Full length article

Sensor-based dead-reckoning for indoor positioning

Ian Sharp\textsuperscript{a,1}, Kegen Yu \textsuperscript{b,\ast}

\textsuperscript{a} Wireless Technologies Laboratory of the ICT Centre at CSIRO, Australia
\textsuperscript{b} School of Civil and Environmental Engineering, University of New South Wales, Sydney NSW 2052, Australia

Abstract

This paper presents a method of indoor position determination using an accelerometer, compass and gyroscope which are typically available in devices such as smartphones. The method makes use of measurements from such a device worn on the body, such as attached to a belt. The accelerometer in the device estimates the stride length indirectly from the vertical acceleration associated with walking, while the compass and gyroscope measure the heading angle. The position of the subject is then determined by combining the stride length distance estimates and the heading information, but corrected periodically at known checkpoints within the building. The method was tested with a range of both males and females wearing the device, at different walking speeds and styles. The experimental results demonstrate that the stride length estimation can be accurate to about 7 percent. The measured data agree closely with a theoretical dynamical model of walking. The results also show that the position of the subject can be determined with an accuracy of 0.6 m when walking along an indoor path.

© 2013 Elsevier B.V. All rights reserved.

1. Introduction

This paper concerns the development of a personal locator for indoor tracking. The requirement to track people inside buildings has wide applications, including security, emergency services, and medical applications in hospitals and nursing homes. The types of technologies that can be applied for indoor positioning include radiofrequency, ultrasonic, and various sensors including accelerometers, gyroscopes and magnetometers. In practice, no one technology has a clear dominance in all applications, so that a practical system may involve deploying a hybrid of two or more types of technology. In this paper the development of a sensor-based indoor position location system is described. However, the system operation requires some form of radio data communications, which could include the cellular phone network, wireless LANs (Wi-Fi), or wireless sensor networks. The particular experimentation described in this paper is based on an outdoor radio location system called Precision Location System (PLS) developed by CSIRO (see Fig. 1), which also incorporated appropriate sensors. However, the radio location function was not utilized, but the data transmission facility was used to communicate with base stations located within the test buildings.

For outdoor applications a GPS-based application is appropriate where the 10–20 m positional accuracy is adequate, but for indoor applications the accuracy required is typically of the order of 1 m. Further, GPS signal blockage into a building and the degrading of positional accuracy due to non-line-of-sight multipath propagation generally means that some other alternative methods of position determination are needed for indoor applications. One possibility due to its widespread adoption for data transmission is WiFi positioning [1–4], but the accuracy of such systems is typically in the range of 3–5 m. For better accuracy other radio location methods such as ISM band systems [5–7] and ultra-wideband (UWB) [8–11] have been shown to have an accuracy of 0.2–0.5 m. However, such systems require special equipment not commercially available, and require base stations to be located throughout the coverage area. With the advent of “smart” phones/Tablets with...
both sensors (accelerometers, gyroscopes, compass) and data communications as standard, an alternative approach is to use dead-reckoning techniques [12,13] for position determination. Dead-reckoning does not provide absolute position determination (as with the above-referenced methods), but rather provides positions relative to the starting point by integrating sensor data associated with both the heading angle and the displacement. Such methods will have errors that increase over time due to the integration of the sensor data, so that some periodic correction of the position data (using some other independent technique) is necessary. Thus while dead-reckoning methods have merit due to the availability of the necessary sensors in commonly used commercial devices, obtaining the desirable accuracy (say 1 m) requires careful attention to its implementation.

1.1. Overview of related work

There are a significant number of GPS-free walking/gait analysis systems and approaches reported in the literature especially for paraplegics or patients with specific diseases such as Parkinson or Spastic Cerebral Palsy [14–16]. Stride/gait information is inferred from inertial measurement unit (IMU) sensors (accelerators, gyroscopes, or both) which are usually attached to the feet or shoes, thighs and legs, or waist [17–20]. To minimize system complexity a number of gait analysis systems only using gyroscope sensors were proposed in [21,22]. A single uni-axial gyroscope attached on each shank can be used to detect the time of gait events and a simplified biomechanical gait model can be employed to reduce the number of sensing units for gait analysis. It is possible to use a smaller number of sensing units on certain body segments to estimate movement of other segments.

In many cases IMU sensors are integrated with other types of sensors to perform a more complicated task or multiple tasks. The built-in sensors in a smart phone can be used to map the environment and monitor user activities. These embedded sensors may include the IMU sensor, light sensor, pressure sensor, thermometers, cameras, GPS receivers, and microphones. In [23] an IMU-based pedestrian trajectory system is proposed, which consists of a stepping aware module, stride length module and walking direction module. Energy consumption is an issue since the IMU sampling is relatively energy hungry. A prototype of dead-reckoning system is reported in [13] for indoor mapping, which consists of a stride length measurement unit (SiLMU), a fiber optic gyro, a compass, and a laser scanner. The SiLMU is an ultrasound-based device which measures the distances between the ankles based on time-of-flight. The ultrasonic transmitter is placed on a foot, while the receiver is placed on the other foot. The length measurement is performed continuously at a rate of 60 Hz. In [24] a step information monitoring and sensing (SIMS) system is reported for coaching support and biomechanics research in sprinting. The system consists of two subsystems: an on-body foot-pressure sensing system and a track-side video-sensing system. The data from the sensors in these two subsystems are fused to generate stride parameters of athletes.

A number of IMU-free sensor systems have been developed or proposed for stride/gait analysis. In [25] video data from two web-cameras and depth imagery from a single Microsoft Kinect were employed to measure stride-to-stride gait variability passively in a home setting. It was intended to assess the fall risk of elderly individuals so that measures can be taken to reduce the fall rate. In [26] a model-based approach is proposed for estimating position, gait and motion parameters. A hierarchical and structural model of the human body is used. Soft kinematic constraints are introduced to supplement the motion model limited by hard kinematic constraints. These constraints are in the form of stochastic distributions obtained from various body configurations during specific activities. In [27] an optical flow sensor attached to the leg of a pedestrian is used to generate optical flow data which are a projection of the velocity and angular velocity of the leg. A dynamic motion (walking) model, termed the spring loaded inverted pendulum model, is exploited to estimate leg states and infer stride length. In [28] textile sensors were fixed on pants and socks worn by healthy subjects. These sensor embedded pants and socks are as wearable and washable as ordinary ones. The data transmission is wireless. The digital signals from these sensors can be analyzed to estimate step length, cadence, walking speed, center of pressure and center of mass trajectory.

1.2. Overview of proposed method

Many of the methods reported in the literature are related in particular to stride length measurement and have particular application areas (such as biomedical research), and typically have sensor arrangements (such as on feet) which would be impractical for general use. Thus the basis of a sensor-based dead-reckoning location system described in this paper is as follows. The sensors are required to measure displacement distance from a starting point, as well as the heading angle of the track. An absolute heading
angle can be obtained from a compass. Indoors the compass data is degraded by magnetic anomalies, but these effects can be ameliorated by using the rate-gyroscopic data to stabilize the heading data. However, determining displacement obtained from a mobile device sensor (accelerometer) is difficult. In principle, the double integration of accelerometer data will determine displacement; inertial navigation systems (INS) using this technique have long been available in applications such as aircraft navigation. However, the high accuracy requirements indoors and the low quality of the accelerometers available in mobile devices make an INS-based method impractical for tracking mobile devices indoors.

The counting of footsteps with a pedometer has long been available, but the determination of the stride length is required for position determination. One commercially available solution is the placement of an accelerometer in special shoes. In this case the integration of the raw accelerometer data can limit the errors, as on each stride the foot will be stationary when in contact with the ground. Thus the speed obtained from the integration of the accelerometer data can be effectively recalibrated (to zero) on each stride, thus minimizing the build-up of errors in the displacement obtained by integration of the calibrated speed. However, the requirement for special shoes for this method makes this method impractical in most situations other than athletics.

For a person walking the distance traveled can be estimated from the stride length and the number of strides taken. The determination of the number of strides taken is relatively simple, as vertical accelerometer data show a clear cyclical pattern associated with walking (see Fig. 3 for example). However, the determination of the stride length is more difficult. The theoretical approach of double integration of the horizontal accelerometer fails in a practical situation, as the accelerometer offsets are typically much greater than the accelerations associated with the mean movement of the body while walking, and the Earth’s gravity acceleration is difficult to accurately eliminate from the data. Thus an alternative approach is necessary.

A method of determining stride length from accelerometer data is described in an application note from Analog Devices [29], the company that manufactures the accelerometers used in the PLS equipment. This technique was the starting point for the investigations reported in this paper. Various experiments were undertaken to measure the stride length and the associated (vertical) accelerometer data. These data were analyzed to develop new algorithms with improved accuracy. Simple mathematical modeling of the walking process was also undertaken, so that the theoretical and empirical models could be compared. The design aim is to achieve a stride length estimate accurate to better than 8% for all people (both male and female), all sizes of people, and for all walking speeds. Such variability makes the determination of suitable algorithms difficult.

2. Determination of stride length

The development of mathematical models for the walking process is a difficult task. One approach is to develop a detailed bio-mechanical model of the walking process, and hence determine the stride characteristics. Because of the complexity of the human body and the motion associated with walking, this approach was not adopted, but rather an empirical approach was used. In complex problems such as determining the stride length of walking, one approach is to undertake a dimensional analysis of all the variables and parameters that could affect the stride length. This analysis allows the number of variables to be greatly reduced, so that more simple functional relationships can be observed. By performing curve fitting, simple analytical formulas can be derived from the measured data.

2.1. Dimensional analysis

Because of the complexity of walking, it is useful to initially analyze the problem using dimensional analysis. This method does not solve the problem, but gives clues on how the measured data should be analyzed to give a more generic understanding of the complex underlying physical situation. While the stride length could be affected by many parameters, the main ones (somewhat restricted by what can be measured) are as follows:

1. The (vertical) accelerometer peak-to-peak amplitude ($A_p$) during the walking process. Note that this differential measurement is not affected by the Earth’s gravity.
2. The stride rate ($R$).
3. The height of the person ($H$).

The first two variables can be directly measured from the accelerometer data, while the third parameter provides some scaling on the size of the human body, where presumably the walking style is somewhat related to the size of the body. Other parameters that may influence the stride length model include the leg length, sex, mass, age and physical fitness, but these extra parameters would probably over-complicate the model. Thus in the proposed model these secondary parameters are all summarized in one parameter, namely the height of the person.

From the above discussion, the basic problem can be summarized as finding a suitable function for the stride length ($S$)

$$ S = f(H, R, A_p). $$

(1)

The standard procedure for dimensional analysis is to assume a power function of the variables of the form

$$ S = KH^a R^b A_p^c $$

(2)

where $a$, $b$, $c$ and $K$ are constants to be determined. In this model, the parameters are only functions of length ($L$) and time ($T$). Equating the powers of these fundamental dimensions results in the following equations

$$ L: a + c = 1 $$
$$ T: -b - 2c = 0. $$

(3)

Thus there are two equations and three unknowns, so that the solution must be expressed in terms of one of the power constants. While the choice is somewhat arbitrary, the choice of $c$ has some physical merit, as will be shown.
Thus (3) can be expressed as
\[a = 1 - c\]
\[b = -2c.\]  
(4)

Using the results of (4), the stride length function becomes
\[S = KH^{-1} R^{-2} A_p^c \left[ \frac{S}{H} \right]^c = \frac{A_p}{HR^2} \mathbf{g} (N_i).\]  
(5)

The term in brackets on the right side of (5) will be referred to as the “Stride Number” \( N_i = A_p / HR^2 \), as it can be observed to be a dimensionless number, as is the normalized stride length \( \hat{S} \). A more general hypothetical function \( (g) \) for the normalized stride length would then be of the form
\[\hat{S} = g(N_i).\]  
(6)

Notice that \( N_i \) can be determined from known or measured data, and thus once the stride-length function \( g(x) \) is known, the stride length can be estimated. The dimensional analysis does not provide any information on the specific function, but rather shows how the data should be organized to achieve a universal function coupling the more basic parameters. The hope is that all types of walking for all people can be described by the one function. The actual function is determined by the analysis of actual measured data, where \( \hat{S} \) is plotted as a function of \( N_i \).

### 2.2. Simple dynamical model of walking

Before considering the measured data for determining the required stride length function, this section will develop a simple dynamical model of walking to establish a theoretical model. The model is based on a simplified walking style. During a stride it is assumed that the leg providing thrust remains straight, while the second leg is off the ground in a motion preparing for another stride. As only the leg on the ground can give any (significant) vertical thrust (there is some inertial thrust from the leg off the ground), the vertical acceleration can be based solely on the geometry of the motion of the leg touching the ground. This geometry is shown in Fig. 2, where \( L_{\text{leg}} \) is the length of the leg and \( \hat{S} \) is the stride length.

With the \( x-z \) coordinate reference at the position of the foot at the start of the step, the position of the pivot point (hip) on the body trunk is given by
\[x = -L_{\text{leg}} \sin \theta\]
\[z = L_{\text{leg}} \cos \theta.\]  
(7)

The dynamics of the pivot point will be very similar to that of the body trunk where the accelerometer is attached. Further, it is assumed that the body moves with a constant speed \( V \) during the walking process, so that
\[V = \frac{dx}{dt} = -L_{\text{leg}} \cos \theta \dot{\theta}\]
\[V_z = \frac{dz}{dt} = -L_{\text{leg}} \sin \theta \dot{\theta} = -L_{\text{leg}} \sin \theta \left[ \frac{-V}{L_{\text{leg}} \cos \theta} \right] = V \tan \theta.\]  
(8)

The vertical acceleration can be calculated by a further differentiation, resulting in
\[A_z = \frac{d^2 z}{dt^2} = V \sec^2 \theta \dot{\theta} = -\frac{V^2 \sec^3 \theta}{L_{\text{leg}}} = -\frac{S^2 R^2}{L_{\text{leg}} \cos^3 \theta}.\]  
(9)

The acceleration that can be measured most easily is the peak-to-peak acceleration during a stride. The above equations describe the acceleration after the initial impulse when the foot hits the ground. Because of the inertia of the body, this impulse is effectively lowpass filtered by the body in a manner that is difficult to analyze. However, it is known that the average long-term vertical acceleration is zero, so that to a first order of approximation the positive and negative acceleration will be the same. This effect is shown in Fig. 3 for actual measured data.

The peak acceleration will occur at the start of the stride when the angle is \( \theta = \theta_0 \). To a first order of approximation this angle can be set to the mean for men and women, with typical values being 28° for men and 25° for women (see below for more details). The exact value is not too critical as in (9) the cosine of this value is used, and thus for small angles there is not much variation. Based on the above assumptions, the differential peak-to-peak acceleration is thus given by
\[A_p = 2A_z(\theta_0) = \frac{2S^2 R^2}{L_{\text{leg}} \cos^3 \theta_0}.\]  
(10)

From the dimensional analysis it is useful to express the result in normalized form, resulting in the expression
\[\hat{S} = K \sqrt{N_i}\]
\[K = \sqrt{\frac{\alpha \cos^3 \theta_0}{2}} \quad L_{\text{leg}} = \alpha H.\]  
(11)

Thus as predicted by the dimensional analysis the (normalized) stride length is a function of the Stride Number. The parameter \( \alpha \) relating the length of the leg to the height of the person is approximately a constant equal to 0.535 for human bodies, as determined from measurements on people, and from other sources such as US MIL STD 1472D [30]. The typical value of \( K \) is calculated to be 0.431 for men and 0.455 for women. Thus to this first order of approximation the algorithm \( K \) parameter is nearly constant, independent of men and women. Notice also
that the dynamics equation is in the same form as described in Section 2.1 by (6), although the dimensional analysis has no knowledge of the particular dynamics of walking.

Although it is not of direct interest in determining the stride length, the above model can be rearranged to provide information on the stride angle of the leg. Noting that the stride angle is given by

\[ \theta = \sin^{-1} \left( \frac{S/2}{L_{\text{leg}}} \right) \]

and using (11), (12) becomes

\[ \theta = \sin^{-1} \left( \frac{K}{2\alpha N_s} \right) = \sin^{-1} \left( 0.415 \sqrt{N_s} \right). \]

Thus the stride number is directly related to the stride angle (according to the model). As will be shown in Section 3, the typical value of the stride number for “normal” walking is 1.3 for men and 1.0 for women, so that the corresponding stride angles are 28° and 25° respectively. The model derived from the measured data (see Section 3) is closely similar to the theoretical model, but the K constant is about 10% smaller, resulting in stride angles about 10% smaller.

Finally, it is observed that the determination of the stride length is equivalent to determining the walking speed, as the stride length combined with the stride rate gives the walking speed, namely

\[ V = SR = K \sqrt{H A_p}. \]

Thus the (horizontal) walking speed is solely a function of the peak vertical acceleration (with the person's height as a parameter), and is independent of the stride rate. The stride rate is difficult to measure accurately on a step-by-step basis, whereas the accelerometer peaks are easy to measure. However, the peak accelerometer readings exhibit considerable noise, as the impulse associated with the foot hitting the ground cannot be measured accurately with relatively low data sampling rates. Thus speed estimates will exhibit considerable noise, and would require some form of filtering, probably using a Kalman filter.

3. Measurements of stride length

To determine the relationship between the measured vertical acceleration, the stride length/rate and the height of the person, a series of experiments were performed on a variety of people, 8 male and 4 female. Some people were tested multiple times, but most were only tested once. The experiment consisted of the subjects walking either a straight-line path of 27 m, or a figure-8 path (see Fig. 11) at three different speeds, namely “slow”, “normal” and “fast”; the definition of these terms was left to each particular person to interpret, as the aim was to obtain test data over a variety of conditions rather than defining specific walking styles. The instructions for the walkers were to walk at a constant rate (as defined above) over the length of the track, but some speed variations can be expected. The data measured were the vertical acceleration which was processed to obtain the peak-to-peak acceleration and the stride rate. From the number of steps and the path length the average stride length and stride rate could be determined. Assuming that the subject walked at a constant rate, then the (average) stride length could be expressed as follows

\[ \bar{S} = f(H, \bar{R}, \bar{A}_p). \]

Thus for each experiment one data point of the function could be determined.

3.1. Determining the empirical models

Empirical models of stride length as a function of the stride rate and the peak-to-peak acceleration can be determined by defining an appropriate equation with the variables/parameters (height, stride rate and the peak acceleration), together with fixed parameters to be determined by least-squares fitting to the measured data. Before considering several such models, it is appropriate to examine the general characteristics of the measured data.

The first characteristic considered is the stride length as a function of the stride rate; some examples are shown in
Fig. 4. Stride length as a function of the stride rate for three different people. The stride length is defined by a function of the stride rate for each person, but each person has a different functional relationship. In particular, male and female data have different characteristics (male: upper two, female: lower). In each case the trendline model fitted to the data is a second-order polynomial.

In general the stride length increases with the stride rate, but there is some evidence that at very fast walking pace the stride length tends to decrease. The other noticeably observation from the plot is that while each person has a consistent functional relationship between the stride length and the stride rate, each person has a different functional relationship. As a result stride rate is a poor predictor of stride length, as there is no universal functional relationship, with each person having an individual style.

The second characteristic considered is the stride length as a function of the peak-to-peak acceleration. An example from the same experiments in Fig. 4 is shown in Fig. 5. The data show that the male data agree quite well with one another, but the female data exhibit a quite different characteristic. The general characteristic is that the stride length increases slowly with the peak acceleration. Thus accelerometer peak-to-peak data provides a much better estimate of stride length than does the stride rate, but there is still considerable variation from person to person. Again it is evident that there is no simple relationship between stride length and vertical acceleration, so a more complex functional relationship is required.

3.2. Dimensional analysis model

Based on the dimensional analysis the normalized stride length is expected to be a function of the stride number \( N_s \). From the analytical analysis, the proposed model is

\[ \hat{S} = KN_s^p. \]  

By fitting the measured data to this model the parameters can be determined to be \( p = 0.463 \) and \( K = 0.392 \). This model can be compared with the analytical dynamical model, where \( p = 0.5 \) and \( K = 0.43 \) for women and \( K = 0.45 \) for men. Thus the measured data agrees quite well with the dynamical model parameters despite its rather simplistic nature.

The data for all the people tested is shown plotted in Fig. 6 together with the model curve given by (16). As can be observed the data show some scatter about the least-squares fit curve, but the normalized stride length is typically within \( \pm 0.05 \) of the model estimate. Fig. 6 has 60 data points, 43 (or 72%) of which are within \( \pm 1 \sigma \); for comparison a Gaussian distribution would have 68% within this limit.

The model stride length is plotted against the actual stride length in Fig. 7. The standard deviation in the error in the stride model is 7.4 cm. Fig. 7 has 60 data points, 42 (or 70%) of which are within \( \pm 1 \sigma \).

3.3. Summary of model performances

The previous section provided several different models for estimating the stride length. This section summarizes their performances in Table 1. The Analog Devices algorithm uses only the accelerometer data and one scaling parameter, and has the worst performance of all the algorithms. The Power algorithm is similar to the Analog Devices algorithm [14], but has two parameters, the scaling parameter and the power parameter. However, the performance is only marginally superior to the Analog Devices algorithm. The algorithm based on dimensional analysis uses

\begin{table}
\centering
\begin{tabular}{|l|c|c|}
\hline
Model & RMS error (cm) & STD \( \sigma_t \) \\
\hline
Analog Devices & 8.8 & 11.5 \% \\
Power & 7.9 & 10.3 \% \\
Dimensional & 7.4 & 9.6 \% \\
General & 5.7 & 7.5 \% \\
\hline
\end{tabular}
\caption{Summary of stride length algorithms and their performances (update).}
\end{table}
The stride rate and the person’s height as well as the peak-to-peak accelerometer data. The algorithm has two parameters to fit to the measured data, and results in a modest improvement in the performance. The General algorithm is based on a general fitting of the data used in the dimensional analysis algorithm, and has four parameters to fit to the measured data in the form

$$S = KH^a R^b A_p^c$$  \hspace{1cm} (17)$$

where $K = 0.241$, $a = 1.022$, $b = -0.087$ and $c = 0.332$. The General algorithm has a significant improvement over the other three algorithms. Note that (17) should not be confused with those obtained from the dimensional analysis, which merely suggests relationships between the variables for the result to be dimensionally correct. The actual problem is more complex with more parameters which are not modeled due to the complexity of walking. However, with measured data and readily definable parameters such as the person’s height, a function suggested by the dimensional analysis (but derived from a least-squares analysis of the data) can have superior performance compared with that suggested by the dimensional analysis alone.
Fig. 7. Plot of the model stride length versus the actual stride length. The solid line is the least-squares fit straight line, and the dotted/dashed lines are is ±1σ relative to the least-square fit. The standard deviation is σ = 7.4 cm.

Fig. 8. Plot of the stride length data associated with walking a path. Notice the shorter stride length while turning corners, where the corners (dots) are defined in time by the peak gyroscope rotation rate as shown in Fig. 10.

which has no knowledge of the actual physical problem. The fact that the Eqs. (4) do not agree well with the least-squares fit parameters of (17) merely indicates that there are other parameters required for a better dimensional analysis.

An example of the estimated stride length during walking along the path in Fig. 11 is shown in Fig. 8. The data show that the typical stride length averages at about 0.8 m, but there is noticeable shorting of the stride when turning corners (Checkpoints). The nominal path is based on straight-line segments, whereas the actual path will be curved at the corners. For this test the walker (not one involved with the testing described in Section 3.2) was instructed to keep as close as possible to the nominal path, but some variation is expected; the magnitude of the path deviation (apart from turning corners) is likely to be small, so that the deviation from the total path length is estimated to be at most about 1–2 m of the entire path length.

4. Determination of heading angle

The second type of data required for position determination is the heading angle. Direct measurement of the heading angle is possible with a compass. Two magnetometers can be used to measure the earth’s magnetic field in two orthogonal directions, and by combining these data the heading angle can be estimated. However, due to
magnetic anomalies in indoor environments this method of angle determination is unreliable. Alternatively, the rate of change of heading can be independently measured using a rate-gyroscope, so that by integration the (relative) heading angle can be determined. These two angle estimates are in a sense complementary, as the compass exhibits poor short-term accuracy but is stable in the long-term, while the gyroscope data exhibit good short-term accuracy, but due to instrumentation offsets, the integrated output will become progressively inaccurate over time. One possible method of providing better heading angle estimation is by combining these two estimates of angle in a complementary filter [12], but the optimum strategy depends on the quality of the respective sensors as determined in the operating environment.

4.1. Measured data characteristics

To test the performance of the sensors the heading angle as determined from the compass and the integrated rate-gyroscope was measured in a typical indoor environment (see Fig. 11). Data from sensors in the mobile device mounted on the hip (see Fig. 1) are shown in Fig. 9, where the nominal changes in heading are 90° associated with the corridors in the building; the actual heading angle is not known, but will be similar except at the turns the angle will change more slowly. Observe that the compass data suffers from magnetic anomalies (particularly near 40 and 80 s positions), while the integrated rate-gyro data has a slow positive drift due to a small calibration offset of about 0.5°/s. Also observe that the heading data include a smaller oscillatory component associated with the swinging of the hips during walking, with each cycle associated with one left-right leg step. These oscillations can be considered as “noise”, and they do not affect the accuracy of the dead-reckoning, as the noise integrates to zero over time periods of a few seconds.

4.2. Alternative approach to heading angle determination

Apart from initializing the heading angle and the slow drift, the quality of the integrated rate-gyro data is superior to the corresponding compass data, so that an alternative method based on the gyroscope is appropriate. Assuming that the rate-gyro offset is constant (or at least slowly changing), this offset can be estimated using the compass data. Even though the compass data will have considerable errors, over a long period of time the compass drift rate will be zero. Thus by comparing the compass and raw integrated rate-gyro data (as in Fig. 9) over a long period of time (say at least one minute), the drift rate of the rate-gyroscope can be accurately estimated, and periodically updated. For example, using the data in Fig. 9 over a period of about 80 s the offset can be estimated to be $-0.56°/s$. By applying this to the raw measured rate-gyro data the drift rate can be kept close to zero, but with a small residual random error which is related to the quality of the rate-gyro hardware. For the data in Fig. 9 this residual error (compared with the nominal heading away from the turns) has a standard deviation of about $\sigma_0 = 2°$ measured over the path length. This residual error in heading will translate into positional errors, as considered in the next section. The corrected integrated gyroscope heading angle is used for the dead-reckoning position determination described in the following section.

5. Determination of position

By combining the displacement inferred from the counted number of steps, the stride length, and the heading data derived from the integrated rate-gyroscope (and
corrected using the compass), an estimate of the position as a function of time can be determined. Note that these positional data are relative to the initial starting point, but if this point is known (using radiolocation or some other technique), then the positions can be determined absolutely. This technique is referred to as “dead-reckoning”.

5.1. Basic dead-reckoning

As shown in Sections 3 and 4, a vertical accelerometer attached to the trunk of a person’s body can be used to both count the foot steps and to estimate the length of the stride to an accuracy of typically better than 8%. Further, by using both a compass and a vertical rate-gyroscope, the heading angle can be estimated to accuracy (standard deviation) of $2^\circ$ (or 0.035 rad) as explained in Section 4.2. By combining these two data sets the vector associated with each stride can be determined, and by integration the path can be determined.

The accuracy of the position fix using this dead-reckoning method can be estimated from the measured data. For the special case of a straight line segment of length $L_{seg}$, the along-track error will be associated with the stride length, and the cross-track errors will be associated with the heading angle. Thus the RMS positional error at the end of segment will be

$$\sigma_p = \sqrt{\left(\sigma_s L_{seg}\right)^2 + \left(\sigma_\theta L_{seg}\right)^2} = L_{seg} \sqrt{\sigma_s^2 + \sigma_\theta^2}. \quad (18)$$

For the above measured performance estimates the positional RMS is $\sigma_p = 0.087 L_{seg}$, where the displacement error STD ($\sigma_s$) is assumed to be 0.08 (see Table 1), and $\sigma_\theta = 0.035$. Thus the major component in the dead-reckoning positional error is associated with the stride length estimation, due to the superior quality of the rate-gyroscope data when compared with the accuracy of estimating the stride length. Thus even if the rate-gyroscope errors were zero, the positional accuracy will be little improved. The position error increases proportionally to the displacement (for both components), so that some other form of correction is required to keep the position errors within reasonable bounds. For example, using (18) if the limit of the STD of the positional error is to be (say) 1 m, the dead-reckoning position must be corrected every 12 m.

5.2. Dead-reckoning with Checkpoint feedback

A key element of the proposed indoor positioning system is the regular updating of the dead-reckoning position at “known” positions. These positions will be referred to as Checkpoints, and are used in association with a map of the coverage area of the positioning system. Note that the intended system would be based on a mobile device such as a “smart” phone or a Tablet device. Such devices would include the sensors (accelerometers, gyroscopes, and magnetometers), data communications such as Wi-Fi, and a display for showing a map and the current position or track. This configuration would allow a navigation system for the person, or the system could also be configured as a tracking device for remote monitoring on computer screens.

Checkpoints can be of several types. The simplest is merely a point on the map that can be manually indicated, either by the person using the mobile device, or an operator of a computer in the tracking system. This mode of operation could be used to initialize the dead-reckoning system, or simply update the position later. The second type of Checkpoint is at a location that can be easily recognized by the sensors, such as a corner associated with corridors. Fig. 10 shows an example of detecting a corner using the rate-gyroscope. A right/left turn can be clearly identified, and given even an approximate estimate of the current position the correct Checkpoint in the coverage area can be identified on map by the software. This identification can be aided if there are base stations (such as Wi-Fi) which can be used for range estimation to reduce the chances of incorrect identification of the Checkpoint. Another type of Checkpoint could be associated with near-field communications (NFC) points located within the building. Because of the short range of NFC, the position would typically be accurate to about a meter or so.

![Z Gyroscope](image)

**Fig. 10.** Rate-gyro data along a path. The positions at corners and the right/left turn status can be clearly identified to sub-second precision. Left turns have a large negative turn rate, and right turns a large positive turn rate. Checkpoints are assumed to be at the peaks in the turn rate. The lower amplitude oscillations are associated with hip swing.
There are two methods that the dead-reckoning could be implemented. The simplest method uses the person’s height, vertical acceleration and the stride model for estimating the displacement. At a Checkpoint the mobile position is reset to the known Checkpoint position—this method is used for the results in this paper. The advantage of this simple method is that it does not require any knowledge of the position error at the Checkpoint.

An example of the estimated path using the above-described techniques is shown in Fig. 11. The Checkpoint type used in this case is associated with the detection of 90° turns along the path. The path data are:

Nominal path length 122.6 m, Raw measured 117.1 m. Note the raw length does not include curved path at turns (under-estimates).
Mean along-track error at checkpoints: −0.85 m.
RMS track error after corrections: 0.52 m.

A more complex method involving feedback is outlined in the next section.

5.3. Improved stride length determination

Because the Checkpoint updating also provides information on the cumulated errors since the last Checkpoint, these errors can be used in a feedback loop to correct the estimates of the stride length. The decoupling of the position error associated with the stride length and the heading angle is not a simple task, as in general the path is not composed of straight lines as shown in Fig. 11. For arbitrary paths a more complex mathematical analysis is required, but is not included in this paper. The more complex algorithms have a feedback loop to calibrate the stride length algorithm for each individual user, but initially the stride length model uses a nominal person’s height. The feedback loop then adjusts the height to better match the estimated errors at each Checkpoint. A similar procedure applies for calibrating the gyroscope data. Measurements show that this calibration must be a continual process, as the walking style can change (somewhat), and people can tire rather quickly when walking continuously. As the calibration-feedback method results in more accurate position estimates, the distance between Checkpoints can be increased compared with the simple method described in Section 5.2.

5.4. Activity monitoring position determination

The location system can be further enhanced as the system can measure activity and orientation as well as position. For example, the posture of the person can be determined from the accelerometer data, so that the difference between standing still, walking, sitting and lying down can be determined. These activities can be further used to assess the position of the person. For example, if the person is stationary and orientated in the direction associated with working on a computer in a room as determined from dead-reckoning, then it can be reasonably assumed that the person is in fact at the location of the computer/desk/chair. This determined position can be used to update the dead-reckoning position in a similar manner to Checkpoints, but the method requires further information matching of the mobile device to a person, and then to a database of locations the person is commonly located at. Access to this database can be facilitated by the data communications capability of the mobile device and suitable application software.
This technique can also be used to match activities/locations for a particular person, thus providing a profile of the activities of the person, as well as the position/track of the person. This type of system can be used for a variety of applications, including monitoring of people in hazardous locations, or elderly people in their home. Any unusual activity could be used to trigger an alarm. Statistical data on activity is also a useful measure of heath, so that medical applications for the technology can be envisioned.

6. Conclusion

In this paper a method of determining the position of people in indoor situations is proposed, based on sensor data available in devices such as smart phones. While the combination of the compass and gyroscope generally provide adequate heading data, the main source of positional error was shown to be related to the measurement of the stride length. By experimentation it was shown that there is no simple relationship between the stride rate and the stride length. However, by using only the vertical accelerometer it was shown that the displacement can be measured to an accuracy of 8%, independent of the walking speed, sex, and gait type by suitable algorithms which normalize according to the person’s height. By combining this displacement data with the heading data, dead reckoning position estimation can be realized, but to achieve positional accuracy of 1 m these positional estimates need to be corrected about every 10 m of travel. Although not implemented in this paper, an enhanced version that uses feedback to calibrate the stride length algorithm is suggested, which would considerably increase the distance between dead-reckoning position updates while maintaining the positional accuracy. A suggested method using the data communications capability allows the position to be corrected at Checkpoints which can be identified by sensors in the phone. Because of the widespread use of smart phones, it is suggested that application software could be developed to allow accurate tracking of people within buildings with little or no additional infrastructure.

Acknowledgments

The authors acknowledge the contribution of members of the Wireless Technologies Laboratory of the ICT Centre at CSIRO, including developing the PLS hardware and software, and performing the experiments used in the analysis in this paper.

References


Ian Sharp is a senior consultant on wireless positioning systems. He has more than 30 years of engineering experience in radio systems. His initial involvement in positioning technology was in aviation, and later in the 1980s with the Interscan microwave landing system. In the later 1980s to the early 1990s, he was the research and development manager for the Quiktrak covert vehicle tracking system. This system is now commercially operating worldwide. From the mid-1990s to 2007, he worked at CSIRO mainly on developing experimental radio systems. He was the inventor and architect designer of CSIRO’s precision location system (PLS) for sports applications. The PLS has been successfully trialled in Australia and the US. He holds a number of patents relating to positioning technology. He is a co-author of the book: Ground-Based Wireless Positioning (Wiley and IEEE Press, 2009).

Kegen Yu received the Ph.D. degree in electrical engineering from the University of Sydney in 2003. He initially worked as an associate engineer at Jiangxi Geological and Mineral Bureau, and then was an associate lecturer and, later, lecturer in the Department of Industrial Automation at Nanchang University. Subsequently, he was a postdoctoral research fellow at the Centre for Wireless Communications, University of Oulu; a research scientist at the CSIRO ICT Centre; a research fellow in the Department of Electronic Engineering at Macquarie University; and a senior research fellow at the Australian Centre for Space Engineering Research and the School of Surveying & Geospatial Engineering, University of New South Wales (UNSW). Currently, he is a senior research associate in the School of Civil & Environmental Engineering at UNSW and an adjunct professor at Macquarie University. He is currently on the editorial boards of the EURASIP Journal on Advances in Signal Processing, IEEE Transactions on Aerospace and Electronic Systems, and IEEE Transactions on Vehicular Technology. He is the lead guest editor for a special issue of Physical Communication on “navigation and tracking” and for a special issue of the EURASIP Journal on Advances in Signal Processing on “GNSS remote sensing”. He coauthored the book Ground-Based Wireless Positioning (Wiley and IEEE Press; a Chinese version of the book is also available) and book chapters in three other books published by Wiley. He has also authored or coauthored over 30 refereed journal papers and more than 30 refereed conference papers. His current research interests include ground-based and GNSS-based positioning and GNSS remote sensing. He is a senior member of the IEEE.