A Survey of Indoor Inertial Positioning Systems for Pedestrians

Robert Harle

***Abstract*—With the continual miniaturisation of sensors and processing nodes, Pedestrian Dead Reckoning (PDR) systems are becoming feasible options for indoor tracking. These use inertial and other sensors, often combined with domain-specific knowledge about walking, to track user movements. There is currently a wealth of relevant literature spread across different research communities. In this survey, a taxonomy of modern PDRs is developed and used to contextualise the contributions from different areas. Techniques for step detection, characterisation, inertial navigation and step-and-heading-based dead-reckoning are reviewed and compared. Techniques that incorporate building maps through particle filters are analysed, along with hybrid systems that use absolute position fixes to correct dead-reckoning output. In addition, consideration is given to the possibility of using smartphones as PDR sensing devices.**

The survey concludes that PDR techniques alone can offer good short- to medium- term tracking under certain circumstances, but that regular absolute position fixes from partner systems will be needed to ensure long-term operation and to cope with unexpected behaviours. It concludes by identifying a detailed list of challenges for PDR researchers.

***Index Terms*—Dead Reckoning, Inertial Navigation, Particle Filters, Wearable Computers**

I. Introduction

SALES of mobile computing devices such as smartphones are now overtaking those of traditional desktop computers. This increased mobility has spurred interest in location awareness and new interaction modalities that can use it. Smartphones can now provide local news and weather, direct users to the nearest bank, navigate vehicles around traffic, and monitor the progress of every jogger, cyclist and hiker.

This location revolution has been underpinned by the deployment of Global Navigation Satellite Systems (GNSSs) such as GPS. These are, however, incapable of tracking indoors—where most people spend the majority of their time. Providing location services within a building has many potential applications, including:

- Safety—location systems provide emergency services with an immediate view of where building users are at any time;
- Security—location-awareness permits automatic locking of sensitive resources if the owner is not present;
- Resource-efficiency—smart buildings can use the knowledge of where its users are to optimise heating, lighting and other resources;
- Automatic resource routing—follow-me applications allow telephone calls to route to the nearest device and for users to efficiently find colleagues;
- Visitor navigation—visitors unfamiliar with a building can quickly navigate to rooms of interest.

Many diverse techniques have been proposed to enable indoor location and there is a large body of literature relating to the problem. The expense and time required to install, configure and maintain these systems has so far prohibited general deployment. One solution to this has been to layer them above deployed communications systems such as GSM, WiFi, and Bluetooth [1], but this can result in sub-optimal positioning since the communications access points are rarely deployed to provide optimal location geometry and coverage overlap.

This work surveys an emerging subset of tracking systems that use inertial sensors to perform dead reckoning. These systems typically compute their own positions and their key advantage is that they require very little, if any, physical infrastructure to function. They also offer a degree of location privacy since the user can choose not to share the information with any third party. Note, however, that failure to share location data severely limits the available location-aware applications.

Interest in these systems is peaking because the crucial sensors have become sufficiently small and inexpensive to enable practical tracking of individuals (who must carry them at all times). Furthermore, the widespread deployment of smartphones—most of which contain the relevant sensors—means a near-ubiquitous deployment of inertial devices exists that users already carry and charge.The challenge now is to exploit these sensors to achieve tracking robustness levels similar to that demonstrated by a GNSS.

This survey is structured as follows: Section II briefly reviews indoor positioning in general; Section II-B examines the invariants to be exploited in ambulatory motion; Section III surveys the different techniques that have been used to detect steps within sensor data; Section IV looks at the application of Inertial Navigation Systems (INS) research; Section V considers an alternative step-and-heading approach; Section VI surveys the use of particle filters and map-matching techniques to improve location estimates; Section VII considers the hybrid relative/absolute systems that have been proposed; and then Sections VIII and IX conclude by identifying open research areas and future research directions.

II. Indoor Positioning Systems

There exist many surveys of wireless positioning systems in the literature. With the possible exception of inertial systems such as those described here, comprehensive coverage is provided by Hightower and Borriello [1], Sun et al. [2], Liu et al. [3], and Gu et al. [4]. A reiteration of their contents is beyond the scope of this work, but there is benefit

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R. Harle is with the Department of Computer Science, University of Cambridge, UK (e-mail: robert.harle@cl.cam.ac.uk).
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in highlighting a few key techniques since hybrid systems are also gaining traction (see Section VII). The following techniques are described in more detail in the cited surveys.

Lateration and angulation systems. These compute distances or bearings between the mobile unit and an array of base stations at known locations. Difficulties arise indoors because radio signals may not propagate along the direct path due to walls and other obstructions. Careful choice of the signal type can assist here: ultrasonic systems have shown high accuracy but are expensive to deploy and maintain; whilst Ultrawideband radio systems such as those supplied by Ubisense[1] can achieve around 20 cm accuracy, but are costly, difficult to retrofit, and require specialist location tags to be carried by users.

Proximity systems. Rather than provide co-ordinate location, these systems provide only coarse location (perhaps the nearest room or building section). Examples include RFID systems and Bluetooth stations. They have the advantage of requiring little calibration, but need a high density of readers to gain reliable, ubiquitous coverage.

Radio fingerprint systems. Perhaps the most successful indoor systems to date are those based on radio fingerprinting. Here, signal properties such as received strength are compared to a database of properties previously collected at a variety of locations (a *radio map*). The closest match is returned as the estimated position. WiFi is a common choice due to its ubiquity. Accuracies of a few metres are typically reported.

Dead-reckoning systems. These systems use sensors on the user to estimate *relative* rather and absolute location i.e. the *change* in position since the last update. They require little or no infrastructure to be pre-installed in buildings, but without an external reference, errors quickly accrue.

Fingerprint systems are a good example of where a tension can form between location and communications performance. The smaller the dimensionality of the fingerprint, the harder it is for a system to reliably distinguish between neighbouring fingerprints and the worse the location performance—i.e. we seek to maximise coverage area overlap between access points. Contrast this with an ideal communication-optimised deployment, where we seek the *minimum* overlap that gives comprehensive coverage. As such, higher-accuracy WiFi positioning systems will often require additional infrastructure and may introduce signal interference that degrades core communications performance [5]. In addition, the cost of continuously using the WiFi radio on a mobile device can be prohibitive. Nonetheless, they are the target of significant research effort.

This survey is concerned with the recent developments in dead-reckoning for walking users and hybrid systems using such techniques—often called Pedestrian Dead-Reckoning (PDR) systems. These systems are of particular importance because they retain the low deployment costs associated with dead-reckoning whilst successfully addressing many of the shortcomings.

[1]http://www.ubisense.net

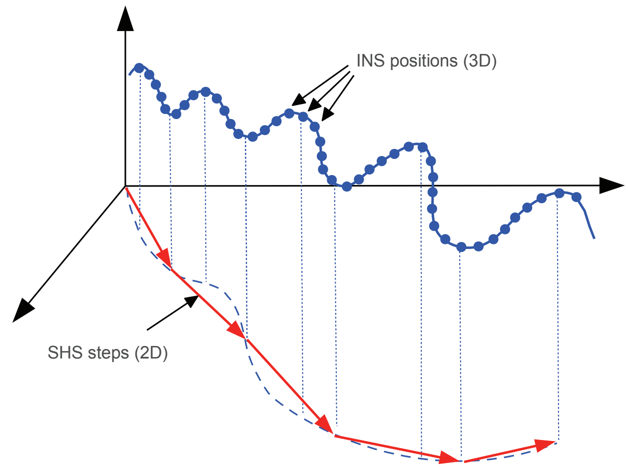


Fig. 1. INS and SHS. An INS computes the full trajectory of a unit in 3D (solid line with position dots), whilst an SHS deals only with gross step vectors in 2D (arrow sequence)

A. Types of PDR

In this work, a distinction is made between Inertial Navigation Systems (INSs) and Step-and-Heading Systems (SHSs)—see Figure 1. An INS is a system that tracks position by estimating the full 3D trajectory of the sensor at any given moment. An SHS is specific to pedestrians, estimating position by accruing {distance, heading} vectors representing either steps or strides[2].

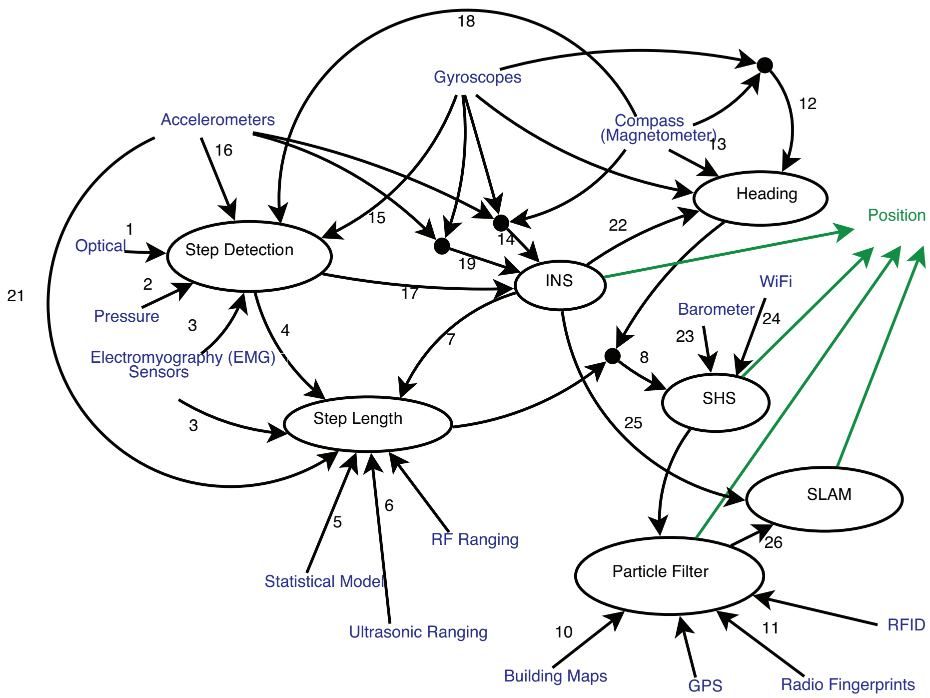
If the output of an INS worn by a pedestrian is somehow sliced into steps, then it forms a subset of an SHS, referred to here as an SHS-INS system. However, other techniques can underlie an SHS with better noise robustness, as discussed shortly. The fundamental cycle for an SHS is:

1) identify subsets of the data corresponding to individual steps or strides;
2) estimate the length of the step; and
3) estimate the step heading or change in heading.

The work on INSs and SHSs owes much to the robotics community. The problem is significantly more challenging in this context since the robot is replaced by a user, meaning: we no longer control how the sensors move and we lose any feedback loop that could ensure a space is completely covered; we are limited by the available sensors; and the movements are more complex. Nonetheless, a number of robotics techniques have proved useful, including:

- Particle filters—these are numerical solutions to the Bayesian estimation framework that allow the incorporation of complex constraints that can help limit drift; and
- Simultaneous Localisation and Mapping (SLAM)—these techniques were developed to allow a robot to locate itself within an environment it has not seen before. The typical sensors used for SLAM (laser rangefinders, cameras) are not applicable to pedestrians but the techniques enable

[2]A *step* is the period between two footfalls on opposite feet, whilst a *stride* is the same quantity but between the same foot.



1. [6]
2. [7]
3. [8]
4. [9]–[12]
5. [13]
6. [14]
7. [15]–[19]
8. [13], [16], [17], [19]–[21]
9. [16], [17], [21]
10. [16], [17], [21]
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12. [12], [14]
13. [11], [13], [20], [26]
14. [15]–[18], [21], [27]–[31], [31]
15. [19], [21], [31], [32]
16. [9]–[12], [12], [15], [17], [19], [28], [29], [33]
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24. [25], [29]
25. [30], [33]
26. [24]

Fig. 2. PDR configurations. System inputs are connected via annotated arrows to ellipses, which represent algorithms and system subunits. Arrow annotations give a numerical key into the list of literature references on the right..

location systems that improve over time as they learn about the environment.

Both of these techniques are addressed in more detail later in this survey. Figure 2 provides a graphical summary of all the sensors and techniques that are surveyed herein. Sensors are connected to system subunits (shown in ellipses) by arrows that represent the flow of data. For example, the arrows starting at the *Accelerometers* label represent accelerometry data that have been used to detect steps; to directly estimate step lengths; and been combined with gyroscopes or with gyroscopes and a compass to form an INS. For each flow of data, the figure gives a set of references to literature that uses that specific sensor or technique.

B. Ambulation

Many of the systems described here succeed by assuming ambulatory motion and deriving related invariants. Ambulation itself can be characterised by the alternate 'vaulting' of the body over a stiffened leg, with the fall being broken by the opposing leg. At any given moment at least one foot is in contact with the ground—there is no flight phase as is found when running. Instead the gait cycle is usually defined in terms of the phases occurring at a specific foot: the primary phases are *stance* and *swing*. In its stance phase the foot of interest is firmly planted on the ground, providing a pivot point over which to vault. In the swing phase, the foot lifts from behind the pedestrian and swings through to break the fall and enter its stance phase.

The transition from stance to swing involves the foot 'peeling' from the floor, providing a final push from the toes. This event goes by many names, but *toe-off* and *push-off* are the most common. The transition back to the stance phase begins with the heel contacting the floor (the *heel-strike* or *foot-down* event) before the foot flattens (the *foot-flatten* event). The foot remains flattened until the transition to the swing begins, and the cycle restarts. The strong periodicity in the movement coupled with the tendency of humans to sustain a consistent pace allows for a variety of constraints to be applied.

III. Detection of the Gait Cycle

The first task of an SHS is the identification of steps or strides within the data. In fact, this is even used in many INSs, as discussed shortly. At a minimum, these algorithms must permit for accurate step counting, although many systems also require accurate step segmentation. We can thus identify two main algorithm types:

- Stance detection—algorithms that identify periods of data throughout which a given foot is planted on the floor. To do this, the sensor is mounted to the foot. Typically these are appropriate for step counting but give poor segmentation output;
- Step cycle detection—algorithms that detect cycles in the sensor data caused by the repetitive motion of walking. This may involve searching for repeating data patterns or for repeating events (e.g. the heel-strike). These are well suited to step segmentation.

Typical stance detection algorithms are threshold-based. The principle is that the sensor will be static during the stance phase and the inertial sensors should report a corresponding lack of activity that thresholding can easily identify. Most algorithms threshold on the accelerometer magnitude [11], [17], [35], although angular velocity thresholds have also been used [21], [32], [36] and combinations have been trialed [27]. Even magnetometer thresholding can give usable stance detection under some circumstances [19]. In some cases applying

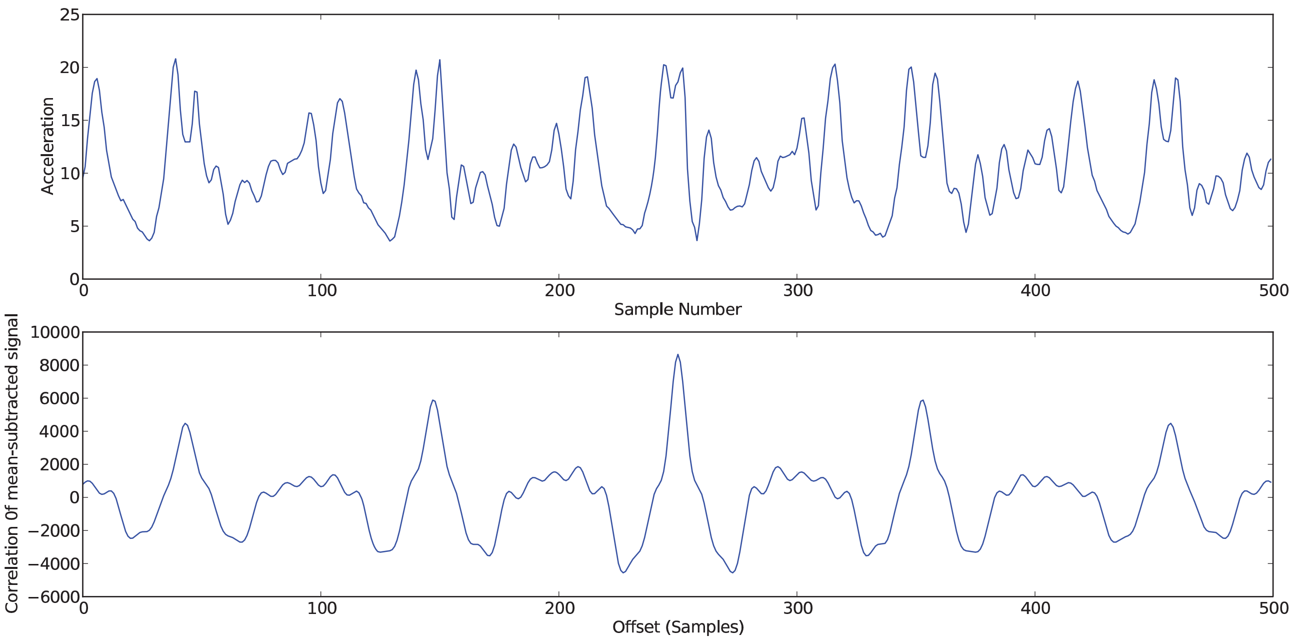

Fig. 3. Autocorrelation-based step cycle detection. The top graph shows the raw acceleration magnitude during five sample strides. The autocorrelation of the mean-subtracted signal is shown in the bottom graph, with strong peaks associated with each stride.

the threshold to the moving variance of the signal has been preferred to applying it to the instantaneous magnitude [15], [19].

A successful stance detection enables step counting simply by assuming one stance period per stride per foot. Jimenez reported errors of just 0.1% and 0.2% based on thresholding accelerometer variance and angular velocity, respectively [19]. However, threshold-based stance detection assumes at least one sensor on the foot. A large deployment of shoe sensors is not inconceivable, but is highly unlikely in the short- to medium-term.

Even were such a deployment achieved, there are limitations to the value of stance detection. Because shoe sensors undergo high accelerations they experience additional movements associated with shoe deformation and bounce. This, combined with the empirical nature of thresholds (see [12]), means the start and end points of a threshold-computed stance period do not represent the true foot-down or toe-off events. Rather they represent an inconsistent subset of the full stance period.

Instead, other techniques have been developed to accurately identify specific events for data segmentation, as well as to allow the sensors to gather data from elsewhere on the body. These include:

- Peak detection—the heel strike is associated with sharp changes to the vertical acceleration. Standard peak detection algorithms can be used to highlight potential strikes. Note that each foot impact may generate multiple local peaks the nearer to the foot it is sited, due to the higher forces resulting in sensor bounce [37], [38]. This can significantly increase the algorithm complexity.
- Zero crossings—a cheaper way to use the cyclic property is to monitor the acceleration value for zero crossings (essentially a form of thresholding) [39]. This is a popular choice for pedometers or activity monitors such as the Actigraph[3] due to its simplicity.
- Auto-correlation or template matching—the cyclic nature of walking leads to strong periodicity in the sensor data, regardless of the attachment site. The cycle can be extracted by seeking maxima in the mean-adjusted autocorrelation of a sequence of sensor data, such as the acceleration magnitude (Figure 3) [38]. Whether the peaks correspond to a step or a stride will depend on where the sensor is attached—the nearer to a foot, the more asymmetric the response for each step. If a sample sequence of data for a step or stride has previously been collected, cross-correlation with this 'template' data can also identify steps or strides using the same process.
- Spectral analysis—this involves computing the frequency spectrum of the cyclic data and identifying strong peaks at typical stepping frequencies. Windowed subsets of the data (with a width that includes at least two cycles) are converted to the frequency domain and the dominant frequency taken as the walking frequency [40].

The last two methods depend on identifying periodicity in the sensor signals. It is difficult to write such algorithms to handle changes in walking speed, to capture one-off steps or to reject false positives caused by any repetitive movement within the expected frequencies. However, it is most common for humans to adopt a natural (and surprisingly consistent) walking pace, for which such algorithms are highly robust.

[3]The Actigraph is a belt-worn unit that provides long-term logging of an internal accelerometer for the purposes of activity monitoring. See http://www.theactigraph.com.

TABLE I
STEP DETECTION SUMMARY.

Author	Citation	Sites	Sensors	Stance	Signals used	Technique summary
Judd	[26]	Unspecified	Acc	No	Vertical acceleration	Low-pass filter, peak detect
Park et al.	[44]	Foot	Pressure	Yes	Vertical force	-
Ladetto	[9]	Lower back, thorax	Acc	No	Vertical and forward acceleration	Wavelet decomposition, peak detect
Jirawimut et al.	[13]	Waist	Acc, Gyro	No	Pitch angle	Low-pass filter, peak detect
Kourogi et al.	[34]	Waist?	Acc	No	Vertical and forward acceleration	Peak detect, test gradient
Randell et al.	[10]	Foot, backpack	Acc	No	Vertical acceleration	Moving average, peak detection (maximum followed by trough)
Stirling et al.	[11]	Foot, torso	Acc	Yes	3D acceleration magnitude	Unclear
Saarinen et al.	[14]	Foot	Ultrasonic ranging	No	Range between feet	Range minima and maxima
Cavallo et al.	[32]	Foot	Gyro	Yes	3D gyro magnitude	Thresholding (15 deg/s)
Foxlin	[27]	Foot	Gyro, Acc	Yes	Raw acc, gyro	Thresholding
Kim et al.	[12]	Ankle	Acc (1D)	Yes	Horizontal, vertical acceleration	Peak detect
Beauregard	[20]	Head	Acc	No	Acceleration magnitude	Low pass filter, zero crossings
Dippold	[42]	Waist	Acc	No	Vertical acceleration	Peak detect
Godha et al.	[15]	Foot	Acc	No	Acceleration magnitude, variance	Moving average, thresholding, zero-crossings
Ojeda et al.	[36]	Foot?	Gyro	Yes	Gyro magnitude	Thresholding across 0.5s intervals
Beauregard et al.	[45]	Foot	Acc. Gyro	Yes	Raw signals?	Unclear
Krach et al.	[17]	Both Feet	Acc. Gyro	Yes	Acceleration magnitude	Thresholding
Jimenez et al.	[19]	Foot	Acc, Gyro, Compass	Yes	Magnitudes	Compares: variance of acc. Magnitude with thresholds on compass or gyro
Castaneda et al.	[35]	Foot	Acc, Gyro	Yes	Magnitudes	Fuzzy logic thresholding
Wang et al.	[8]	Calf	EMG	N/A	EMG signal	Peak detect
Goyal et al.	[39]	Waist	Acc	No	Vertical acceleration	Double integration, peak detection. One per zero-crossing
Ria et al.	[23]	Various (pocket, handheld)	Acc	No	Not specified	Autocorrelation
Faragher et al.	[24]	Hip	Acc	No	Acceleration magnitude	Thresholding

All of these techniques are usually applied to accelerometer signals, often after applying a low-pass filter to remove noise. Filter cut-off frequencies of around 20 Hz retain the step periodicity, although filtering down to 2 or 3 Hz has also been used successfully [41]. It should be noted that most implementations claim to use only the vertical acceleration, but do not compensate for changes in the global pose of the sensor during a step. Instead they assume that one of the accelerometer axes remains vertical throughout. This assumption is most valid for inertial sensors attached to the torso of the body [9], [42], although it has proved acceptable on the foot [10].

Many of the algorithms are tested on flat surfaces, which is appropriate for the majority of buildings. However, Ladetto reports that the assumptions used by many PDR systems break down on inclines of 10% or more [9]. More recently, Wang et al. have demonstrated that different gait patterns corresponding to different inclines can be distinguished autonomously to accuracies exceeding 90% [43]. From this we can conclude that a modified PDR system could cope with long ramps found within a building for wheelchair access.

Table I summarises some prominent positioning systems in terms of the sensors and signals they use, and whether they perform stance detection or step cycle detection. The lack of uniform testing methodologies makes quantitative comparison difficult here—in many cases the step detection component is only a small part of work that receives only minimal scrutiny. It is an open research problem as to which of these techniques works best when given a diverse test population, a wide range of environments and unconstrained day-to-day movements.

A. Non-Inertial Sensors for Step Detection

A variety of non-inertial sensors can also facilitate step or stance detection: Park et al. used pressure sensors embedded in the sole of the shoe [44]; Toth et al. used impact switches in a similar manner [46]; Saarinen et al. used ultrasonic ranging between the feet [14]; and Wang et al. used electromyography (EMG) sensors attached to the calf [8]. Whilst effective, these solutions all require more invasive attachment to the user and rarely offer any benefit over the use of inertial sensors (which are still needed for subsequent PDR analysis anyway).

B. Detection Accuracies

The techniques are often presented as offering robust step counting and/or stance detection. This is perhaps unsurprising since the sensors undergo significant changes throughout a gait cycle and each cycle is strongly correlated with the last. The observed accuracies will depend on many factors, but step counting accuracies in excess of 99% are commonly quoted under laboratory conditions with few false negatives.

In reality, finding a robust and reliable technique for step cycle detection away from the foot is not simple. Quoted accuracies are rarely derived from testing on a representative sample of the population and do not account for different heights, weights, shoes, surfaces or gaits. It is also rare to see the test subjects act freely—invariably they are tasked with performing a long, continuous walk. Under such circumstances the sensor signal exhibits strong self-similarity which simplifies detection. Less constrained motions (stumbles, side-steps, shuffles, etc.) are problematic, and arbitrary cyclic motions may trigger the frequency-based techniques.

The most comprehensive pedometry (step counting) studies have been carried out within the medical domain. For example, Marschollek et al. provided a detailed study with over 200 test subjects that varied in age from 7 to 88 years old, with varying degrees of health. Using a waist-mounted accelerometer and a variety of processing algorithms, they found errors in the step counts of 8.4% in healthy subjects (using a variant of thresholding) and as high as 29.3% in mobility-impaired subjects (using autocorrelation). They conclude that "none of the algorithms work very well", although insufficient details are given to reproduce the algorithms employed and more sophisticated variants have now been proposed.

More recently Rai et al. described an autocorrelation algorithm ostensibly for step counting but capable of segmenting data into strides. Their Normalised Auto-correlation based Step Counting (NASC) algorithm [23] was tested on walking and non-walking data collected from six people. They used a smartphone accelerometer in a variety of positions including handheld, in a pocket and in a handbag. They report false positive rates of 0% and false negative rates of 0.6%. These results are very encouraging, but there is insufficient detail in the testing methodology to be able to extrapolate them to a larger population outside the laboratory.

IV. INSs in more Detail

An INS uses triaxial accelerometers and gyroscopes to track orientation and position changes [47]. In the *strapdown* configuration used by pedestrians the sensors are combined into a rigid package and firmly attached to the body[4]—we speak of the *world* frame of reference (with axes in the horizontal and vertical planes) and the *sensor* frame of reference (with three mutually perpendicular measurement axes pointing in arbitrary world directions).

In robotics the attitude of the sensor can often be constrained such that, for example, the sensor z-axis coincides with the vertical world axis. Tracking position then involves subtracting the gravitational signal from the vertical accelerometer signal and performing double integration on the remaining 3D acceleration (i.e. integrating once to velocity and twice to displacement). In a PDR context, however, the sensor is not only unlikely to be axis-aligned, it will also continuously rotate with respect to the world frame during the walking cycle. We must therefore track the rotation of the sensor using the angular velocities provided by the gyroscopes. This introduces a third integration to each position update.

Inevitably, measurement errors are present within the sensor data, and the triple integration of them results in a potentially cubic growth in time (*drift*). INSs for aviation, marine and the military use highly accurate sensors that keep the error sources very small and permit tracking for many hours. These are too bulky and expensive for a PDR, which must instead use Micro Electro-Mechanical Systems (MEMS) technology. MEMS sensors are small and highly portable but they are also subject to more significant error sources. Open-loop integration of MEMS inertial sensors is only possible for a minute or two before the drift dominates [47].

Strapdown inertial navigation algorithms have been well studied and the standard approach to limit drift uses an Extended Kalman Filter (EKF) in the complementary or indirect form, whereby the filter tracks the *errors* in the system state rather than the system state directly. A 15-state model is commonly used: three states each for position, velocity and attitude errors plus six states to model the accelerometer and gyroscope biases [27], [48]. The process structure is illustrated in Figure 4.

A. Zero Velocity Updates (ZUPTs)

To counter drift it is necessary to regularly close the integration loop by applying external constraints to the system. The most widespread PDR constraint is provided by Zero Velocity Updates (ZUPTs). ZUPTs assert that the sensor is stationary and can be applied during the stance phase *provided the sensor is attached to the foot*. ZUPTs were first used in a PDR context in the NavShoe project by Foxlin[5], who reported good results in 2005 [27]. ZUPTs are easily incorporated into the INS structure of Figure 4 by formulating them as pseudo-measurements of zero velocity.

The application of ZUPTs means that open loop integrations only occur during the swing phase of the foot to which the sensor is attached. For such short durations, drift accrual is limited and longer tracking durations are thus feasible. For a reliable output, however, ZUPTs must only be applied when the foot (and hence sensor) is completely static. Issues can arise when the sensor is attached any higher than the ball of the foot. The peeling motion associated with the transition from stance to swing means the heel rises soon after the foot-down event and hence a sensor in the mid-foot will start experiencing an acceleration as the foot levers up. These small accelerations occur before the strict end of the stance phase and it is necessary to account for these errors by applying a non-zero covariance alongside the ZUPT pseudo-measurement.

B. The Use of Magnetometers

Many commercial inertial sensor units contain triaxial magnetometers in addition to the accelerometers and gyroscopes necessary for an INS. Magnetometers provide a direct estimate of the user's absolute heading, which is particularly useful for correcting the inevitable heading drift that accrues in an INS, even with ZUPTs applied. Magnetometer readings are incorporated into the framework of Figure 4 by applying them as absolute heading measurements.

However, the Earth's magnetic field is relatively weak at its surface and modern buildings, filled with metal and conducting

[4] An alternative configuration uses a gyro-stabilised platform to maintain the pose of the accelerometers with respect to the global axes. Such systems are accurate but bulky and expensive, making them inappropriate for pedestrian navigation.

[5] Foxlin's article itself credits a 1996 DARPA project for the introduction of ZUPTs for a PDR.

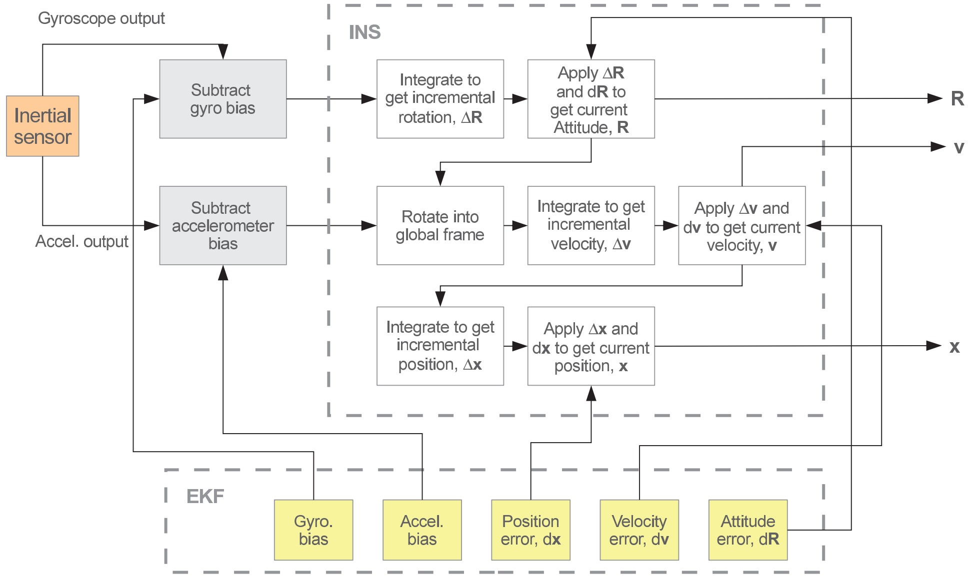

Fig. 4. The standard INS solution involving a 15-state Extended Kalman Filter

wires, can overpower the natural signal, leading to local 'disturbances'. Afzal et al. performed detailed experiments indoors and concluded that different building materials have significantly different effects on magnetometers, with heading errors of up to 100° observed [49]. In their office environment, Rai et al. report magnetic errors were contained to within 15° at 90% of their test locations, with a maximum deviation of 30° observed.

A common correction algorithm is to reject any readings where the magnitude lies outside some tolerable range of the expected value. Afzal et al. noted that this can be overzealous since vertically polarised magnetic fields will affect the magnitude but not the horizontal heading [50]. To use this knowledge, however, requires that the pose of the sensor in the world frame of reference be known except for horizontal heading so there are practicality issues.

Combining both gyroscope and magnetometer inputs has yielded some success since the two sensors have complementary error characteristics—gyroscopes give poor long-term orientation, while magnetometers are subject to short-term orientation errors. Kim and Park exploited this by comparing the angular velocities measured by the gyroscope with those computed from successive magnetometer readings [12]. A significant difference was taken to signify the presence of a magnetic disturbance and the compass measurements were discarded. Their results indicated an improvement but only considered one environment that was not reported to suffer from strong magnetic disturbances.

Magnetic disturbances can also be modelled within the EKF framework of Figure 4 as per [27], [39]. By assuming a high spatial frequency of disturbances, the EKF is able to estimate the covariance in the heading measurement. However, Foxlin noted that the large number of updates typically applied during a stance phase can bias the result strongly, and so used only a single magnetometer reading per step [27].

In summary, there are many proposals for techniques to address magnetic disturbances to aid in heading determination. However, more detailed testing in a wide variety of environments is needed before any firm conclusions can be drawn. In the meantime, fusing gyroscope output with the compass provides a heading estimation (or heading change estimation) that is reasonably robust in most environments.

C. Results of INSs with ZUPTs

Ultimately, integration drifts limit the usefulness of pure INS-based techniques for anything other than short-term indoor tracking. ZUPT-based INSs typically exhibit return-to-start errors[6] of the order of a few metres in the literature. However, the testing usually involves contrived situations where the user's initial position is known and they are told to walk along prescribed paths without stopping. Little consideration has been given to more natural situations, where a user may move to avoid obstacles, may sit and swing their legs, may amble aimlessly, or may perform some unusual activity such as jumping or skipping. The practicality of requiring a foot-mounted sensor (for ZUPTs) also detracts from the solution. Nonetheless, ZUPT-based INSs have been shown to give good medium-term tracking accuracies when combined with building maps (see Section VI).

V. Step and Heading Systems (SHSs)

A drift-free INS provides a full 3D trajectory for a sensor. Whilst useful, this level of detail is not necessary in most tracking scenarios. Navigation in 2D in the horizontal plane and using step vectors rather than complete limb trajectories is sufficient. Step and Heading Systems (SHSs) output a series

[6] A return-to-start error is the error in predicted position after a user performs a walk that brings them back to their start position, and is useful when the true path of the walk is not available.

of {step length, step heading} or more often {step length, step heading change} polar vectors that can be summed in a 2D vector space to track position. Although these vectors could be derived simply by degrading the INS output (forming an SHS-INS), they can also be estimated *without* using the triple integration that leads to fast drift accrual in an INS. As an example, step cycle detection can be used to identify the sensor data associated with a single step and the length may then be directly estimated from its duration (i.e. no integration).

A. Length Estimation

In fact, the simplest approach to estimating step length is to assert it as constant. Pedestrians have a natural walking pace with a surprisingly constant step length. However, this natural walking pace is adjusted when rushing, ambling or walking with others. Weinberg reported that the step length can vary by as much as 40% between pedestrians walking at the same speed, and up to 50% across the range of walking speeds of an individual [41]. Note that in short tests where participants are asked to walk continuously along a specified route, they are likely to adopt their natural walking pace and this may lead to an overly optimistic tracking accuracy.

Weinberg also described a dynamic step length estimation procedure based on the maximum vertical displacement of the hip ("bounce"). The stride length was shown to be a function of the bounce and the vertical angle between the highest and lowest point of the hip during a single stride [41]. This angle is taken as constant although it is actually related to the leg length of the user. Nonetheless the step lengths are reported to be within 8% of their true values, which may be sufficient for some uses.

An alternative is to base step lengths on the observed step *frequencies*, which can be estimated using the step detection techniques in Section III. Research in the medical community has shown a tight coupling between the step frequency and the walking speed (which is little more than a proxy for step length). Although the precise relationship is non-trivial (see [51]), it is common to fit a linear relationship, which is sufficient to achieve an RMS error of 5.6% [52].

Direct measures of each step have also been used. For example, Saarinen used ultrasonic sensors mounted on the front and back of each shoe [14] and similar range-finding techniques have been used elsewhere. Such techniques unquestionably produce higher quality displacement estimates. However, the increase in accuracy is often negligible since the larger *heading* drift is typically the limiting factor. Finally, some systems estimate step lengths iteratively by evaluating the paths produced using different lengths and using building maps to choose an optimal length (see also Section VI) [23].

B. Heading Estimation

Heading estimation within an SHS is typically no different than for an INS since there are so few sensors available as inputs. Single integration of gyroscope signals provides estimates of heading change. Because SHSs can avoid using subsequent integration for the step length, the overall drift does at least grow linearly rather than cubically. In addition, some systems use only a single gyroscope mounted parallel to the torso, making the assumption that it remains (near) vertical during walking. As in Section IV-B, magnetometers may also be used directly or fused with the gyroscope outputs to estimate heading.

C. SHS-INS Systems

Some systems derive PDR events from an underlying INS. To do this they use the step detection techniques described in Section III to segment the INS output into steps. These are then summarised as {length, heading} pairs. Such SHS-INS systems naturally suffer from the same drift accrual found in pure INS systems and they are used merely because SHS outputs are simpler to handle when working with the higher-level filters necessary to incorporate other constraints such as maps [53].

VI. Incorporating Map Matching

Whilst the techniques previously described aim to minimise the rate of drift accrual, they cannot prevent it. Longer-term tracking of pedestrians has been achieved by incorporating external measurements and environment information. Building maps in particular are a popular way to address medium-term drift.

Abdulrahim et al. proposed constraining movements to lie along paths parallel to the external building walls [54]. For a typical rectangular building, this constraint allows movement in one of two perpendicular directions. Over a series of eight walking loops that varied in duration from 12–40 minutes and in length from 0.5–3 km, they achieved an average return-to-start error of 4.62 m using ZUPTs and orientation constraints, versus an error of 153.62 m when only ZUPTs were applied. Whilst these results are encouraging, errors of 5 m lead to room ambiguity. It is also unclear how the system would cope with free movements outside of contrived test conditions.

A. Particle Filters

The problem is similar to the routing problem faced by vehicular navigation systems, where noisy position estimates must be constrained to lie on public roads. Here, however, the tracking error is often comparable to the distances between route intersections (i.e. office doors) and users can quickly change direction at will. Consequently not all of the vehicular routing techniques are useful in a PDR context.

One of the key difficulties is representing the complex shapes of buildings as constraints. Unlike ZUPTs, wall outlines are not easily related to raw sensor data and instead we feed the output from an SHS into a higher level particle filter to form an SHS-PF.

A Particle Filter is a numerical approximation to a Bayesian filter [55]. It is made up of many 'particles', each representing a possible 2D position and heading for the user in this context. Some positions are perhaps more likely than others, so each particle contains a weight value that represents the probability of it being correct based on all the information to date. A particle filter is iterative, with three traditional steps to each iteration:

TABLE II
SHS-PF SUMMARY.

Authors	Ref	System Description	No. Users	Evaluation	Particle Scheme	N_{init}	N_{track}	Initialisation	Accuracy Quoted
Woodman et al.	[53]	PDR-INS + PF	1	16-minute walk. Three floors.	Variable	Variable (136,000–170)	≈170	WiFi-assisted	0.73m 95th percentile
Woodman et al.	[22]	PDR-INS + PF (as above)	1	35-minute walk. Three floors. WiFi containment	Variable	Variable (<228,001)	≈170	WiFi-assisted	No details
Woodman et al.	[48]	PDR-INS + PF (as above)	1	Five 10–15 minute walks. Three floors.	Variable	4478049	≈500	Uniform Prior	0.62m 95th percentile
Beauregard et al.	[45]	PDR-INS + Backtracking PF	1	10-minute walk. Two floors. Manual ground truth.	Fixed	2000	2000	Manual?	0.74m
Klepal et al.	[16]	PDR-INS + Backtracking PF (as above)	1	Multiple walks of up to 10 minutes. Manual ground truth.	Fixed	2000	2000	Manual?	1.321m
Krach et al.	[56]	PDR-INS on each foot + PF	1	No details	No details	No details	No details	Uniform prior	"Corridor width"

1) **update**—each particle is displaced according to a motion model (usually a constant velocity taken from the previous iteration);
2) **correct**—each particle is assigned a weight based on the similarity between the motion-model step estimate and the measured heading vector;
3) **resample**—a new particle set is generated by copying particles in the current set in proportion to their weights (this ensures that the particle set is distributed over likely locations rather than unlikely ones).

SHS-PF systems were demonstrated independently in 2008 by Krach and Robinson ([56]); Widyawan, Klepal and Beauregard ([16]); and Woodman and Harle ([53]). All three choose to incorporate a new step vector into the update phase (step 1 above) rather than into the weight assignment (step 2) as described above. Without this modification, step 1 may move many of the particles in significantly different directions to those described in the measured step vectors. Consequently they would be assigned low probabilities in step 2 and we would require more particles (and hence more processing power) to ensure enough particles with high probability persisted at the true position. i.e. each particle with state (x_t, y_t, θ_t) incorporates a step event with step length l and heading change $\delta\theta$ as follows [48]:

$$x_{t+\delta t} = x_t + (l + n_l)\cos(\delta\theta + n_\theta), \quad (1)$$
$$y_{t+\delta t} = y_t + (l + n_l)\sin(\delta\theta + n_\theta), \quad (2)$$
$$\theta_{t+\delta t} = \theta_t + \delta\theta + n_\theta, \quad (3)$$

where n_l and n_θ are noise terms drawn from the step length and heading uncertainty models, respectively. The three SHS-PF systems mentioned above used zero-mean white Gaussian noise processes to generate these terms, with variances appropriate to the confidence in the current step event.

In the assignment of weights in step 2, all three systems assigned weights of zero to those particles that crossed a wall boundary. This prevented those particles from being resampled in filter step 3. The remaining particles were either assigned an equal weight (Widyawan et al.) or assigned a weight using the observed change in height of the step (Woodman and Harle).

A summary comparison of the three systems is provided in Table II, which also considers incremental updates to the works. Broadly speaking, the three had more in common than not. Notable differences include:

- The Woodman implementation made use of the KLD resampling algorithm, which dynamically varies the number of particles in a filter;
- The Beauregard implementation introduced *backtracking*, whereby the filter kept a limited history of each particle's ancestors to allow deletion of an entire trajectory when a particle was killed due to a wall constraint. This is a variant of backward belief propagation also used by Rai et al. [23] and is useful to improve position estimates made in the past when live positioning is not a requirement.
- The Krach implementation combined two SHS-INS systems—one for each foot—to feed the particle filter.

The evaluations of these systems indicate tracking accuracies of around 1 m are feasible, but all were limited to single users walking continuously for tens of minutes (Table II) using foot-mounted sensors. Most people spend the majority of their day in a sedentary state so it is not unreasonable to assume walking durations of this magnitude. Nonetheless, these evaluations are not sufficient to assert an arbitrary user can be tracked throughout a day using an SHS-PF system.

B. Handling Lower Quality Inputs

To some extent, deficits in the quality of the SHS inputs can be compensated for in an SHS-PF framework by increasing the variances associated with each step event. In turn, this will require an increase in particle number to better represent the underlying probability distribution. However, this increase may only be a small percentage increase and a worthwhile trade-off to permit the use of lower grade sensors or simpler SHS techniques.

For example, many of the different techniques for step length estimation discussed in Section V-A have little effect on the SHS-PF tracking accuracy since they all provide estimates within small percentages of the true value. Where step *counting* is robust, it may even be possible to infer the characteristic step length by including it as a state variable within the particle filter as per [23]. Similarly, Woodman simplified the EKF used in his INS system to avoid modelling the accelerometer and gyroscope biases with little consequence when fed into an SHS-PF [48].

C. Computational Demands and Scalability

Particle filters typically require greater storage and processing resources than other fusion techniques. The minimum number of particles required at any moment is related to the uncertainty in the user's position. Woodman identified two key regimes: *localisation* and *tracking*. In the latter there is minimal uncertainty in the user's position, the particle cloud having converged about their location. In the former, there is large uncertainty in the user's position and the particle cloud is spread across a large floor area. This large uncertainty requires many more particles to represent adequately.

Evaluations such as those performed by Beauregard et al. avoid the localisation problem by seeding the filter with a prior centred on the user's initial position, allowing it to begin in the tracking regime. This allows a constant number of particles to be used, but is not a practical solution. Even if the initial location is known, the filter may fail and need to be re-initialised without knowledge of the user's location.

A more general prior would cover the entire tracking area. For the three-floor 8725 m^2 building used by Woodman, over 4,000,000 particles were needed to adequately represent such a prior [53]. This number should be contrasted with the 500 particles needed for the tracking phase[7].

Both Woodman and Krach consider the convergence problem and conclude that coarse location information from an auxiliary system would be highly beneficial. In [22], a WiFi radio map (constructed using the PDR system itself) was used to infer a containment region for the user, across which the particles were uniformly distributed. This reduced the initial particle count to less than 250,000. Using KLD resampling, this number fell to below 500 as the filter entered the tracking regime (the time taken for this depends on the environment and the path taken through it).

Because the computation demands of an SHS-PF filter can be significant, care must be taken to optimise the efficiency of the processing code. In his thesis, Woodman described a series of optimisations in depth, including segmenting the floor into polygons, particle clustering, and more [48].

VII. Smartphone and Hybrid Systems

One of the key attractors for PDR systems is the wide deployment of appropriate sensors in smartphones. However, we can exert very little control over where the smartphone is attached and hence what it measures. Smartphones may be carried in front pockets, back pockets, side pockets, shirt pockets, backpacks, handbags, on belt clips or in the hand. They may be firmly held in place, or free to move, and may be moved from their current position without warning. Steinhoff and Schiele experimented with an INS fed by sensors in the trouser pockets of eight test subjects [57]. They reported errors of 14.4% (95th percentile) of the distance travelled compared to a foot-mounted ground truth sensor. Whilst promising, such errors will accrue quickly to limit tracking ability.

If a system is able to recognise where a smartphone is being carried it may be able to adapt its algorithms to better detect the walking cycle through an SHS approach. Even so, very few systems have demonstrated an ability to cope with ill-defined movements such as shuffling or even side steps. Any PDR system is likely to need occasional position corrections from an external (absolute) positioning system.

The most popular hybrid systems combine PDR with WiFi fingerprinting in an attempt to address the shortcomings of both. With fingerprinting, the main difficulties are associated with comprehensively surveying the building to form a radio map and in keeping that map up-to-date. Woodman and Harle eased the data collection problem by using their SHS-PF system to track a user augmented with a shoe sensor moving through a building. By constantly scanning for WiFi they were able to build a radio map with little effort. They used this map to provide coarse portion-of-building position estimates with which to constrain the particles within their SHS-PF as mentioned in the previous section. Areas with densities of access points insufficient to support detailed WiFi fingerprinting merely resulted in larger containment areas for the particles (representing the increased uncertainty).

This approach can be inverted to use the PDR system to support WiFi fingerprinting. The Zee system proposes positioning primarily through fingerprinting, but with a radio map that is crowd-sourced from the subset of users with SHS-capable smartphones [23]. The system used an SHS-PF with a floor map in a similar manner to that described above. Because it is not intended as the core location mechanism, the SHS-PF component need only run when sufficient resources are available, although the more frequent this is, the more updates to the radio map are possible. In [23], Rai at al. describe a 15-hour test with a single user that successfully builds a WiFi radio map over the course of a few hours. Full crowdsourcing (with multiple users and heterogeneous devices) was left as future work, but this is a promising direction.

Faragher et al. described a hybrid system that did not depend on a centrally-established database of signals, nor on a pre-supplied building map [24]. It took as input an SHS based on an accelerometer and compass, as well as radio signal strength measurements from the WiFi and GSM cellular radios. It divided the building area into a regular grid and applied a Simultaneous Localisation and Mapping (SLAM) technique to correct drift. The basis of this approach was to constantly monitor the radio fingerprints to detect any loops in the path taken. The loops could then be used as a constraint to recompute the full path taken. Ferris et al. have also developed their WiFiSLAM system [58] into a commercial venture that uses SHS input in a similar manner[8] for more details.

VIII. Open Research Issues

PDR systems are still in their infancy. Major issues include:

Consistent evaluation methodologies and metrics. There is presently little consensus regarding how to evaluate PDR systems, which hinders their comparison. The outputs from a system can be affected by the characteristics of the test subjects, by the building size, layout and construction materials, or by the test procedure followed (including duration and the degree of 'natural' activity). It is common to report results for a single user over a series of contrived walking tests. Such tests serve as proof-of-concept but there is a growing need

[7]Note that each number quoted here would scale linearly with the number of people being tracked and the floor area.

[8]See http://wifislam.com

for thorough system evaluations over sustained periods with a diverse set of test subjects.

Unconstrained sensor sites. Smartphone-based PDR systems are highly attractive, but they introduce new difficulties by loosening the attachment constraints. Any deployed system must cope with the sensors changing orientation in a pocket, or being taken out to use, etc. In addition, there is often a heading offset between the direction a smartphone is facing and the direction the user is moving. This offset must be accounted for if using absolute heading measurements from a compass.

Sensor calibration. The output of MEMS sensors will vary over time as temperature and other environmental effects affect their bias and scaling factors[9]. Where foot-mounted sensors are used, ZUPTs permit measurement and adaptation to the current bias. However, for unconstrained smartphones there is typically no opportunity to estimate the sensor biases online, and no opportunity to perform a user-controlled recalibration. This is particularly important for the heading estimation. Possible solutions to this problem include deriving constraints from the ambulatory movement and incorporating a feedback loop from a map-matching stage. For example, a gyroscope bias in the horizontal plane would produce a curved path. If a higher-level particle filter determined the most likely movement was in a straight line, a per-step horizontal heading bias might be used to correct future heading measurements.

Battery power requirements. In the move to mobile devices such as smartphones, it is important to understand the associated energy costs. An SHS-PF system utilising gyroscope, accelerometers, magnetometers and WiFi signals will put a large draw on the available battery power. Understating which sensors are required and when will be crucial to maintaining sufficient system users.

Processing power requirements. Similarly, the processing power demanded by the bandpass filters, peak detectors, autocorrelators or particle filters in PDR systems cannot be overlooked. Understanding how to deploy these systems online on the devices themselves (and not offline on desktop machines as with most current literature) will be important. With particle filters in particular, there are parallelisation opportunities that might be able to exploit the imminent wave of GPU-enabled smartphones.

Wearability. The three research systems in Section VI-A are all built on SHS-INS foot-mounted systems. This ensures high quality PDR input to the particle filter, but foot-mounted systems are impractical. To enable larger scale, more natural testing, it will be necessary to have PDR techniques that do not require foot-mounting. To date, this implies a need for an SHS approach.

Initialisation. Bootstrapping the particle filter with an SHS-PF is a significant challenge. Work is needed to understand the necessary number of particles for a given map and the expected time taken before a user is unambiguously tracked.

IX. CONCLUSIONS

This work has surveyed inertial Pedestrian Dead Reckoning (PDR) systems. These have successfully adapted techniques for strapdown inertial navigation in the military domain and sensor fusion in the robotics domain to apply to the less-constrained motion of walking. Demonstrated systems have made use of the small, inexpensive MEMS sensors that are now becoming ubiquitous through smartphone market penetration. The higher error characteristics of these sensors mean that high accuracy inertial navigation through the traditional triple integration is only possible for foot-mounted sensors, where strong constraints can be applied. Away from the foot, Step and Heading Systems (SHSs) have begun to dominate, where each step is identified and characterised in terms of a length and heading vector.

Sub-metre tracking errors have now been demonstrated throughout a large, three-story building with the use of map-matching through a particle filter and foot-mounted sensor. A pure PDR system may be able to track a constantly-walking user indefinitely if the path they take through the building allows wall constraints to be regularly applied. Difficulties arise during periods of non-walking activity, when false positives and false negatives in the step detection, combined with compass and gyroscope errors will contribute positional error that will accrue over time.

For many building users, however, the bulk of the day is spent seated in a small number of locations, with walking transitions between them. Under such circumstances a pure PDR system may be able to offer room-level tracking by weighting the position estimates towards likely rooms (their own office rather than that of their neighbour, for example). More generally, however, occasional absolute position corrections from an external positioning system will be required for long-term tracking.

There are many choices for an absolute positioning system to partner a PDR system. To date, the emphasis has been on including WiFi radio mapping and this shows great promise with significant scope for innovation. Crucial in this context is that the advantages and disadvantages of the two systems broadly counter each other: PDR drift can be addressed using WiFi positions; map surveying is eased by crowd-sourcing from PDR handsets. This should also apply to other system pairings—for example, passive RFID systems allow users to be inexpensively tagged but need a large number of deployed readers to achieve complete coverage. Combined with a PDR system, however, complete coverage is not necessary. The readers need only supply occasional position/proximity fixes at strategic locations, with the PDR system filling in between. This eases installation and maintenance.

It seems likely we will see the emergence of hybrid systems with a variety of positioning modalities to augment PDR. Absolute position fixes will be obtained opportunistically from whatever is installed in the current building—be it WiFi, Bluetooth, GSM, RFID, or some future communications medium. The current high-level SHS-PF architecture allows for great flexibility and can be used to power such hybrid systems.

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[9]Each sensor channel is subject to bias, which is a temperature-related offset in the output.

REFERENCES

[1] J. Hightower and G. Borriello, "Location systems for ubiquitous computing," *Computer*, vol. 34, no. 8, pp. 57–66, 2001. [Online]. Available: http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=940014

[2] G. Sun, J. Chen, W. Guo, and K. Liu, "Signal processing techniques in network-aided positioning: a survey of state-of-the-art positioning designs," *IEE Signal Processing Mag.*, vol. 22, no. 4, pp. 12 – 23, july 2005.

[3] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *IEEE Trans. Syst. Man Cybern. C. Appl. Rev.*, vol. 37, no. 6, pp. 1067 –1080, nov. 2007.

[4] Y. Gu, A. Lo, and I. Niemegeers, "A survey of indoor positioning systems for wireless personal networks," *IEEE Commun. Surveys Tutorials*, vol. 11, no. 1, pp. 13 –32, quarter 2009.

[5] M. A. Ergin, K. Ramachandran, and M. Gruteser, "Understanding the effect of access point density on wireless lan performance," in *Proc. 13th annual ACM international conference on Mobile computing and networking*, ser. MobiCom '07. New York, NY, USA: ACM, 2007, pp. 350–353. [Online]. Available: http://doi.acm.org/10.1145/1287853.1287902

[6] F. Aubeck, C. Isert, and D. Gusenbauer, "Camera based step detection on mobile phones," in *Indoor Positioning and Indoor Navigation (IPIN), 2011 International Conference on*, sept. 2011, pp. 1 –7.

[7] R. Harle, S. Taherian, M. Pias, G. Coulouris, A. Hopper, J. Cameron, J. Lasenby, G. Kuntze, I. Bezodis, G. Irwin, and D. Kerwin, "Towards real-time profiling of sprints using wearable pressure sensors," *Computer Communications*, vol. 35, no. 6, pp. 650 – 660, 2012. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0140366411001265

[8] Q. Wang, X. Zhang, X. Chen, R. Chen, W. Chen, and Y. Chen, "A novel pedestrian dead reckoning algorithm using wearable EMG sensors to measure walking strides," in *2010 Ubiquitous Positioning Indoor Navigation and Location Based Service*. IEEE, Oct. 2010, pp. 1–8. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5653821

[9] Q. Ladetto, "On foot navigation : continuous step calibration using both complementary recursive prediction and adaptive Kalman filtering," *ION GPS*, vol. 2000, no. Perrin, pp. 1735–1740, 2000. [Online]. Available: http://www.ladetto.ch/LAQ/publications/ion2000_ql.pdf

[10] C. Randell, C. Djiallis, and H. Muller, "Personal position measurement using dead reckoning," *Seventh IEEE International Symposium on Wearable Computers 2003 Proceedings*, pp. 166–173, 2003. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1241408

[11] R. Stirling, J. Collin, K. Fyfe, and G. Lachapelle, "An Innovative Shoe-Mounted Pedestrian Navigation System," in *GNSS 2003 (Graz, Austria, 2225 April)*, 2003. [Online]. Available: http://www.citeulike.org/user/fish2000/article/4026900

[12] J. W. Kim and C. Park, "A Step , Stride and Heading Determination for the Pedestrian Navigation System," *Technology*, vol. 3, no. 1, pp. 273–279, 2005. [Online]. Available: http://www.scirp.org/Journal/PaperDownload.aspx?paperID=282& fileName=nav20040100034_69728139.pdf

[13] R. Jirawimut, P. Ptasinski, V. Garaj, F. Cecelja, and W. Balachandran, "A method for dead reckoning parameter correction in pedestrian navigation system," *IEEE Trans. Instrum. Meas.*, vol. 52, no. 1, pp. 209–215, 2003. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1191431

[14] J. Saarinen, J. Suomela, S. Heikkila, M. Elomaa, and A. Halme, "Personal navigation system," *2004 IEEERSJ International Conference on Intelligent Robots and Systems IROS IEEE Cat No04CH37566*, pp. 212–217, 2004. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1389354

[15] S. Godha, G. Lachapelle, and M. E. Cannon, "Integrated GPS / INS System for Pedestrian Navigation in a Signal Degraded Environment," *ION GNSS 2006 Fort Worth TX*, vol. 2006, no. September, pp. 26–29, 2006. [Online]. Available: http://plan.geomatics.ucalgary.ca/papers/06_ION_GNSS_Godha_et_al_ Session_A5.pdf

[16] M. Klepal and S. Beauregard, "A Backtracking Particle Filter for fusing building plans with PDR displacement estimates," *2008 5th Workshop on Positioning Navigation and Communication*, vol. 2008, pp. 207–212, 2008. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=4510376

[17] B. Krach and P. Roberston, "Cascaded estimation architecture for integration of foot-mounted inertial sensors," in *Position Location and Navigation Symposium 2008 IEEEION*, no. 1. IEEE, 2008, pp. 112–119. [Online]. Available: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=4570047

[18] W. Soehren and W. Hawkinson, "Prototype personal navigation system," *IEEE Aerosp. Electron. Syst. Mag.*, vol. 23, no. 4, pp. 10–18, Apr. 2008. [Online]. Available: http://ieeexplore.ieee.org/xpl/freeabs_all.jsp?arnumber=4493437

[19] A. R. Jimenez, F. Seco, C. Prieto, and J. Guevara, "A comparison of Pedestrian Dead-Reckoning algorithms using a low-cost MEMS IMU," *2009 IEEE International Symposium on Intelligent Signal Processing*, pp. 37–42, 2009. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5286542

[20] S. Beauregard, "A helmet-mounted pedestrian dead reckoning system," *Sensors Peterborough NH*, pp. 15–16, 2006. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.113.6770&rep=rep1&type=pdf

[21] O. Woodman and R. Harle, "Pedestrian localisation for indoor environments," in *Proc. 10th international conference on Ubiquitous computing*. ACM, 2008, pp. 114–123.

[22] ——, "RF-Based Initialisation for Inertial Pedestrian Tracking," *Pervasive Computing 7th International Conference Pervasive 2009 Nara Japan May 1114 2009 Proceedings*, vol. 5538, pp. 238–255, 2009. [Online]. Available: http://books.google.com/books?hl=en&lr=&id=5tbD9CcTjtkC&oi=fnd&pg=PA238&dq=RF-Based+Initialisation+for+Inertial+Pedestrian+Tracking&ots=qT4AsXjx6J&sig=sXZNZWOUhwcXIE_dH2RxlHEDPLY

[23] A. Anshul Rai, K. K. Chintalapudi, P. Venkat, and R. Sen, "Zee : Zero-effort crowdsourcing for indoor localization," in *Proc. 18th Annual International Conference on Mobile Computing and Networking (MobiCom)*, august 2012.

[24] R. Faragher, C. Sarno, and M. Newman, "Opportunistic radio slam for indoor navigation using smartphone sensors," in *Position Location and Navigation Symposium (PLANS), 2012 IEEE/ION*, april 2012, pp. 120 –128.

[25] H. Leppkoski, J. Collin, and J. Takala, "Pedestrian navigation based on inertial sensors, indoor map, and wlan signals," *J. Signal Processing Systems*, pp. 1–10, 2012. [Online]. Available: http://dx.doi.org/10.1007/s11265-012-0711-5

[26] C. T. Judd, "A Personal Dead Reckoning Module," in *ION GPS*, vol. 97, 1997, pp. 1–5. [Online]. Available: http://www1.cs.columbia.edu/ drexel/CandExam/DRM_ION97paper.pdf

[27] E. Foxlin, "Pedestrian Tracking with Shoe-Mounted Inertial Sensors," *IEEE Computer Graphics and Applications*, vol. 25, no. 6, pp. 38–46, Nov. 2005. [Online]. Available: http://dl.acm.org/citation.cfm?id=1100858.1100874

[28] S. Godha and G. Lachapelle, "Foot mounted inertial system for pedestrian navigation," *Measurement Science and Technology*, vol. 19, no. 7, p. 075202, 2008. [Online]. Available: http://stacks.iop.org/0957-0233/19/i=7/a=075202?key=crossref.62f138def5eb253e6b2e377c08aaa17e

[29] K. Frank, B. Krach, N. Catterall, and P. Robertson, "Development and Evaluation of a Combined WLAN and Inertial Indoor Pedestrian Positioning System," Sep. 2009. [Online]. Available: http://elib.dlr.de/54517/2/hybridIndoorPositioning.pdf

[30] P. Robertson, M. Angermann, B. Krach, and M. Khider, "Inertial Systems Based Joint Mapping and Positioning for Pedestrian Navigation," *Building*, pp. 2096–2107, 2009. [Online]. Available: http://elib.dlr.de/60179/1/ion_final_footSLAM2.pdf

[31] S. Superiore and S. Anna, "Dead-Reckoning Method for Personal Navigation Systems Using Kalman Filtering Techniques to Augment Inertial / Magnetic Sensing," *Advances*, no. April, pp. 251–268, 2009. [Online]. Available: http://www.intechopen.com/source/pdfs/6333/InTech-Dead_reckoning_method_for_personal_navigation_systems_using_kalman_filtering_techniques_to_augment_inertial_magnetic_sensing.pdf

[32] F. Cavallo, A. Sabatini, and V. Genovese, "A step toward GPS/INS personal navigation systems: real-time assessment of gait by foot inertial sensing," in *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2005, pp. 1187–1191. [Online]. Available: http://ieeexplore.ieee.org/xpl/freeabs_all.jsp?arnumber=1544967

[33] P. Robertson, M. Angermann, and B. Krach, "Simultaneous localization and mapping for pedestrians using only foot-mounted inertial sensors," in *Proc. 11th international conference on Ubiquitous computing - Ubicomp '09*. New York, New York, USA: ACM Press, Sep. 2009, p. 93. [Online]. Available: http://dl.acm.org/citation.cfm?id=1620545.1620560

[34] M. Kourogi and T. Kurata, "Personal positioning based on walking locomotion analysis with self-contained sensors and a

wearable camera," in *The Second IEEE and ACM International Symposium on Mixed and Augmented Reality, 2003. Proceedings.* IEEE Comput. Soc, 2003, pp. 103–112. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1240693

[35] N. Castaneda and S. Lamy-Perbal, "An improved shoe-mounted inertial navigation system," in *2010 International Conference on Indoor Positioning and Indoor Navigation*. IEEE, Sep. 2010, pp. 1–6. [Online]. Available: http://ieeexplore.ieee.org/xpl/freeabs_all.jsp?arnumber=5646858

[36] L. Ojeda and J. Borenstein, "Non-GPS navigation with the personal dead-reckoning system," *Proc. SPIE*, vol. 6561, no. 1, pp. 65 610C–65 610C–11, 2007. [Online]. Available: http://link.aip.org/link/PSISDG/v6561/i1/p65610C/s1&Agg=doi

[37] L. Fang, P. Antsaklis, L. Montestruque, M. McMickell, M. Lemmon, Y. Sun, H. Fang, I. Koutroulis, M. Haenggi, M. Xie, and X. Xie, "Design of a Wireless Assisted Pedestrian Dead Reckoning SystemThe NavMote Experience," *IEEE Trans. Instrum. Meas.*, vol. 54, no. 6, pp. 2342–2358, Dec. 2005. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1542534

[38] H. Ying, C. Silex, A. Schnitzer, S. Leonhardt, M. Schiek, S. Leonhardt, T. Falck, P. Mähönen, and R. Magjarevic, *4th International Workshop on Wearable and Implantable Body Sensor Networks (BSN 2007)*, ser. IFMBE Proceedings, S. Leonhardt, T. Falck, and P. Mähönen, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2007, vol. 13. [Online]. Available: http://www.springerlink.com/content/j6p5122528482578/

[39] P. Goyal, V. J. Ribeiro, H. Saran, and A. Kumar, "Strap-down Pedestrian Dead-Reckoning system," in *2011 International Conference on Indoor Positioning and Indoor Navigation*. IEEE, Sep. 2011, pp. 1–7. [Online]. Available: http://ieeexplore.ieee.org/xpl/freeabs_all.jsp?arnumber=6071935

[40] T. Levi, R. and Judd, "Dead reckoning navigational system using accelerometer to measure foot impacts," 1995.

[41] Harvey WeinBerg, "AN-602: Using the ADXL202 in Pedometer and Personal Navigation Applications," Analog Devices, Tech. Rep., 2002. [Online]. Available: http://www.analog.com/static/imported-files/application_notes/513772624AN602.pdf

[42] M. Dippold, "Personal dead reckoning with accelerometers," in *Third International Forum on Applied Wearable Computing IFAWC2006*. Citeseer, 2006. [Online]. Available: http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Personal+Dead+Reckoning+with+Accelerometers#0

[43] N. Wang, E. Ambikairajah, S. Redmond, B. Celler, and N. Lovell, "Classification of walking patterns on inclined surfaces from accelerometry data," in *Digital Signal Processing, 2009 16th International Conference on*, july 2009, pp. 1 –4.

[44] S. Park, "Pedestrian inertial navigation with gait phase detection assisted zero velocity updating," in *2009 4th International Conference on Autonomous Robots and Agents*. IEEE, Feb. 2000, pp. 336–341. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=4803999

[45] S. Beauregard and M. Klepal, "Indoor PDR performance enhancement using minimal map information and particle filters," in *2008 IEEE/ION Position, Location and Navigation Symposium*. IEEE, 2008, pp. 141–147. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=4570050

[46] C. Toth, D. A. Grejner-Brzezinska, and S. Moafipoor, "Pedestrian Tracking and Navigation Using Neural Networks and Fuzzy Logic," in *2007 IEEE International Symposium on Intelligent Signal Processing*. IEEE, 2007, pp. 1–6. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=4447525

[47] O. J. Woodman, "An introduction to inertial navigation," University of Cambridge COmputer Laboratory, \cite{Goyal2011}, Tech. Rep. 696, 2007. [Online]. Available: http://www.cl.cam.ac.uk/techreports/UCAM-CL-TR-696.pdf

[48] O. Woodman, "Pedestrian Localisation for Indoor Environments," Ph.D. dissertation, University of Cambridge, 2010.

[49] M. H. Afzal, V. Renaudin, and G. Lachapelle, "Assessment of indoor magnetic field anomalies using multiple magnetometers," in *ION GNSS*, no. September, 2010, pp. 21–24. [Online]. Available: http://plan.geomatics.ucalgary.ca/papers/gnss10_multiplemagnetometers_harisa_20sep10.pdf

[50] ——, "Magnetic Field based Heading Estimation for Pedestrian Navigation Environments," *Test*, no. September, pp. 21–23, 2011.

[51] J. E. Bertram and A. Ruina, "Multiple walking speed-frequency relations are predicted by constrained optimization." *J. theoretical biology*, vol. 209, no. 4, pp. 445–53, Apr. 2001. [Online]. Available: http://dx.doi.org/10.1006/jtbi.2001.2279

[52] S. Yang and Q. Li, "Ambulatory walking speed estimation under different step lengths and frequencies," in *2010 IEEE/ASME International Conference on Advanced Intelligent Mechatronics*, vol. 24, no. 17. IEEE, Jul. 2010, pp. 658–663. [Online]. Available: http://pubget.com/paper/pgtmp_b9eb4337a72a54df9fd9c76a5023be80

[53] O. Woodman and R. Harle, "Pedestrian localisation for indoor environments," in *Proc. 10th international conference on Ubiquitous computing - UbiComp '08*. New York, New York, USA: ACM Press, Sep. 2008, p. 114. [Online]. Available: http://dl.acm.org/citation.cfm?id=1409635.1409651

[54] K. Abdulrahim, C. Hide, T. Moore, and C. Hill, "Using Constraints for Shoe Mounted Indoor Pedestrian Navigation," *J. Navigation*, vol. 65, no. 01, pp. 15–28, Jan. 2012. [Online]. Available: http://journals.cambridge.org/abstract_S0373463311000518

[55] J. Hightower and G. Borriello, "Particle Filters for Location Estimation in Ubiquitous Computing : A Case Study," *Computing*, vol. vol, pp. 88–106, 2004. [Online]. Available: http://www.springerlink.com/index/uyhre47hg6junvn4.pdf

[56] B. Krach and P. Robertson, "Integration of foot-mounted inertial sensors into a Bayesian location estimation framework," *2008 5th Workshop on Positioning Navigation and Communication*, vol. 2008, no. 2, pp. 55–61, 2008. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=4510357

[57] U. Steinhoff and B. Schiele, "Dead reckoning from the pocket - an experimental study," in *Pervasive Computing and Communications (PerCom), 2010 IEEE International Conference on*, 29 2010-april 2 2010, pp. 162 –170.

[58] B. Ferris, D. Fox, and N. Lawrence, "Wifi-slam using gaussian process latent variable models," in *Proc. 20th international joint conference on Artifical intelligence*, ser. IJCAI'07. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 2007, pp. 2480–2485. [Online]. Available: http://dl.acm.org/citation.cfm?id=1625275.1625675

Robert Harle received the M.Sci. degree in Physics and the Ph.D. degree in Engineering from the University of Cambridge, UK. He is now a Lecturer in the Cambridge University Computer Laboratory and a Fellow of Downing College, Cambridge. His research interests include all forms of wired and wireless sensing, with a particular focus on indoor positioning and wearable sensors for sport and health.