PERSONAL NAVIGATION: EXTENDING MOBILE MAPPING TECHNOLOGIES INTO INDOOR ENVIRONMENTS

Navegação pessoal: Tecnologias de mapeamento móvel na ampliação da navegação em ambientes internos

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ABSTRACT

This paper discusses some unconventional methods for indoor-outdoor navigation, based on the integration of self-contained sensors, including GPS, IMU, digital barometer, magnetometer compass, and a human locomotion model. The human locomotion model is used as navigation sensor and it is handled by Artificial Intelligence (AI) techniques that form an adaptive knowledge-based system (KBS), which is trained during the GPS signal reception, and is used to support navigation under GPS-denied conditions. A complementary technique used in our solution, which facilitates indoor navigation, is the image-based method (Flash LADAR). In this paper, the system design and an example performance analysis in the mixed indoor-outdoor environment are presented.

Keywords: Multi-sensor Navigation; Dead Reckoning; AI Methods; Human Locomotion Modeling; Image-based Navigation.

1. INTRODUCTION

The ability to determine one’s position in absolute or map-referenced terms, relative to objects in the environment, and to move to a desired destination point is an everyday necessity. Recent years have brought an explosion in the development of portable devices that support this functionality. Systems that were traditionally used for sensor geo-location in mobile mapping, such as the Global Positioning System (GPS) and inertial measurement units (IMU's), are now miniaturized and cost effective, facilitating portable, inexpensive navigation of mobile users. A Personal Navigation Assistant (PNA), also known as Personal Navigation Device (PND), is a portable electronic tool which combines positioning and navigation capabilities. Position is usually provided by GPS, and possibly by other sensors (not necessarily of the navigation type in the traditional sense). The most commonly used PNA's are the hand-held GPS units, which are capable of displaying the user’s location on an electronic map backdrop. However, the newest generation of PND's offers many more features, such as real-time traffic information, location of points of interest, and utilizes maps of entire continents. They offer sophisticated navigation functions and feature a variety of user interfaces including maps, turn-by-turn guidance and voice instructions that have been developed primarily for car navigation. Dead Reckoning (DR) navigation using data collected by independent self-contained sensors, such as gyroscopes, accelerometers and barometers can be used in GPS-challenged environments, but in the truly indoor settings, other means of navigation must be used.

Personal navigators (PNs) have been studied for about a decade in different fields, such as visual surveillance, rescue work, security and emergency services, police safety and military applications (Grejner-Brzezinska et al., 2008). The common issue in all these applications is to provide position/heading information for the individual users in environments with or without GPS availability. With no line-of-sight blocked, or under short GPS losses of lock, a GPS/IMU system provides the navigation capabilities within a specified accuracy, depending on the type of IMU and GPS measurement/solution type. This integration is normally facilitated by an Extended Kalman Filter (EKF). Since personal navigation is normally requested for mixed indoor-outdoor environments, the main challenge is in designing a system capable of maintaining the navigation solution during prolonged losses of GPS signals.

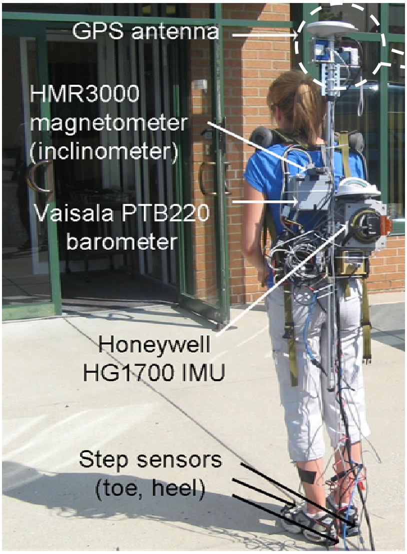
One of the methods used in indoor navigation is based on optical tracking systems, also referred to as image-based navigation (Moafipoor, 2006; Veth and Raquet, 2007). The GPS/IMU/camera sensor combination is often used in modern navigation systems, where GPS/IMU directly provides the attitude and position of the captured digital imagery. The vision modules are usually designed to track navigation information by matching the captured images with the pre-registered images stored in a database. However, these approaches are very difficult to implement in a large-scale environment. A more practical solution, proposed here, is based on the technique called feature tracking-based navigation. In this algorithm, when the GPS/IMU data are available, the captured images are geo-referenced. Then, when the user enters new environments and subject moves out of the GPS signal availability, the new captured images that overlap with the geo-referenced images are used to estimate the user's position.

Recent innovations in laser ranging technology enable the utilization of laser "images" instead of traditional 2D photographic image acquisition to facilitate the feature based navigation methodology. Navigation from 3D Flash Laser Ranging (LADAR) scene reconstruction utilizes the range distance to static features common in images acquired from two or more separate positions, which allows for tri-lateration of the user's position. The challenge, given limited a priori knowledge of the sensor environment, is to locate and match "*n*" features from an initial image in the subsequent image(s). Algorithms enabling this objective are limited in the instance of true 3D scene reconstruction and frequently invoke the use of nonlinear estimation techniques. In our current system implementation, motion of both the acquisition device and features in the environment are subject to movement. By utilizing the Flash LADAR image in tandem with the IMU, a linear feature-based algorithm to achieve the identification of common static features between two images, along with the error estimates is facilitated. Since the algorithm is based on linear methodologies, it enables rapid processing while generating robust, accurate position and error estimation data. The algorithm provides an effective solution to the problem of feature identification and provides an essential link towards enabling navigation from 3D ranging imagery

2. EXPERIMENTAL SYSTEM PROTOTYPE

The primary sensors, used in the current PN prototype, include a dual frequency GPS receiver, Honeywell tactical grade HG1700IMU, Vaisala PTB220 barometer, HMR3000 magnetometer compass, and a set of four step sensors (micro-switches) that support human locomotion modeling, as shown in Figure 1. The additional sensors, recently added to this architecture, are a 7Megapixel Cannon digital camera and SR3000 Flash LADAR. Details related to the Flash LADAR system can be found in (Lange 2000; Oggier 2003).

Figure 1 - Personal Navigator: sensor configuration.



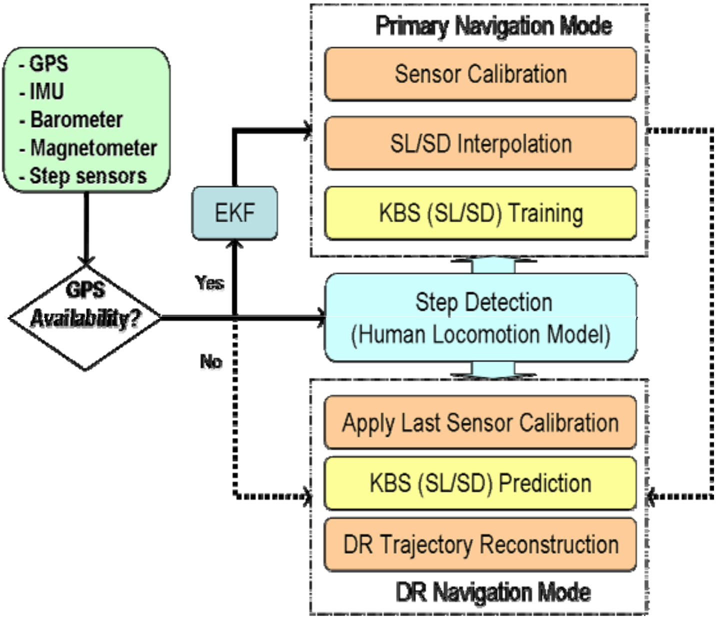
Sensors used in the current prototype
Honeywell HG1700 IMU
HMR3000 magnetometer (inclinometer)
Vaisala PTB220 barometer
GPS
Canon digital camera
SR3000 flash LiDAR

3. NAVIGATION IN DEAD RECKONING MODE VIA SELF-CONTAINED SENSORS

An important aspect of this design is to use human body as a navigation sensor to facilitate DR navigation in GPS-challenged environments. DR navigation is a relative measurement approach, the fundamental idea of which is to integrate incremental motion information over time. Starting from a known position before the GPS outage, successive position displacements, derived in the form of changes in step direction (SD) and step length (SL), are accumulated. DR navigation is achieved through a sequence of processes, where each step in this process exhibits a full range of functions to accomplish and has different rates of complexity, success, and failure. Figure 2 shows the general architecture of DR navigation designed for the multisensor PN system. The first stage of the process is to perform individual sensor calibrations, as well as sensor inter-calibration. This task is achieved using the EKF and carried on until the filter reaches a steady state, indicating that the system is ready to navigate.

Once the sensors are calibrated, two interconnected procedures are performed as a by-product of the primary navigation solution: first, updating the sensor calibration parameters and recording the calibration sets, and second, training a knowledge-based system (KBS) to support the human locomotion modeling and predict the SL/SD parameters (Grejner-Brzezinska et al., 2007). SL and SD are both modeled in our application using artificial neural networks and fuzzy logic (Kosko, 1991; Lin and Lee, 1996); see, e.g., Grejner-Brzezinska et al., 2006; Moafipoor et al., 2008a; Moafipoor, 2009.

Figure 2 - Extended architecture of the Personal Navigator

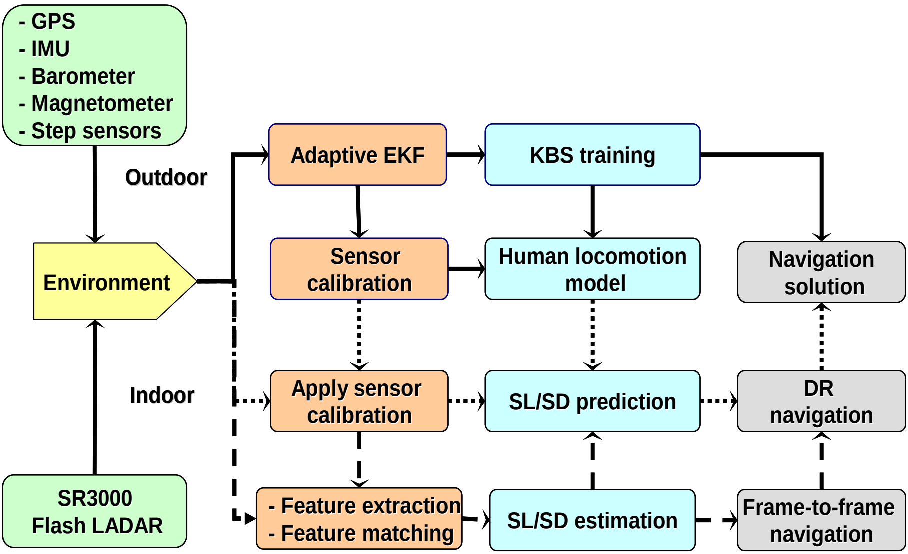


The central idea of fuzzy DR navigation is to determine the classes of complex body locomotion by which the SL/SD can be predicted more meaningfully (Grejner-Brzezinska et al., 2007; Moafipoor, 2009). Later, in the absence of GPS signals, the data streams from the remaining sensors are corrected based on the last recorded calibration parameters, and sent to the KBS module for prediction of DR navigation parameters.

Study on the DR navigation supported by the self-contained sensors exhibits two main limitations in the challenging environments: first, the imperfection of sensors over time (and thus, a gradual error increase), and second, the low redundancy condition. The self-contained sensors, particularly IMU, require a continuous calibration; otherwise, their quality would degrade over time. The DR navigation is a relative navigation approach, and thus, the outliers associated with the previous estimates will be propagated into the next estimates and will accumulate over time/distance traveled. If the redundancy is high, measurement outliers could be simply identified and eliminated or replaced by a new observation. To this end, it is important to increase the reliability of the system by integrating more observations from non-inertial sensors, such as Flash LADAR images, as discussed later.

The current fuzzy logic system aggregates various types of external information in the form of fuzzy rules developed using the training datasets, acquired during the KBS design and training process (Moafipoor et al., 2008b). In the current prototype implementation, 56 fuzzy rules have been formulated by fuzzy definition of individual behaviors of the variables provided by the self-contained sensors. However, due to the flexible architecture of the fuzzy engine, it can facilitate an easy addition of constraints, such as, the hallway layout for indoor navigation obtained from Flash LADAR images.

Figure 3 - Primary navigation and DR navigation modes of Personal Navigator.



By adding more observations, the reliability of the system is also increased, and facilitates accurate tracking and trajectory reconstruction. As a result, the architecture of the system can be extended, as illustrated in Figure 3.

In the extended architecture, once each frame of LADAR image is pre-processed, the features of interest are extracted and tracked in subsequent frames. This procedure supports the estimation of the frame's displacement providing a feedback to SL and SD estimation. Next, these estimates are added to the fuzzy KBS in the form of fuzzy rules, to constraint the DR navigation.

It also should be noted that Figure 3 incorporates a separate module for the feature-based navigation system. This enables multiple redundancies to the PN system, which enhances the overall performance. The feature-based component of the PN system is discussed in the following section.

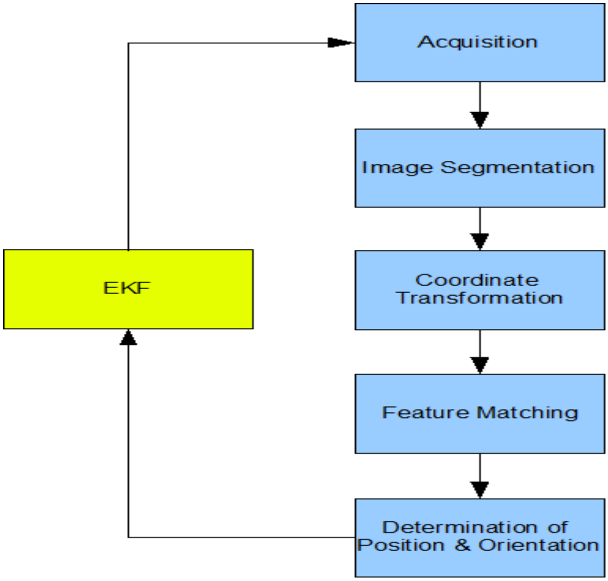
4. FEATURE-BASED NAVIGATION BY LADAR IMAGERY

As previously noted, the IMU sensor system provides excellent positional information over short temporal spans, but integration errors grow rapidly and require external information to enable continuous calibration/navigation. One possible option is the utilization of relative positioning; if static features can be matched from sensor data acquired from two different positions, the relative position from the last known position (GPS) can be estimated with considerable accuracy.

Laser ranging data can be utilized to reconstruct the 3D scene, as acquired from a particular pose; by matching static features between two different scene reconstructions, both relative position and orientation can be determined. The challenge is two-fold; first, to extract n features from the first laser "image", and secondly to match them against m features in the second laser image to determine matches. Given that both the acquisition device (Flash LADAR camera) and the features within the object space are potentially moving and that limited a priori information is available about the scene(s), the problem of feature correspondence is not trivial. However, by leveraging the available IMU information, it is possible to constrain the problem and achieve a tractable solution (Markiel, et al., 2007). The position and orientation "update" acts as a substitute for the missing GPS and enables the EKF to calibrate the IMU system. The resulting feedback loop enables an accurate navigation solution to be maintained while the GPS signal lock is absent.

The process of feature-based matching from 3D laser ranging imagery consists of four modules. It was demonstrated that the algorithm can generate RMS errors in the millimeter range when utilized on an image to image basis (Markiel et al., 2008). A general flow for the feature-based navigation system element is shown in Figure 4. The first module presents an innovative method for image segmentation based upon the eigenvector signatures of linear based features. Pixels with similar signatures are merged to create features; the edges of these features are converted to a binary image to enable rapid evaluation and processing of feature edges in later modules. A key innovation is the utilization of statistics drawn from the image data to drive thresholding heuristics. The two images are treated as samples drawn from a larger, unknown distribution of range values and compared to verify the condition of homogeneity. After verification, the heuristics are dynamically adjusted based upon changes to the distribution of range values. Since the algorithm does not rely on a priori values to determine the segmentation characteristics, the program can operate on an automated basis.

Figure 4 - General flowchart for feature based navigation from LADAR imagery



The second module converts the previous image to the same coordinate frame as the current image. This is accomplished by a two-step process. First, information from the inertial system provides an initial estimate of the necessary adjustment. This initial transformation incorporates errors inherent to the inertial system and must be refined. An additional innovation is the implementation of a RANSAC (Random Sampling Consensus) style approach to finalize the transformation. The range of solution space is constrained by the error information from the initial inertial data, which enables the algorithm to determine the solution based exclusively upon the sensor data. After the quaternion-based transformation of the previous image is complete, the image is motion compensated to adjust for pixels which are not relevant to the transformed image due to the change in pose and associated change in field of view. A key issue in comparing imagery is the ability to match features between images. The problem of locating n features from the initial image amongst m features in the current image is not trivial; in general, the problem is not well posed. The third module of the algorithm resolves the challenge of feature matching by comparing eigenvector signatures for feature edge pixels in each image. The algorithm again leverages statistics derived from the image to enable automated, heuristically based evaluation of matching features.

The final module triangulates the position of the mobile unit based upon the known ranges to matched features. Position, scale, and orientation solutions are made possible by implementing the closed form algorithm proposed by Horn (Horn, 1987). The information is then returned to the integrated system to update the inertial system. This aspect of the program directly emulates a traditional GPS/IMU tightly coupled integration schema with two important variations. First, the feature-based, triangulated position is utilized instead of the GPS coordinates/measurements, and secondly, the covariance matrix for the corrected position is updated at each iteration. This reflects the variable uncertainty due to differences in image matching results. After updating, the inertial unit returns coarse information for the relative change in pose during the acquisition of the next image, and the algorithm initiates a fresh sequence of feature matching and position evaluation.

5. EXAMPLE EXPERIMENTS

This section provides a performance evaluation of the PN prototype, with a special emphasis on DR navigation supported by the human locomotion model and Flash LADAR images. The current target accuracy of the system is 3-5 m CEP50 (circular error probable, 50%).

The field tests started in the outdoor environment, where the sensor calibration process was completed, followed by the DR navigation indoor. The system performance of the adaptive KBS is primarily evaluated in terms of the quality of the navigation solution in the confined environment. Then, the additional experiments were conducted to determine the navigation trajectory using the Flash LADAR images, and explore its limitations in the DR mode in terms of the trajectory length and duration. For this purpose, a series of datasets was collected at the Center for Mapping (CFM) building, at The Ohio State University. The floor plan of the building was previously acquired by classical surveying methods, and several control points were established in the hallways to accuracy better than 1-2 cm in E and N, and 5 mm in height. The main objective of the control points was to facilitate the prediction of the user’s position and to provide the reference trajectory.

5.1 Outdoor Experiment

In order to calibrate the system and to test the performance of the KBS modules in SL/SD modeling, the mobile users performed several maneuvers outside the CFM building as a part of the calibration process. Next, the reference step length, interpolated from the GPS/IMU solution for the micro-switch time events, was compared to the KBS-based SL values. The resulting accuracy of the predicted SL had the mean (STD) equal to 0 cm (4 cm). The SL obtained this way was subsequently integrated with the calibrated magnetometer heading to reconstruct the navigation trajectory. Figure 5 illustrates an example DR trajectory. The original trajectory is plotted in blue, and the DR trajectories reconstructed by fuzzy logic SL and the calibrated magnetometer heading are plotted in red. The 167m trajectory was reconstructed with a CEP (50%) less than 1m, indicating the accurate calibration of the sensors and accurate training of the KBS module (see Table 1).

Figure 5 - Reference and the KBS trajectories, 167 m trajectory.

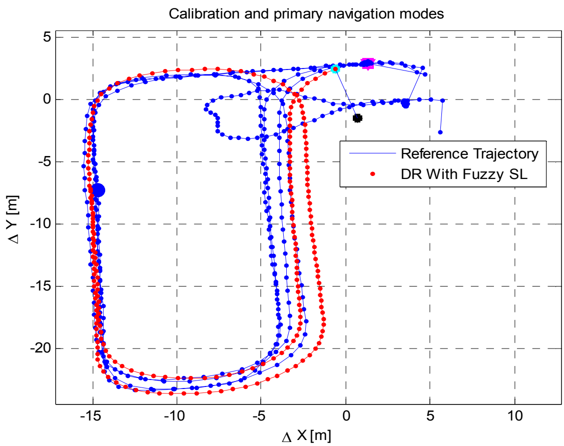


Table 1 - Statistical fit to reference trajectory of a DR trajectory generated using SL predicted with fuzzy logic and SD estimated by the calibrated magnetometer compass (outdoor).

Test data set	Mean [m]	Std [m]	Max [m]	End Misclosure [m]	CEP (50%) [m]
167 m	0.86	0.4	1.6	3.12	0.73

5.2 Indoor Experiment with Self-Contained Sensors

Once the sensor calibration was completed, the system is ready to switch to indoor navigation, where it is expected that SD and SL may be subject to larger point-to-point deviations, due to magnetic disturbances and unexpected obstacles en route, such as, for example, climbing stairs. The SD was provided by the integration of gyro and magnetometer.

Thus, the main objective of the next test was to evaluate the system's performance in terms of KBS-SL/SD modeling and the trajectory reconstruction in the indoor settings. For this test, a part of the dataset was selected, where the operator walked one and half indoor loops for about 97m in 2 minutes. The SD was provided by the integration of gyro and magnetometer. The heading obtained this way was subsequently integrated with the KBS-based fuzzy logic SL. Figure 6 shows the trajectory reconstruction result. The square symbols in Figure 6 represent the ground control points that were followed by the operator, representing the reference trajectory. The statistical results of the reconstructed trajectory using fuzzy logic SL and SD observations from the integrated of gyro/magnetometer shows a performance with CEP (50%) less than 2m (see Table 2).

The performance evaluation presented here shows only an example of the series of tests performed to date. In general, the accuracy of CEP50 better than 5 m was demonstrated for trajectories up to ~700 m in the indoor environment (for more details see, e.g., Moafipoor et al., 2008a and b; Moafipoor 2009).

Figure 6 - Center for Mapping floor plan and DR trajectory reconstruction based on fuzzy logic SL modeling integrated with gyro/magnetometer heading.

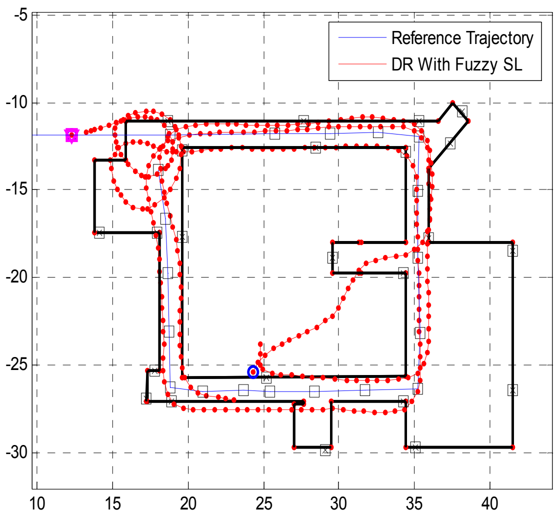


Table 2 - Statistical fit to reference trajectory of DR trajectory generated using SL predicted with fuzzy logic and SD estimated by the gyro/magnetometer heading (indoor).

Test data set	Mean [m]	Std [m]	Max [m]	End Misclosure [m]	CEP (50%) [m]
194 m	1.59	1.41	3.82	3.38	1.3

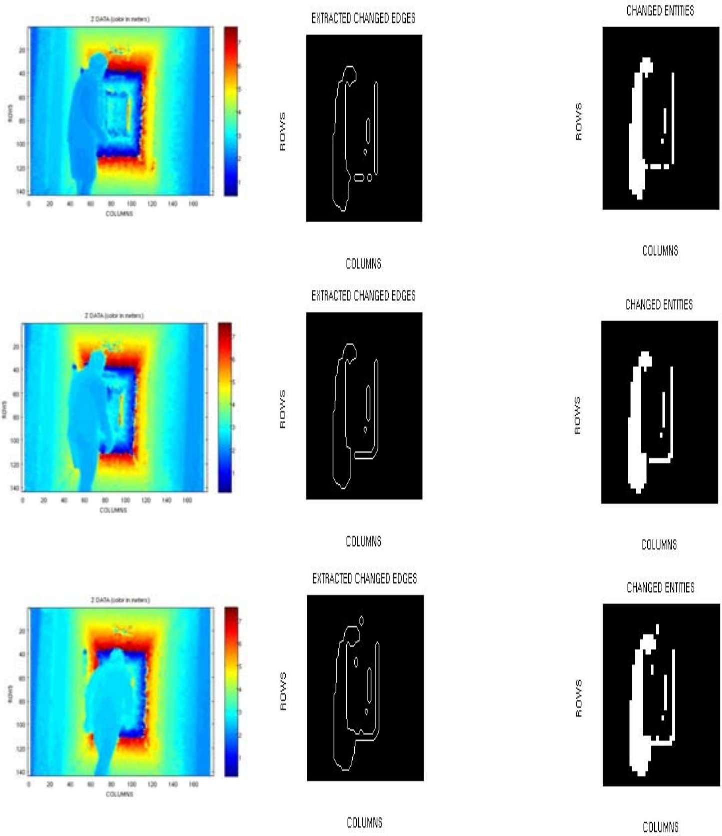
5.3 Ladar-Based Navigation: Experimental Results

To demonstrate the performance of the algorithm described in section 4 we have applied it to a number of acquired datasets (Markiel, 2007). The first demonstration shows the extraction of change edges and entities for a person moving down an indoor a hallway. The second, and more challenging exercise, involves the extraction of a moving person in an outdoor scene. The outdoor environment represents a greater challenge due to the corrupting influence of external light sources, which interfere with the low power Flash LADAR signal and generate considerable noise.

The results indicate an overall identification of the non-static entity (the person) while limiting the incorrect classification of static features. Some error is induced along the floor and wall edge owing to three sources of error. First, the platform for the camera is not stable due to being held by hand and introduces a movement not related to the environment. This is most evident along the right side of the image where a highly reflective metallic strip along a window frame causes an unusual variance in the reflected signal, resulting in a different parameter structure despite a small change in camera orientation. Secondly, the overhead lighting introduces interference to the reflected signal; this characteristic is exhibited along the floor where the two signals interact in reflection. On other occasions, we have observed artifacts extending directly from the light source.

One possible countermeasure to this condition would be to interlink the intensity data with the ranging data; abrupt changes in intensity could indicate the presence of external light sources which should be ignored. This represents a potential improvement to the existing algorithm which requires further testing and evaluation. Finally, the range of the camera is limited to approximately 7.5 meters.

Figure 7 - Test One, time series of Flash LADAR images (a), extracted non-static edges (b) and entities (c).



(a) (b) (c)

At this point, range ambiguity exists which becomes a virtual "surface" during scene reconstruction; note that phase unwrapping is a potential solution to extend the range of the camera.

While we have not engaged in specific efforts to optimize the processing time for the algorithm, the performance is quite stable. In general, a 718 kb image can be processed in ~18 seconds on a commercially available 32 bit processor laptop with 2GB of memory. This result is also encouraging since the future efforts may involve considerable increases in both frame rate and pixel density.

Finally, the positional errors for a series of images from test one are presented in Table 3; note that the image-to-image performance is only considered. While later images in the sequence were identified for positional difference, the inertial errors increase rapidly without a positional fix, increasing the uncertainty of the rotational correction. The results presented are reflective of conditions while drift errors remain below 1 cm for a sequence up to 30 images. The same results are presented in Table 4 without the benefit of rotational corrections, indicating the contribution of the rotational changes to the positioning error. Table 5 indicates the differences between them to examine the change resulting from rotational correction; the remaining error is due to the matching errors and random error characteristics.

5. SUMMARY AND CONCLUSIONS

This paper discussed two unconventional techniques of indoor-outdoor navigation, one based on the integration of GPS, IMU, digital barometer and magnetometer compass with human locomotion model handled by Artificial Intelligence techniques, and another one, based on the Flash LADAR image sequence matching. Both solutions are designed for indoor navigation, where GPS signals are not available.

The primary novelty of the multi-sensor approach presented here is the use on AI techniques to support dead reckoning navigation mode, and image-based navigation derived from the 3D Flash LADAR images. The scene reconstruction utilizes the range distance to static features common in images acquired from the subsequent positions, which allows for triangulation of the user's position. By utilizing the Flash LADAR image supported by the IMU-based orientation, a linear feature-based algorithm is facilitated. It was demonstrated that this approach provides an effective solution to the problem of feature identification, which serves as an essential link towards enabling navigation from 3D ranging imagery.

The two DR modules, (1) based on the AI techniques and (2) Flash LIDAR image-based are presently being integrated together to provide more reliable and continuous navigation solution, with more sensor redundancy, as compared to each solution individually. While the design and implementation details are provided in the references listed here, this paper only discussed the generic concept design and an example performance implementation of both modules. Future work includes a performance evaluation of the integrated human locomotion/image-based personal navigation.

Table 3 - Positional error from sequential images with motion compensation from indoor test.

With Motion Compensation			
Image 2~3	X	Y	Z
Position Error	-0.0066	-0.0040	0.0175
Position σ	0.0114	0.0069	0.0304
Image 3~4	X	Y	Z
Position Error	-0.0027	0.0026	0.0017
Position σ	0.0047	0.0045	0.0029
Image 4-5	X	Y	Z
Position Error	-0.0045	-0.0014	-0.0012
Position σ	0.0078	0.0024	0.0022
Image 31~32	X	Y	Z
Position Error	-0.0022	-0.0062	0.0014
Position σ	0.0039	0.0108	0.0024

Table 4 - Positional error from sequential images without motion compensation from indoor test.

Without Motion Compensation			
Image 2~3	X	Y	Z
Position Error	-0.0066	-0.0040	0.0175
Position σ	0.0115	0.0068	0.0304
Image 3~4	X	Y	Z
Position Error	-0.0027	-0.0001	0.0024
Position σ	0.0047	0.0002	0.0041
Image 4-5	X	Y	Z
Position Error	-0.0045	-0.0013	-0.0012
Position σ	0.0079	0.0023	0.0022
Image 31~32	X	Y	Z
Position Error	-0.0027	-0.0056	0.0107
Position σ	0.0047	0.0097	0.0185

Table 5. Differences between the results listed in Table 3 and Table 4.

Delta			
Image 2~3	X	Y	Z
Position Error	0.000028	-0.000028	-0.000002
Position σ	0.000049	-0.000048	-0.000004
Image 3~4	X	Y	Z
Position Error	0.000010	-0.002456	0.000703
Position σ	0.000017	-0.004253	0.001218
Image 4-5	X	Y	Z
Position Error	0.000035	-0.000038	0.000001
Position σ	0.000060	-0.000066	0.000002
Image 31~32	X	Y	Z
Position Error	0.000476	-0.000616	0.009314
Position σ	0.000825	-0.001067	0.016132

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