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Assessment of Foot Kinematics During Steady State Running Using a Foot-Mounted IMU

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Abstract

The continuous sensing of kinematics provides an opportunity to monitor changes in sporting technique or to aid in injury rehabilitation. Inertial sensors are now small enough to integrate into footwear providing a potential platform for continuous monitoring that does not require additional components to be worn by the athlete. We investigate the suitability of using foot mounted inertial sensors to assess foot kinematics in steady state running by employing inertial navigation and pedestrian dead reckoning techniques. The results are evaluated by comparison with an optical motion capture system. Two techniques are assessed, the use of an Extended Kalman Filter with zero velocity updates and a linear de-drifting technique. Assessment of two example metrics, foot clearance (FC) and mean step velocity (SV), produced a bias and standard deviation of $0.000\text{m} \pm 0.008$ (FC) and $0.04\text{m/s} \pm 0.03$ (SV) using the linear de-drifting technique. Similar results were obtained using an Extended Kalman Filter approach calculating FC with a bias of $0.002\text{m} \pm 0.029$ and SV with a bias of $0.03\text{m/s} \pm 0.02$.

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1. Introduction

Biomechanical assessment of movement is a complicated but valuable component of today's elite sports training. Assessment of running gait is particularly important and is usually assessed within a laboratory setting

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using video or optical motion capture. These assessments are often characterised by expensive equipment, manual analysis and subjective metrics. Furthermore the restricted space of a laboratory necessitates evaluation either using a small number of steps or, more often, a treadmill. In neither case is the athlete free to move naturally and there is little guarantee that the gait exhibited is that found in the true sporting arena.

In order to address these issues and to bring such kinematic assessment to a wider audience, low-cost inertial sensors are being embedded within consumer products, allowing athletes to be assessed in their natural setting and, additionally, more frequently. Such in-field constant-assessment brings with it additional benefits, including tracking the progress of injury rehabilitation and enabling longitudinal sports science and biomechanical studies.

Foot-mounted sensors are popular since lightweight sensors can be embedded within shoes in a convenient, unobtrusive way. They may be able to capture rich data, and have already attracted commercial interest (e.g. the Nike+ shoe). In the future, such sensors may be able to track relevant performance metrics or detect compensatory patterns that are the result of poor biomechanics.

Previous studies have investigated the use of foot-mounted sensors for biomechanical analysis. Mariani (2010) examined their use to assess walking gait. The study combined the strapdown inertial navigation algorithm and linear de-drifting. This technique is useful for walking, for example a mean error of 1.5cm (sd 6.8) in stride length was achieved. It remains unclear how these techniques would perform in a running scenario due to the faster motion involved.

Previous work by Foxlin (2005) and Jiménez (2010) has described the use of inertial strapdown navigation techniques with a foot-mounted inertial measurement unit (IMU) and Extended Kalman Filter (EKF) to provide tracking of walking humans for navigation, referred to as pedestrian dead reckoning (PDR). Pseudo-measurements, including Zero-Velocity Updates (ZUPTs) [Foxlin 2005], input into the EKF have been shown to enable correction of the drift that accrues over time in an inertial system. As a rule of thumb, these systems are capable of estimating the distance traveled by a walker to within 1%. However, it remains unclear how these techniques can deal with intra-step metrics rather than position since these systems are usually assessed based on the error in the end position of a closed loop walk.

A preliminary investigation into strapdown PDR techniques for running has also been performed by Bichler et al. (2012) with the addition of Global Positioning System (GPS) data as input to a Kalman filter. This pilot study looked at the results for a number of stride parameters, including stride length, but the video reference system did not allow strong conclusions to be made about the results.

The purpose of this study is to assess the suitability of shoe-mounted sensors for the purpose of tracking the three dimensional trajectory of the foot during steady state running. We evaluate the validity of two approaches against a gold standard measurement system, the Vicon optical motion capture system.

2. Methods

2.1. Data Collection

Capture of inertial sensor data was facilitated using the ION (Imperceptible On-body Node) sensor platform [Harle (2012)] (Fig 1) with the addition of an MPU-6000 IMU providing a $\pm 16g$ accelerometer and $\pm 2000^\circ/s$ gyroscope. IMU signals were sampled at 1kHz and logged to on-board flash memory. Ground truth was captured using an optical motion capture system (Vicon) sampling at 240Hz. The ION sensor was placed on the lateral side of the shoe in line with the ankle, as seen in Fig 1.

A treadmill was used to capture many steps in a limited motion capture area. While the biomechanics of treadmill running may be different to overground running, results should be applicable to kinematic assessment of overground running since, from a sensing perspective, treadmill running differs from overground running only in frame of reference. The treadmill was set up without any inclination, measured with a spirit level.

The ION sensor was attached to a jig containing 3 retro-reflective markers (Fig 1) for the motion capture system. The jig adds an additional 30 grams of weight to the system (45 grams total) but remains comfortable for test runs. The jig was laser cut and the MPU-6000 and retro-reflective markers were aligned with laser-etched outlines to ensure alignment between the jig and the inertial sensor axes.



Fig. 1. ION and Jig attached to shoe.

2.2. Procedure

Five participants took part in the study (3 male, 2 female). Ethics committee approval was obtained. Each participant performed a 10 second calibration, standing still and upright while sensor data was logged. Participants were then asked to warm up on the treadmill for a few minutes to familiarise themselves with the environment and treadmill speeds. Once the warm up period was complete, the athlete rested for two minutes and the rest of the experimental process was explained.

Four ninety-second runs were completed, with data logging, by each participant. Each run was performed at a predetermined treadmill speed, approximately 2.3m/s, 2.7m/s, 3.0m/s and 3.4m/s, as measured by the Vicon system. Prior to and immediately after each run, the athlete was asked to stamp their feet three times in order to facilitate simple synchronisation between the Vicon and ION systems. A single sensor placed on the right foot was used to conduct the experiment.

Due to the acceleration and deceleration of the treadmill at the start and end of each run the middle 90 steps were taken from each run to provide a total of 1800 steps for analysis.

The static calibration measured gravity in the IMU frame of reference. This was then used to align the IMU and Vicon frames of reference, it also provided an estimate of pitch and roll of the IMU.

2.3. Data Processing

The inertial strap-down algorithm is known to drift quickly as integration errors accrue. In order to achieve usable results, assumptions about the position and velocity of the foot during the stance phase are made to constrain the system. The most common assumption is that the velocity of the foot is zero during this stance phase. This is clearly incorrect during treadmill running. Instead a constant velocity is assumed, i.e. that of the previously measured velocity of the treadmill belt. We also assume that, for the special case of running over flat ground, the foot has approximately the same pitch and roll during the same point in each stance phase and that the height of the foot is zero throughout it. Each of these assumptions were used in the two methods we evaluate, namely orientation reset with linear de-drifting (RST), and extended kalman filter (EKF).

2.3.1. Step Segmentation and Mid-stance detection

In order to make use of the above constraints, periods of gait in which the foot is in contact with the floor must be detected. Heel strike was detected using the large changes in acceleration associated with this event. Peaks in the derivative of the magnitude of the acceleration were found to reliably segment the inertial data into segments that start at one heel strike and end at the next. The mid-stance phase was used to provide time points to apply the constraints described previously. For each step (after segmentation based on heel strike) mid-stance was detected by finding the minimum value of the magnitude of angular velocity.

2.3.2. Vicon Data Processing

Position data was obtained for three markers from the Vicon system. The laser cut jig had precise dimensions that allowed vector arithmetic to be used to obtain the position and orientation of the ION sensor from the raw Vicon data. The positional data was then numerically differentiated to obtain velocity data.

2.3.3. Orientation Reset and Linear De-drifting (RST)

One of the major sources of drift in inertial navigation systems is orientation error. Drift in sensor orientation results in errors when subtracting the effect of gravity from the sensor signals. Residual components of g cause errors to accrue rapidly. In order to combat the resultant drift, the orientation of the sensor is reset at mid-stance for each step using the estimate for the attitude of the sensor obtained during static calibration. At the same time velocity is reset to the speed of the treadmill belt (or zero for overground running).

This technique deals with one of the larger sources of error in inertial systems. During the time between resets there will still be some drift, and this drift is predominately caused by sensor biases. By assuming a constant bias in each of the accelerometer axes we can model drift in velocity. Since a constant bias in acceleration results in a linearly growing error in velocity after integration we apply linear de-drifting to the resulting velocity. The de-drifted velocity signal is then integrated to obtain position.

2.3.3.1. Complications due to sensor saturation

During the course of the experiments we found that the foot experiences accelerations greater than 16g at heel strike. The resultant sensor saturation lasts for a small number of samples, typically 1-4ms. Sensor saturation is present predominantly in the z-axis in the ION's frame of reference, which is approximately vertical during the stance phase. This sensor saturation causes underestimation of the velocity in the z-axis just after heel strike. Linear de-drifting of the velocity in the z-axis is therefore not applicable as the errors are dominated by saturation rather than bias. Other axes are affected due to foot angle at heel strike but the z-axis is disproportionately affected. This does limit the ability of linear de-drifting of velocity to correct errors but improvements were still found.

In order to correct drift in the vertical axis, we also attempted to de-drift the vertical position channel based on the height of the foot at heel strike. At just prior to heel strike the height of the foot is very close to its height during mid-stance (typically within 1-2cm) and at this point sensor saturation has yet to occur. By approximating the height of the ION at this point to be close to that at mid-stance we can once again apply de-drifting to the signal based on domain specific knowledge.

The resulting drift in position based on a constant bias in acceleration will be quadratic in nature due to the double integration, so in this instance we obtain a value for the sensor bias by modeling a quadratic drift. Velocity and position in the vertical axis is then re-integrated using this bias.

2.3.4. Extended Kalman Filter (EKF)

In this method an Extended Kalman Filter was used. The implementation was very similar to the implementation described in Foxlin (2005). At each mid-stance event, the velocity of the treadmill belt was used as a 'pseudo-measurement'. The algorithms in Foxlin (2005) were also updated to include a zero-height pseudo-measurement and these were provided at the same time as each velocity update. It should be noted that a constant velocity update contains information regarding the heading of the sensor that would not be present in a zero velocity update. As a result the method used here may perform better than a ZUPT based EKF.

2.4. Evaluation

The algorithms presented produce the full trajectory of the foot for each individual step, along with foot velocity and foot angle at 1 kHz. This may be beneficial in itself and so we evaluate the error in the trajectory at two points to show the progression of error due to drift. These points correspond to the time of maximum foot height $t(MFH)$ and the time of heel strike $t(HS)$ on a per-step basis. These were selected because they fall near the middle and the end of each step and so capture the progression in drift. The maximum error before heel strike (due to large errors after heel strike which make post heel strike data unusable) is also assessed to show any large changes in error between $t(MFH)$ and $t(HS)$. For trajectory evaluation the following statistics are calculated for each step: position error is calculated as $s_{i,t}^{err} = \|s_{i,t}^{inertial} - s_{i,t}^{vicon}\|$ and velocity error is calculated as $v_{i,t}^{err} = \|v_{i,t}^{inertial} - v_{i,t}^{vicon}\|$, where t is the intra step time and i is the step number. Error in attitude is assessed as $\theta_{i,t}^{err} = \cos^{-1}\left(\frac{A \cdot B}{\|A\| \|B\|}\right)$ where A and B represents the vector $[0 \ 0 \ 1]^T$ in the ION frame of reference as measured by the INS solution and

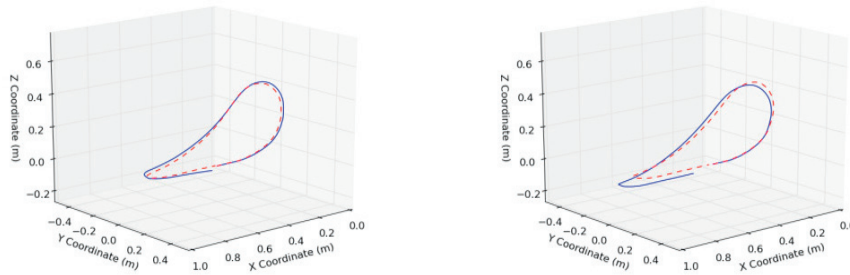


Fig. 2. Two inertial solutions (blue, solid) compared to the reference system (red, dashed). Left, INS solution provided by RST. Right, INS solution provided by EKF. Both are solutions for the same step. The speed of the treadmill during this step is 3.4m/s.

Vicon respectively. The mean and standard deviation of these statistics over all steps are presented in Table 1 for both EKF and RST methods.

It is also possible to extract kinematic features from the trajectory, which may be of interest to coaches and sport scientists. We pick two such statistics, mean stride velocity (SV) and foot clearance (FC) previously used by Mariani et al. SV was defined as mean velocity in the ground plane (the XY plane) and FC defined as maximal foot height during swing phase. Both statistics were calculated from Vicon data and RST/EKF results.

Evaluation was performed over all available steps for the RST method. However, to allow the Kalman filter to settle, the results of the first 10 steps of each trial were discarded for the EKF method while producing the statistics below.

3. Results

Table 1 presents the errors evaluated for each speed using both the EKF and RST methods. Better results were in general achieved using the RST method, though the EKF method did perform better for some velocity metrics, in particular showing slightly lower maximal error in velocity across all speeds. The EKF method produced larger errors in position and so could not as accurately recreate the foot trajectory with the current sensor setup, likely due to sensor saturation as discussed in section 2.3.3.1. Figure 2 shows two example steps solved using the RST and EKF methods. The errors shown in Table 1 indicate that both methods appear usable. The RST method appears to perform better for position and orientation while the EKF method may be more suited to analysis involving velocity.

Figure 3 shows Bland-Altman plots for the Vicon and RST derived SV and FC measurements. The Bland-Altman plots for the FC statistic show that there is some correlation between the measured FC and the error, the limits of agreement are -0.01m to 0.02m. FC showed an overall bias of $0.000\text{m} \pm 0.008$. Analysis of SV showed an overall bias of 0.04m/s with a standard deviation of 0.03 with the limits of agreement -0.01m/s to 0.09m/s. The Bland-Altman plot for SV shows an increase in error for faster motion. There were good Pearson correlations between the RST and Vicon systems, 0.996 for the SV measurement and 0.997 for the FC measurement.

Using the EKF method, FC showed a bias of $0.002\text{m} \pm 0.029$, with limits of agreement -0.06m to 0.06m. SV showed a bias of $0.03\text{m/s} \pm 0.02$, with limits of agreement -0.01m/s to 0.06m/s. The Bland-Altman plots are not shown for the EKF method due to space limitations. Pearson correlations for SV and FC were 0.998 and 0.931, respectively.

4. Conclusions

The results show that foot worn sensors could be a viable way to assess running kinematics. Both methods provide a promising way of logging the rich data provided by the full foot trajectory in an unconstrained environment. Limits of agreement suggest usable results for the mean stride velocity (SV) and foot clearance (FC) metrics. Limitations in the sensor resulted in accelerometer saturation at heel strike and may have compromised the

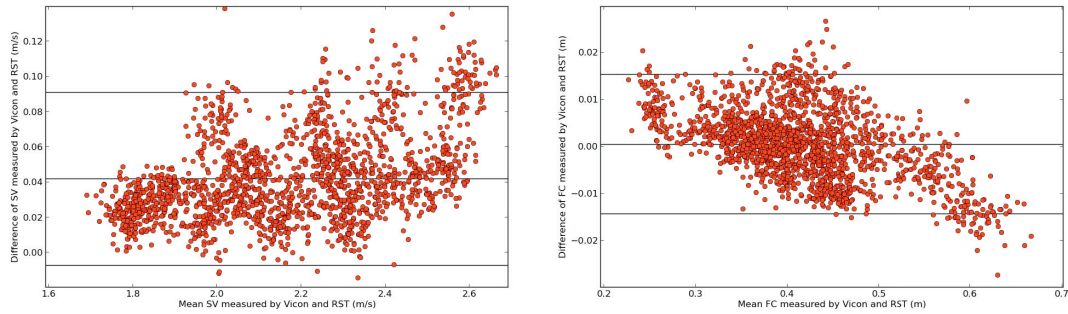


Fig. 3. Bland-Altman plots showing agreement between RST and Vicon for SV and FC. Horizontal lines show bias (mean error) and limits of agreement ($1.96 \cdot \text{sd}$ of differences).

results. Further work should seek to repeat this experiment with a sensor suited to the high accelerations that occur at heel strike to see if results can be improved. The technique has limitations, requiring running over flat ground (e.g. on a running track) and this study was limited to an evaluation of straight line running, further work might seek to detect periods of free form running (e.g. over varied terrain) where these constraints can be applied. Further, care should be taken when assessing the EKF methods applicability to overground running, subsequent work should seek to assess the effect of zero velocity vs. constant velocity pseudo measurements. Foot worn inertial sensors provide clear potential for assessing running kinematics in an unobtrusive way that could enable in-depth longitudinal monitoring in the future and give coaches richer data as to how their athletes are performing over time.

Table 1. Error results for 4 different speeds and 3 methods, lowest values are highlighted.

Speed (m/s)	Method	$s_{i,t}^{err}(MFH)$	$v_{i,t}^{err}(MFH)$	$\theta_{i,t}^{err}(MFH)$	$s_{i,t}^{err}(HS)$	$v_{i,t}^{err}(HS)$	$\theta_{i,t}^{err}(HS)$	$max_t(s_{i,t}^{err})$	$max_t(v_{i,t}^{err})$	$max_t(\theta_{i,t}^{err})$
		mean \pm std (m)	mean \pm std (m/s)	mean \pm std (degrees)	mean \pm std (m)	mean \pm std (m/s)	mean \pm std (degrees)	mean \pm std (m)	mean \pm std (m/s)	mean \pm std (degrees)
2.3	RST	0.03\pm0.01	0.14 \pm 0.07	2.06\pm0.74	0.02\pm0.01	0.17 \pm 0.09	1.92\pm1.09	0.03\pm0.01	0.40 \pm 0.12	3.23\pm0.84
	EKF	0.03 \pm 0.02	0.11\pm0.05	5.01 \pm 0.85	0.06 \pm 0.03	0.15\pm0.08	3.17 \pm 0.75	0.06 \pm 0.03	0.29\pm0.07	5.44 \pm 0.90
2.7	RST	0.03\pm0.01	0.25 \pm 0.08	1.96\pm0.85	0.03\pm0.02	0.17 \pm 0.07	2.36\pm1.13	0.04\pm0.02	0.49 \pm 0.13	3.52\pm0.85
	EKF	0.03 \pm 0.02	0.12\pm0.06	5.23 \pm 1.06	0.06 \pm 0.03	0.16\pm0.08	3.29 \pm 1.17	0.07 \pm 0.03	0.31\pm0.09	5.61 \pm 1.06
3.0	RST	0.04\pm0.02	0.31 \pm 0.08	1.85\pm0.84	0.04\pm0.02	0.19 \pm 0.10	2.75\pm1.06	0.05\pm0.02	0.58 \pm 0.15	3.73\pm1.01
	EKF	0.04\pm0.02	0.16\pm0.08	5.53 \pm 1.24	0.08 \pm 0.04	0.18\pm0.09	3.58 \pm 1.35	0.08 \pm 0.04	0.36\pm0.12	5.92 \pm 1.29
3.4	RST	0.05\pm0.02	0.40 \pm 0.12	1.95\pm0.90	0.05\pm0.02	0.20\pm0.09	3.18\pm1.19	0.06\pm0.02	0.70 \pm 0.20	4.11\pm1.19
	EKF	0.05 \pm 0.03	0.21\pm0.11	5.92 \pm 1.39	0.10 \pm 0.05	0.23 \pm 0.10	3.89 \pm 1.82	0.10 \pm 0.05	0.43\pm0.16	6.40 \pm 1.60

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