Everywhere Navigation

Integrated Solutions on Consumer Mobile Devices

The promise of micro-electro-mechanical system (MEMS) technology has teased the GPS community for several years. Recent integration of MEMS with GPS and Wi-Fi demonstrates new urban and indoor positioning capabilities. This article explores these cutting edge technologies and the appropriate filter solutions, while considering consumer costs and benefits for navigation applications in challenging RF environments.

Wikimedia Commons

NASER EL-SHEIMY AND CHRIS GOODALL
TRUSTED POSITIONING INC.

Consumer demand for positioning information is currently being met by a plethora of wireless positioning technologies. The most popular consumer positioning technology, GNSS, is only one option along with several methods that use cellular networks to provide location, such as wireless local area networks (WLANs), wireless personal area networks (WPANs), radio frequency identification (RFID) tags, and ultrawideband (UWB) communications.

Although GNSS, WLAN (e.g., Wi-Fi), and WPAN (e.g., Bluetooth) have become common technologies, their navigation performance does not yet enable ubiquitous navigation systems. Wireless systems provide absolute positioning information, but when signal reception is unreliable or becomes inaccurate due to multipath, interference, or signal blockage, backup systems are needed.

Inertial sensors have been used in many high-end military, industrial, survey and enterprise machine guidance systems for several decades, and especially within INS/GPS systems using fiber-optic gyroscope (FOG) or ring laser gyroscope (RLG) technology. These systems are extremely accurate and reliable, but their cost, size, and power requirements exclude them from the personal navigation market, which has turned to wireless positioning technologies.

Wireless positioning technologies can make use of received signal strength (RSS), time of flight (TOF), and angle of arrival (AOA) to calculate a location using one of four common geometric arrangements. TOF, including both time of arrival and time difference of arrival, and AOA use multiple points of signal transmission to find a target location.

Examples of such methods include cell tower trilateration and Wi-Fi positioning from router access points. If a single terminal can perform both direction finding and distance measurement then it can be used by itself to determine the location of a target, which is the fourth method.

The location estimate of these wireless techniques typically depends on the measurement of the time of flight (TOF) between a transmitter and receiver, or through use of the received signal strength (RSS). RSS accuracy is usually worse than that of TOF due to interference and multipath created by local environments, especially indoors or in urban environments. TOF methods can be more accurate, but they require additional hardware for timing and synchronization between a transmitter and a receiver.

Simplistic methods place the location of the target at the location of the nearest terminal; so, the accuracy of these methods depends on the proximity of the target to the terminal. These methods are often a first step towards a more complex TOF or RSS calculation of the location.

Regardless of the wireless positioning method, all of these techniques suffer from local interference, multipath, or time synchronization errors. Urban and indoor environments further challenge the utility of these wireless methods due to inaccurate TOF or RSS measurements.

The line-of-sight problem has plagued navigators for hundreds of years, from clouds blocking their view of the stars to buildings blocking a direct path for satellite signals. The age-old remedy has been the augmentation of the primary navigation technology by integrating other sensors to help determine the navigation solution in such scenarios.

MEMS Sensor Constraints

Wireless positioning methods are crucial in any consumer navigation system, but when the wireless methods cannot operate or when the wireless system accuracy is very poor, other complementary sensors are used to aid in the solution.

Motion sensors, such as accelerometers and gyroscopes, are capable of tracking relative position, velocity, and orientation changes with respect to a previous position, velocity and orientation — a technique generally known as dead reckoning. The accumulation, or integration, of the relative motions over time allows the navigation solution to be extended from a previous known position.

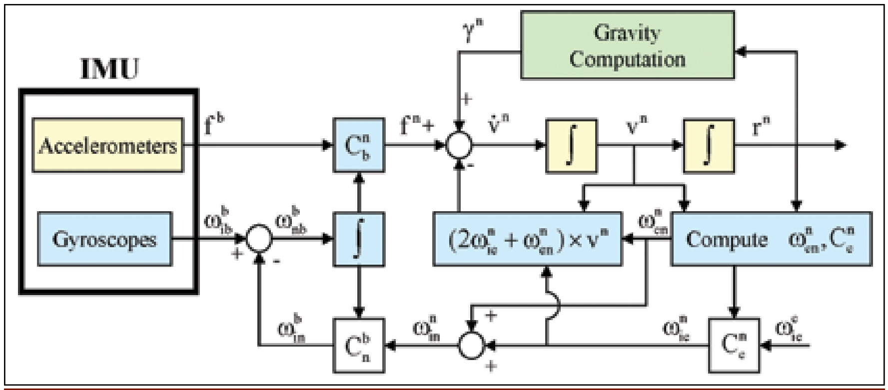

FIGURE 1 INS mechanization in the local level frame (after E. H. Shin, 2005)

Three accelerometers and three gyroscopes comprise an inertial measurement unit (IMU). An IMU is capable of extending position estimates beyond wireless positioning capabilities and can also provide orientation estimates. In fact, one of the first mainstream consumer applications, interactive games on handheld devices use these low-cost motion sensors to provide feedback to the gamer via the screen, as part of the game.

Currently, all commercial low-cost inertial sensors use MEMS, which have been investigated for navigation purposes by many researchers. Mechanization is a common method of integrating the specific forces and angular rates output from MEMS IMU's. Mechanization transforms these measurements through calculations to a coordinate frame of reference, such as a local level frame or navigation frame. A typical mechanization architecture is shown in **Figure 1**.

MEMS are challenging when used in a conventional mechanization because of their large errors, extreme stochastic variances and quickly changing error characteristics. **Equation 1** relates several inertial error parameters to accumulated position error in the horizontal plane, as a function of time. The inertial parameters include mechanization and filter prediction without absolute GNSS updates, over a period of time represented by Δt.

$$\delta p(t) = \delta p(t_0) + \delta v(t_0)\Delta t + \delta b_a(t_0)\frac{\Delta t^2}{2} + \delta b_g(t_0) g\frac{\Delta t^3}{6} + \delta\theta_{r,p}(t_0) g\frac{\Delta t^2}{2} + \ldots \qquad (1)$$

$$\ldots + \delta\theta_A(t_0) V\Delta t + \delta_{SFa}(t_0)\frac{\Delta t^2}{2} + \delta_{SFg}(t_0) g\frac{\Delta t^3}{6}$$

The terms in this equation are defined as:

- $\delta p(t)$ the positional error drift after time t
- $\delta p(t_0)$ the initial position error at the start of the GNSS signal outage
- $\delta v(t_0)$ the initial velocity error at the start of the GNSS signal outage
- Δt the time difference between the start of the GNSS signal outage and the current time
- $\delta b_a(t_0)$ the accelerometer offset bias at the beginning of the GNSS signal outage
- $\delta b_g(t_0)$ the gyroscope offset bias at the beginning of the GNSS signal outage
- g the local gravity constant
- $\delta q_{r,p}(t_0)$ the non-orthogonality error due to roll or pitch errors at the beginning of the GNSS signal outage
- $\delta q_A(t_0)$ the non-orthogonality error due to azimuth errors at the beginning of the GNSS signal outage
- V the average velocity during the GNSS signal outage
- $\delta_{SFa}(t_0)$ the accelerometer scale factor error at the beginning of the GNSS signal outage in specific force [m/s^2]
- $\delta_{SFg}(t_0)$ the gyroscope scale factor error at the beginning of the GNSS signal outage [rad/s]

Equation 1 indicates that residual gyroscope errors create the largest positional drifts with respect to time, because they are multiplied by the cube of the GNSS signal outage interval.

To provide some insight, a typical consumer-grade MEMS gyroscope bias error of 0.01 degrees per second, induces a position drift error of 62 meters during a one-minute interval without GNSS updates. Equation 1 assumes that the gyroscope bias error is fixed and unchanging throughout the outage; however, this is not always the case, especially for longer GNSS signal outages.

Many MEMS inertial gyroscopes have in-run bias stabilities in the range of 0.003 to 0.03 degrees per second. Without absolute updates to estimate the gyroscope bias changes, the gyroscope bias errors could quickly drift and dominate the position error contribution.

Several numerical methods have been developed to constrain the rapid accumulation of biases during filter prediction. Some methods constrain the platform motion, which is often vehicular or walking for consumer applications. Other methods include nonlinear estimation of the errors to provide better accuracy and less accumulation over time. The advantage of the nonlinear techniques is best seen during GNSS signal outages of several minutes or more.

Detection of static periods and application of zero velocity updates can constrain the error growth during periods of no motion. If both accelerometers and gyroscopes are used to detect static periods, such as described in the paper by I. Skog listed in the Additional Resources section near the end of this article, then heading constraints, such as zero integrated heading response, can also be applied during static period.

When a platform is moving, other constraints can be applied, such as nonholonomic constraints (NHCs). NHCs limit the velocity in the lateral and vertical directions and can be used for both pedestrian and vehicular applications. NHCs must be applied with care, due to their strength, or standard deviation, which should adjust adaptively based on the dynamics and alignment accuracy of the device frame to the platform frame, as well as the mode of conveyance.

The NHC is simply a zero velocity update along the lateral and vertical axes of the platform:

$$\left.\begin{array}{l} v_y^b \approx 0 \\ v_z^b \approx 0 \end{array}\right\} \qquad (2)$$

where
b = device frame
y = lateral component of the velocity
z = vertical component of the velocity

The velocity has to be converted into the platform frame to apply NHCs; so, the alignment of the device frame to the platform frame is very important.

Pedestrian dead reckoning (PDR) is

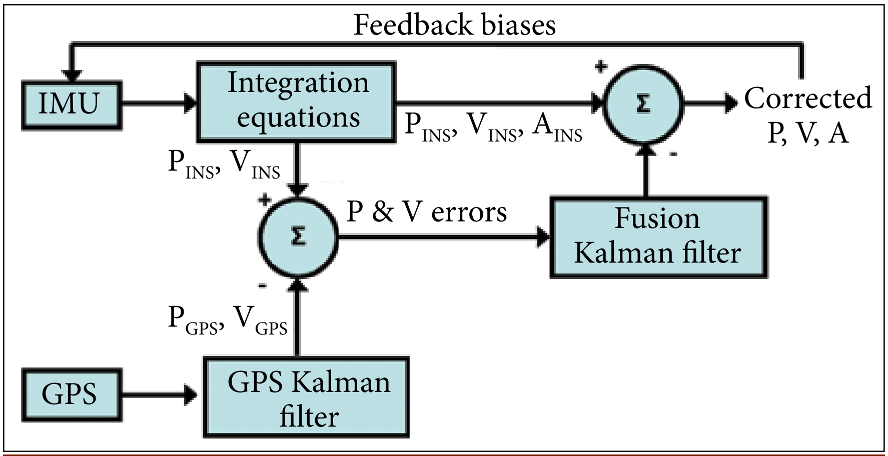

FIGURE 2 **Loosely coupled architecture**

also commonly used to obtain or constrain position when the mode of conveyance is detected as walking. PDR is used to approximate horizontal movement of a person by detecting steps, estimating stride length, and approximating the distance moved based on a heading estimate from an attitude and heading reference system (AHRS) that typically comes from the mechanization of the inertial measurements. PDR relies on knowledge of the platform heading, which could differ from that of the device; so, care has to be taken when applying these updates or constraints.

Other sensors, such as magnetometers and barometers, may also be used to constrain the inertial solution drift during prediction. Properly calibrated magnetometers can constrain the heading drift within several degrees, but they are subject to distortion caused by magnetic effects. Calibration for hard-iron effects is a challenging problem on its own, and magnetometers also face short-term soft-iron effects that can temporarily cause the magnetometer to output entirely wrong readings.

Hard-iron distortions stem from permanent magnets or magnetized material on the compass platform. Consequently, these effects remain the same and in a fixed location relative to the compass regardless of orientation. Hard iron effects are often very apparent within vehicles, and their effect has to be removed before a magnetometer can be used for navigation in such an environment. Soft-iron distortions reflect the effects of the Earth's magnetic field on any magnetically soft material surrounding the compass.

Filtering techniques do exist that can use the magnetometer and gyroscope readings to detect and reject erroneous readings, if their time correlation is short. Once properly calibrated and filtered, magnetometers can provide absolute device heading estimates to within a few degrees.

Barometers also can be used to help with altitude estimation and for multipath mitigation of erroneous wireless signals, especially for GNSS. Barometers suffer from bias offsets and longer term drifts, but their relative height accuracy during periods of several minutes can be better than 20 centimeters.

GNSS can be used to calibrate the bias offset while a Gauss Markov process can be used to estimate the accuracy of the barometer bias drift during longer term periods without other absolute updates, such as from GNSS. After calibration, barometers can be used to constrain the height drift and help alleviate the effects of GNSS multipath from contaminating the navigation solution.

Integrated Sensor and Wireless Navigation Filters

The use of traditional mechanization, platform updates, and complementary sensors, has made stand-alone MEMS navigation in consumer devices possible; however, the integration of wireless and sensor navigation techniques is a more desirable solution.

Several methods can be used to integrate wireless positioning techniques with inertial sensors. The three common methods are loosely coupled, tightly coupled, and deeply coupled integration. The terms centralized and decentralized have also been used to refer to tight and loose coupling, respectively.

A loosely coupled architecture is the simplest to implement because the inertial and GPS navigation solutions are generated independently before being weighted together in a separate filter. The advantages of the loosely coupled strategy are that the INS errors are bounded by the GPS updates, the INS can be used to bridge GPS updates, and the GPS can be used to help calibrate the deterministic parts of the inertial errors online.

Another advantage is this architecture can be used to integrate existing GPS with available inertial systems, such as those currently found in vehicles or mobile phones, since it does not require access to the raw GPS signals. This does not alleviate the need for precise timing synchronization, but timing synchronization is a requirement for all wireless/sensor integrations.

The loosely coupled integration strategy, using position and velocity updates from GPS, is shown in **Figure 2**. P stands for position, V for velocity, and A for attitude. In this case a Kalman filter is used as an example of the fusion filter.

The main drawback to a loosely coupled integration strategy is that it requires at least four GNSS satellites in view to operate in *update mode*; otherwise it operates in *prediction mode* and ignores any available signals from fewer than four satellites. As MEMS errors grow faster in prediction mode, use of any GNSS signals present is wise.

A tightly coupled integration strategy alleviates such constraints by combining the integration process into a single filter. Any number of GPS satellites can be used as measurements to further constrain the inertial error drift.

The comparison of parameters in a tightly coupled filter is different from the loosely coupled architecture. Instead of comparing positions and velocities, the tightly coupled architecture differences

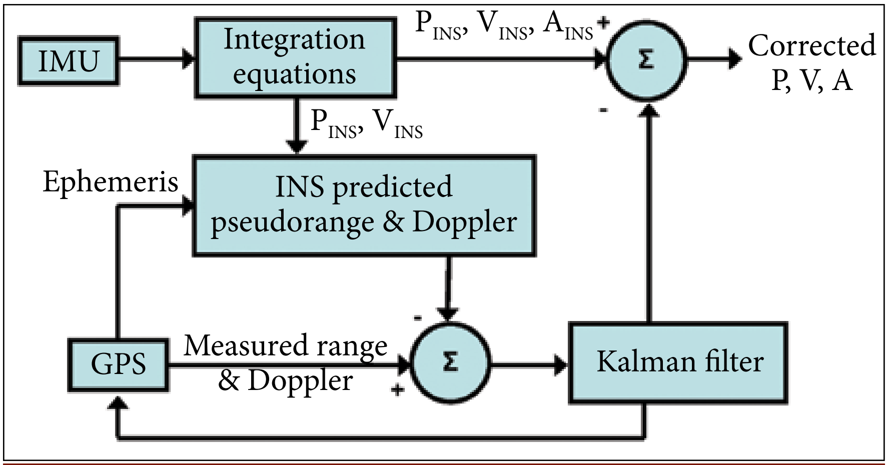

FIGURE 3 Tightly coupled architecture

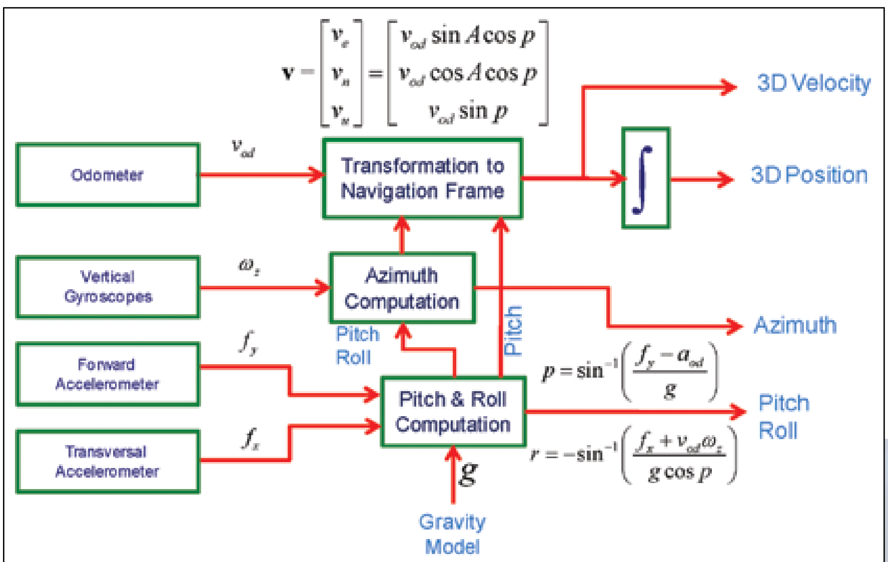

FIGURE 4 Minimal configuration for tight integration of vehicle sensors with MEMS and GNSS

raw GPS pseudorange and Doppler measurements from those predicted by the inertial unit. The filter output is a correction to the inertial outputs as shown in the block diagram in Figure 3 and can also be fed back to the GPS receiver in the form of INS-derived velocity and Doppler information to aid the code and carrier tracking loops.

Deep integration, in this case, combines measurements into a single filter, but combines GPS and inertial data at the earliest possible stage. Immediately after the RF signal is shifted to some lower intermediate frequency (IF), inertial measurements are used. The inertial data is used at this stage to provide a dynamic reference trajectory that aids the receiver correlators during signal integration. Furthermore, a replica GPS signal, both code and carrier, can be generated by an integrated tracking and navigation filter.

The fusion filter does not necessarily have to be a classic Kalman filter, but can use more nonlinear filters, such as the extended Kalman filter (EKF), the unscented Kalman filter (UKF), and the particle filter (PF). Each one of these filters has increasing ability to estimate nonlinear models, whether total state or error state. If the motion model is highly nonlinear then using a PF will result in the best accuracy because of minimal truncation and round-off error in the estimation. For further discussion about filters in integrated navigation systems, see the papers by E. H. Shin *et alia* and J. Georgy *et alia* in Additional Resources.

The integration of vehicle sensors can also be used in dedicated consumer vehicle navigation systems. Many commercial systems use dead reckoning in combination with a single gyroscope for heading determination. These dead reckoning solutions typically provide two-dimensional (2D) position information. A loosely or tightly coupled filter with a full IMU and mechanization also can accept platform speed readings, such as those from an odometer, which update the filter's velocity estimates.

Our company has achieved tight integration of speed readings with inertial sensors to provide an accurate three-dimensional (3D) navigation solution. This method decouples the motion of the platform from the output of the inertial readings of the device. Through this decoupling, the positioning solution during GNSS signal outages is significantly improved because the dependence of the error on the outage duration is highly decreased.

In this position solution, the error due to accelerometer biases and the two horizontal gyroscope biases reduces to being linearly proportional to the outage duration, instead of quadratically proportional to the accelerometer bias, and cubically proportional to the horizontal gyroscope bias. A minimal configuration of such a system is shown in Figure 4. This model is nonlinear and preferably uses a nonlinear filter, such as a PF, for better estimation performance.

The connection of the mobile device to the vehicle speed may be through typical wired connections, but with increasing vehicle wireless connectivity it is likely that mobile phones may be able to receive sensor information from the vehicle in the near future. This would enable a full suite of products that could be freely moving within the vehicle, tethered to the dash but movable, or simply tethered to the vehicle platform and communicating to the vehicle sensors wirelessly.

The use of vehicle speed and decoupling is also very useful for estimating the orientation of a mobile device with respect to the vehicle platform. If this estimation is resolved correctly then platform constraints, such as NHC, can be applied.

The communication between vehicle and mobile device would also enable tight integration of map information with the vehicle and mobile sensors. This helps constrain the solution in the harshest of urban environments to within one or two traffic lanes using very low-cost MEMS sensors.

However, the orientation of a mobile device used by a person can freely change. This misalignment between the device and the person platform, and within the vehicle, can be resolved through absolute updates using GNSS.

A trade-off often occurs between accuracy and real-time iteration efficiency for different types of filters. For example, we have designed an implementation for guidance applications that uses an EKF solution with a traditional mechanization approach that can operate in real-time with iteration times less than one millisecond on a one gigahertz processor. For in-vehicle systems using platform speed inputs we have created a PF solution, which estimates nonlinear models, that has iteration times of about 10 milliseconds on the same processor.

The EKF can be used to estimate many problems that are just slightly nonlinear with only small errors, but the PF is needed when the models are nonlinear, otherwise the entire purpose of using nonlinear modeling will be obfuscated by use of a linearized filter. This situation is similar to water through a pipe: the outflow diameter of a pipe has to be the same size or larger than the inflow to ensure continuous throughput of water.

Many different integration models exist; the designer of the model should carefully choose the most appropriate filter based on iteration time, system/measurement models, and accuracy requirements of the final system.

MEMS Improvements to Wireless Real-Time Navigation

Most commercially available real-time wireless positioning and navigation systems rely on a combination of wireless methods for positioning. These wireless methods work well in clear signal propagation areas, but suffer from availability and inaccuracy in urban and indoor areas. To combat the availability problem, GNSS manufacturers use high-sensitivity receivers to accept more signals, which can lead to decreased accuracy.

In order to illustrate this problem, **Figure 5** shows the results of a field trial with commercially available GNSS receivers performed in downtown Taipei where a person walked down a street, entered a 13-story building, and walked around inside. The GPS-only solution is shown as a path (left panel) and as points (right panel) to demonstrate the multipath and availability problems. This GPS receiver had errors of more than 80 meters but was able to always produce a solution by simply repeating the last known position during periods of complete signal blockage.

Figure 6 shows the results from a field trial along the same Taipei course using an integrated solution in which GPS was combined with mobile phone grade gyroscopes, accelerometers, a 3D magnetometer, and a barometer. For illustration purposes only, the reference path was drawn using a mapping application and database to emulate the true path. For an actual truth reference analysis,

FIGURE 5 GPS-only results walking in downtown Taipei

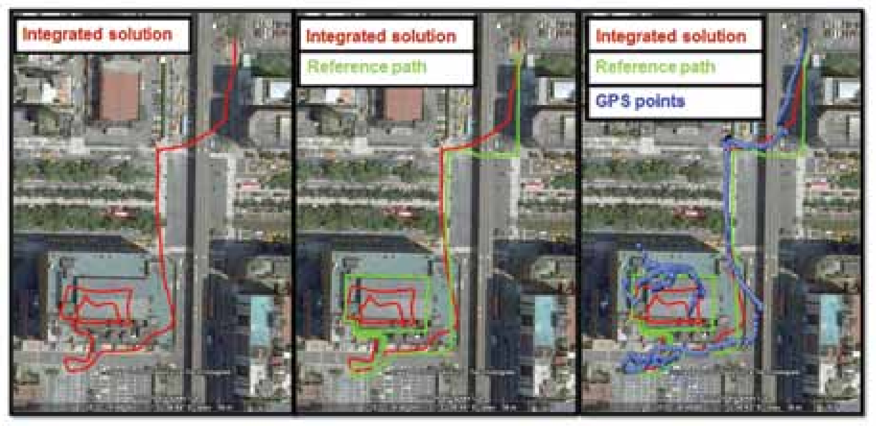

FIGURE 6 Comparison of GPS-only (blue) and integrated (red) positioning solutions, with reference truth (green) path in downtown Taipei

we would expect the truth solution to be accurate to 10 meters.

The person's path through the building is clear, with distinct turns, in comparison with the noisy GPS-only solution. The integrated solution largely rejected the noisy GNSS indoor signal and indicates a drift of about 18 meters after six minutes indoors.

The integrated solution also produced improved height accuracy in comparison to the GPS-only solution. **Figure 7** shows the results of the height from the integrated solution (red points) versus the GPS-only height (blue points). As indicated, GPS was able to make a few height measurements on the 12th floor because the roof of the building had windows through which the signals could be received, but the remainder of the GPS heights had errors of 20 to 40 meters.

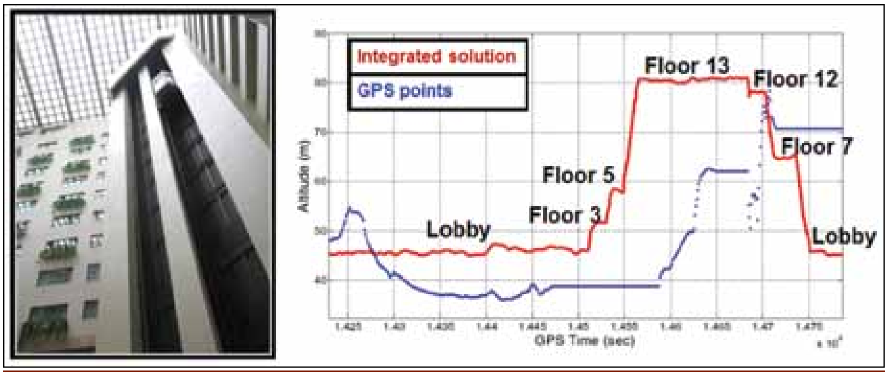

FIGURE 7 GPS-only (blue) and integrated (red) height solution for indoor positioning

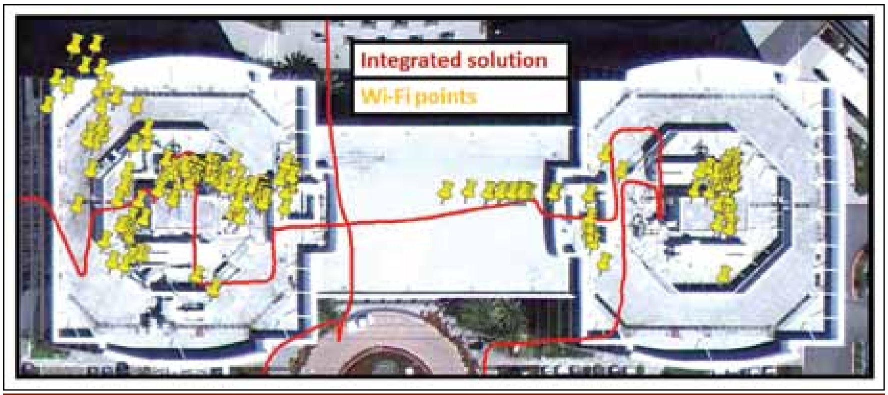

FIGURE 8 Integrated Wi-Fi positioning system with sensors (yellow pins = Wi-Fi only, red line = Wi-Fi + IMU)

Wi-Fi Integrated with Sensors

GPS is not the only absolute wireless positioning method that has gained mainstream popularity. Wi-Fi positioning systems are also quite prevalent in existing consumer devices. **Figure 8** shows an indoor Wi-Fi positioning solution represented by the yellow pins. The Wi-Fi solution was further integrated with a MEMS IMU carried in a backpack by a person while walking through two buildings.

The Wi-Fi solution was available 35 percent of the time and had errors greater than 30 meters, while the integrated solution (red line) had estimated errors within 10 meters of the true trajectory. The figure clearly shows all the turns along the path. Even Wi-Fi positioning from known access points (APs) requires integration with sensors to obtain usable indoor position accuracy. Furthermore, the integration of sensors with Wi-Fi could help reduce the number of required APs to achieve a specified accuracy level.

Another option involves increasing the amount of infrastructure, such as using more Wi-Fi APs or installing a large amount of WPAN such as RFID's. These solutions can provide very accurate indoor positioning, but the cost to deploy and maintain these types of systems often limits them to more customized or local systems.

The use of integrated inertial sensors to bridge the gaps in APs is a nice option to balance infrastructure costs with high accuracy and availability of the navigation solution.

The Future of Urban Navigation

If a wired or wireless connection is available, sensors in the vehicle and a mobile device can be integrated, resulting in significant gains in navigation accuracy when driving in urban environments.

We performed tests of such a system in several major urban cities worldwide including Detroit, Toronto, Calgary, Houston, Taipei and San Francisco. Figures 9 and 10 illustrate the results from the San Francisco test in an environment containing tunnels, tall buildings, and frequent altitude changes that challenge a 2D solution.

A mobile device was placed loosely on the back seat of the vehicle and had a wired connection to the On-Board Diagnostics-II (OBDII) communication port of the vehicle that transferred vehicle speed information at one hertz with a resolution of 0.3 meters per second. The device used this speed information to decouple the motion and resolve the misalignment in real-time. The sensors within the device could then be used to contribute to the navigation solution.

Figure 9 shows the results of both the GPS-only and the integrated solution through the first tunnel. The GPS receiver tried to maintain lock through the tunnel, by modeling the motion of the vehicle for about 30 percent of the tunnel length. Eventually the modeling failed, and the GPS began repeating its last known location.

Figure 10 shows another path through a different tunnel in San Francisco, which is followed by driving through an urban canyon created by tall buildings. The GPS receiver is subject to more multipath in this downtown scenario. The integrated solution used the sensors to help smooth the inaccurate GPS position estimates.

FIGURE 9 Tunnel trial #1 in San Francisco

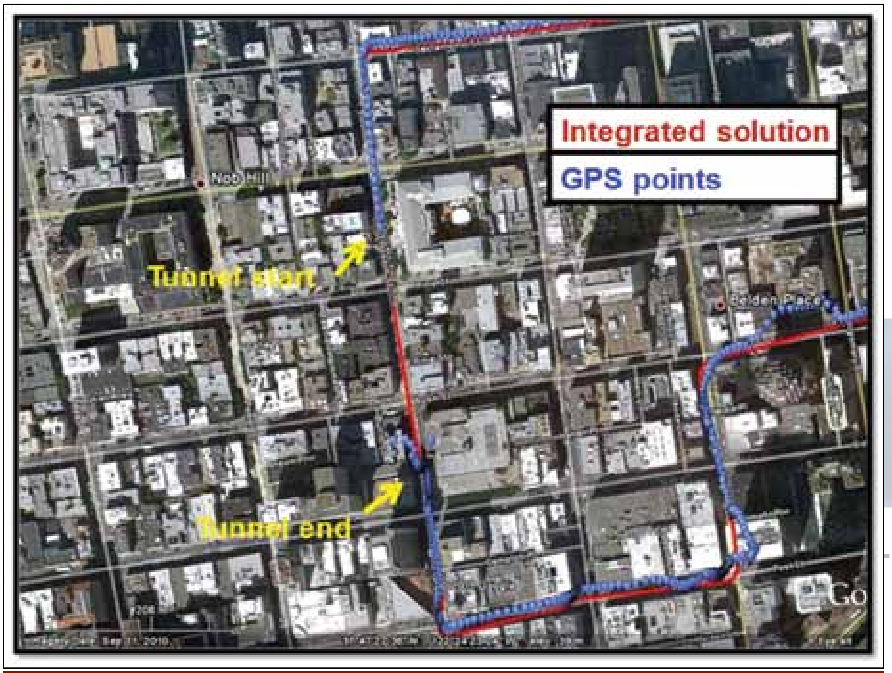

FIGURE 10 Tunnel trial #2 in urban San Francisco

The results show that integrated vehicle and mobile sensors achieved better than 20-meter accuracy in nearly all urban environments using phone-grade MEMS sensors and vehicle speed from the OBDII communication port. Improved accuracy of less than 5 meters is likely when maps and improved MEMS sensors are used, potentially enabling new applications that go beyond consumer navigation, such as assisted driving from a mobile device.

Improved Navigation Solutions through Smoothing

Not all applications require immediate feedback from the navigation system, and some systems that do require immediate feedback can also benefit from improved navigation information at a later time. Tracking, performance monitoring, and indoor wireless surveys are just a few examples of such applications.

In these cases, backward smoothing (BS), which makes full use of the information logged in both the forward and backward directions, can improve the navigation performance significantly with some latency in the improved navigation solution.

This latency is often defined by the application and could range from a few seconds to a few hours. Personnel tracking may accept latencies of 30 seconds to provide an improved navigation solution through smoothing. Surveying may accept latencies of several minutes or even hours depending on the site being surveyed.

Any application that can accept a latency to obtain an improved navigation solution can use smoothing of the forward and backward navigation solutions. The forward and backward solutions can be performed on the same processor using multiple cores or in serial using the same processing core.

In BS, an optimal smoothed estimate of the state vector at epoch k is obtained as a combination of forward and backward estimates. The forward estimate is obtained by using all measurements up to k, in the case of EKF estimates. The backward estimate is obtained by using all or some of the measurements after k.

Because BS uses more measurements, the resulting estimates are generally more accurate, and can never be worse than the forward filter estimates. Several categories of backward smoothing exist including fixed-interval, fixed-point, and fixed-lag smoothers. In INS/GNSS applications, BS estimates are required for all points in post-mission analysis, including those obtained during intervals of GNSS signal outages. Fixed-interval BS is the most appropriate smoother for bridging these outages.

For smoothing the EKF solutions, the fixed-interval Rauch-Tung-Striebel Smoother (RTS) can be used. Unfortunately, not all the techniques that apply to EKF-based smoothing apply to nonlinear smoothing or a total state approach, such as the implementation in Figure 4 Minimal configuration for tight integration of vehicle sensors with MEMS and GNSS.

In this scenario, a two-filter smoother (TFS) is more appropriate. The backwards filter can be implemented in several ways for the TFS, but the most intuitive way is to correctly transform all the sensor readings to create a situation in which the vehicle starts at the end of the trajectory and moves to the original starting location.

Another instance of the forward filter can then be used with the same system model (motion model) but applied to the transformed sensor data to provide the backward solution. Finally, the two filters are blended together based on estimated variances to give the smoothed navigation solution.

Conclusion

MEMS inertial technology has progressed to the point where the combination of smart integration software and robust hardware, enables consumer navigation and positioning applications where stand-alone wireless techniques currently fail.

Many consumer applications exist, with the two mainstream applications being for pedestrian and vehicle navigation. Navigation can be real-time or post-mission, but in either case accurate and seamless solutions will always be required by the end-user.

The use of MEMS significantly enhances the navigation and positioning results of wireless-only solutions. New applications will demand more accuracy. MEMS sensors may be replaced by better hardware. End-user expectations will become higher. The road to "everywhere navigation" will be long, but marked by continuous improvements.

Manufacturers

The integrated GPS/inertial solution designed by Trusted Positioning Inc. (TPI), Calgary, Canada, and used in the Taipei, Taiwan, trials incorporated an LEA-5T GPS receiver, **u-blox AG,** Thalwil, Switzerland; an ITG-3200 3D gyroscope triad from **Invensense,** Sunnyvale, California, USA; a BMA150 accelerometer and a BMP085 barometer from **Bosch Sensortec**, Reutlingen, Germany; and an HMC5883L 3D magnetometer, **Honeywell Aerospace**, Plymouth, USA. The mapping software and imagery was Google Earth by **Google**, Mountain View, California, USA. The one-gigahertz microprocessor used in the EKF and PF integrated implementations is the AM3703 from **Texas Instruments**, Dallas, Texas, USA.

Additional Resources

[1] Bensky, A., *Wireless Positioning Technologies and Applications,* Artech House Inc., 2008

[2] Gelb, A., *Applied Optimal Estimation,* The M.I.T. Press, Massachusetts Institute of Technology, Cambridge, Massachusetts, USA, 1974

[3] Georgy, J., "Advanced Nonlinear Techniques for Low Cost Land Vehicle Navigation," Ph.D. thesis, Department of Electrical and Computer Engineering, Queen's University, Kingston, Ontario, Canada, 2010

[4] Georgy, J. and Noureldin, A., "Low-Cost Post-Mission Positioning and Orientation Solution for Land-Based Mobile Mapping Using Nonlinear Filtering," *Proceedings of the ION GNSS 2010,* Portland, OR, September 21-24, 2010, 2010

[5] Gonthier, M., "Smoothing Procedures for Inertial Survey Systems of Local Level Type," Ph.D. thesis, Department of Civil Engineering, Division of Surveying Engineering, University of Calgary, Calgary, Alberta, Canada, UCGE Report No. 20008, 1984

[6] Groves, P. D., *Principles of GNSS, Inertial and Multisensor Navigation Systems,* Artech House Inc., 2008

[7] Gutmann, J., and L. Marti and G. Lammel, G., "Multipath Detection and Mitigation by Means of a MEMS Based Pressure Sensor for Low-Cost Systems". *Proceedings of ION GNSS 2009,* Savannah, Georgia, USA, September 22–25, 2009

[8] Jansson, P., "Precise Kinematic GPS Positioning with Kalman Filtering and Smoothing: Theory and Applications," Ph.D. thesis, Department of Geodesy and Photogrammetry, Royal Institute of Technology, Stockholm, Sweden, Division of Geodesy Report No. 1048.

[9] Li, Y., and P. Mumford and C. Rizos, "Seamless Navigation through GPS Outages: A Low-Cost GPS/INS Solution," *Inside GNSS,* August 2008

[10] Meditch, J. S., *Stochastic Optimal Linear Estimation and Control,* McGraw-Hill, Inc., USA, 1969

[11] Niu, X., and N. El-Sheimy, "Development of a Low-cost MEMS IMU/GPS Navigation System for Land Vehicles Using Auxiliary Velocity Updates in the Body Frame," *Proceedings of the ION GPS 2005,* Long Beach, California, USA, September 13–16, 2005

[12] Niu, X., and S. Nassar, Z. Syed, C. Goodall, and N. El-Sheimy, "The Development of an Accurate MEMS-Based Inertial/GPS System for Land-Vehicle Navigation Applications," *Proceedings of the ION GNSS 2006,* Fort Worth, Texas, USA, September 26–29, 2006

[13] Shin, E. H., "Estimation Techniques for Low-Cost Inertial Navigation," Ph.D. thesis, MMSS Research Group, Department of Geomatics Engineering, University of Calgary, Calgary, Alberta, Canada, *UCGE Report No. 20219*

[14] Skog, I., "Low-Cost Navigation Systems – A Study of Four Problems," doctoral thesis in signal processing, KTH Electrical Engineering, Stockholm, Sweden, 2009

[15] Syed, Z., "Design and Implementation Issues of a Portable Navigation System," Ph.D. thesis, MMSS Research Group, Department of Geomatics Engineering, University of Calgary, Calgary, Alberta, Canada, *UCGE Report No. 20288,* 2008

[16] Yang, Y., "Tightly Coupled MEMS INS/GPS Integration with INS Aided Receiver Tracking Loops," Ph.D. thesis, MMSS Research Group, Department of Geomatics Engineering, University of Calgary, Calgary, Alberta, Canada,*UCGE Report 20270,* 2008

Authors

Naser El-Sheimy is the CEO of Trusted Positioning Inc. and the leader of the Mobile Multi-sensor Research Group at the University of Calgary, Alberta, Canada. He holds a Canada Research Chair (CRC) in Mobile Multi-Sensor Geomatics Systems. His area of expertise is in the integration of GNSS/INS/imaging sensors for navigation, mapping and GIS applications with special emphasis on the use of multi-sensors in portable navigation systems. He achieved a B.Sc. degree in civil engineering and an M.Sc. degree in surveying engineering from Ain Shams University, Egypt, and a Ph.D. in geomatics engineering from the University of Calgary. El-Sheimy is also the scientific director for TECTERRA, a not-for-profit Centre of Excellence for Commercialization and Research (CECR) established to enable the commercialization of geomatics technology across Canada.

Chris Goodall is a cofounder and the vice-president, applications, at Trusted Positioning Inc., Calgary, Alberta, Canada. He has been working in developing, deploying and testing multi-sensor navigation systems for over 7 years. Goodall obtained his B.Sc. in systems design engineering at the University of Waterloo, Canada and his Ph.D. in geomatics engineering in 2008 from the University of Calgary. IG