Integrated GPS/INS System for Pedestrian Navigation in a Signal Degraded Environment

S. Godha, G. Lachapelle, and M. E. Cannon
Positioning Location and Navigation Group (PLAN)
Department of Geomatics Engineering, Schulich School of Engineering
University of Calgary, Calgary, Alberta, Canada

BIOGRAPHIES

Mr. Saurabh Godha is a Research Engineer in the PLAN Group and he holds an MSc from the Department of Geomatics Engineering, at the University of Calgary. He completed his B.Tech in Civil Engineering from the Indian Institute of Technology (IIT), Bombay. His current research is focused on integrated IMU/GPS navigation systems for pedestrian and vehicular navigation.

Dr. Gérard Lachapelle is a Professor of Geomatics Engineering at the University of Calgary where he is responsible for teaching and research related to location, positioning, and navigation. He has been involved with GPS developments and applications since 1980. He has held a Canada Research Chair/iCORE Chair in wireless location since 2001 and heads the PLAN Group at the University of Calgary.

Dr. Elizabeth Cannon is Professor of Geomatics Engineering and Dean of the Schulich School of Engineering at the University of Calgary. She has worked extensively in various GPS related areas and on the integration of GPS and INS for precise aircraft positioning. Dr. Cannon is a Past President of the Institute of Navigation and the recipient of the 2001 Kepler Award.

See http://PLAN.geomatics.ucalgary.ca for details.

ABSTRACT

This paper evaluates the performance of a shoe/foot mounted inertial system for pedestrian navigation application. Two different grades of inertial sensors are used, namely a medium cost tactical grade Honeywell HG1700 inertial measurement unit (IMU) and a low-cost MEMS-based Crista IMU (Cloud Cap Technology). The inertial sensors are used in two different ways for computing the navigation solution. The first method is a conventional integration algorithm where IMU measurements are processed through a set of mechanization equation to compute a six degree-of-freedom (DOF) navigation solution. Such a system is referred to as an Inertial Navigation System (INS). The integration of this system with GPS is performed using a tightly coupled integration scheme. Since the sensor is placed on the foot, the designed integrated system exploits the small period for which foot comes to rest at each step (stance-phase of the gait cycle) and uses Zero Velocity Update (ZUPT) to keep the INS errors bounded in the absence of GPS. An algorithm for detecting the stance-phase using the pattern of three-dimensional acceleration is discussed. In the second method, the navigation solutions is computed using the fact that a pedestrian takes one step at a time, and thus positions can be computed by propagating the step-length in the direction of pedestrian motion. This algorithm is termed as pedestrian dead-reckoning (PDR) algorithm. The IMU measurement in this algorithm is used to detect the step, estimate the step-length, and determine the heading for solution propagation. Different algorithms for stride-length estimation and step-detection are discussed in this paper. The PDR system is also integrated with GPS through a tightly coupled integration scheme. The performance of both the systems is evaluated through field tests conducted in challenging GPS environments using both inertial sensors. The specific focus is on the system performance under long GPS outages of duration upto 30 minutes.

INTRODUCTION

A pedestrian navigation system (PNS) is a subject of great interest today for applications that require ability to track and locate personnel, for example safety-of-life applications and commercial applications. From safety applications view point, a PNS helps military personal to navigate through forest areas and deep canopies, and help finding and rescuing the fire-fighting crews. From recreational and commercial point of view, it helps user to navigate through unfamiliar urban areas, to find the shortest route to a particular destination and to access location-based services (LBS). All these features and services ultimately lead to a safer transportation and able management of time, energy and resources. One of the most important components required to get a location of a specific person is a positioning technology.

The issue of positioning might appear fairly easy to resolve given technologies like Global Positioning System (GPS), which has now been fully operational for more than ten years. However, a closer look into this
technology reveals its limitations from a personal positioning perspective. A PNS typically has to operate in areas where GPS signals are either blocked or severely degraded (such as urban areas, forest areas and indoors), which limits its capability to maintain continuity of positioning. Having said that, technological advancements have now made it feasible to track GPS signals under degraded signal environments, using long pre-detection integration (PIT) times, for instance high-sensitivity GPS (HSGPS) receivers, and assistance from external sources, i.e. assisted GPS (AGPS) (Karunanayake et al 2004). However, the reliability and accuracy of such techniques is questionable (Mezentsev 2005). Therefore, to enable continuity in personal navigation and to ensure navigation when the subject moves indoors, integration of GPS with other complementary self-contained navigation sensors, such as inertial measurement unit (IMU), is necessary. Thus, the specific objective of this work is to develop and test a PNS based on the use of a GPS that operates with a high level of availability in urban areas, in conjunction with an IMU.

Two independent systems are designed. The first system uses a low-cost MEMS-based IMU in conjunction with a GPS receiver. While a MEMS IMU forms an attractive low-cost option for the system design for widespread use in consumer applications, its ability to deliver the required accuracy and reliability for high-end safety applications, specifically under unfavorable GPS conditions, is limited (e.g. Kubrak et al 2005, Kasameyer et al 2005, Jirawimut et al 2005, Lachapelle et al 2006). Keeping that in mind, another system is designed, which uses a medium-cost tactical grade IMU along with GPS. The rationale behind development of such system is the steady growth in the MEMS technology which is expected to deliver low cost MEMS IMUs with accuracies comparable to tactical grade IMUs, in near future. The aim is to see the kind of performance that can be expected, given the superior quality of sensors.

While the quality of sensor is undoubtedly a deciding factor for the performance of the system, its placement on the user’s body is another important factor. Different placement of the sensor, such as on user’s shoulder, belt and shoe enables different complementary navigation constraints/algorithms that reduce system sensitivity to sensor errors, thereby enhancing its navigation capability. The algorithm development and performance test results in dense urban canyons with sensor placed on user’s shoulder are presented in Lachapelle et al (2006). This paper focuses on system design with sensor placed on shoe/foot (see Figure 1). Foot placement, although less convenient, is advantageous in the sense that inertial system can be reset every time the foot strikes on the ground. The ultimate anticipated advantage of this is the seamless extension of the systems navigation capability to the indoor environments.

Two different methods of integrating GPS and IMU together are investigated. The first method involves the use of conventional GPS/INS (inertial navigation system) integration algorithms whereby the output of an IMU is integrated to obtain the navigation solution, coupled with frequent updates from GPS (Farrell & Barth 2000, El-Shemy 2004). Both GPS and INS sensors are integrated at the measurement level (i.e. tight coupling) using an Extended Kalman Filter (EKF), in an effort to achieve best positioning results in areas with restricted GPS coverage. To prevent INS error accumulations in the occasional absence of GPS, Zero Velocity Updates (ZUPT) are provided to the system, which is every time the foot strikes the ground. This can significantly extend the ability of inertial system to keep accuracies within bounds for longer periods.

The second method of integrating GPS and IMU for PNS makes use of the fact that the user takes one step at a time, and thus propagates the step-length in the direction of motion (in a local level frame). This method of obtaining navigation solution is called pedestrian dead-reckoning (PDR). The algorithm involves three components, namely determination of the heading of the pedestrian through gyro signal, detection of the step through accelerometer signal, and the estimation of the step-length through updates from GPS (when available) or through the magnitude of accelerometer signal (Ladetto 2000, Kim et al 2004, Mezentsev 2005, Shin et al 2005, Lachapelle et al 2006). The algorithm makes use of GPS updates to calibrate PDR parameters (e.g. step-length and heading) and then bridge the navigation solution using the estimated parameters in the absence of GPS. Most of the currently developed PDR algorithms use GPS position to update the PDR parameters, i.e. GPS and PDR are integrated using a loosely coupled integration mode (e.g. Kim et al 2004, Mezentsev 2005). In this paper tight coupling of GPS and PDR is investigated, whereby GPS pseudorange measurements are used for updating the PDR parameters. The apparent advantage of this method of integration lies during partial GPS availability (e.g. Lachapelle et al 2006), where a tightly coupled system can provide superior updates to the integrated system.

Both algorithms have certain advantages and disadvantages. The biggest advantage of INS algorithm is that it can efficiently track the different modes of walking, for instance walking forward, backward, side-stepping or any other non-standard pedestrian motion, without any
need for extra modeling. Furthermore, it can easily be configured to adapt to different modes of transportation, for instance if a PNS user travels in a vehicle. This is helpful since a user typically combines different modes of walking and transportation in order to reach to a particular destination. However, the disadvantage is that in the absence of aiding source (GPS or ZUPTs) it experiences third order growth in position errors with time which degrades the PNS navigation performance. PDR algorithm on other hand experiences error growth which is a function of distance traveled or steps taken (Mezentsev 2005, Lachapelle et al 2003), but is applicable only to walking mode, where it needs extra modeling to adapt to different kinds of walking scenario. If the user travels in a vehicle, a PDR algorithm cannot be used to generate a navigation solution. The aim of this paper is to demonstrate the performance level that can be achieved using both the algorithms when the person is walking with IMUs mounted on the foot/shoe.

The GPS receiver being used in this study is a High Sensitivity GPS (HSGPS) and a conventional GPS receiver. A HSGPS receiver uses longer pre-detection integration time (PIT) and data wipe-off methods, to track degraded power GPS signals, which a conventional receiver fails to track. Higher number of satellites tracked by HSGPS, is clearly an advantage for navigation solution computations; however, reliability monitoring of these measurements need to be efficient, since HSGPS is susceptible to high measurement noise and multipath (Mezentsev 2005). The IMUs used includes MEMS-based Crista units from Cloud Cap Technology and a tactical grade Honeywell HG1700 unit. The IMUs are shown in Figure 2 and their physical and technical characteristics are listed in Table 1. The Crista IMU is very small in size and weighs only 37 gm (Crista- Interface/Operation Document 2005), and thus can easily be mounted on shoe. This sensor thus forms an easy attachment system and provides no or little hindrance to natural gait pattern. However, the same cannot be said for HG1700 IMU, which is rather a bulky system (refer to Table 1).

The emphasis of this paper is on (1) the performance of the designed systems under long GPS outages to represent the system performance in indoor environments where GPS signals are usually not available; and (2) the performance in signal degraded environment which primarily features a blend of frequent complete and partial GPS outages. The results are presented in terms of position accuracy, and navigation solution continuity and availability using different methods.

### Table 1: Characteristics of Each IMU (Petovello 2003, Crista- Interface/Operation Document 2005)

<table>
<thead>
<tr>
<th>IMU</th>
<th>HG1700</th>
<th>Crista</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Grade</strong></td>
<td>Tactical</td>
<td>Automotive</td>
</tr>
<tr>
<td><strong>Physical Characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size (cm)</td>
<td>19.3 x 16.0 x 10</td>
<td>5.2 x 3.9 x 2.5</td>
</tr>
<tr>
<td>Weight (gm)</td>
<td>3600</td>
<td>37</td>
</tr>
<tr>
<td><strong>Accelerometers</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>In Run Bias (mg)</td>
<td>1</td>
<td>2.5</td>
</tr>
<tr>
<td>Turn On Bias (mg)</td>
<td>-</td>
<td>30</td>
</tr>
<tr>
<td>Scale Factor (PPM)</td>
<td>300</td>
<td>10000</td>
</tr>
<tr>
<td>Velocity Random Walk (g/√Hz)</td>
<td>2.16e-006</td>
<td>370e-006**</td>
</tr>
<tr>
<td><strong>Gyros</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>In Run Bias (°/hr)</td>
<td>1</td>
<td>&lt;1040</td>
</tr>
<tr>
<td>Turn On Bias (°/hr)</td>
<td>-</td>
<td>5400</td>
</tr>
<tr>
<td>Scale Factor (PPM)</td>
<td>150</td>
<td>10000</td>
</tr>
<tr>
<td>Angle Random Walk (°/hr /√Hz)</td>
<td>7.5**</td>
<td>226.8**</td>
</tr>
<tr>
<td>Cost</td>
<td>&gt;$20000</td>
<td>&lt;$2000***</td>
</tr>
</tbody>
</table>

* With Enclosures
** Obtained from Static Testing in Lab
*** In single quantity

The paper continues with accelerometer signal analysis when sensor is placed on foot, followed by discussion of GPS/INS, stance-phase detection, GPS/PDR, step detection and step-length estimation algorithms. Then the results are presented for both systems under different operating conditions. Conclusions are then drawn from the test results and analyses.

### GAIT CYCLE AND ACCELEROMETER SIGNAL

This section analyzes the accelerometer signal, and correlates it with the gait cycle. In general, a gait cycle can be divided into four phases (Willemsen et al 1990, Chai 2004, Sterling 2005), namely: (1) Push-off – heel off the ground and toe on the ground; (2) Swing – both heel and toe off the ground; (3) Heel Strike – heel on the ground and toe off the ground; and (4) Foot stance phase – heel and toe on the ground at rest. When the sensor is placed on the shoe, the signature of the signal demonstrates specific repeatability corresponding to each gait phase (as shown in Figure 3).

As can be noted from Figure 3, the signature of the accelerometer signal features a sudden spike during the push-off phase. Such spikes facilitate detection of the beginning of the user’s step for the PDR algorithm. The next phase is the swing phase, during which the
acceleration increases gradually and then falls back right before the heel-strike phase. The acceleration pattern during this phase can be used effectively to determine the type of step (forward/backward). The heel-strike phase features another spike which helps to determine the end-time of a stride. The last phase is the stance-phase during which the foot is at rest and thus acceleration becomes constant and remains around gravity. The stance-phase, and therefore the periods when Zero Velocity Updates (ZUPTs) can be provided to the system (for INS algorithm), can be determined easily using this constant acceleration pattern. Figure 4 shows the percentage of gait cycle that corresponds to each phase, under normal walking. As can be noted, the stance-phase typically corresponds to about 25% of a gait cycle. Assuming a cycle time of 1-1.2 s (for an adult walking at normal speed), the amount of time the sensor is at rest is about 0.25-0.30 s, which is deemed sufficient to reset the INS.

GPS/INS INTEGRATION

In the INS algorithm approach, a set of mechanization equations is used to convert the raw IMU measurements into useful position, velocity and attitude information (Savage 2000). In the context of this work, the mechanization is implemented in the Earth-Centered Earth-Fixed (ECEF) frame. The INS mechanization is a two step process (El-Sheimy 2004). In the first step, the body sensed angular rates are integrated to compute the transformation matrix (rotation matrix) from IMU body-frame to ECEF-frame. A gyro senses the angular rates due to Earth rotation and the rotation due to user motion. To get the actual user angular velocity, the Earth rotation rate should be transformed into the body frame, and removed from the measured angular rates. Once the angular rate is obtained, a transformation matrix is computed using a quaternion approach (Savage 2000, Farrell and Barth 2001). In the second step, the computed transformation matrix is used to rotate the accelerometer sensed measurements from the IMU body-frame to the ECEF-frame. The output of an accelerometer represents the sum of actual user acceleration, Coriolis acceleration and gravity. The sensed acceleration information must therefore be compensated for Coriolis acceleration and gravity in order to determine the total acceleration of the user. This acceleration is integrated to obtain the velocity and position solutions. This procedure can be written in mathematical terms as follows (El-Sheimy 2004):

\[
\begin{bmatrix}
\dot{r'} \\
\dot{v'} \\
\dot{R'_e}
\end{bmatrix} =
\begin{bmatrix}
\dot{r'} \\
\dot{v'} \\
\dot{R'_e}
\end{bmatrix}
- 2\Omega_{e_i} \times \dot{v'} + \gamma'
= R'_e (\Omega_{e_i} + \Omega_{b_e})
\]  

Equation (1) processes the raw measurements obtained from the INS without accounting for their inherent errors. To correct for these errors, an INS filter (Kalman filter) is set-up which estimate the errors in the INS output, using measurement updates from GPS (or ZUPTs if a stance phase is detected). GPS updates are provided in differential mode, whereby single-differenced pseudo-range measurements are used as measurement update for the INS filter. This method of integrating GPS and INS is referred to as tightly coupled integration strategy, and is explained graphically in Figure 5. For a detailed discussion of the design of the system and measurement model for the INS filter, refer to Godha (2006).

Stance Phase Detection

The stance phase in a gait cycle is detected using the 3D acceleration signal. It is basically a pattern classification problem, where the pattern being looked is the case when the magnitude of the 3D acceleration sensed by accelerometers is close to the gravity (see Figure 3). The

---

Figure 3: Accelerometer Signal and Gait Phases

Figure 4: Gait Cycle (adapted from Chai (2004))

Figure 5: Tightly Coupled Integration Strategy
method implemented in this paper identifies this pattern based on magnitude of the accelerometer signal and the moving acceleration variance over the 'n' samples. The value of n is taken as 3, which is obtained empirically through signal analysis. If the acceleration magnitude and computed moving variance is within the predefined threshold values, the stance-phase is declared and ZUPTs can be performed. Further to prevent any faulty ZUPT to the system another condition that maintains a minimum time window between the detected step and the time for next ZUPT is used. Figure 6 shows the accelerometer signal and variance pattern and the detected ZUPTs using this algorithm.

Figure 6: Accelerometer moving variance and detected steps and ZUPTs

The use of frequent ZUPTs in the INS filter not only helps to limit the growth of the velocity errors (by resetting them to zero), but also helps in estimation of several attitude and inertial sensor errors. The velocity error dynamics equation in Local Level frame (LLF) can be written as (El-Sheimy 2004):

\[
\begin{bmatrix}
\dot{\delta x}^u \\
\dot{\delta y}^u \\
\dot{\delta z}^u
\end{bmatrix} = 
\begin{bmatrix}
0 & f^u & -f^w \\
-f^u & 0 & -f^e \\
f^w & f^e & 0
\end{bmatrix}
\begin{bmatrix}
\delta \psi \\
\delta \theta \\
\delta \phi
\end{bmatrix} + 
\begin{bmatrix}
\delta \phi^u \\
\delta \theta^u \\
\delta \psi^u
\end{bmatrix}
\]  

(2)

where, ‘dot’ represent the time derivative, \(\delta \phi^u\) denotes the velocity errors in LLF, f is the specific force in LLF, \(\delta \phi\) is the pitch error, \(\delta \theta\) is the roll errors, \(\delta \psi\) is the heading errors and \(\delta \phi^u\) is the accelerometer sensor errors in LLF.

It can be noted from Equation (2) that the errors in north and east velocities are related to errors in pitch and roll, respectively, through specific force in up directions, which is typically close to gravity (9.8 m/s²). Consequently, a strong coupling exists between the tilt estimation and the horizontal velocities, and thus, any dynamical change in estimation of one over time will show on the other. This means that accurate estimation of velocity error states through ZUPTs not only improves the accuracy of velocity estimation, but also the accuracy of computed roll and pitch angles (and the subsequent x and y gyro biases). However, the heading errors (and the subsequent z gyro bias) are poorly observable through these measurements. Heading errors can primarily be estimated when system/person is moving (since those are related to velocity errors through horizontal acceleration). Since ZUPTs essentially are the measurements derived when the system is at rest, it does not help much to improve their estimation. Thus, heading error is the primary error contributing factor in the INS/ZUPTs integrated system, and aiding from GPS or other sources such as a magnetometer is required to control this error.

**GPS/PDR INTEGRATION**

The PDR algorithm makes use of the pedestrian dynamics to provide the navigation solution. The algorithm involves three phases (Mezentsev 2005): (1) Detect a step (using the accelerometer signal); (2) Estimate the step-length; and (3) Estimate heading (using the gyro signal). Once the heading and step-length parameters are obtained, the navigation solution is then propagated as:

\[
E_{k+1} = E_k \pm S_{k, k+1} \sin \psi_k \\
N_{k+1} = N_k \pm S_{k, k+1} \cos \psi_k
\]

(3)

where the subscript k denotes the parameter value at time \(t_k\), E is the east position coordinate, N is the north position coordinate, S is the step-length, and \(\psi\) is the heading. As can be noted from Equation (3), the PDR algorithm is implemented in a Local-Level Frame (LLF). Also, it can be noted that the accuracy of PDR prediction depends directly on the accuracy of the step-length and the heading estimation (Mezentsev et al 2005). One important limitations of this algorithm is that, it does not provide the information about the user’s position in the vertical direction. Yet, the height information is important for many PNS applications such as navigation in multi-floor buildings. To obtain height information, external auxiliary sensors such as a barometer, is typically used (e.g. Lachapelle et al 2003, Kubrak et al 2005).

**Step Detection**

Different approaches can be used to detect a step based on accelerometer signal, including the approaches based on analysis of magnitude of signal, signal crossing the gravity value and signal variance based approaches. Here, an approach similar to stance-phase detection method is used for identification of the steps. The moving accelerometer variance over ‘n’ samples is computed, which is then checked periodically against a certain threshold variance \(\text{thres}(V)\). When the computed variance crosses the threshold value, a step is declared. For this particular case, the n is taken as 30 samples (this however is a function of sensor sample rate; here a fixed 100 Hz is will be used in all data collections). Figure 7 shows the pattern generated by the moving variance and the instants when steps are detected. Once a step is declared, the algorithm detects the type of step, i.e. forward or backward step, by analyzing the slope of the forward acceleration signal (see Figure 8). Depending on
the type of step, the PDR mechanization is adjusted accordingly to facilitate the accurate position prediction. Table 2 demonstrates the accuracy of this method of step-detection.

![Figure 7: Steps Detected](image1)

**Figure 7: Steps Detected**

![Figure 8: Acceleration Profile of Forward and Backward Step](image2)

**Figure 8: Acceleration Profile of Forward and Backward Step**

Table 2: Accuracy of Step Detection

<table>
<thead>
<tr>
<th>Test No.</th>
<th>Actual Steps</th>
<th>Detected Steps</th>
<th>Percentage Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>138</td>
<td>138</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>113</td>
<td>113</td>
<td>-</td>
</tr>
<tr>
<td>3</td>
<td>200</td>
<td>201</td>
<td>0.5 %</td>
</tr>
<tr>
<td>4</td>
<td>174</td>
<td>174</td>
<td>-</td>
</tr>
<tr>
<td>5</td>
<td>166</td>
<td>166</td>
<td>-</td>
</tr>
<tr>
<td>6</td>
<td>104</td>
<td>104</td>
<td>-</td>
</tr>
<tr>
<td>7</td>
<td>100</td>
<td>100</td>
<td>-</td>
</tr>
</tbody>
</table>

**Stride Length Estimation**

The distance between the point of initial contact of one foot and the point of initial contact of the ‘opposite’ foot is called step-length (Thompson 2002). However, when sensor is attached on foot, ‘stride-length’ is rather a more generic term to use, which is defined as distance between successive points of initial contact of the ‘same’ foot (see Figure 9) (ibid). Right and left stride lengths are normally equal. In this study, two different approaches are used for stride-length computations.

The first approach derives the stride-length using GPS measurements, whereby the stride-length is modeled as random walk process as part of the estimation filter. This approach works effectively for navigation purpose as long as GPS is available (complete/partial). When GPS outage is encountered, the system fixes the stride-length to the last computed value for the period GPS is unavailable.

\[ S_{r+1} = S_i + w_s; \quad w_s \sim N(0, \sigma_s) \quad (4) \]

The second approach uses the INS to compute the stride length. Since frequent ZUPTs are provided to the INS, the velocity estimates obtained from INS are very accurate. Thus, the stride length can be computed by fractional integration of this velocity during the stride period. The stride length computation begins with the detection of step, whereby the velocities are integrated over short time periods (typically of 0.05 seconds) until the end of stride is detected. This approach of stride-length determination is tested to be very effective and the total distance propagated is often seen to be within 1-2 % of the actual distance traveled, as shown in the Table 3.

![Figure 9: Gait Model Illustrating Stride-Length (adapted from Miyazaki (1997))](image3)

**Table 3: MEMS INS Estimated Stride-Length/Distance Error**

<table>
<thead>
<tr>
<th>No.</th>
<th>Approx Actual Distance (m)</th>
<th>Mean Stride Length (m)**</th>
<th>Estimated Mean Stride-Length (m)**</th>
<th>Estimated Distance (m)</th>
<th>Distance Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>77.98</td>
<td>1.77</td>
<td>1.72</td>
<td>76.03</td>
<td>2.5</td>
</tr>
<tr>
<td>2</td>
<td>77.98</td>
<td>1.28</td>
<td>1.29</td>
<td>77.91</td>
<td>0.1</td>
</tr>
<tr>
<td>3</td>
<td>77.98</td>
<td>1.30</td>
<td>1.30</td>
<td>77.07</td>
<td>1.1</td>
</tr>
<tr>
<td>4</td>
<td>233.94</td>
<td>1.34</td>
<td>1.33</td>
<td>232.85</td>
<td>0.5</td>
</tr>
<tr>
<td>5</td>
<td>233.94</td>
<td>1.41</td>
<td>1.39</td>
<td>230.51</td>
<td>1.3</td>
</tr>
</tbody>
</table>

*Computed by dividing total distance by total actual steps
**Computed using INS velocities

**PROCESSING SOFTWARE**

The GPS/INS integration software used herein is described by Godha (2006). This software was further extended herein to incorporate the PDR algorithm. It computes three different navigation solutions simultaneously, namely (1) the GPS-only solution, (2) the GPS/INS solution, and (3) the GPS/PDR solution. The GPS/INS and GPS/PDR systems are implemented using both a loosely and a tightly coupled integration strategy; however, the results presented in this paper deals with tight coupling only. Both GPS/INS and GPS/PDR
systems run in parallel, whereby the GPS/PDR system takes the heading input (and the GPS receiver clock offset) from the GPS/INS system. The GPS/PDR system works well for both when the sensor is placed on shoulder (results presented in Lachapelle et al (2006)) and when it is placed on the foot. The detailed implementation design is shown in Figure 10.

**Figure 10: PDR and INS Implementation in Software**

**TEST SET UP I**

A test was conducted at the CCIT building of the University of Calgary on July 27th 2006. The inertial data was collected using a tactical grade HG1700 IMU and a MEMS-based Crista IMU. The Crista IMU was mounted on top of the HG1700 IMU and then both sensors are attached to the user’s feet with the help of a foot mounting system built specifically for this purpose. Both sensors collected data at 100 Hz rate. The GPS data was logged using three different GPS receivers, namely NovAtel OEM4 receiver, SiRF Star III HSGPS receiver and u-blox HSGPS receiver. The technical characteristics of each receiver are listed in Table 4. The OEM4 receiver provides low noise code, Doppler and carrier phase measurements and thus is used for generating the reference solution for the analysis presented herein. The u-blox receiver data was used to generate the performance testing results of the designed system. All the three receivers were connected to one GPS antenna via signal splitter, which was then attached to backpack system on the user’s shoulder. GPS data rate was set as 1 Hz for all the three receivers. The base station was set up at the PLAN group antenna network on the roof of the CCIT building which are equipped with geodetic quality antennas.

**Table 4: Technical Characteristics of GPS Receivers**

<table>
<thead>
<tr>
<th></th>
<th>OEM4</th>
<th>Star III</th>
<th>u-blox</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channels</td>
<td>24, L1/L2</td>
<td>12, L1</td>
<td>16, L1</td>
</tr>
<tr>
<td>Tracking Sensitivity (dBW)</td>
<td>-171</td>
<td>-189</td>
<td>-188</td>
</tr>
<tr>
<td>Data Rate (Hz)</td>
<td>1-20</td>
<td>1-10</td>
<td>1-4</td>
</tr>
</tbody>
</table>

Data collection run began with the initialization period of about 5 minutes outside the CCIT building, and then the user walked for about 37 minutes in and out of the CCIT building as shown in Figure 12. Figure 12 also shows the satellite visibility with u-blox receiver over the trajectory. The area around CCIT building is a relatively open area (see Figure 11) with parking lots in north and west of the building and an open field towards the east. The user started walking in parking lot in region A, and traveled through region B and C before coming back to the start point. The GPS satellite visibility was relatively good during this period with only sporadic partial outages noticed in north-west corner of the region A and C, and also in the region B while returning to the start point (see Figure 12). Then the user entered the CCIT building from the front door (to the first floor), where he walked to the end of the corridor and then returned and came out of the same door (region D). The total duration of this walk inside the building was about 257 seconds, and the trajectory is distinguished by the red line in the Figure 12. The user then walked through region E and entered the basement of the CCIT building from the back door. The GPS availability was slightly degraded before entering the CCIT building through region E because of presence of buildings on both the sides of the walkway to the door. Inside the building the user walked in the CCIT corridor (basement) and then returned to go towards the Engineering building, eventually to exit through the back door of Engineering building (region F). The duration of this walk inside the building was about 181 s and is shown by brown color in Figure 12. Then the user walked through the parking lot (region G) towards the start point, which marked the end of the test.

The overall test duration, including the initialization period was about 42 minutes, whereby about 1025 steps were taken amounting to the total distance of around 1.4 km. The distance to the base station during the period remained under 150 m, thus virtually eliminating the effects of the baseline dependent residual differential GPS errors. Only INS algorithm results are shown for this particular data set.
The reference solution for the error analysis of the designed system is generated through the tight integration of geodetic grade NovAtel OEM4 receiver with HG1700 IMU. The data was smoothed in the end using a Rauch-Tung-Streible (RTS) smoother. When the user is walking outside the building, the accuracy of this solution is bounded by GPS accuracies. The combination of these two equipments in open area conditions was earlier shown to provide accuracies on the order of few decimeters (e.g. Godha (2006)). The accuracy of the solution inside the building can be judged by comparing the computed solution to CCIT indoor surveyed points, which are accurate to few centimeters level. The survey points are mostly on the corner of the walls in the CCIT corridor as shown in Figure 13 (points 250, 251 and 253). The proximity of the computed solution to these points (see Figure 14) gives an indication of the accuracy of the solution.

Furthermore, accuracy can be judged by the filter estimated errors in the solution, which is shown in Figure 15. As can be seen, maximum error is only a little over 1.1 m with an overall RMS value of 0.45 m. Thus, the overall accuracy of the computed reference solution is judged to be at the meter level.

**GPS Only Results**

This section quantifies the quality of the solution obtained from the u-blox receiver. The results were obtained, using two different estimation algorithms: (1) Least Square (LSQ) and (2) Extended Kalman Filter (EKF). The obtained results are shown in Figure 16. As can be seen, the GPS-only solution obtained using EKF (red line) is accurate to meter level, but is available only for 79% of the time. Several periods of drift in the solution can be noted, which represents the periods when less than four GPS satellites were visible. The EKF predicts the solution during this period based on the last computed velocity estimates, leading to a drift. With LSQ the errors are around 1.4 m, whereby the solution was available for only 66 % of the time. Figure 17 shows the horizontal dilution of precision. As can be noted, when the user is walking outside, the HDOP remained under 3 for majority of the time, apart from brief periods when it reached up to 10. Overall, the GPS-only measurements/solution when available is fairly accurate and will be used to reset the INS periodically.
GPS/INS Integration Results

Two different processing cases are considered with each IMU (HG1700 and Crista IMU). The first case evaluates the accuracy of the u-blox receiver integrated with both IMUs, when GPS satellite visibility is the same as shown in Figure 12. In the second case, complete GPS outages of varying durations (2-30 minutes) are simulated in order to determine the long-term prediction capabilities of the designed systems in the absence of GPS.

HG1700 IMU Results

Figure 18 shows the results obtained when no GPS outage was simulated, while Figure 19 shows the zoomed version of a specific portion of the trajectory.

As can be seen from the figures, that the system performed quite well when moving outside (of building), which was actually expected since GPS was available. The INS (aided by frequent ZUPTs) bridged the partial outages noticed in regions A, B, and C, without any apparent error accumulation. However, when the user walked inside the building (where GPS was unavailable), small error accumulation was noticed which were driven primarily by the errors in the heading estimation. As stated earlier, the heading errors are poorly observable through ZUPT measurements. However, since HG1700 IMU consists of a high quality Ring Laser gyros (1˚/hr) the heading errors did not grow very fast leading to errors on the order of only 3-3.5 m after about 3-4 minutes of prediction (refer to Figure 19). The overall horizontal RMS error over the trajectory is seen to be about 1.1 m, with a maximum value of 3.3 m. This maximum error was seen at the end of the 257 seconds walk inside the building (where GPS was not available).

To demonstrate the long term prediction capability of the designed system, several complete outages of durations 2, 4, 8, 10, 15, 20 and 30 minutes were simulated over the trajectory. Figure 20 shows the trajectory obtained when three 10 minutes GPS outages were simulated.

As visible from Figure 20, the integrated system performed quite well and remained closely aligned with the reference solution during the outage periods. Performance was usually good in the beginning of the outage, but due to continuous error accumulation (heading) trajectory got slightly skewed with respect to actual trajectory. However, the horizontal position errors remained under 8 m (see Table 5), which is significant given that the GPS outage lasted for about 10 minutes. The overall RMS position error during the outage was about 5 m. This performance is primarily attributed to the frequent ZUPT measurements which prevented the velocity errors from growing. After 10 minutes of prediction, the velocity error was confined to a maximum...
value of 18 cm/s (2D). Thus, the accumulated errors are mainly because of incorrect direction of velocity propagation due to the errors in heading estimation.

Figure 21 shows the maximum horizontal position errors over different outage durations. The green dots show the maximum error at the end of individual simulated outages while the red dot shows the RMS value of these maximum errors. Table 5 summarizes the horizontal position error statistics for different outage durations. The first row in Table 5 lists the value corresponding to the red dot in Figure 21. The second row lists the horizontal RMS error computed ‘over’ the outage duration.

As can be noted, after 30 minutes of GPS outage, the maximum horizontal error (or the track closure error) is seen to be around 23 m. This error corresponds to about 1.8% of the total distance (1300 m) traveled during the outage, while a position drift rate of about 1.2 cm/s or 45 m/hr. The RMS position error over the 30 minute outage duration is seen to be about 13 m.

Table 6 summarizes the attitude error statistics for 30 minute outage period while Figure 22 shows the heading error growth over the outage duration. As expected, the errors in roll and pitch are confined to few arc-seconds because of frequent ZUPTs; however, the heading error grew to about 5.5° with an RMS value of 1.5°.

As visible from the trajectory, the performance is good when the user is walking outside (since GPS was available), but it degraded when the user entered in the building (green line in Figure 22). As in the case of HG1700 IMU results, the primary error source is the heading error accumulation, but the effect in this case is more pronounced because of large sensor errors in gyros contained in the Crista IMU. The gyros in the Crista IMU feature large sensor noise and in-run bias instability of about 1040 °/hr (refer to Table 1). Since these errors are not accounted properly by the ZUPT measurements, the heading errors accumulated fast. After 257 seconds of prediction, the horizontal position error reached about 18.1 m. The shape of the trajectory is somewhat preserved but the trajectory is skewed which is essentially the effect of gradual accumulation of the heading error. Similar results were seen when the user entered the building second time, which lasted for about 181 s. The overall RMS error over the trajectory was seen to be about 3.2 m. This error level is still reasonable given the quality of
inertial sensor used and GPS availability (more than four satellites were visible only for about 65% of the time).

To get a statistical assessment of long term prediction capability of the MEMS IMU based system, GPS outages of duration 2, 4, 8, 10, 15, 20 and 30 minutes were simulated over the same period as in the case of HG1700 IMU. The computed position errors are shown in Figure 24 and the error statistics is summarized in Table 7.

![Figure 24: Crista IMU: Horizontal Position Errors over Varying Outage Durations](image)

<table>
<thead>
<tr>
<th>Outage Duration (Minutes)</th>
<th>2</th>
<th>4</th>
<th>8</th>
<th>10</th>
<th>15</th>
<th>20</th>
<th>30</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max.</td>
<td>6.9</td>
<td>11.7</td>
<td>21.5</td>
<td>31.2</td>
<td>42.2</td>
<td>54.1</td>
<td>63.2</td>
</tr>
<tr>
<td>RMS</td>
<td>2.9</td>
<td>6.6</td>
<td>12.4</td>
<td>16.5</td>
<td>19.1</td>
<td>21.4</td>
<td>25.9</td>
</tr>
</tbody>
</table>

As can be noted, the results are much degraded relative to HG1700 IMU, which is not surprising given the difference in the quality/cost of both the sensors (refer to Table 1). The heading errors grew rapidly to about 58.1° for the outage duration of 30 minutes (see Table 8), causing a position drift to about 63 m, with an RMS value of 26 m. This error level is about three times degraded relative to HG1700 IMU, and corresponds to drift rate of about 3.5 cm/s. However, clearly the performance can be improved significantly by providing external heading aiding, perhaps from a magnetometer. Such aiding not only helps to prevent heading from diverging, but also helps in estimation of gyro biases, which helps to improve performance when the aiding source is unreliable. The addition of magnetometer will be the subject of our future investigations.

![Table 8: Heading Error after 30 Minutes GPS Outage](image)

<table>
<thead>
<tr>
<th>Heading Errors</th>
<th>Max.</th>
<th>RMS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>58.1°</td>
<td>20.4°</td>
</tr>
</tbody>
</table>

TEST SETUP II

The results shown in the previous sections are representative of the system performance when the user walks in a relatively open environment for some time (1-3 minutes) and then moves inside a building for duration of up to 30 minutes (since no GPS was made available). However, dense urban and forest areas mainly feature partial outage conditions. To see how the MEMS IMU based system perform under such environment a test was conducted at Edworthy Park in Calgary, Canada. This area was chosen since it features dense foliage environments, with lines of trees on both side of the walkway, which causes significant signal blockage and attenuation (see Figure 25). The test was conducted with the Crista IMU mounted on the shoe, while HG1700 IMU was kept in the backpack system (on the shoulder) to provide the reference solution. GPS data was again collected with NovAtel OEM4, SiRF Star III and u-blox receiver. Unfortunately, the u-blox receiver did not logged data properly because of the loose cable, so the results presented in this section are generated through integration of MEMS-based Crista IMU with OEM4 receiver using both INS and the PDR algorithm.

![Figure 25: Test Area](image)

The duration of the test run was about 18 minutes, whereby the user took about 660 steps and walked a total distance of about 900 m (approximately). Figure 26 shows the reference trajectory (smoothed solution from tightly coupled OEM4/HG1700 integrated system) and the satellite visibility seen over the trajectory (with OEM4 receiver). As can be noted, satellite visibility is quite poor, with fewer than four satellites visible for about 61% of the time. GPS satellites were not visible at all for about 9% of the total test duration.

![Figure 26: Trajectory and Satellite Visibility](image)
Figure 27 shows the trajectories obtained through tightly coupled GPS/INS and tightly coupled GPS/PDR integrated systems, and Table 9 lists the corresponding error statistics.

As can be noted, the results from both the GPS/INS and GPS/PDR systems are similar. Both systems bridged the partial and complete outages quite well, without any significant error accumulation. The trajectories remained fairly closely aligned with the reference trajectory, with only small deviations visible at different portions of the trajectory. The RMS position errors of GPS/INS and GPS/PDR system are on the order of 3 m, while maximum errors seen are 12.0 and 14.1 m, respectively.

The results from both the algorithms seem similar, because the heading solution for the PDR algorithm is derived from the INS. So, any error caused by heading estimation in INS estimate, will show in PDR estimate as well. However, it should be noted that heading can easily be computed separately for the PDR, but since it was available from INS in the software, a separate algorithm was not implemented. The primary difference in the two solutions lies in the fact that, in INS the accelerometer measurements are used to compute the velocities (for solution propagation) while in PDR algorithm, the stride-lengths (for distance propagation) are entirely based on GPS measurements (and is independent of INS). As discussed earlier, the stride lengths for the PDR algorithm are computed using two different ways. One is using GPS, as part of the estimation filter, and other through fractional integration of velocity computed by INS. The results shown in Figure 27 are obtained using the GPS estimated stride-lengths only, and INS estimated stride-lengths were not used in position computation through PDR. The fact that the obtained PDR solution is similar to the INS solution indicates that the system (tightly coupled GPS/PDR) was able to estimate the stride-lengths quite well through GPS, which is available only partially for majority of the time. Figure 28 shows the computed stride-lengths using both the methods.

As can be noted from Figure 27 that, the GPS estimated stride-lengths is very similar to the one obtained from the INS. The GPS stride-length estimate was initialized with the value zero, and it converged to the correct value within few seconds, even though the satellite visibility was poor in the beginning (refer to Figure 26). Although, some problematic areas can also be noted, for instance between step numbers 380 to 480, where the estimate seems to be unreliable in the light of the consistent stride lengths provided by the INS.

The obvious limitation of using GPS alone for stride-length estimation is that, during the complete outages, the stride-length is fixed to the last computed value. However, since the complete outage durations were small in the selected test run and since the user traveled with fairly consistent stride-lengths, the effect of this error is not clearly visible in Figure 27. If the outage duration is long, this can introduce large errors into the PDR solution. This issue can be addressed by modeling the stride-lengths as a function of mean acceleration measured during a stride and frequency of walking, e.g. Gabaglio and Merminod (1999), Leppäkoski (2002) and Shin et al (2005). Figure 29 show the computed mean acceleration during a stride, cadence and stride-times. The shown stride time corresponds to the period for which the foot was moving (including push-off, swing, and heel strike phase).
From comparison of Figure 28 and Figure 29, a correlation can be noticed between the mean acceleration, cadence and the INS estimated stride-lengths. Thus, stride-lengths can be defined as a function of acceleration, and cadence, where the function parameters can be estimated using GPS, when available. In turn when GPS is not available, the system can compute the stride-lengths using the estimated parameters, and the system acceleration and cadence.

Having said that, it can be noted from the Figure 27 and Table 5 that the PDR algorithm does not offer any specific advantages over the INS algorithm in terms of accuracies for the ‘sensor-on-foot’ system. The errors in INS are efficiently controlled by ZUPTs which eliminates the problem of third-order error growth with time. Thus, it is preferable to use INS algorithm for navigation solution computation for the ‘sensor-on-foot’ system, given its added advantages in terms of the flexibility, adaptability and ability to provide six degree-of-freedom (DOF) navigation solution.

CONCLUSIONS

This paper evaluated the performance of foot mounted inertial system, integrated with GPS. Two different inertial sensors were used, a tactical grade HG1700 IMU and a MEMS based Crista IMU. The inertial measurements were used in two different algorithms to compute the navigation solution, namely the INS and the PDR algorithm. In the INS algorithm, frequent ZUPTs were used to keep the INS velocity and position errors bounded. For the PDR algorithm, different methods of step-length computations were discussed.

To evaluate the performance of INS based system, a test was conducted in a relatively open area. Long term prediction capability of the system was evaluated by simulating GPS outages of varying durations, of upto 30 minutes. For 30 minutes of independent navigation, the HG1700 IMU and the MEMS-based IMU based INS/ZUPTs integrated system is seen to provide accuracies better than 23 m and 63 m, respectively. The primary source of error accumulation for both the sensor system is seen to be heading error accumulation, since heading errors are poorly observable through ZUPT measurements. So, to constrain the heading errors aiding from external source, such as from a magnetometer, is required.

To see the designed system performance under sporadic GPS conditions, a test was conducted in dense foliage environments using the Crista IMU. Results were generated using both INS and PDR algorithm, where both were seen to perform significantly well. The PDR algorithm is not seen to provide any specific advantages over INS algorithm in terms of navigation accuracies, and thus INS is the optimal algorithm to use for sensor-on-foot system because of its specific advantages.

Future research will focus on improving the accuracy of the heading estimate, through offline IMU calibration and through use of external magnetometer sensors. The use of external barometric sensor will also be explored to strengthen the INS vertical component. The research will also continue with PDR algorithm, specifically for the case of shoulder/waist mounted inertial sensors. The systems performance will be evaluated under variety of operating conditions, including dense urban and forest areas, using different conventional and high-sensitivity GPS receivers.

ACKNOWLEDGEMENTS

The author would like to thank Dr. Walid Abdel-Hamid and Mr. Sidney P. Kwakkel for their help in field test runs, and AUTO21 Networks of Centres of Excellence (NCE) and Informatics Circle of Research Excellence (iCORE) for providing the financial support for this research.

REFERENCES

El-Sheimy, N. (2004) Inertial techniques and INS/DGPS Integration, ENGO 623- Course Notes, Department of Geomatics Engineering, University of Calgary, Canada


