

TERRAIN-BASED NAVIGATION: A TOOL TO IMPROVE NAVIGATION AND FEATURE EXTRACTION PERFORMANCE OF MOBILE MAPPING SYSTEMS

Navegação terrestre: Um instrumento para melhorar a navegação e o desempenho na extração de feições do sistema de mapeamento móvel.

C. TOTH^{a, b *}
D.A. GREJNER-brZEZINSKA^b
J.H. OH^b
J. N. MARKIEL^b

^a Center for Mapping, The Ohio State University, Columbus, Ohio, USA

^b Satellite Positioning and Inertial Navigation (SPIN) Laboratory
Dept. of Civil and Environmental Engineering and Geodetic Science
The Ohio State University
e-mail: toth@cfm.ohio-state.edu

ABSTRACT

Terrain-referenced navigation (TRN) techniques are of increasing interest in the research community, as they can provide alternative navigation tools when GPS is not available or the GPS signals are jammed. Some form of augmentation to cope with the lack of GPS signals is typically required in mobile mapping applications in urban canyons and is of interest for military applications. TRN could provide alternative position and attitude fixes to support an inertial navigation system, since such systems inevitably drift over time if not calibrated by GPS or other methodologies. With improving imaging sensor performance as well as growing worldwide availability of terrain high-resolution data and city models, terrain-based navigation is becoming a viable option to support navigation in GPS-denied environments. Furthermore, the feedback from the imaging sensors can be used even during GPS availability, which increases the redundancy of the measurement update step of the navigation filter, enabling more reliable integrity monitoring at this stage. The relevance of TRN to mobile mapping applications is twofold: (1) the

* Corresponding author.

process of obtaining real-time position and attitude fixes for the navigation filter is based on feature extraction, and, in particular, on the capability to separate the static and dynamic objects from the image data, and (2) the use of already available terrain data, including surface models (DSM), raster or vector data in CAD/GIS environments, such as city models, can effectively support the extraction processes. These two tasks could overlap, although the separation of the static and dynamic objects should work without any terrain data, and in fact, this is, to a large extent, the idea behind the removal of vehicles (moving objects) from imagery. The overall TRN concept, where LiDAR and optical imagery are matched with the existing terrain data is discussed and initial performance results are reported.

Keywords: Navigation; Feature Matching; Kalman Filtering; LiDAR.

1. INTRODUCTION

In GPS/INS (Global Positioning System/Inertial Navigation System) navigation systems, the GPS measurements are used to correct and calibrate the INS (or IMU) typically via a conventional Kalman filtering algorithm. However, satellite navigation signals are extremely vulnerable to interference, primarily due to their low power. Unintentional interference sources include broadcast television, mobile satellite services, ultrawide-band communications, over-the-horizon radar and cellular telephones (Carroll *et al.*, 2001). As soon as GPS measurements are lost, the INS begins to drift as there are no positional fixes for sensor calibration. For example, aircraft-grade INS can typically maintain horizontal position accuracy within 100 m through GPS outages of more than 10 minutes. However, lower cost INS, common in guided weapons, unmanned air vehicles and general aviation (civilian) aircraft, can only maintain this accuracy for a few minutes at best. To attain robust navigation in a GPS challenged or jamming environment, alternative navigation systems are required, such as terrain-referenced navigation (TRN) techniques (Runnalls *et al.*, 2005).

The potential of laser range scanners for supporting navigation was recognized in studies (Campbell *et al.*, 2005; Haag *e. al.*, 2006), and a laser range scanner based navigation system for aircraft guidance was presented in Haag *e. al.* (2006). Their referencing is based on matching laser points from the onboard LiDAR (Light Detection and Ranging) system to a stored DEM (Digital Elevation Model). They use the criterion of minimum SSE (Sum of Squared Error), which is very similar to MAD (Mean Absolute Deviation) of TERCOM (Terrain Contour Matching, conceived by Chance-Vought in 1958), for a referencing method. Bergman (1999) used the point mass filter and nonlinear Bayesian approach for aircraft terrain navigation. Madhavan and Messina, (2003) introduced an unmanned ground vehicle navigation system using 3D LiDAR data matching which applies an ICP (Iterative Closest Points) algorithm, a technique introduced by Besl *et al.*, (1992) for 3D shape registration. Toth *et al.*, (2008) applied ICP to recover aircraft

trajectory from distorted LiDAR data. Habib *et al.*, (2006) suggested an automatic surface matching method which uses ICP and MIHT (Modified Iterated Hough Transform) for registering LiDAR data. Rusinkiewicz and Levoy, (2001) provided a speed comparison of ICP convergence with respect to different sampling, matching, weighting methods, etc.

Research on the optical image based navigation can be classified into feature-based or optical flow-based approaches (Veth and Raquet, 2006). The feature-based technique determines the corresponding distinct invariant features between a pair of image frame sequences or the current image frame and the reference to estimate the relative motion. The optical flow-based method tries to determine the relative velocity and angular rates with the restriction of the small motion image difference. Since the SIFT is quite efficient in finding invariant features and exhibits robust performance, there has been intense research on exploiting SIFT for image-based navigation (Frank-Bolton *et al.*, 2008; Lopez *et al.*, 2008; Wendt *et al.*, 2008; Liu *et al.*, 2008). Fletcher *et al.* (2007) chose the SIFT in order to improve feature tracking for the fusion of optical and inertial sensors, and Strelow (2004) exploited SIFT matching to limit drift in long-term motion estimation.

The paper is structured as follows: first, a general characterization of various sensors available to support a tightly coupled navigation solution is provided. Second, an overview of the integrated system is discussed, indicating the utilization of multiple sensors to support updates to the inertial system. The third section discusses a series of algorithms currently being researched at the SPIN Laboratory to derive positional and/or attitude information from sensor data that can be used as fixes in the navigation filter. In the final section some recent implementations of the methods outlined in section three are demonstrated, followed by a brief summary.

2. SENSOR CHARACTERIZATION

There are many kinds of remote sensors used for acquiring terrain features. Conventional terrain-based navigation methods, such as TERCOM (Klass, 1974) and SITAN (Hostetler and Andreas, 1983) have used radar altimeter and barometric altimeter that measure height above ground level and reference height above the mean sea level respectively. With improving imaging sensor performance as well as growing worldwide availability of terrain high-resolution data, a variety of sensors has been available. Sensors can be classified depending on the sensing principle: the vision sensor (camera) and the range measurement sensor (laser or RADAR). Each type of sensor can be used separately or a combination of the systems can also be used because each sensor has advantages and disadvantages for supporting navigation. For example, the range measurement sensor cannot acquire spectral information, but the vision sensor does. In contrast, without enough light a vision sensor cannot provide reliable features while the range measurement sensor has the capability to generate a dataset.

2.1 Optical Sensors

The passive vision sensors for supporting navigation should provide reliable position and attitude fixes for the navigation filter when sufficient ambient light is available. The position and attitude estimation algorithms that have been well established over the past require that the cameras are precisely calibrated. Since there are a large variety of cameras available, the important aspects to choose a camera are the sensor type, resolution, the number of spectral bands, frame rate and interface. For position and attitude estimation, the perspective projection type camera (frame) is preferred because the linear push-broom line scanner has weak geometry. In general, the image resolution should be high enough to meet the navigation accuracy requirements but low enough for efficient data processing. Color/multi-spectral sensors are often required to obtain rich spectral information for terrain feature extraction. The highest performance cameras currently available are the large-format digital aerial cameras, such as the UltraCamXp (Vexcel), DMC (Intergraph) and ADS80 (Leica Geosystems). The drawbacks of using these systems exclusively for the purpose of navigation are the size and expense. The medium-format mapping frame cameras, such as the RCD105 (Leica Geosystems), DSS (Applanix), AIC (Trimble), etc., are also capable of delivering relatively high resolution imagery, as these mapping cameras, if precisely calibrated, can provide accurate imagery with better than 20 cm resolution (GSD) at 1000 meter flying height. There are many choices of megapixel industrial cameras available, such as real-time machine vision cameras with smaller image sizes, such as Pulnix, Basler, PixeLINK's PL-A/B series, Sony XCL/XCD series, Allied GC/GE/GS series, etc.

2.2 Ranging Sensors

There are many kinds of range measurement sensors: SAR, altimeter, sonar, LiDAR and flash LADAR (Laser rADAR, a widely used acronym in military terminology). Among them, LiDAR and Flash LADAR will be discussed here because LiDAR is the most widely used range measurement device while Flash LADAR is relatively new but has the potential for supporting navigation.

LiDAR is an optical ranging system that involves the accurate measurement of the time of flight (TOF) of a very short but intense pulse of laser radiation to travel from the laser ranger to the object being measured and to return to the instrument after having been reflected from the object. It can be installed on airborne and terrestrial platforms and is widely used for collecting explicit 3D data very precisely and efficiently. LiDAR can be classified according to the scanning mechanism and sensor platform (Shan and Toth, 2008). Most of the airborne LiDAR systems, such as ALTM (Optech) and ALS (Leica Geosystems) families, employ the bidirectional scanning mechanism yielding sawtooth pattern point data. A Palmer scan showing an elliptical scan pattern is used in NASA's ATM, Airborne Oceanographic LiDAR (AOL) and some models in the TopoEye series. For the terrestrial laser scanners for

navigation and SLAM (Simultaneous Localization And Mapping), SICK products are widely used. Recently Velodyne introduced the HDL-64E system, which with its 64 sensors can achieve a high data rate and was effectively supporting autonomous navigation during the DARPA Urban Challenge.

Flash LADAR is an active 3D-image-acquiring sensor which provides the range, azimuth and elevation of each set of measurements to create a 3D scene. The resulting output is a triple of Cartesian coordinates for each pixel in the image, enabling the direct reconstruction of the object space in 3D. Its potential for navigation was demonstrated in previous research (Markiel *et al.*, 2008; Haag *et al.*, 2008). The most used commercial systems are the SR3000/4000 (SwissRanger) and Flashlamp (Advanced Scientific Concepts Inc.). One of the significant advantages and disadvantages of flash LADAR is the speed of data collection (30–3 frames per second) and the relatively short range (3–30 meters), respectively. Flash LADAR technology currently offers moderate image resolution (100–200 by 100–200 sensor size) and suffers from ambient radiation, as the SNR is very low due to the requirements for eye-safe operation.

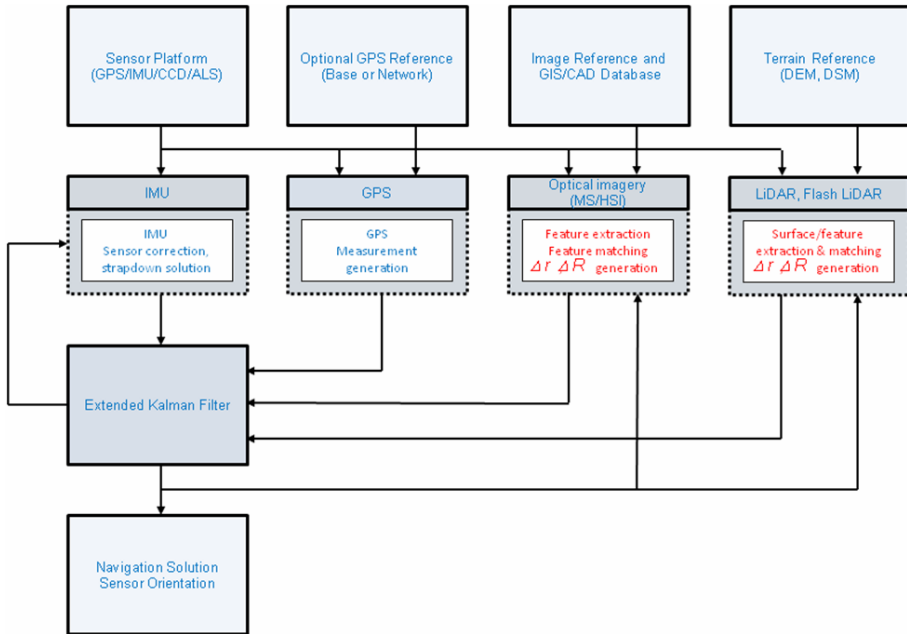
3. NAVIGATION COMPONENT

Figure 1 provides an overview of the conceptual implementation of the navigation filter, which extends the basic system of the well-known GPS/INS tandem of sensors, tightly coupled via an Extended Kalman Filter (EKF). The inertial system provides short-term information relative to position, attitude and velocity, while the GPS updates enable the system to correct for the inevitable drift in the inertial sensor. Thus, the integrated solution results in excellent performance.

When GPS updates are not available, updates are instead provided to the EKF by means of a positional/attitude solution derived from imagery and/or terrain reference information. If GPS remains available, the imagery/terrain position creates a redundancy in the information set, and thus the opportunity to enhance the resulting solution may then support a stronger navigation solution and improve mapping performance.

The OSU AIMS-Pro® is a custom software system developed by The Center for Mapping at The Ohio State University which expands the traditional GPS/INS tightly coupled integration model to enable the utilization of other sources of position and orientation information within the basic traditional schema. The software enables navigation solutions to be derived for both aerial and ground-based navigation platforms and has the ability to generate both loosely and tightly coupled solutions. It currently handles a number of commercially available inertial units, such as the H764D, HG1700, LN100, LN200, xSens and Crossbow devices; the system can easily be configured to handle other inertial systems with minimal effort. Additionally, the system can integrate a wide variety of other navigation related devices, such as digital compasses, step length sensors, or odometers.

Figure 1 - The conceptual structure of the OSU AIMS-Pro® software system.



Time synchronization is essential for any multisensory system, as it forms the basis for data integration and fusion by providing accurate co-registration in time and, subsequently, in spatial domains. Generally, GPS time-tagging of all sensory data is implemented at the data acquisition level. In the context of mobile mapping, there are two aspects of time synchronization, depending on whether relative or absolute TRN is considered. If simultaneously or near simultaneously acquired data are used for TRN, then the static and non-static objects should be first identified during processing, so the matching uses only the static features, common in consecutive observations. For example, building facades scanned by LiDAR are static objects, and subsequently are ideal for TRN, while data such as moving vehicles scanned should be removed from the data set. When existing terrain data are used for TRN, the time difference between two acquisition times is generally large, typically measured in years, and thus the object scene could have changed a lot. This is less an issue for open areas, as the terrain is not likely to change, but it is important for urban areas experiencing rapid changes. Therefore, the use of TRN in absolute context requires additional sophistication to cope with the changes between the current and past data.

4. MATCHING COMPONENT

4.1 General Discussion

Regardless of data acquisition method, the resulting image data stream provides a temporally spaced set of measurements, i.e., a sequence of data frames. To facilitate mapping or navigation from these measurements requires the transformation of such data into information to support the mapping/navigation solution. Specifically, for any particular epoch, it is desirable to identify elements that relate measurements collected at two distinct times. A key issue in comparing imagery is the ability to match features between data frames. The problem of locating n features from the initial data frame among m features in the current frame is not trivial; in general, the problem is not well posed.

4.2 Features

A variety of features may be derived from the data, such as points, lines, surfaces, and objects, all possible elements present in a given frame. The choice of feature extraction represents a trade-off between the desire to establish unique descriptors and the associated computational complexities required to manipulate the resulting elements. Other factors such as processing speed, real-time vs. post-processing, and data acquisition may also impact the choice of feature extraction.

The simplest method is the extraction of points; the penalty for this abstraction is the need to validate the uniqueness of points during the matching process. At the SPIN Laboratory, three point-based methods are currently under active research, including methodologies for establishing the integrity of the results. The first system is based upon the Scale Invariant Feature Transform (SIFT) algorithm (Lowe, 2004), the second is an eigenvector-based solution developed internally by one of the authors (Markiel, 2009), and the third one is ICP matching. The first two methods differ, as the SIFT method does not necessitate the presence of an inertial unit, while the eigenvector algorithm requires the presence of integrated sensors (such as an IMU) to provide coarse estimates of pose.

4.3 SIFT Algorithm

The SIFT algorithm was initially developed by David Lowe in 1989; the algorithm is currently enjoying considerable interest in the image matching community for a wide variety of purposes. Interested readers are referred to (Lowe, 2004; Mikolajczyk and Schmid, 2005; Bakken, 2007). The SPIN Laboratory has been conducting considerable tests related to the application of SIFT to various data types, including aerial photographs, LiDAR imagery, and hyperspectral imagery. In addition to experimentation within a data type (LiDAR to LiDAR, for example), current studies are also examining cross-image results (such as optical imagery to LiDAR).

SIFT features are determined by a four-step algorithm that isolates point features from the image based upon intensity gradients. The resulting output consists of two vectors for each SIFT point; the first vector of length four and the second of length 128. The first vector contains the location (in terms of x , y coordinates based upon pixels), the scale, and the orientation of the feature. The second vector is called the descriptor and represents the stacked summary of 4×4 gridded gradient vectors taken in 8 orientations. Matching of SIFT features is accomplished by comparison of each 128 parameter vector in the first frame to all of the descriptors in the second frame. The search is generally completed by means of the well known kd-search tree. In practice, matching SIFT features obtained from two different poses can be utilized to triangulate position of the acquisition device if range information is available to the targeted points of interest.

The algorithm is exceptionally advantageous to frame matching from several viewpoints; it is highly robust to rotation, translation, and changes in illumination. Research at the SPIN laboratory has demonstrated some concerns related to scalability, matching of n descriptors to m descriptors can rapidly become computationally intractable for large values of n and m . The problem can be constrained in a number of ways, such as limiting the search space or imposing relational requirements on the solution. This does introduce additional complexity to the matching problem but often becomes a practical reality when tens of thousands of SIFT features are extracted for each frame.

4.4 Eigenvector Approach

One challenge is to separate moving features from static elements from a time series of LADAR image frames. The range to the static features is known from the Flash LADAR data; locating the same static features from a new position permits the opportunity to triangulate location. Research at the SPIN Laboratory by one of the authors has focused on the utilization of eigenvector “signatures” for point features as a means to facilitate matching. The algorithm comprises four steps:

- Segmentation
- Coordinate frame transformation
- Feature matching
- Position and orientation determination

The algorithm utilizes the eigenvector descriptors to merge points likely to belong to a surface and identify the pixels corresponding to transitions between surfaces. Utilizing an initial coarse estimate from the INS (EKF) system, the results from the previous frame are transformed into the current coordinate reference frame by means of a RANSAC (Random Sampling Consensus) methodology. Matching of static transitional pixels is accomplished by comparing eigenvector “signatures” within a constrained search window. Once matching features are identified and determined to be static, the closed form quaternion solution (Horn, 1987) is utilized to derive the position and orientation of the acquisition device, and the result

“updates” the inertial system in the same manner of a GPS unit within the common GPS/INS integration. The algorithm is unique in that the threshold mechanisms at each step are derived from the data itself, rather than relying upon a-priori limits. Since the algorithm only utilizes transitional pixels for matching, a significant reduction in dimensionality is generally accomplished and facilitates implementation on larger data frames.

The algorithm has been applied to Flash LADAR data and initial results are quite promising; inertial drift after a quarter hour was constrained to less than 1 meter (Markiel, 2009). Current constraints on the available technology limit the sensor to indoor use; however, other technologies are either in existence (Velodyne) or in development (CSEM) to extend the range and other capabilities of the laser ranging devices.

4.5 ICP-based Surface Matching

The ICP (Iterative Closest Point) matching algorithm is a widely used method for registration of 2D or 3D point cloud data sets. The ICP algorithm finds the closest points between two point sets for registration. Then, typically 3D rigid body transformation estimation is applied between the corresponding point sets to determine translations and rotations iteratively. The ICP matching can be expressed in the following equation (1):

$$\min_{(R,T)} \sum_i \|M_i - (RD_i + T)\|^2 \quad (1)$$

where $R = 3 \times 3$ rotation matrix

$T = 3 \times 1$ translation vector

$M, D =$ point sets

$i =$ point index

To obtain reliable matching results, some factors affecting the matching performance should be considered. First, there should be distinct features available in the terrain, such as terrain relief and break-lines. Without unique features, the algorithm may generate incorrect and false matching. The matching accuracy tends to increase as the terrain relief increases and usually quickly stabilizes once the relief reaches a certain level of complexity. Another issue of using ICP matching for LiDAR data is that quite different samplings of point clouds can be obtained for the same object due to differences in the scanner position and occlusions, which often occur over break-lines, such as building walls. This is an important factor affecting the matching results more than the point density. Therefore, invariant matching entities, which are less affected by occlusions, such as roof planes, should be preferred for processing.

5. EXPERIMENTAL RESULTS

5.1 Optical Image Matching Based on SIFT

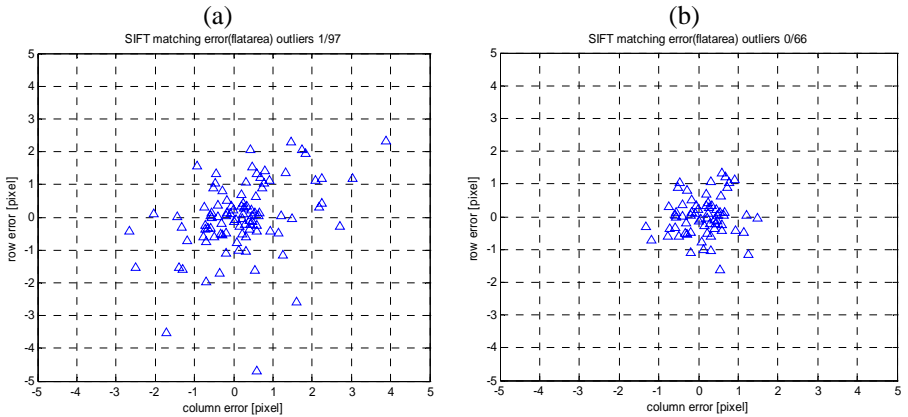
Before using it for position and attitude estimation, SIFT matching was evaluated by using various pairs of parent images and derived corrupted images to see if reliable matching information could be obtained. As an example, image corruption was introduced by using a 0.4 scale difference, 0.4 shear and 45° rotation, representing large distortion. Figure 2a shows the SIFT matching accuracy. There is only one outlier with a more than five pixel error, and, in general, there are several points with low matching accuracy. Figure 2b shows the result after outliers were removed based on RANSAC, resulting in improved accuracy of about one pixel.

The position and attitude estimation test was performed using a simulated aerial frame camera with 41mm focal length and 20 micron CCD pixel size. The ground resolution is approximately 15cm at the flying height of 300m. With the assumption of the availability of reference data, the estimation is performed based on single photo resection (SPR) that does not require any image overlap. Note when sufficient image overlap is available, the relative orientation or the bundle adjustment technique can be alternatively used. It should be noted that SPR shows better precision than DLT (Direct Linear Transform) because it is based on the prior information of the interior orientation parameters (IOP), such as the focal length and principal point coordinates. With one pixel of image measurement error, which was shown from the previous SIFT matching error, the test produced errors of 0.55m (flight direction), 0.35m (across flight direction), 0.09m (height) and 0.07°, 0.11°, 0.01° (yaw, pitch, and roll, respectively).

5.2 Flash LADAR with Eigenvector Approach

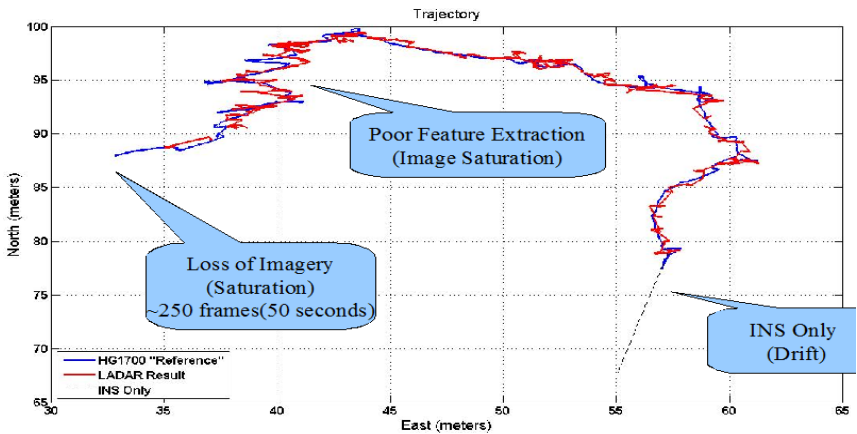
The eigenvector approach discussed in 4.4 has been implemented on data collected with an integrated system comprising an inertial unit, a Flash LADAR camera, GPS receiver, and an Extended Kalman Filter via the AIMS-Pro® system of The Ohio State University. The system was initialized by remaining stationary at an external position for five minutes, followed by several loops in the associated parking lot. A zero velocity update (ZUPT) was then performed prior to entering a building. The interior of the building was traversed with stop points at known (previously surveyed) positions along the motion path. During the traverse, non-static elements were introduced to the environment that required the system to separate them out before position updates could be established.

Figure 2 - The SIFT matching accuracy; (a) before outlier removal, and (b) after outlier removal.



The result of one such test is reflected in Figure 3. The finely dashed line in the lower right hand corner reflects the immediate drift experienced by the unsupported inertial solution. The solid blue line indicates the trajectory of the solution based upon the HG1700 inertial unit, while the red line reflects the tightly coupled system of the Flash LADAR based solution and the inertial solution.

Figure 3 - Tightly coupled navigation solution (IMU with Flash LADAR-based update).



The results indicate the algorithm has definite promise; the solution in the forward direction possesses strong geometry for extracted features (along the length of the walls), resulting in an accurate estimation of both position and orientation. The lack of strong geometry in the vertical axis is problematic and leads to solutions dependent heavily on the inertial information, since limited solutions are possible on the part of the feature-based algorithm. This problem could likely be overcome by periodically moving the camera along the “X” and “Y” axes (pitch and roll) to acquire an improved solution.

The algorithm itself is remarkably stable in performance; in this test the total run time without GPS signal was over ten minutes. When sufficient features are available to determine position, the feature-based solution can provide an accurate solution that betters the performance of a relatively high-grade inertial system. The results clearly indicate the essential need for strong geometry during the image acquisition process; an automated system would most likely need to rotate slightly in all three axes during periodic “calibration stops” to ensure an optimum solution for all three directions/orientations.

Short “outages” of LADAR data as a result of signal saturation are not devastating to the solution. So long as the subsequent images are nearly identical in terms of pose, the system can recover and continue to generate a meaningful solution. Longer outages can easily become problematic, particularly with respect to the vertical axis. Since the LADAR feature-based system is dependent on the inertial system to provide a constrained estimate of pose between images, a long gap results in the Kalman Filter solution being largely dependent on the drifting inertial unit. If the gap becomes too large, the feature-based solution may not find an accurate solution during the RANSAC-based search; increasing the number of RANSAC iterations carries a clear computational cost. Gaps of a few seconds are “recoverable” with good pose/geometry; extended periods can easily invalidate the solution. The best possible case in this instance would be to “reset” the unit and start again; potentially the travel path could be retraced until a previously known set of features could be recovered.

5.3 LiDAR Based on the ICP Matching

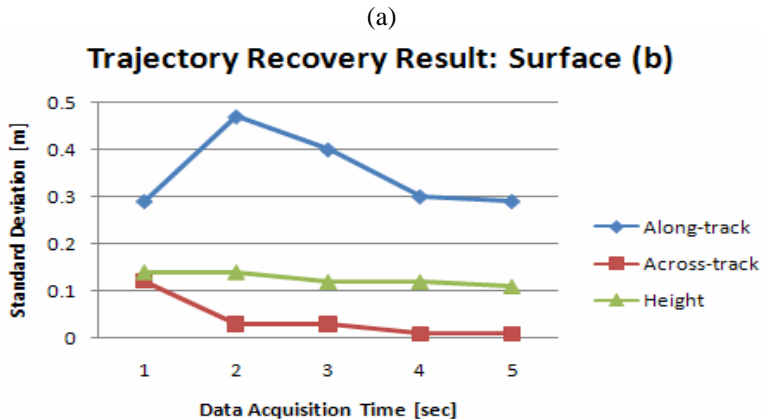
The test discussed in this section was performed using the simulated aerial LiDAR data. For the simulation, typical airborne LiDAR system parameter settings and error terms were used; the laser repetition rate (pulse rate) is set to 70 kHz and the platform speed is fixed at 220 km/h. To visualize the effects of terrain relief on the matching accuracy, several reference surfaces were generated for comparison. From each reference terrain, each LiDAR point cloud is simulated using the developed LiDAR simulator which imitates the bidirectional scanning mechanism. Then the ICP matching is performed between each simulated LiDAR data set and reference terrain. Following the ICP matching, the six-parameter rigid-body transformation parameters are computed via standard least squares adjustment

techniques. The position correction is made by applying the computed parameters to the INS-generated position.

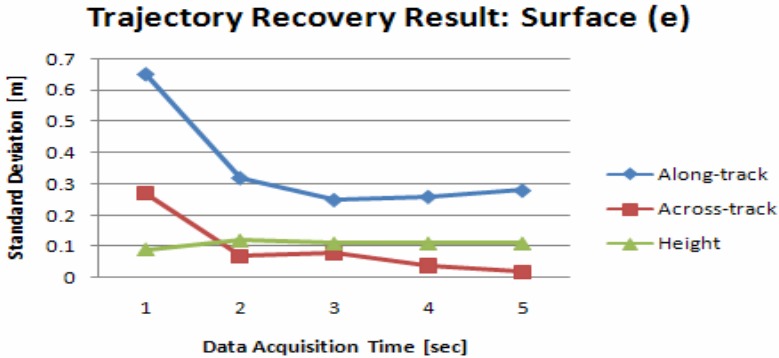
It should be noted that since the assumed LiDAR scanning is bidirectional, matching using only several LiDAR profiles may easily fail due to not enough features. Therefore, a certain number of profiles, acquired with a high scan rate, are assumed to be available to compute the linear scanner position drift and the rigid body transformation. For navigation grade INS, the short time gap (such as 1-5 seconds, corresponding to 70-350 laser profiles in the case of a 70Hz scan rate) should be sufficient to approximate the linear drift. To assess the effect, the number of scan lines for matching are changed and tested.

Figure 4 shows the standard deviation of the estimated position. The abscissa shows the assumed data acquisition time for the LiDAR profiles with the linear drift, in other words, the LiDAR data acquired for the time that is assumed to have a linear drift. Note that surface (e) has more distinct features than surface (b) and shows slightly better accuracy except for the test with one-second data acquisition time. The accuracy errors decrease and the solution stabilizes quickly as the longer time assumption is used. The height is well estimated in all test cases. Our initial analysis seems to indicate that the matching is affected to a larger extent by the linear drift assumption than by the terrain features for smaller bundles of LiDAR profiles.

Figure 4 - The estimated position accuracy from the LiDAR surface matching ((a) surface with small terrain relief (b) surface with high terrain relief).



(b)



6. DISCUSSION

Terrain-based navigation offers the opportunity to provide positional updates to an inertial system in the absence of (or in support of) GPS location. The challenge is to utilize data acquired by external sensors to facilitate a (near) real-time positional and orientation update to the integrated system to enable an ongoing correction to the navigation solution. In this paper we have demonstrated the practical feasibility of three different methods to address this challenge.

The utilization of SIFT features provides strong, robust solutions to a variety of potential image problems (corruption) and indicates the potential for an exceptional positional solution. Two issues remain: (1) the method does not provide depth information natively, and, therefore, requires additional processing to achieve the positional fix, and (2) the algorithm has issues with scalability; constraints are required to limit the number of SIFT features generated for large images or the matching algorithm will become rapidly intractable.

The LIDAR method provides ranging information and has demonstrated sub-meter accuracy; but the current state of technology renders the sensor highly susceptible to external radiative energy sources (room lighting for example) that can easily “blind” the sensor. The algorithm utilized in the noted experiments also requires the periodic rotation of the sensor in both the vertical and horizontal axes to enable a stronger solution; this additional motion and processing represents a time and computation lag to the solution in terms of generating a real-time, high-speed solution.

The methods and related experiments outlined above indicate that a comprehensive solution may be achieved by integrating multiple sensors via an extended Kalman Filter. Spurious sensor position information can be easily excluded, while the presence of redundant information at relatively low weight (and cost) can be practically achieved. The methods and algorithms outlined in this paper

reflect both the promise of navigation in GPS challenged environments and the need for supporting research to leverage new sensor technologies with cutting edge algorithmic developments in order to realize the objective of robust navigation without regard to the environment. The SPIN Laboratory at The Ohio State University continues to research and develop unique, innovative solutions to the navigation problem and is grateful for the opportunity to share a portion of the unique, innovative research currently ongoing in this field.

7. CONCLUSION

Terrain-referenced navigation has been used in military applications for decades. Recent improvements in sensor performance and real-time capabilities have made this concept a viable approach to mobile mapping. In contrast to past applications, the primary objective in mobile mapping is to improve the georeferencing solution of the platform, in particular in densely built-up urban areas. The TRN technique can tremendously help terrestrial mobile LiDAR systems, where the surveyed area is typically covered by several observations, acquired from near positions within a short time, such as using multiple 2D or 3D laser sensors. Given the dense point cloud and the strength of direct 3D observation, which preserves object shape, there is a strong geometry to recover the relative sensor pose, which, ultimately, can be used as fixes (position and/or attitude) to the EKF-based navigation filter. The TRN technique applies to optical imagery (2D), except the 3D data should be recovered from the imagery, which is known to be quite a challenge in general.

The benefit of using TRN in mobile mapping is apparent, but the implementation is far from being obvious. There are three major obstacles that need to be overcome to make TRN operational in mobile mapping practice. First, the amount of the acquired data is still a concern, as both images and point clouds could come in volume that proper recording needs significant recourses. Second, the real-time processing of the data stream poses a serious challenge in terms of processing capacity. The third issue is the complexity of the object space surveyed, which could include a variety of objects, coming in different shapes and with different dynamics. While the first two problems will slowly go away with improving computer technology, the third item requires significant research developments in the general case.

REFERENCES

References from Journals:

BERGMAN, N., LJUNG, L., AND GUSTAFSSON, F. Terrain navigation using Bayesian statistics. *Control Systems Magazine*, IEEE Volume 19, Issue 3, Jun 1999, pp.33-40.

- BESL, P.J., NEIL D. MCKAY. A Method for Registration of 3-D Shapes. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 14, No. 2, 1992, pp. 239-256.
- HORN, B. Closed-form Solution of Absolute Orientation Using Unit Quaternions. *Journal of the Optical Society of America A*, Vol. 4, 1987, page 629.
- HOSTETLER, L.D., ANDREAS, R.D. Nonlinear Kalman filtering techniques for terrain-aided navigation. *IEEE Transaction on Automatic Control*, AC-28, pp. 315-323, March 1983.
- KLASS, P.J. New Guidance Technique Being Tested. *Aviation Week & Space Technology*, pp.48-51, Feb 25, 1974.
- MIKOLAJCZYK, K. AND SCHMID, C. A Performance Evaluation of Local Descriptors. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 27, No. 10, October 2005.
- WENDT, F., BRES, S., TELLEZ, B., AND LAURINI, R. Markerless outdoor localisation based on SIFT descriptors for mobile applications, *Lecture Notes in Computer Science*. 2008, pp. 439-446.

References from Books:

- SHAN, J., AND TOTH, C. *Topographic Laser Ranging And Scanning*, CRC Press. 2008.

References from Other Literature:

- CAMPBELL, J. L., F. VAN GRAAS, M. UIJT DE HAAG. Terrain Referenced Precision Approach Guidance. *Proceedings of the ION National Technical Meeting*, San Diego, CA, 2005.
- CARROLL, JAMES et al. Vulnerability assessment of the transportation infrastructure relying on the global positioning system. *Technical report, Volpe National Transportation Systems Center*, August 2001. Report for US Department of Transportation.
- FLETCHER, J., VETH, M. AND RAQUET, J. Real-time fusion of image and inertial sensors for navigation. *Proceedings of the Annual Meeting - Institute of Navigation 2007*, pp.534-544.
- FRANK-BOLTON, ALVARADO-GONZALEZ, A. M., AGUILAR, W., AND FRAUEI, Y. Vision-based localization for mobile robots using a set of known views, *Advances in Visual Computing. Proceedings 4th International Symposium, ISVC 2008*. pp.195-204.
- HAAG, M.U., VADLAMANI, A., CAMPBELL, J.L., AND DICKMAN, J. Application of Laser Range Scanner Based Terrain Referenced Navigation System for Aircraft Guidance. *Proceedings of the Third IEEE International Workshop on Electronic Design, Test and Applications (DELTA '06)*, 2006, pp. 269-274.
- HAAG, M.U., VENABLE, D. AND SOLOVIEV, A. Implementation of a Flash-LADAR aided inertial navigator, *Position, Location and Navigation Symposium. 2008 IEEE/ION 5-8 May 2008*. p.560.

- LIU, J., WANG, M., AND ZHANG, J. Monocular Robot Navigation Using Invariant Natural Features, *Proceedings of the 7th World Congress on Intelligent Control and Automation*, Chongqing, China, June 25 - 27, 2008.
- LOPEZ, D.G., SJO, K., PAUL, C., AND JENSFELT, P. Hybrid Laser and Vision Based Object Search and Localization, *2008 IEEE International Conference on Robotics and Automation* Pasadena, CA, USA, May 19-23, 2008.
- MADHAVAN, R., AND MESSINA, E. Iterative Registration of 3D LADAR Data for Autonomous Navigation, *Proceedings of IEEE Intelligent Vehicles Symposium*, 2003, pp. 186-191.
- MARKIEL, J.N. An Algorithm for Automated Feature Extraction from Laser Ranging Data. *17th William T. Pecora Memorial Remote Sensing Symposium*, November 16-20, 2008a, Denver, Colorado, American Society for Photogrammetry & Remote Sensing (ASPRS).
- MARKIEL, J.N., GREJNER-BRZEZINSKA, D., AND TOTH, C. An algorithm for the extraction of static features from 3D Flash LADAR datasets: Supporting navigation in GPS challenged environments. *Position, Location and Navigation Symposium, 2008 IEEE/ION 5-8 May 2008b*. p.552.
- MARKIEL, J.N. Feature Based Navigation by Tightly Coupled Integration of Multiple Sensors. *Joint Navigation Conference*, Orlando, Florida, June 1-4, 2009.
- RUNNALLS, A.R., GROVES, P.D. AND HANDLEY, R.J. Terrain-Referenced Navigation Using the IGMAP Data Fusion Algorithm. *Proceedings of the 61st Annual Meeting of the Institute of Navigation*, pp. 976-986, June 2005.
- RUSINKIEWICZ, S., AND LEVOY, MARC. Efficient Variants of the ICP Algorithm, *Proceedings of Third International Conference on 3-D Digital Imaging and Modelling*, 2001, pp. 145-152.
- STRELOW, D. *Motion estimation from image and inertial measurements*, doctoral dissertation, tech. report CMU-CS-04-178, Robotics Institute, Carnegie Mellon University, November, 2004.
- TOTH, C. GREJNER-BRZEZINSKA, D.A., AND LEE, Y-J. Terrain-based navigation: Trajectory recovery from LiDAR data, *Proceedings of IEEE/ION PLANS*, pp. 760-765, May 2008.
- VETH, M.M. AND RAQUET, J. Fusion of low-cost imaging and inertial sensors for navigation, *Proceedings of the Institute of Navigation - 19th International Technical Meeting of the Satellite Division, ION GNSS*, 2006. pp.1093-1103.
- References from websites:**
- LOWE, D. "Distinctive Image Features from Scale-Invariant Keypoints", <http://www.cs.ubc.ca/~lowe/papers/ijcv04.pdf> (accessed 29 June 2009)