A Research on internal navigation by IMU Unit

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1.INTRODUCTION

To fulfill the requirement of providing precise locations in such GPS-denied environments, new systems and techniques are required. The cost, size, weight, and power reductions made possible by using a micro-electro-mechanical systems inertial measurement unit (MEMS IMU) in an integrated navigation system allow it to be used in almost any military system where reliable navigation information is required, including the dismounted soldier. The problem of using such small inertial systems, however, lies in the magnitude of MEMS sensor errors: they are currently orders of magnitudes larger than traditional inertial sensors. Even a calibrated MEMS IMU on its own will drift away from its true position very quickly. After GPS is lost, maintaining adequate position accuracy depends critically on other aiding information.

This article describes one method in which the error growth rate of a small MEMS IMU can be considerably reduced without the addition of extra equipment (e.g., velocity and distance traveled sensors) most often used to provide such aiding information. The method relies on mounting the IMU in or on the user's boot. Since the IMU is used in a "strapdown" mode (rigidly attached to the operator) and is operated as a full inertial navigation system (INS), the trajectory of the boot is tracked at a very high updated rate (typically 100 Hz). Velocity measurements are particularly useful to bound IMU drift in inertial navigation systems and a widely used non-sensor velocity measurement is the Zero Velocity Update (ZVU). Whenever the system is stationary, its velocity relative to the Earth's surface is zero. This is effectively a three-axis velocity that can be used to form Kalman filter measurements which bound IMU error growth. In this design the boot, and thus the IMU, is stationary for a fraction of a second during each step cycle as the boot strikes the ground. By analyzing the MEMS sensors, this "stance phase" of each step can be identified. As soon as a stance is identified, a signal is sent to the Kalman filter to perform a ZVU. Because the boot trajectory is being tracked, it doesn't matter which way a step is taken, or if the user is climbing stairs. If the user is standing, continuous ZVUs are processed. If the user is running, it becomes more difficult to identify stance phases, and they are shorter in duration but occur at a higher rate.

2.STRAPDOWN INERTIAL NAVIGATION

INSs have been used in the military and in commercial aviation for decades. An INS consists of accelerometers, gyroscopes and a computer pro-cessor. The raw, incremental velocity data sensed by the accelerometers and the incremental angular orientation sensed by the gyroscopes are collected at a high rate (100 Hz typically) by the strapdown navigator algorithm ([1, 2]) running in the computer. The gyro data is mathematically integrated to provide changes in orientation of the nominally orthogonal accelerometer triad, and the data from the thus rotated accelerometers is mathematically integrated to compute a change in position of the IMU (relative to fixed inertial space). Given an initial position in some geographic coordinate frame, this change in position is used to compute the current location of the system. This computation converts a simple IMU into an INS capable of calculating a complete initially derived navigation solution.

However, errors in the accelerometer and gyro measurements are also mathematically integrated in the strapdown algorithm and produce ever increasing navigation errors. External measurements are used to limit navigation errors. Prior to the availability of GPS measurements, external velocities were used to limit velocity error growth, thus slowing the rate of position error growth. To limit INS error growth in the absence of external measurements, large and power-hungry high-quality accelerometers and gyros are used, so for a dismounted soldier a traditional INS is not at all practical.

In the 1970s, scientists began carving tiny machines out of silicon. These tiny MEMS integrate mechanical devices with related electronics, and sometimes various optical and fluidic elements. By the 1990s, MEMS devices were commonplace in a number of consumer devices, wtih MEMS accelerometers being used to detect crashes and deploy automotive airbags, for example. Their use has been rapidly expanding, and their quality has been steadily improving ever since. Of particular interest here are MEMS accelerometers and gyroscopes that are being assembled into tiny, inexpensive, and robust IMUs. While MEMS IMUs offer significant advantages over traditional units in terms of cost, size, weight, and power consumption, at present they are not able to provide accuracy even approaching that of any but the poorest of traditional sensors.

3.THE CASE FOR FOOT-MOUNTED INERTIAL NAVIGATION

We can expect many dismounted patrols to occur where GPS signals are blocked or attenuated. This might be under a forest canopy, in hilly or mountainous terrain, in and among buildings, in caves or tunnels, and so on. In a combat environment, intentional jamming and spoofing is also possible. In fact, the "platform" that is most likely to be operating in a hostile GPS environment (the dismounted soldier) is the platform least likely to have a robust navigation system.

There is significant work going on worldwide investigating various methods for robust person-al navigation. Most consist of MEMS inertial sensors, GPS, and a digital compass. Altimeters, speed sensors, cameras and image processing, radio frequency identification (RFID) readers, and other sensors have also been added. Some rely on a priori information such as maps and radio beacons. Some representative approaches can be found in [3, 4].

Many personal navigators place inertial sensors near the user's center of gravity in a waist-mounted pouch. When GPS is not available, the inertial sensors are used to detect footfalls. The system then dead reckons using step detection and prediction algorithms and compass heading. The main disadvantage of this configuration is its reliance on a priori step prediction algorithms that have to be able to detect step direction (front, back, side) and adjust step lengths as the user changes pace [5, 6].

An alternative design (e.g., [5–9]) places the IMU on or inside the user’s footwear. The primary advantage of a boot-mounted IMU comes from the trajectory of a walking foot. At each step, there is a brief period when the foot is on the ground and stationary. During this “stance” phase of the step, the IMU velocity is known (i.e., zero). In effect, these ZVUs (also known as ZUPTs or Zero Updates) act just like a three-dimensional velocity sensor. At roughly 1 s intervals, the system’s Kalman filter receives an accurate 3D velocity update. These regular, frequent ZVUs are especially valuable during GPS outages to help control IMU error growth.

Although the notion of applying ZVUs to an INS at detected stances may imply that this technique only works for relatively standard motion regimes such as walking and running forward, this is not the case. Since the strap down navigation algorithm tracks the complete motion of the foot in between ZVUs, the foot is free to take any path — up, down, backward, sideways, circular, sliding, short stride, long stride, and so on — without a significant difference in the resulting solution. The only requirement for the technique to succeed is that there be frequent short periods when the foot is not moving relative to the Earth. Studies comparing torso-mounted step prediction dead reckoning systems with foot mounted INS systems [5, 6] have shown that they perform similarly in standard motion regimes, but foot-mounted INS systems require much less tuning and generally perform better under arbitrary motions not explicitly anticipated by step prediction methods.

Figure 1:The IMU and embedded magnetometer

The use of ZVUs to control error growth in a foot-mounted INS is described in more detail in this article with the examination of a prototype system called Minimal Personal Navigator (MiPN), being developed at the Ottawa laboratories of Defense R&D Canada (DRDC). The MiPN software is based on the broader Extensible GPS Inertial MEMS (EGIM) software pack-age. The basics of the Kalman filter algorithm and the EGIM implementation have been described elsewhere (e.g., [1, 10]).

Figure 1 shows MiPN in action. A small civilian GPS receiver is mounted on the user's left shoulder; the IMU is attached to his right foot. Processing and display functions are provided by an ultra mobile PC attached to his belt. The IMU chosen for MiPN is the MicroStrain 3DMGX2. This IMU contains 3-axis gyro, accelerometer, and magnetic sensor triads. The embedded coaxial 3-axis magnetometer in the 3DM-GX2 is especially significant, as it allows the development of specialized sensor processing to allow magnetic heading updates to be used in conjunction with ZVUs to control INS error growth.

3.1 THE INTEGRATION FILTER ARCHITECTURE

A typical integration architecture is shown in Fig. 2. Accelerometer and gyro data from the foot-mounted IMU are collected and integrated at a high rate (100 Hz typically) by the strap-down navigator algorithm to compute the INS-derived position. However, any errors in the gyros and accelerometers are also integrated, resulting in large position error growths. These errors are controlled by "aiding" the INS with additional information.

When GPS data is available, the GPS derived positions are compared with the INS derived positions. The differences are fed into a 15-state loosely coupled Kalman filter (in the case of MiPN) that estimates the errors in the INS (3 position error states, 3 velocity errors, 3 attitude errors, 3 gyro bias errors, and 3 accelerometer bias errors). The mechanization of this portion of the error-state INS-GPS Kalman filter is relatively standard and not described further in this article. It has been fully documented in [10], and the method is described in numerous texts (e.g., [11]). The output of the Kalman filter is an estimate of the errors in the strapdown navigator, which is used to both compensate its output (labeled "corrected inertial data" in Fig. 2) and "reset" it, so the errors remain small to ensure that several mathematical assumptions and simplifications in the algorithms remain valid.

Of more interest in the present article is the upper portion of Fig. 2, which shows the additions that have to be made in the system to properly exploit the use of the data from the foot mounted IMU and embedded magnetic sensors to bound the INS error growth when GPS is not available. These additional algorithms are called Stance Detection (SD), Zero Velocity Update (ZVU), and Magnetic Failure Data Exclusion (MFDE). SD and MFDE are described in the following sections.

3.2 STANCE DETECTION

To properly process ZVUs, the stance phase of each step must be accurately identified in real time. Falsely detecting and processing a ZVU when the IMU is not stationary has the potential to destabilize the navigation processing. As a result, stance detection will be biased toward the minimization of false ZVU signals at the expense of missing a few true ZVUs.

It is instructive to look at some real data (collected with a MicroStrain Inertia-Link™ IMU) before describing stance detection algorithms. Figure 3 (left) shows a 5 s sample of the Z-gyro data while the operator was walking. The sensor coordinate frame was oriented roughly X back, Y down, Z right. The very repeatable, cyclic nature of the signal (with a period of about 1.2 seconds) represents the step cycle of the foot to which the IMU is attached. The flat near-zero section is the stance phase of each step.
Figure 3 (right) shows a representative sample of walking data from the Y-accelerometer. Again, the stance phase is clear to a human observer. Since the IMU is not physically level, each accelerometer senses a portion of the gravity signal, with the Y (down) accelerometer getting the largest portion.

To describe the automatic stance detection algorithms, we begin by selecting the best inertial parameter for the task. The IMU provides a triad of measurements from the accelerometers and gyros, so the technique described here makes use of vector norms, or root sum square (RSS). The norm includes motion in any direction (sensitivity does not depend on the mounting orientation or the direction of the motion), and it is a positive scalar quantity, allowing a single-tailed test criterion.

The gyro RSS values are shown on the left of Fig. 4. Again, the stance phase is clearly differentiated, but now the stance phases are identified as minima. Accelerometer RSS values are shown on the right of Fig. 4. A number of problems are apparent in trying to identify a stance using accelerometer data. Most significantly, the stance does not occur at a minimum. The accelerometers measure both the "constant" gravity vector (which is equivalent to an upward acceleration) and the accelerations due to boot dynamics. When the boot is stationary, the accelerometers measure gravity only (as evidenced by the flat sections of the plot on the right of Fig. 4). Downward acceleration of the boot tends to counteract the apparent upward acceleration caused by gravity. The effect is a reduction of the measured acceleration RSS (an accelerometer in freefall measures zero net acceleration). Thus, automatic stance detection will generally be easier with gyro data than with accelerometer data.

Stance detection algorithms take one of two general forms: fixed or adaptive. The use of fixed criteria is relatively simple and is deduced from an empirical analysis of real data such as that shown in Fig. 4 for a sufficiently large number of expected environments. For example, in MiPN, the stance detection method based on fixed criteria is as follows: if the gyro incremental angle RSS stays below a threshold of 0.005 radians for 0.06 s, a stance is declared detected. It has been found that this fixed criterion provides good stance detection sensitivity with minimal false alarms in the environments tested: walking on pavement, running on pavement, walking on snow, and walking on stairs.

Alternatively, adaptive stance detection techniques generally use some kind of moving statistical process to compute the detection criteria based on data collected in the near past. In MiPN, the adaptive stance detection works as follows. An a priori estimate based, for example, on the fixed criteria above is used as the initial criteria. When a stance

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phase is detected using the initial criteria, the mean and variance of the stance data is computed. After a certain number of data points have been collected, the stance detection threshold is updated using the computed standard deviation. After the initial

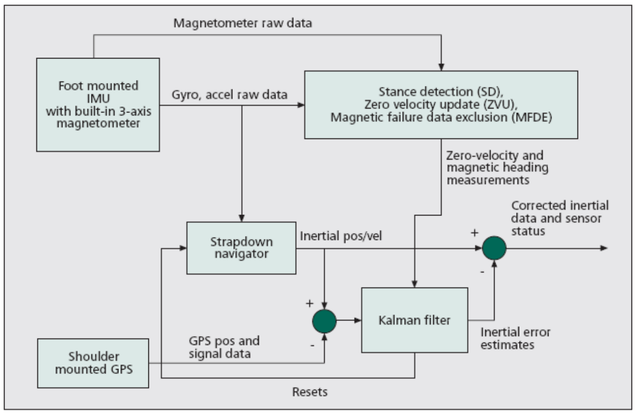

Figure 2. *MiPN integration architecture.*

recalibration, the detection criteria would continue to be adjusted. The procedure uses a moving average with overlap: as each new data point is collected, its effect is added to a running mean and variance calculation, and at the same time, the effect of the oldest data point is removed. This would reliably identify the stance phases of steps taken at different rates, with longer (walking) and shorter (running) stance phases and on different surfaces.

Its cautioned that a stance detection technique based on gyro data alone may not work well when the user is moving but not walking (e.g., on a vehicle, elevator, escalator, or moving sidewalk). Unaided, it may falsely call for ZVUs in these situations. Accelerometer data might be of some use is such situations, but only during acceleration (e.g., as the elevator starts to move or the user steps onto the escalator). These are challenging circumstances that require special techniques and are beyond the scope of this article.

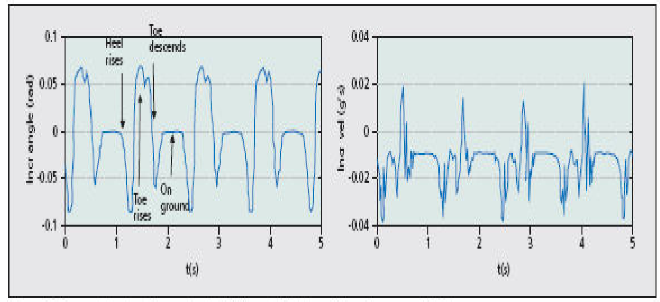

Figure 3. *Foot motion data, 5-s sample: pitch (Z) gyro (left), down (Y) accelerometer (right).*

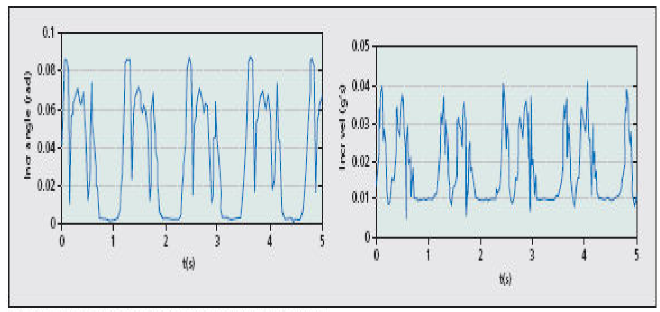

Figure 4. *RSS walking data, 5-s sample: gyros (left), accels (right).*

3.3 DIGITAL COMPASSES AND MAGNETIC FAILURE DATA EXCLUSION

A stationary INS equipped with conventional high-accuracy gyros and accelerometers can fully estimate its sensor axes' orientation based exclusively on internal information: using the direction of the gravity vector as measured by the accelerometers to find level and the direction of the Earth rotation vector measured by the gyros to find heading. While MEMS accelerometers can provide adequate tilt estimates, current MEMS gyros are not accurate or sensitive enough to detect the Earth rate and thus cannot provide initial heading: heading must be provided by external information. The most practical way of estimating heading for our personal navigator is with a magnetic compass. A modern digital compass, equipped with an orthogonal triad of magnetometers, measures the full 3D magnetic field vector. Magnetic heading can be defined as the projection of the Earth's magnetic field vector onto the horizontal plane. However, to make use of the information, we need the orientation of the magnetometers relative to horizontal; that is, we need to "level" the compass. The direction of the gravity vector (and by extension the horizontal plane) can be determined by an orthogonal triad of accelerometers, provided there are no dynamic accelerations. If the orientation of the accelerometers relative to the magnetometers is known (normally they are aligned), we have all the information we need to deter-mine magnetic heading.

In brief, the accelerometer measurements of the gravity field are used to compute the roll and pitch of the compass. To avoid large roll and pitch errors, the device must not be experiencing any dynamic accelerations. If the compass is mounted on a boot, accelerations will be zero only while the boot is stationary on the ground. Fortunately, using stance detection techniques, we know when the boot is stationary, and thus can safely compute a magnetic heading. The IMU chosen for MiPN contains orthogonal triads of gyros, accelerometers, and magnetometers. The same accelerometers used in the strapdown navigator are used to level the magnetometer measurement vector.

We have thus far assumed that the signal measured by the magnetometers is entirely made up of the Earth's field. This assumption can be justified in certain environments. However, where the MiPN is designed to operate (in urban and indoor locations), significant magnetic anomalies must be expected. These anomalies arise from magnetic materials near the magnetometers. The effects depend on the amount of magnetic material and its distance. Anomalies physically connected to the magnetometers (e.g., steel in the toe of the boot to which the IMU is attached) can be significant, but can be reduced through calibration techniques. External anomalies are much more problematic. Since the effects of external anomalies cannot be estimated, all we can do is attempt to detect them and suspend magnetic heading calculations when anomalies are detected.

It is often the case that the most difficult magnetic environments are the same as those where GPS is most likely to be disrupted. For example, upon entering certain buildings, just as GPS signals are lost, the level of magnetic anomalies increases. Figure 5 shows the effects of magnetic anomalies on the DRDC Ottawa campus. It shows measured magnetic field strength on a typical MiPN test run. It starts out-doors near a three-story building, continues past a parking lot, between some other buildings, and eventually goes indoors (at 65,600 s). Most spikes when outside are caused by buried, unseen magnetic disturbances. Away from these objects, the measured field is fairly consistent (at about 0.55 Gauss). Upon entering the building we observe a trend to lower field strengths and much higher levels of noise.

Our (conflicting) goals are to improve the heading solution of the INS with magnetic heading updates, yet protect the solution from corruption due to magnetic anomalies: we want to detect magnetic "failures." With a simple screening of the magnetic RSS values, it is easy to detect and reject certain anomalies, such as those shown by the large spikes in the outdoor portion of Fig. 5. However, inside buildings, where anomalies are more persistent, virtually all magnetic data might also be rejected. But indoors, when GPS is not available, magnetic heading measurements are most needed. Are there useful magnetic heading estimates during the indoor portion of this run? Can they be identified? Experience has shown that some-times usable magnetic headings can be calculated even in the presence of magnetic anomalies. Heading errors are dependent on the effects of the anomalies on individual elements of the measured field vector. For example, if the anomalies produce an effect that only impacts the magnetic field in the vertical direction, there will be no effect on heading. Anomalies causing horizontal deflections of the magnetic field tend to have the largest impact on heading accuracy. So, even though vertical or horizontal anomalies of equal magnitude cause equal changes in magnetic RSS, they can have very different effects on heading accuracy. These observations led to the conclu-sion that magnetic heading failure detection should not be based exclusively on magnetic RSS values.

One answer is to look at heading directly. There are two available heading estimates. The first is based exclusively on magnetometer and accelerometer measurements. This is the value used to update the Kalman filter. The second heading estimate comes from the Kalman filter. This is an optimal estimate based on all previous inertially sensed rotations (via the strap down navigator) and filter updates. The filtered heading error is expected to change slowly between compass heading measurements, at a rate deter-mined by the filter-estimated gyro biases. When a compass heading measurement is available, it is used to remove the heading drift accumulated since the previous compass update. If that compass heading has a large error because of magnetic anomalies, the filter might be reset to the incorrect heading. In a worst case, the filter might be destabilized. In MiPN, a series of tests were developed to reject, as well as possible, unreliable magnetic heading estimates while accepting any heading estimate that might improve navigation performance. These magnetic anomaly tests examine both the magnetic signal itself and the heading derived from the magnetometer measurements.

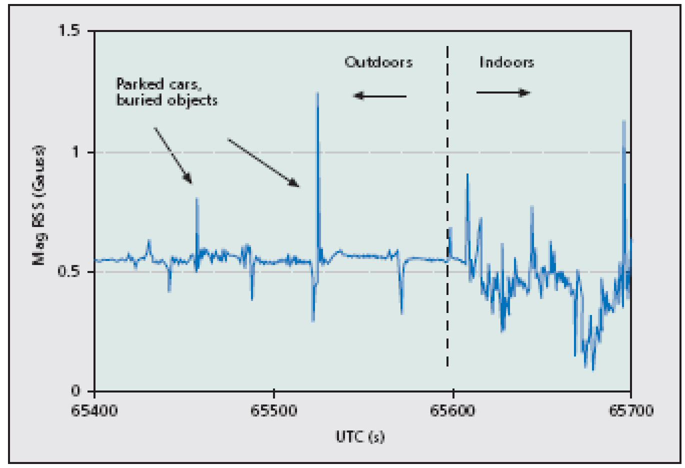

Figure 5. *Sample measured magnetic RSS, outdoors to indoors.*

3.4 These tests comparison:

- The RSS of the measured magnetic field strength vector, *F,* against a predicted value, *F* ^ (because the Earth's magnetic field changes only slowly with position): $^{33}F^{33}$ – $^{33}F^{\wedge 33}$ < ã1
- The heading derived from the magnetometers, *m,* with Kalman filter heading estimates,*f* (because gyro measurements are not affected by magnetic effects and assuming the filter heading has not been corrupted by previous bad heading measurements): ^{3}m –f^{3} < ã2
- The changes in magnetic heading, Ä*m*, and gyro-based heading, Ä*g*, between calculation epochs (magnetic anomalies degrade quickly with distance and thus their effects on a moving platform tends to change quickly, while filtered gyro heading errors are expected to change slowly with time): ^{3}Ä*m* – Ä*g* ^{3} < ã3
- The changes in the magnetic orientation, ÄÖ*m*, and gyro-based orientation, ÄÖ*g*, about the optimum axis between calculation epochs:
- $^{3}\Delta\Phi m$– $\Delta\Phi g^{3}$ < ã4

In total four parameters are tested against empirically determined thresholds, ã1 … ã4, and a magnetic heading

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is accepted only if all four tests pass. We call this technique Magnetic Failure Data Exclusion (MFDE). Tests showing the results of MFDE are shown in the next section.

4.TEST RESULTS

Figure 6 shows the track results from a typical indoor test run processed in four different ways. GPS is lost (actually, MiPN starts rejecting erratic GPS position measurements) just as the user enters the building in the lower right. The approximate true path is shown in yellow. The blue track represents inertial navigation without any ZVUs or magnetic heading updates. The unaided strapdown inertial solution rapidly drifts from the true position and becomes useless. The green track shows inertial navigation with ZVUs but no magnetic heading. The benefits of ZVU updates on each detected footfall are significant,

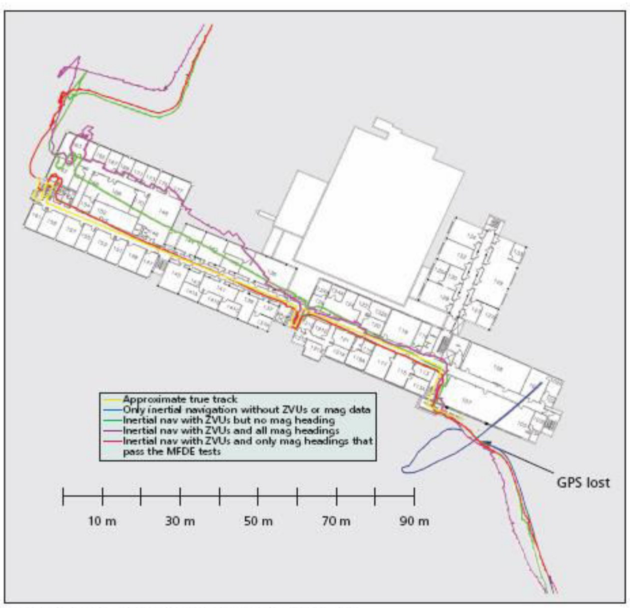

Figure 6. MiPN track improvement with different techniques.

yet there is still a residual heading bias we wish to compensate for with magnetic heading. The purple track shows inertial navigation with ZVUs and all magnetic headings used. Initially the track is improved, but undetected magnetic anomalies about midway through the building corrupt the solution significantly. The red is the fully compensated result — inertial navigation with ZVUs and with only those magnetic headings that pass the MFDE tests allowed to update the solution. The resulting track stays within about 2 m of the true track throughout the entire in-building run.

5.CONCLUSION

For the soldier environment, size, weight, and power consumption are the highest priorities, so for the article at hand, the primary motivation was to use only a minimal set of the smallest sensors available and exploit the available data to the fullest extent to provide an acceptable level of performance. This is an efficient technology. Developing a robust, accurate, inexpensive, small, lightweight, and unobtrusive navigation system for use by a dismounted soldier (or any user on foot) in GPS denied environments is a huge challenge that is seeing a very broad number of approaches pursued in the research and development community.The solution described uses one small foot-mounted MEMS IMU/magnetometer device and one GPS antenna/receiver unit, integrated with some proven traditional algorithms (strapdown inertial navigation, Kalman filter error modeling, zero velocity updates) and some relatively newer ideas (stance detection, magnetic data exclusion techniques). The key to this is the foot mounting arrangement and the benefits this provides to a strapdown navigator, with the formation of velocity measurements at every footfall with no additional hardware. Although there is consider-able debate around mounting devices to a soldier's boot, at present this may be the price to pay for those who want an indoor navigation system that weighs nothing, costs nothing, and consumes no power, but works without error.

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