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Measurement of stride parameters using a wearable GPS and inertial measurement unit

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Abstract

Both GPS and inertial measurement units (IMUs) have been extensively used in biomechanical studies. Expensive high accuracy GPS units can provide information about intrastride speed and position, but their application is limited by their size and cost. Single and double integration of acceleration from IMU provides information about short-term fluctuations in speed and position, but suffers from integration error over a longer period of time. The integration of GPS and IMU has been widely used in large and expensive units designed for survey and vehicle navigation. Here we propose a data fusion scheme, which is a Kalman filter based complementary filter and enhances the frequency response of the GPS and IMU used alone. We also report the design of a small (28 g) low cost GPS/IMU unit. Its accuracy after post-processing with the proposed data fusion scheme for determining average speed and intrastride variation was compared to a traditional high cost survey GPS. The low cost unit achieved an accuracy of $0.15\,\mathrm{ms}^{-1}$ (s.d.) for horizontal speed in cycling and human running across a speed range of $3–10\,\mathrm{ms}^{-1}$. The stride frequency and vertical displacement calculated based on measurements from the low cost GPS/IMU units had an s.d. of 0.08 Hz and 0.02 m respectively, compared to measurements from high performance OEM4 GPS units.
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Keywords: GPS; Inertial measurement units; Data fusion; Stride parameters

1. Introduction

GPS is a popular method of determining speed over ground in biomechanical studies. Simple and light weight units have been used for recording flight paths of the birds (von Hünerbein et al., 2000) and monitoring the speed of thoroughbred horses in field studies (Pfau et al., 2006; Vermeulen and Evans, 2006). The accuracy of these simple low cost GPS systems for determining speed has been evaluated (Witte and Wilson, 2004, 2005). More accurate differential GPS (DGPS) has been applied in other sport research (Larsson and Henriksson-Larsen, 2001, 2005; Larsson et al., 2002). The dynamic performance of low cost GPS units is limited by low sample rate (usually 1 Hz) and the quality of the radio stage.

High performance GPS receivers can achieve much higher position accuracies (about 2 cm) at higher update rates (e.g. 20 Hz) and quote speed accuracies of around $0.03\,\mathrm{ms}^{-1}$ (Terrier et al., 2000; Terrier and Schutz, 2003). Higher accuracy is achieved by operating at two GPS frequencies, analysing Doppler effects and phase shift in the GPS signal relative to those received at a local base station, and the resolution of integer ambiguity. These techniques have been used to determine stride parameters in human running (Terrier et al., 2001, 2005). These systems are, however, designed for survey or military applications, and the receivers are usually expensive (£5000), heavy (1 kg) and rely on large, expensive antennas to reject multipath (reflected) signals. Besides, this method is very sensitive to sudden satellite loss due to obstructions or speed fluctuation.

Inertial measurement unit (IMU) containing gyroscopes and accelerometers can be used to track short-term changes in speed and position by integration of the sensor data. We have shown that low cost IMUs can track movements

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within a stride (around 400 ms duration) with a similar accuracy to optical motion analysis (Pfau et al., 2005). Even high-end units are however susceptible to integration errors and drift over longer time periods.

Data fusion of IMU and GPS data using a Kalman filter is often used to augment accuracy and frequency response of GPS measurements (Haid and Breitenbach, 2004; Wendel and Trommer, 2004; Caron et al., 2006). Such systems are again designed for survey and military applications based on high-end GPS receivers, and their application in locomotion studies is, therefore, limited by cost and size.

It is still uncertain whether low-end GPS units combined with an MEMS-based IMU can provide measurements of sufficient quality to monitor high dynamic movements. Here we hypothesise that a combination of a very low cost IMU—a \$10 accelerometer—can be combined with a low cost GPS unit to enhance the GPS accuracy and dynamic response to the point where stride wise fluctuations in height (potential energy) and speed can be determined by a single unit.

2. Methods

2.1. Materials

Four models of GPS unit were used:

(1) A dual frequency, high accuracy GPS receiver with a maximum sampling frequency of 20 Hz (OEM4; NovAtel, Canada), plus an external GPS antenna (£5700 for the receiver and antenna; 1.5 kg for the whole system including cable, power and data logger).
(2) A low cost WAAS/EGNOS equipped GPS unit with built in antenna, processing algorithm, data logger and a sampling frequency of 1 Hz (Trine, EMTAC; USA; £200).
(3) A GPS watch designed for runners at the maximum sampling frequency of 1 Hz and with post-processing and filtering on board (Garmin Forerunner 305; £200).
(4) A single frequency GPS receiver outputting raw pseudo-range data at 10 Hz (LEA-4T; U-blox, Switzerland; £150). A manufacturer's demo unit was used in the first experiment and a GPS/IMU system was designed, built by the authors and used in the second experiment. The self-designed GPS/IMU unit is composed of the receiver, a modified active helical antenna (GeoHelix-S, Sarantel, UK), a $\pm 6g$ tri-axial accelerometer (MMQA7260; Freescale, USA), and ARM7 (a low-power 32-bit microprocessor core optimised for cost and power-sensitive consumer applications) based logger designed in house. Accelerometer data were low pass filtered at 150 Hz (3 dB per octave). The total mass of the system is 28 g (shown in Fig. 1).

A commercial IMU was used in the first experiment (MTx; Xsens, Enschede, The Netherlands; www.xsens.com). This unit contained a three-dimensional (3D) accelerometer with the range of $\pm 10g$, a 3D gyroscope with the range of $\pm 900^{\circ}\,s^{-1}$, a 3D magnetometer, and a temperature sensor (to correct temperature drift). The inertial sensor data were sampled at 250 Hz.

2.2. Data collection

We performed two experiments to compare the performances of different GPS receivers with and without IMU data fusion under dynamic conditions.

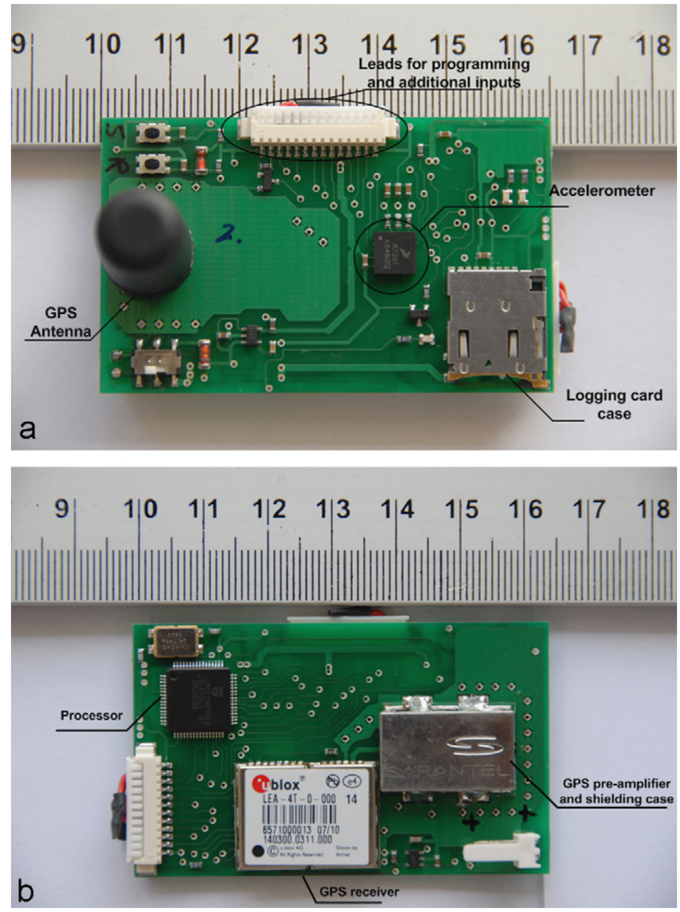

Fig. 1. Custom designed GPS/IMU system with a single frequency GPS receiver, a tri-axial accelerometer and ARM7 based logger: (a) front view and (b) back view.

2.2.1. Experiment 1

The objective of this experiment was to evaluate the performance of GPS units in determining speed in cycling with speed fluctuation caused by cyclic pedal strokes. The experiment was carried out on a 400 m outdoor running track where the cyclist was asked to perform six laps around the same track with two laps at the speed of around 3, 5.5 and 8.5–10 $m\,s^{-1}$, respectively. A commercially available speedometer provided feedback of the speed to the cyclist. The front wheel of the bicycle was instrumented with nine magnets evenly distributed on wheel spokes and a Hall effect sensor, which output a voltage spike when a magnet passed within 2 mm. The analogue signal from the sensor was connected to an AD card (NI DAQ 6236; National Instruments), and then logged at 10 kHz onto a laptop. The speed calculated from the magnet-based sensing systems was used as the gold standard for horizontal speed. The antennas for different GPS units (OEM4, Ublox and Trine) and the IMU were mounted on top of a small wooden platform, which was supported by a camera tripod attached to the back rack of the bike. The GPS data were logged into a laptop using GPS logging software (Wlog v3.21; NovAtel, Canada).

2.2.2. Experiment 2

This was designed to evaluate the performance of different GPS units for running with intrastride fluctuations and sustained acceleration and deceleration. The runner wore a cycling helmet, on top of which the custom designed Ublox/IMU unit and the antenna of the dual frequency GPS receiver (OEM4) were mounted. The receiver, power supply, data logger (Antilog) and connecting cables (total weight 1.3 kg) for the OEM4 system were attached to a belt and worn by the runner. The runner was also wearing the Garmin GPS watch on his wrist. The runner ran on a country road and performed constant speed running and several rounds of acceleration and deceleration. Horizontal speed, intrastride speed and height (PE) features were examined.

A local base station using a dual frequency OEM4 was used in both experiments, with a maximum distance of 2 km between the base station and the moving rover. Informed consent was obtained from the participants before the experiment.

2.3. Data analysis

The horizontal speed of the bicycle in the first experiment was determined by the temporal location of the voltage spikes from the magnetic detector. The accuracy of this method changes with the actual cycling speed and the voltage sampling frequency. The higher the sampling frequency and the lower the actual speed, the higher the accuracy of the measurement becomes. Measurements from this method were used as the criterion in this experiment.

Raw pseudo-range data from different GPS units were processed in differential mode to calculate position and the horizontal and vertical speeds using the GPS post-processing software (GravNav v7.60; Waypoint; Calgary, Canada) with kinematic ambiguity resolution (KAR) and other settings as per manufacturer's defaults.

The accelerations from IMU were projected from the sensor coordinate system to the global system before fusing with the GPS data (Pfau et al., 2005):

$$a_{\mathrm{global}}(t) = R_{sg}(t) \cdot a_{\mathrm{sensor}}(t), \tag{1}$$

where $R_{sg}(t)$ is the rotation matrix, which can be derived from the orientation in the form of Euler angles defined as the angles of rotation about the x, y, z axes in order (roll: r, pitch: p, yaw: y) (Pfau et al., 2005):

$$R_{sg}(t) = \begin{bmatrix} \cos p \cos y & \cos p \sin y & -\sin r \\ \sin r \sin p \cos y - \cos r \sin y & \sin r \sin p \sin y + \cos r \cos y & \sin r \cos p \\ \cos r \sin p \cos y + \sin r \sin y & \cos r \sin p \sin y - \sin r \cos y & \cos r \cos p \end{bmatrix}. \tag{2}$$

In the cycling experiment when the commercial inertial sensor (MTx) was used, the Euler angles were calculated from the manufacturer-provided software (MT Software, v2.8.4; Xsens Technologies, the Netherlands) using some combination of angular acceleration integration and magnetic field measurement. In this case, the local sensor axes can be rotated to global axes and the rotated 3D accelerations from the IMU and 3D velocities from GPS units were integrated. Horizontal speed was calculated as the vector sum of the component velocities to the north and to the west.

In the running experiment, only a 3D accelerometer was used. This poses problems to project sensor axes to global axes, but it is possible to project sensor axes to the body axes with the assumption that yaw is zero. To achieve this, the sensor was attached so that 'x'-axis was aligned with the heading direction, and only the data collected with the runner running on a straight line were considered. Therefore, the yaw was assumed to be zero; the roll and pitch were assumed to be constant and calculated based on the inertial measurements with the sensor mounted at the experimental position but at stationary condition (a_{x0}, a_{y0} and a_{z0}):

$$r = \arcsin\left(\frac{a_{y0}}{\sqrt{a_{x0}^2 + a_{y0}^2 + a_{z0}^2}}\right),$$
$$p = \arcsin\left(-\frac{a_{x0}}{\sqrt{a_{x0}^2 + a_{y0}^2 + a_{z0}^2}}\right), \quad y = 0. \tag{3}$$

The sign in the definition for roll and pitch should be determined by the definition of the coordinate system. In this experiment, the coordinate system followed the right-hand rule with 'x'-axis along the forward direction and 'z'-axis along the vertical downward direction. The sign of the rotation was also defined by the right-hand rule. Thus, when there is a positive rotation about 'x'-axis (roll), the gravity 'g' will generate a positive value on a_y; and when there is a positive rotation about 'y'-axis (pitch), the gravity 'g' will generate a negative value on a_x. Therefore, there was a negative sign in the definition of pitch.

Based on the assumption that yaw was zero, the rotation matrix was simplified to

$$R_{sg}(t) = \begin{bmatrix} \cos p & 0 & -\sin r \\ \sin r \sin p & \cos r & \sin r \cos p \\ \cos r \sin p & -\sin r & \cos r \cos p \end{bmatrix}. \tag{4}$$

Specifically, the rotated accelerations along the horizontal forward–backward and vertical direction (a_x' and a_y') are

$$a_x' = \cos p \cdot a_x - \sin r \cdot a_z,$$
$$a_z' = \cos r \sin p \cdot a_x - \sin r \cdot a_y + \cos r \cos p \cdot a_z. \tag{5}$$

The rotated accelerations were integrated with the horizontal and vertical speeds calculated from GPS units. Movement along the side-to-side direction was ignored, so the problem was reduced to a 2D (horizontal and vertical) problem.

The error introduced by non-zero yaw in the rotated forward–backward acceleration is

$$\begin{aligned} \delta a_x' &= (\cos p \cdot a_x - \sin r \cdot a_z) - (\cos p \cos y \cdot a_x + \cos p \cdot \sin y \cdot a_y \\ &\quad - \sin r \cdot a_z) \\ &= \cos p \cdot (1 - \cos y) \cdot a_x - \cos p \cdot \sin y \cdot a_y. \end{aligned} \tag{6}$$

The maximum error introduced by 10° in yaw is $(1 - \cos 10°) \cdot a_x - \sin 10° \cdot a_y = 0.015a_x - 0.17a_y$ when the pitch is zero ($\cos p = 1$). Considering the fact that acceleration in the side-to-side direction (a_y) is much smaller than the acceleration in forward–backward direction (a_x), and only data collected with the runner running along a straight line were evaluated; so the head was quite stable, the error introduced by the assumption of zero yaw in the calculation of forward–backward acceleration is small (around 2% with 10° of yaw and 6.5% with 20° of yaw).

A Kalman filter (Caron et al., 2006) based complementary filter (see Fig. 2) was used to improve the estimate of speed by combining speed measurements from the GPS and the rotated accelerations from the inertial sensors.

A standard discrete Kalman filter (Smyth and Wu, 2007) was used. Consider the system

$$X_{k+1} = FX_k + \omega_k,$$
$$Z_{k+1} = HX_k + b_k, \tag{7}$$

where X_k is the state to be estimated; Z_k is the measurement vector; F and H are the matrices for the system process model and measurement model; and $\omega(k)$ and $b(k)$ are the noise on the process and measurement, respectively, and are assumed to be drawn from a zero mean multivariate normal distribution with covariance Q_k and R_k.

The states to be estimated and the parameters in the Kalman filter are

$$X(k) = \begin{bmatrix} v(k) \\ a(k) \end{bmatrix}, \quad F = \begin{bmatrix} 1 & \Delta T \\ 0 & 1 \end{bmatrix}, \quad H = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix},$$
$$R = \begin{bmatrix} \sigma_{\mathrm{GPS}}^2 & 0 \\ 0 & \sigma_{\mathrm{IMU}}^2 \end{bmatrix}, \quad Q = \begin{bmatrix} 0 & 0 \\ 0 & \sigma_a^2 \end{bmatrix}, \tag{8}$$

where $v(k)$ is the speed measurement from GPS; $a(k)$ is the rotated acceleration derived from the IMU; ΔT is the measurement update time interval; σ_{GPS} and σ_{IMU} are the standard deviation associated with the original measurements from GPS and inertial sensors, respectively; σ_a is the possible change of the acceleration during the sampling interval which is related to the sampling frequency and the character of the locomotion.

The algorithm was applied over a range of sampling frequencies at 5, 10, 20, 50 and 100 Hz. The optimum sampling frequency was defined as the lowest one, which minimised the error between the measurement system and the standard. The optimum sampling frequency for the data

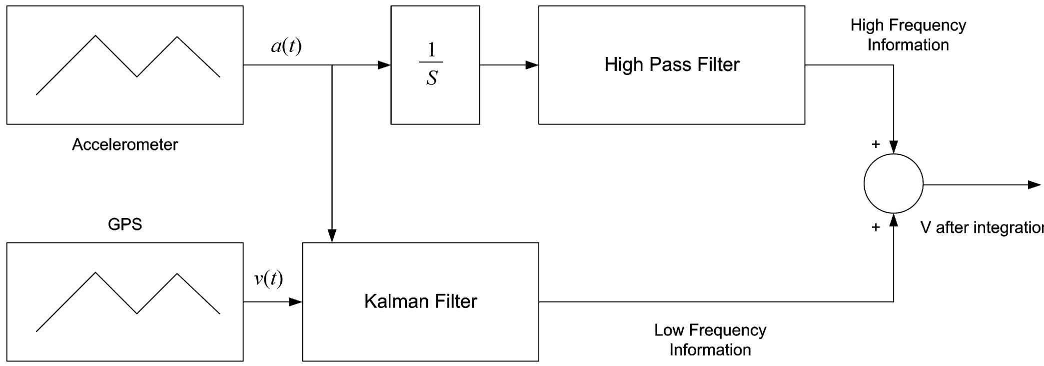

Fig. 2. Kalman filter based complementary filter for GPS/IMU integration.

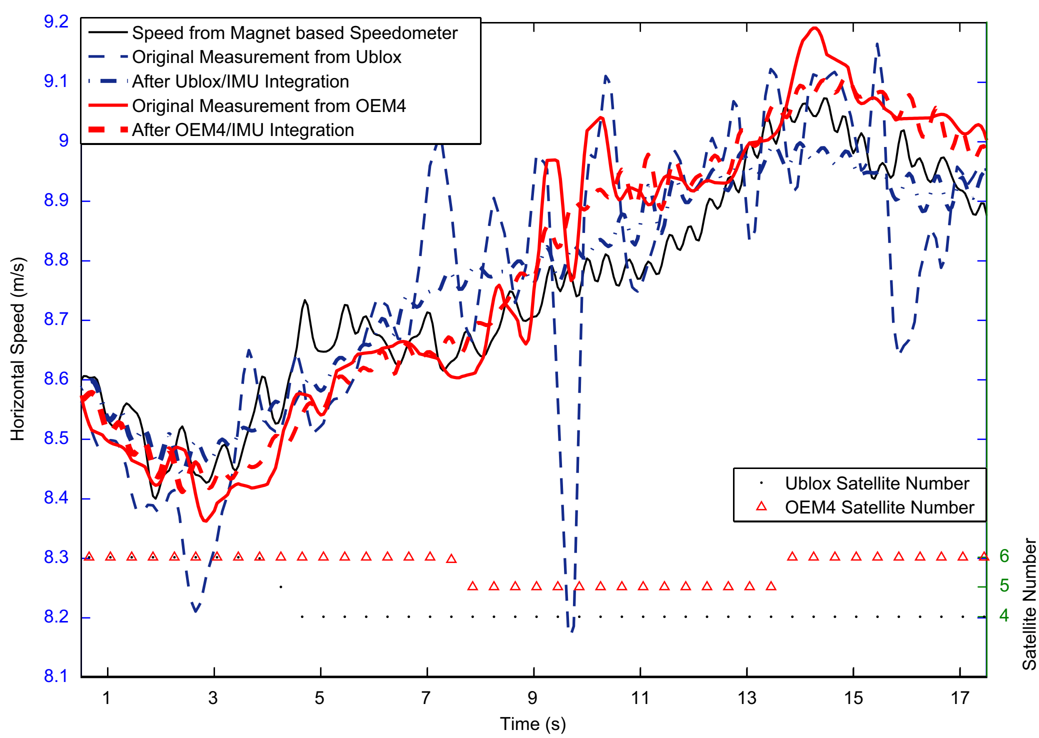

Fig. 3. Measurements of horizontal speed from magnetometer, different GPS units and the results of GPS/IMU fusion.

fusion scheme is a function of the frequency content of the movement to be tracked. Among the sampling frequencies that have been tested, the optimum sampling frequency, for the current implementation algorithms in cycling and running, was found to be 20 Hz. Therefore all the measurements from different GPS systems and the inertial sensors were re-sampled at 20 Hz; accordingly $\Delta T = 0.05$ in this study. The noise figures, σ_{GPS} and σ_{IMU}, were initially set to be the figure given by the manufacturer, and then scaled by 0.1, 1, 10 and 50, respectively. For optimal filter design, statistical tests were performed on the innovations (difference between the predicted and observed observations) for different parameter settings to make sure that the innovation covariance does not underestimate the actual covariance in the signal estimate. A larger value for σ_{IMU} was used when installation caused vibration and high noise in the inertial measurements. A larger value for σ_{GPS} was used for the single frequency GPS receiver and when the sky view was poorer. All the algorithms were realized using custom software written in MATLAB. Priori knowledge about the dominant frequency of the locomotion was used to set the cut-off frequency of the high pass filter for the inertial sensor.

3. Results

3.1. Results from cycling experiment

The speed measurements from different receivers without and with IMU integration were compared with the measurements from the magnetic speedometer in Fig. 3. These are representative of the data recorded and several features were consistent. Speed fluctuated at about 2 Hz, which was attributed to the cyclist's pedal strokes and possibly mounting vibration. The original measurements from OEM4 closely followed the fluctuations in cycle speed and the fusion with IMU data provided little benefit for its accuracy. The original Ublox measurements were much noisier and the pedal strokes were not observable, but pedal strokes could be identified after the data fusion with

IMU. The results after Ublox/IMU data fusion were similar to the measurements from OEM4, and also comparable to the measurements from wheel speedometer.

Fig. 4 shows standard deviations of measurements from different systems taking the speedometer as ground truth. The IMU improved the accuracy of all three systems, but the benefit was the greatest for the Ublox. After the integration with IMU, the standard deviations of the speed measurements were reduced from 0.051 to 0.039 ms^{-1} for the dual frequency DGPS (OEM4), and from 0.16 to 0.06 ms^{-1} by 60% for the low cost single frequency DGPS (Ublox). The maximum error observed from the Ublox was reduced from 0.53 to 0.16 ms^{-1} after the integration. Improvement on Trine was not as large because of the Kalman filter embedded on board smoothing individual speed values.

It was found that by carefully choosing the cut-off frequency, a Butterworth low pass filter generated similar results in terms of s.d. as the Kalman filter based complementary filter for the measurements from the OEM4; this can be attributed to better initial performances in terms of frequency response and accuracy of the OEM4. The low pass filter did not make much difference on the measurements from Trine; this was because the data from Trine were already heavily filtered on board. However, the integration showed a major advantage over low pass filtering when the low cost Ublox unit was used. By utilising the high frequency response from the inertial sensor, the integration with IMU enhanced the frequency response of the original GPS measurements and the final estimates after integration can also track the high frequency transient and unsteady manoeuvres. A traditional Kalman filter or low pass filter can only remove the high frequency noise or reduce discontinuities in the measurements so as to improve steady state measurement accuracy. But they can result in many artefacts and delay in the measurements of sporting and unsteady movements.

3.2. Results from running experiment

The original measurements of horizontal speed in running from different GPS units were shown in Fig. 5. The OEM4 provided reliable information about the horizontal speed for human running with sustained acceleration and deceleration; and the measurements from OEM4 were used as the criteria to evaluate the reliability of other GPS units.

Original measurements from the Ublox were noisy, and it was difficult to differentiate the intrastride speed variation from measurement noise. The accelerometer incorporated in the custom designed Ublox/IMU unit provided useful information about intrastride acceleration speed and position fluctuation. The noise on the original measurements from Ublox was reduced after the data fusion, and the information about the intrastride variations was reconstructed by utilising the high frequency measurements from inertial sensors (see Figs. 6 and 7).

The wrist mounted GPS (Garmin) gave smooth measurements, but showed a very slow response during acceleration and deceleration, presumably due to substantial low pass filtering. This shows the disadvantage of low pass filtering when measuring unsteady activity with sudden change in the acceleration. The GPS/IMU integration provided much more responsive and reliable evaluation of the speed in this case.

Using the results from the OEM4 as the reference, the maximum error in horizontal speed observed from Ublox was reduced from 2.01 to 0.39 ms^{-1} after the integration, and the standard deviation of the speed

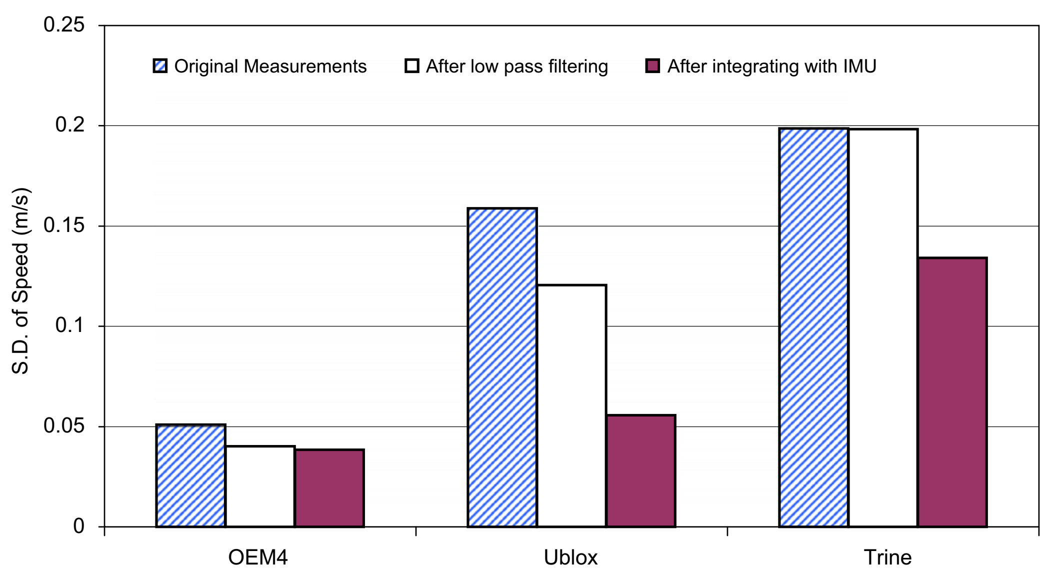

Fig. 4. Standard deviations (ms^{-1}) of speed measurements from different GPS units and those after low pass filtering and after fusion with inertial sensors. This shows the benefit of GPS/IMU integration.

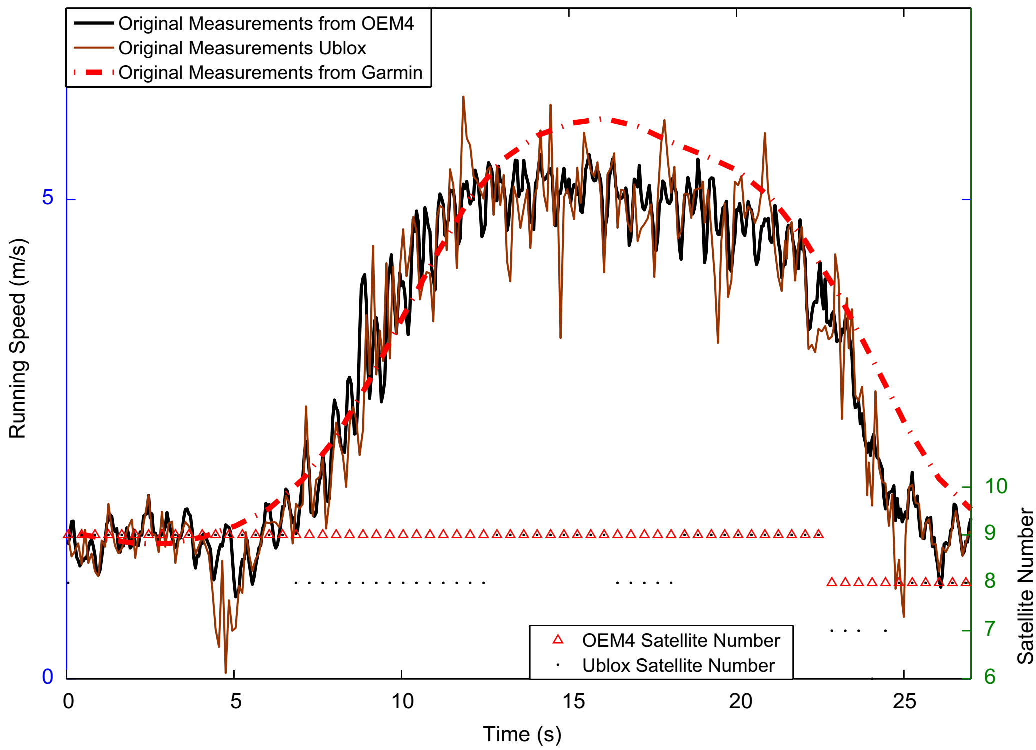

Fig. 5. Original measurements from different GPS units in running with acceleration and deceleration showing noise on Ublox and substantial lag due to filtering in Garmin.

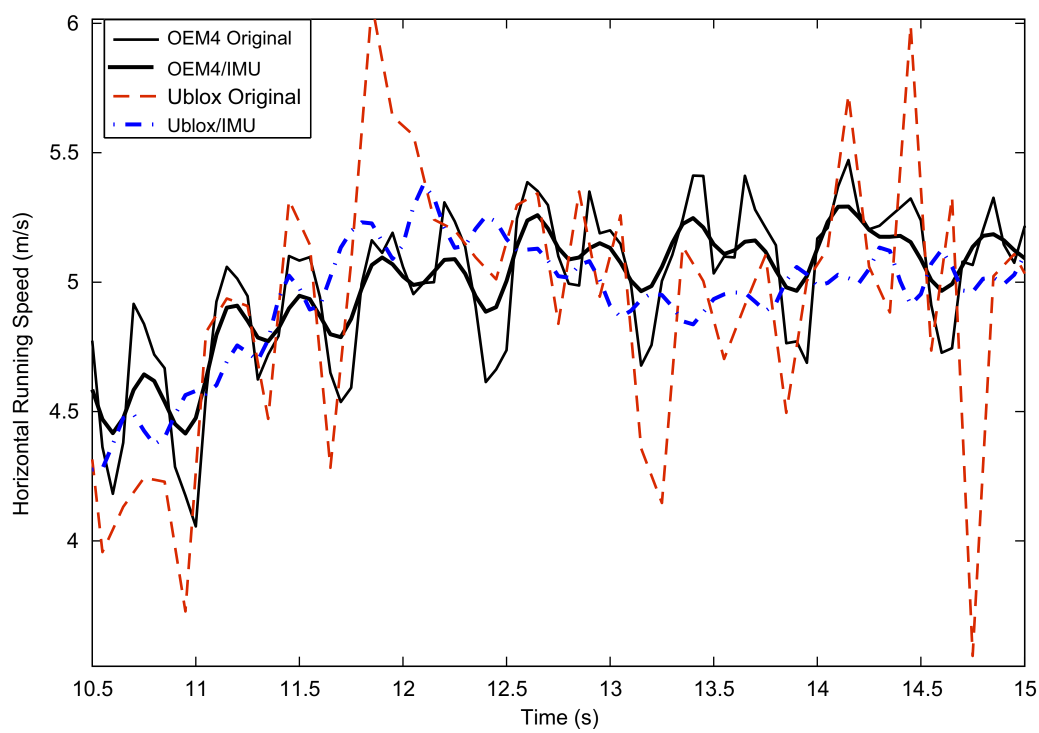

Fig. 6. GPS/IMU integration reduced random errors and reconstructed intrastride variation in speed for human running.

measurements was reduced from 0.34 to 0.15 ms^{-1} with running speed between 3 and 5 ms^{-1}. The estimation error based on Ublox/IMU integration is 0.08 Hz (s.d.) for stride frequency and 0.02 m (s.d.) for maximum vertical displacement, respectively, compared with those estimated from OEM4 measurements.

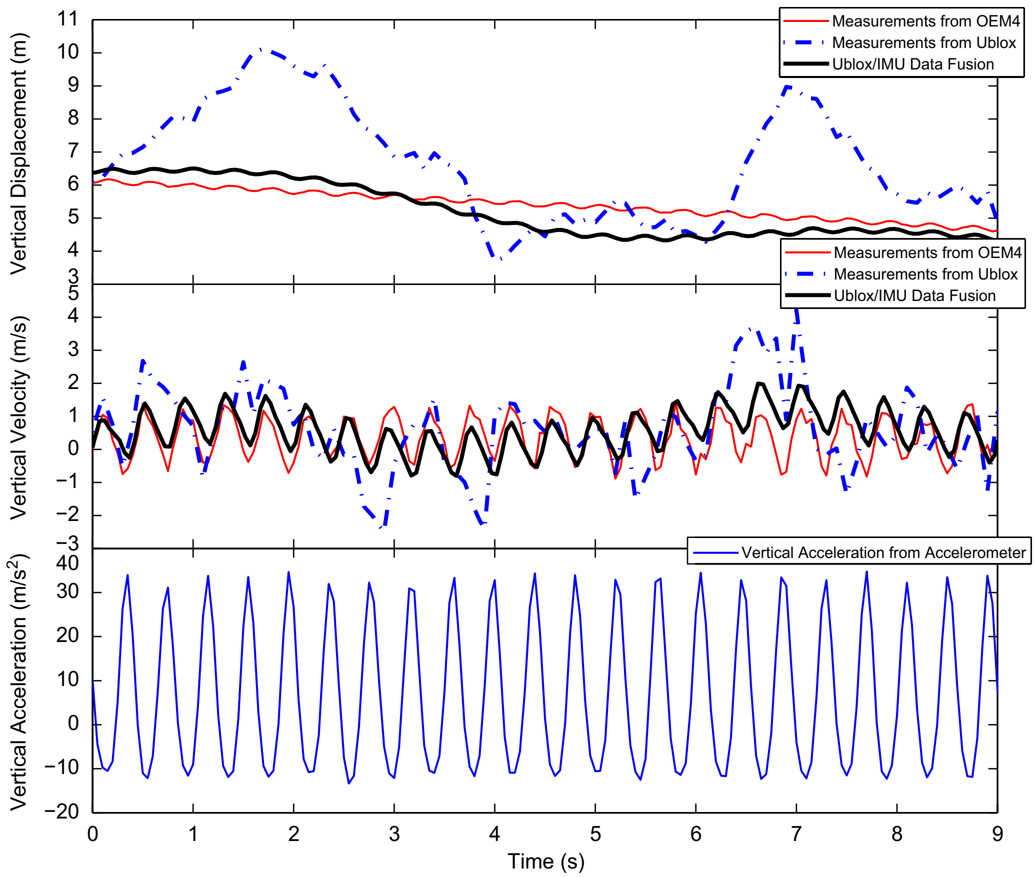

Fig. 7. Vertical velocity and displacement from GPS/IMU integration provided useful information about step frequency and intrastride potential energy variation.

4. Discussion

The horizontal speed measurements from the DGPS (OEM4) with KAR in this experiment ($0.05\,\mathrm{ms}^{-1}$ in cycling) are less accurate compared to what Terrier and Schutz (2003) obtained in a previous research (compared to $0.02\,\mathrm{ms}^{-1}$ in walking and $0.03\,\mathrm{ms}^{-1}$ in running). This was because KAR requires five or more satellites for a solution and the optimal accuracy is obtained with at least seven GPS satellites (Terrier and Schutz, 2005), while the number of satellites available was between five and six during this experiment. Another cause of measurement error in the cycling experiment was the vibration of the antenna, which was mounted on a camera tripod attached to the back rack of the bicycle.

The original measurements from lower cost single frequency GPS unit (Ublox) were much noisier than the OEM4 with a standard deviation between $0.16\,\mathrm{ms}^{-1}$ in cycling and $0.34\,\mathrm{ms}^{-1}$ for running. The GPS unit with on-board Kalman filter (Trine and Garmin) output highly filtered smooth measurements but showed a time delay when there was acceleration and deceleration in the movement.

The integration of low cost GPS receiver (Ublox) and inertial sensors using a Kalman filter based complementary filter enhances the frequency response of the measurement system by combining the good low frequency responses from the GPS and good high frequency response from the IMU. Compared to traditional low pass filtering, GPS/IMU integration showed the advantage of providing more responsive and reliable measurements of the speed especially for unsteady movements with quick changes in the acceleration. This algorithm reduced the measurement errors caused by poor GPS reception, cycle slip and integer ambiguity and reduced the measurement standard deviation by 60%. Results from Ublox/IMU data fusion also followed the speed fluctuation within a stride faithfully, which allowed for the calculation of stride parameters. The custom designed low cost Ublox/IMU module achieved the reliability of $0.15\,\mathrm{ms}^{-1}$ in horizontal speed, 0.08 Hz in step frequency and 0.02 m in vertical displacement for human running, compared to the measurements from OEM4. The comparatively large error shown in the running experiment could have been caused by poor sky view on the country road, and was also related to the fact that measurements from the OEM4 instead of other higher accuracy measurements were used as the criteria. The differences between the results after Ublox/IMU integration and those from the OEM4 were the combination of the errors from these two independent sources of measurements.

Direct use of range, phase and Doppler data from GPS to integrate GPS signals and inertial sensors is called tight or close coupling. A loosely coupled design was used in this study by combining the speed measurements from GPS and acceleration from IMU. According to recent research by Waegli et al. (2007), the loosely coupled design is more robust while the closely coupled can be beneficial, where satellite observations can be used even in the absence of GPS-position fix. The tuning of the Kalman filter was time consuming. The optimal parameters are somewhat different for locomotion with different speeds and acceleration; for different inertial sensor specifications and will also change with different satellite number and geometry. Future studies will focus on close coupling, different algorithms for data fusion and filter parameter tuning.

The configuration of the inertial sensor depends on the locomotion to be tracked, and there is a trade off between cost and performance. Dynamic range of the accelerometer is important, a $\pm 10g$ accelerometer on a 10 bit AD converter means that each bit is equal to $0.2\,\mathrm{ms}^{-2}$. Orientation is also important since a misalignment of 5° in pitch results in gravity acceleration appearing as a horizontal acceleration of $0.9\,\mathrm{ms}^{-2}$, and a misalignment of 10° in yaw result in 2% of error in the rotated backward–forward acceleration. In the custom-designed module used in this study, three orthogonal accelerometers were used, but there was no gyroscope. It was assumed that one of the accelerometers was along the direction of the heading; so the yaw was zero and the attitude of the sensor was constant. For further research, gyroscopes and magnetometers can be incorporated to provide more accurate information about the orientation and the attitude. In addition a pressure transducer based altitude metre (as used in some model aircraft autopilot units and mountaineering GPS units) could be incorporated, and may enhance the GPS accuracy of vertical position.

5. Conclusion

Low cost single frequency GPS units are of substantially lower accuracy than high cost dual frequency units especially under poor reception conditions (small satellite number, intermittent obstruction of satellite view and rapid acceleration and deceleration). On board Kalman filter using measurements from previous time stamps can improve the measurement accuracy at the cost of dynamic response. Integration of measurements from low cost single frequency GPS units and a low cost tri-axial accelerometer improves speed measurements by utilising the filtered low frequency responses from the GPS and the high frequency responses from the inertial sensors. The proposed algorithm gives measurements that are efficient for the estimation of stride frequency and mechanical energy fluctuations.

Conflict of interest statement

There are no financial or personal relationships with other people or organisations that could inappropriately influence this work. The source of grants and funding are listed in the 'Acknowledgements' section of the manuscript and none of them could bias this work.

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