantities such as walking speeds, stride length and heel ground reaction forces. They pointed out that inertial sensors contained measurement errors which accumulated when integration was used to derive secondary quantities. Sabatini et al. [2] proposed a strap-down integration method to reduce these errors when calculating velocity and displacement. Roetenberg et al. [3] proposed a 6 DOF magnetic system with inertial sensors to track position and orientation. The magnetometer was used to update inertial measurements using a complementary Kalman filter structure. However this method relied on knowledge of ferrous materials in the vicinity of measurement.

The major limitations of direct integration of sensor data have been reported as sensor noise [4], bias drift, and sensitivity and offset process variations [5], [6]. These dramatically impair the derivation of secondary quantities such as displacement [7]. In our previous work [8], we showed that large differences between inertial sensor measurements resided in the lower frequency ranges when compared to video data. The results suggested that these errors could be removed by band pass filtering if the spectral components did not overlap with real motion data. In this paper, we investigate the impact applying various band pass filters on the calculated displacement. The cross-correlation of the toe acceleration Fast Fourier Transform (FFT) spectra is used to assess the quality of filtered acceleration signals compared to the corresponding video accelerations.

In section II, we provide a brief theory of digital filters, the Fourier transform and a description of metrics used to assess the filtering quality. This is followed our experimental methodology, results and finally discussion of the major findings in sections IV and V respectively.

II. BACKGROUND THEORY

A. Digital Band-pass Filters

Digital filters are primarily used to attenuate noise frequencies from a discrete signal. In this paper, we selected the IIR (Infinite Impulse Response) Butterworth filter approach as it achieves defined stop band frequencies with fewer coefficients than FIR (Finite Impulse Response) filters. The band pass filter is described by a transfer function with static coefficients and usually specified by f_L is the low frequency cutoff, f_H the high frequency cutoff and filter order [9].

B. The Fourier Transform and Power Spectrum

The Discrete Fourier Transform (DCT) is used to characterize a discrete signal in the time domain, as a sum of unique harmonics of sines and cosines in the frequency

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domain. This can be written in general form as in Proakis et al. [10]:

$$x(n) = \frac{1}{2}a_0 + \frac{1}{N}\sum_{n=1}^{N-1} a_k \cos\left(\frac{2\pi nk}{N}\right) + b_k j\sin\left(\frac{2\pi nk}{N}\right) \qquad (1)$$

where a_0 is the DC bias (zero frequency), a_k and b_k are Fourier coefficients for the harmonics k = 1,2…N and have the same units as x(n). The FFT algorithm is usually implemented to calculate DCT coefficients. The power magnitude is used to determine signal frequencies for major gait activities and is defined as:

$$P_k = a^2{}_k + b^2{}_k \qquad (2)$$

C. Assessing Band-Pass Filter Quality

The quality of band-pass filtering was assessed by calculating the correlation coefficient ρ of FFT power spectra between accelerations calculated from video displacement and IMU measured accelerations. It indicates the strength and direction of a linear relationship between two random variables X and Y. The correlation is 1 in the case of an increasing linear relationship and -1 in the case of a decreasing linear relationship. It is defined as [11]:

$$\rho_{FFT_x, FFT_y} = \frac{\mathrm{cov}(FFT_X, FFT_Y)}{\sigma_{FFT_x}\sigma_{FFT_y}} \qquad (3)$$

where in this case, X and Y are the power spectra of the IMU's filtered acceleration and the video respectively. Cov(X,Y) is the covariance between two random variables X and Y, and σ_x and σ_y is the respective standard deviation. The root mean square error (RMSE) between the displacement measured by video and that obtained by integrating the IMU data is defined as:

$$RMSE(d_{IMU}, d_{Op}) = \sqrt{\frac{\sum_{i=0}^{N}\left(d_{IMU}(i) - d_{Op}(i)\right)^2}{N}} \qquad (4)$$

where d_{IMU} and d_{Op} represent the vertical toe displacement calculated from IMU data and video data respectively.

III. EXPERIMENTAL METHODOLOGY

A. Experimental Setup

Experiments were performed in the Victoria University Biomechanics Laboratory. Gait data was collected from 2 healthy subjects with no recorded gait disabilities. Video data was recorded using the Optotrak Certus NDI system while sensor data was collected using an IMU package consisting of a single tri-axis accelerometer and dual-axis

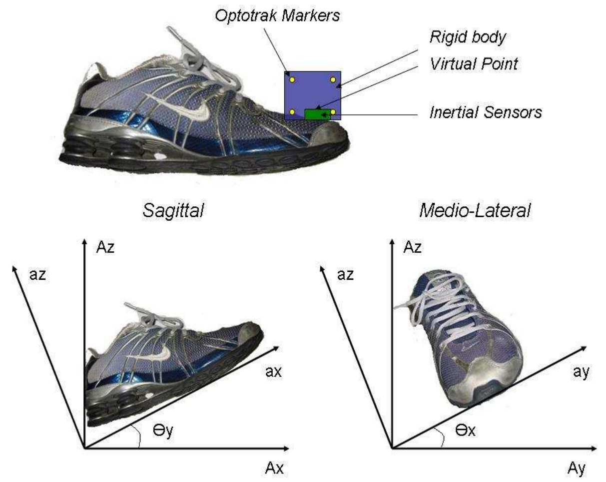

Fig. 1: Experimental setup depicting Optotrak markers and inertial sensor placement; rotation in the medio-lateral and sagittal plane depicted by θx and θy respectively.

gyroscope package described in [8]. The sensors were mounted at the distal end of the shoe together with a rigid body containing 4 Optotrak markers. A virtual point corresponding to the center of the IMU was positioned as shown in Figure 1. The sampling rate for both systems was set to 500Hz and recordings were manually triggered simultaneously. The sensor outputs were connected to a National Instruments DAQ board and control software was written in Labview 8.6.

Static data was recorded from the subjects at least 30 seconds to estimate sensor noise, offset bias and to determine the start of the walking activity. Immediately after this phase, the subjects started walking on the treadmill. Data was recorded for at least 30 seconds each so that a minimum of 20 gait cycles could be collected per trial. Subjects walked at four speeds, namely 2.5, 3.5, 4.5 and 5.5km/h.

B. Sensor Data Processing

The sensor outputs were converted to accelerations and angular velocities using datasheet equations [5][6]. Subsequently, the gyroscope's raw signals were band-pass filtered with a lower cut-off frequency of 0.1Hz and the higher cut-off frequency of the gyroscope's and the accelerometer's low-pass filter were varied in steps of 1Hz from 8Hz to 50Hz. The vertical toe acceleration was computed from the Euler transformation matrix as:

$$Az = a_x\sin\theta_y\cos\theta_x + a_y\sin\theta_x + a_z\cos\theta_y\cos\theta_x - g \qquad (7)$$

where ax, ay and az are accelerations measured in the respective IMU's axis, g is gravitational acceleration and the angles θx and θy are derived by the integration of gyroscope angular speed ω_x and ω_y taken with respect to the planes as depicted in Figure 1. The IMU vertical acceleration Az was band pass filtered with filter order = 4, f_L = 0.7Hz and

f_H =35Hz to remove remaining biases [8]. The Optotrak data was low-pass filtered with a 4th order Butterworth with $f_L = 35Hz$. As human gait is predominantly a low frequency activity [12], the high frequency noise due to differentiating the Optotrak and sensor noise is removed. The displacement RMSE is calculated between the toe-off times of the first and last gait of the recorded data for all trials.

IV. EXPERIMENTAL RESULTS

Figure 2 shows on the left and right columns the isolines of the vertical acceleration FFT's cross correlation coefficient of both subjects. At 2.5km/h the highest isoline for subject 1 and 2 were 0.82 and 0.87 respectively over the range of 25-50Hz for the accelerometer and 8-35Hz for the gyroscope of both subjects. The lowest value of 0.71 remained in the region of 8-10Hz for the accelerometer and 20-50Hz for the gyroscope. The correlation increased at 3.5km/h to 0.93 (subject 1) and 0.89 (subject 2) over the region of 40-50Hz for the accelerometer and a wider range for the gyroscope from 35-50Hz, whilst the lowest correlation of 0.86 and 0.81 for subjects 1 and 2 remained in the same region of 2.5km/h. At 4.5km/h and 5.5km/h the highest correlations were 0.93 and 0.95 for subject 1 and 0.89 and 0.92 for subject 2, where the optimal cutoff frequency regions remained in the same region of 20-50Hz for the accelerometer and 8-35Hz for the gyroscope.

Table 1 depicts the maximum and minimum values of correlation coefficient ρ in figure 2 for the two subjects (S1 and S2) and the respective accelerometer (fA) and gyroscope (fG) cut-off frequencies over the 4 walking speeds. Table 2 shows the RMSE in centimeters, considering the displacement over the complete motion in all gaits (RMSE 1) and only the displacement from the toe-off time and maximum peak during the stance phase (RMSE 2) for the highest cross-correlation coefficients.

The displacement achieved at 5.5km/h for both subjects with the optimized cut-off frequencies of highest cross correlation is depicted in figure 3.

V. DISCUSSION

The isolines for both subjects show lower correlations of spectra in slower walking speeds, whereas in faster walking the cross correlation achieves higher values. Table 1 also depicts this trend, as the highest and lowest correlation points at each walking speed increases as the walking speed is faster. This is also confirmed by results in table 2 which also shows that the RMSE 1 and 2 decreases in general as the walking speed is faster suggesting that slow time varying sensor errors are better filtered out for faster gait motion. Figure 3 demonstrates drift free displacement with trends mirroring that of the Optotrak system. This confirms our earlier expectations and results [8].

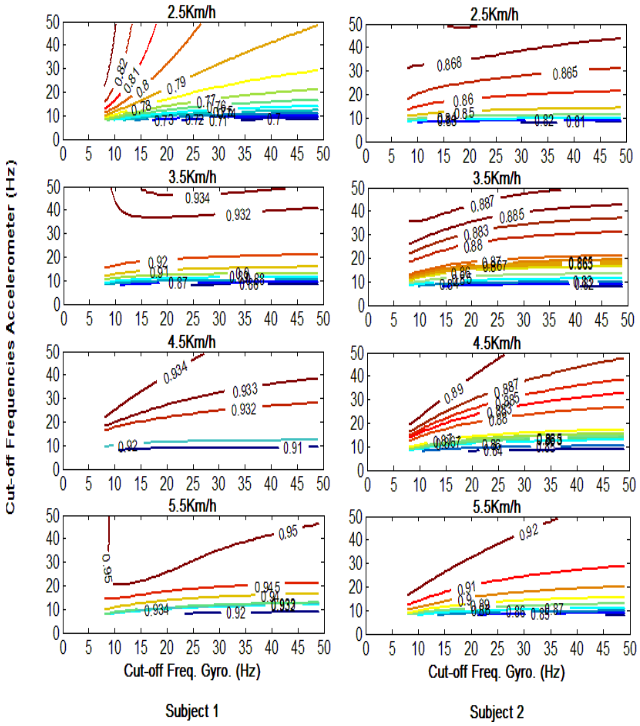

Fig. 2: Isolines of cross-correlation coefficient of two healthy subjects at 4 different walking speeds as a function of cut-off frequencies for the gyroscope and accelerometer.

TABLE 1: CROSS CORRELATION Ρ FOR 2 SUBJECTS OVER 4 DIFFERENT WALKING SPEEDS.

Speed (km/h)	ρ	S1		S2	
2.5	Max	0.840	fA=50Hz fG=8Hz	0.871	fA=50Hz fG=18Hz
	Min	0.694	fA=8Hz fG=50Hz	0.808	fA=9Hz fG=49Hz
3.5	Max	0.934	fA=50Hz fG=24Hz	0.889	fA=50Hz fG=13Hz
	Min	0.856	fA=8Hz fG=50Hz	0.810	fA=8Hz fG=50Hz
4.5	Max	0.935	fA=49Hz fG=10Hz	0.897	fA=50Hz fG=8Hz
	Min	0.903	fA=8Hz fG=50Hz	0.833	fA=9Hz fG=50Hz
5.5	Max	0.952	fA=49Hz fG=15Hz	0.932	fA=49Hz fG=8Hz
	Min	0.915	fA=8Hz fG=49Hz	0.839	fA=8Hz fG=49Hz

TABLE 2: COMPARISON OF VERTICAL DISPLACEMENT RMS AND NRMS ERRORS AT FOUR WALKING SPEEDS FOR 2 HEALTHY SUBJECTS

	S1		S2	
Speed (km/h)	RMSE1 (cm)	RMSE2 (cm)	RMSE1 (cm)	RMSE2 (cm)
2.5	3.06	7.19	3.86	5.34
3.5	3.11	7.41	4.69	8.91
4.5	3.54	2.71	3.83	8.19
5.5	2.96	3.55	3.56	7.23

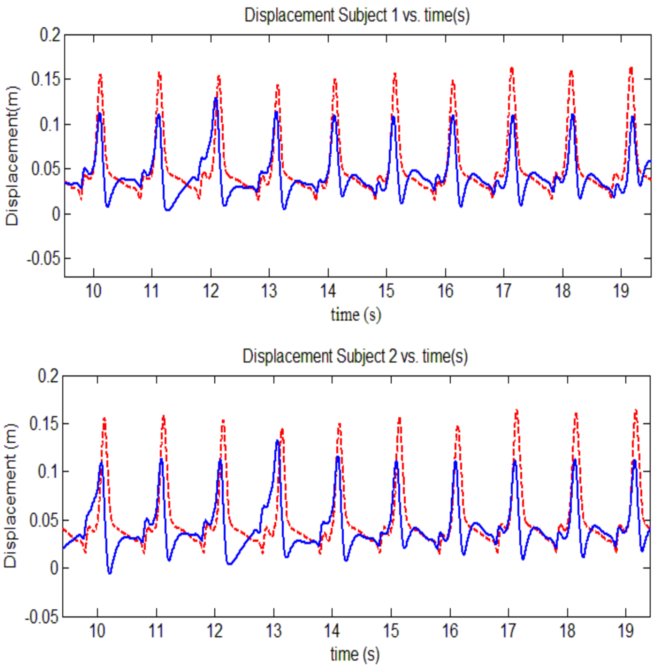

Fig. 3: The vertical displacement of subject 1 and 2 using the IMU (blue solid line) and the displacement by Optotrak (red dotted line).

However, the results also suggest that the higher correlations were found when cut-off frequencies of 45-50Hz were used for the accelerometer and 8-10Hz for the gyroscope. These were obtained despite the final filtering of the resultant acceleration at 35Hz, firstly suggesting that the transformation in (7) maps raw sensor frequencies to different frequency regions in the final resultant acceleration. Secondly, this result also implies that higher frequency harmonics of the raw acceleration also play a significant role in the reconstruction of the vertical displacement calculation and hence should not be disregarded as high frequency noise. It is unknown at this time how the frequency spectra of the individual sensors are related to the final resultant acceleration. Future work will be required to mathematically model this behavior and ascertain their relationship if any.

The results in table 2 indicate that band pass filtering is better applied to faster motion, in this case during the swing phase of the gait cycle i.e, from toe off to maximum displacement. Figure 3 depicts better displacement reconstruction in this phase than in the stance phase (less motion) where a large ripple in IMU measured displacement is observed as opposed to the stance phase measured by the Optotrak. The hypothesis is that the band-pass filter removes motion frequencies below the lower cut-off of 0.7Hz causing a ripple due to the averaging effect of the recursive filter. This effect can be improved in the future by using adaptive filtering techniques such as adaptive Butterworth filters [13] with reduced phase shift error.

As opposed to strap-down integration methods, Kalman filters and sensor fusion algorithms [3] that try to compensate for cumulative integration errors, band-pass filtering promises a more fundamental solution of tackling these sensor errors at their origin. This technique shows potential of reducing the need for additional ‘correctional’ sensors such as the magnetometer. Future work will focus on the study of a broader range of band-pass filters, more subjects with various non-periodic walking styles to further quantify the limitations and advantages of this technique.

VI. Conclusion

This work has revealed that inertial sensors can show good performance comparable to video based systems. A simple technique such as band pass filtering instead of low pass filtering can remove a large source of sensor error and potentially minimize the requirement for more complex methods such as gait event detections and strap down integration. This could reduce the computational needs of future on-chip implementations of algorithms and portable devices for measuring displacement and velocities from inertial sensors.

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