# An Advanced Approach for Navigation and Image Sensor Integration for Land Vehicle Navigation

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*Abstract*—**In the last couple of decades, the demand of navigation technology has been increased and the technology has been expanded in several application areas including automated car navigations and mobile mapping systems. However, there has been little research and study on the integration of GPS, IMU, and image sensors such as CCD, and video camera. This paper aims at aiding inertial navigation sensors with image sensor measurements and distance measurements even in the environment of no courtesy of GPS. Using extended Kalman filtering technique, a novel integration scheme, a multi-modal approach, is presented in this paper for various sensors such as IMU, GPS, odometer, and CCD cameras to improve positioning accuracy. Experimental results show that the proposed multi-modal approach can be used to enhance positioning accuracy during GPS outages.**

***Keywords; IMU, photogrammetry, multi-modal***

## I. INTRODUCTION

Most of the land vehicle navigation heavily depends on the GPS to provide the vehicle's positioning information. However, GPS is capable of continuously providing users with navigation solutions only when there is a direct line of sight to more than 4 satellites. When a vehicle enters into urban canyon area, positioning information gets deteriorated due to signal blockage and attenuation. To overcome this limitation, the integration of additional devices to bridge GPS data gap is required. Typical integration scheme combines a GPS receiver with low cost INS such as gyroscopes and accelerometer. However, this system has accumulative errors over time and this operation is heavily dependent on the period of GPS signal outage. To reduce this poor performance with low cost INS over time, bimodal approach was introduced in our previous paper. This novel bimodal approach is achieved through the integration of visual measurements acquired by image sensors such as CCD[1],[2]. However, there are some difficulties for practical use such as high-resolution image sensors and accumulative wrong pixel selection. Therefore, enhancing 3D positioning accuracy of feature points would be necessary to build up this approach. We extend our previous research by the combination of distance measuring instruments and image sensor measurements to an extended Kalman filtering scheme. For the better performance, we utilized the image processing technique, such as block matching method, to correct the accumulative pixel errors by processing sequential image frames. Block matching is performed as a means of correlating a block from the first image with a block of the second [3]. The position at which the first block correlates in the second image is then later used to infer 3D position data of feature points. This paper is organized as follows. In Section 2, background study is performed. In Section 3, we present details of the proposed multi-modal approach. Experimental results are covered in Section 4. Position accuracy analysis is presented for land vehicle test. Finally, conclusions are given in Section 5.

## II. BACKGROUND STUDY

The emphasis of this section is to review a general loosely coupled GPS/IMU integration approach, space intersection and resection in photogrammetry, and the bimodal approach in previous research.

### *A. GPS/INS/odometer Integration*

GPS/IMU/odometer integration is required to meet the positioning accuracy and availability in a local area. There are basically two integration approaches based on extended Kalman filtering technique, namely loosely coupled and tightly coupled approaches [4],[5]. With regard to loosely coupled approach, it manages GPS, IMU and odometer as an independent system. GPS or odometer solutions are fed back into Kalman filtering to estimate IMU errors. In contrast, tightly coupled approach deals with GPS, IMU and odometer as a one system and one sensor. Therefore, only single filter is adopted to complete the integration system [3]. Integration of GPS and IMU is the moderately affordable and economic solution as highly accurate position and attitude information is required. The general and popular approach to integrate IMU and GPS information is via Kalman filtering technique that is defined as to minimize the mean square errors of both systems [5],[6]. However, the lack of GPS visibility can't provide measurements and update the state estimates in Kalman filtering routine. Odometer devices are also employed to aid and compute the position and orientation to fill in the gaps when GPS signal is temporarily interrupted. Integration of GPS and IMU is the moderately affordable and economic solution as highly accurate position and attitude information is required.

### *B. Photogrammetry*

Photogrammetry provides the measurement of spatial dimension, position and orientation of three-dimensional objects from two-dimensional images [6]. The fundamental issue in photogrammetry is to determine object space coordinates from corresponding 2-D image coordinates. Fig. 1 illustrates the photogrammetric process and derives the collinearity equation as described in (1).

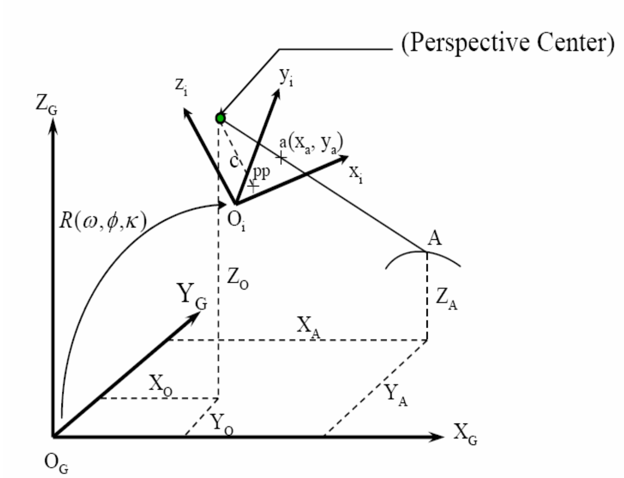


**Fig. 1.** Photogrammetric process

$$x_a - x_p = -c\frac{R_{11}(X_A - X_0) + R_{12}(Y_A - Y_0) + R_{13}(Z_A - Z_0)}{R_{31}(X_A - X_0) + R_{32}(Y_A - Y_0) + R_{33}(Z_A - Z_0)}$$
$$y_a - y_p = -c\frac{R_{21}(X_A - X_0) + R_{22}(Y_A - Y_0) + R_{23}(Z_A - Z_0)}{R_{31}(X_A - X_0) + R_{32}(Y_A - Y_0) + R_{33}(Z_A - Z_0)} \quad (1)$$

where,

$x_a$, $y_a$ = image coordinates

$x_p$, $y_p$, c = Interior orientation parameters (principal point, focal length)

$X_0, Y_0, Z_0$ = coordinates of projection center

$X_A, Y_A, Z_A$ = object coordinates

$R_{11} \sim R_{33}$ = elements of orientation matrix

### C. *Bimodal Approach*

The bimodal approach presented in our previous approach focused an image-based approach to compensate the poor performance of low cost IMU. The bimodal approach starts right after GPS blockage happens. It locates the last frame with GPS signal and calculates a 3D coordinate of a chosen feature point. After calculating the 3D coordinate of the feature point, we can derive the position and attitude information of the vehicle using system calibration parameters, i.e., lever arm parameters. Then, this positioning information are fed back into the Kalman filter to be combined with data from IMU. In this approach, measurements are the errors in the derived position from IMU and image based calculation. By performing this approach, we can still continuously provide position and attitude information even without GPS signals. Our past work heavily relied on the assumptions that no error in position and attitude information is generated from image frames [1].

## III. ADVANCED APPROACH SYSTEM DESSIGN

Our previous bimodal approach is limited in practical application because of accumulative errors while processing image frames. So this section challenged this obstacle by introducing image processing technique and local sensor displacement error model between image and navigation sensors. Our approach is based on the loosely coupled approach to integrate multiple measurements.

### A. *Mathmatical Modeling*

In multi-modal approach, uncertain parameters introduced by image processing and photogrammetric approaches contribute to deteriorate positioning accuracy. Therefore, the discussion in this section covers the proper modeling of respective sensors.

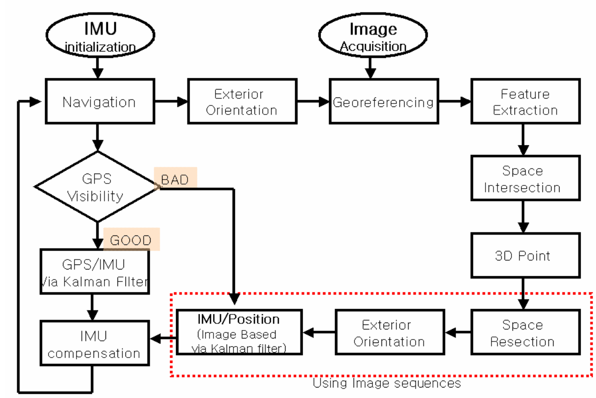


**Fig. 2.** Proposed multi-modal approach

As shown in Fig. 2, the measurements derived from DGPS, odometer, or image derived EOPs are utilized to correct contaminated IMU signals. The function of Kalman filter scheme is to detect and isolate inertial outputs. The state of the system augmented with the INS error state consists of a scale factor error and positioning errors from image processing and geo-referencing schemes. Many different inertial error models are available in literatures which are all equivalent [7],[8]. Using inertial data as nominal trajectory non-linear equations are linearized and shown as the following matrix form of dynamical equation of linearized Kalman filter [7].

$$\delta\dot{x} = F \cdot \delta x + w \quad (2)$$

where,

F = state transition matrix

w = state noise vector

The measurements model used in this paper extend respective multi-sensor measurements into integrated Kalman Filter. There are three kinds of observation available to the integrated filter: DGPS measurements, odometer measurements, and image derived position. DGPS measurements are available at 1Hz, DMI measurements at 200Hz, and image derived measurements at 1Hz.

The relative sensor measurements can be written as (3).

$$\tilde{r}_{IMU} = \tilde{r}_{im} - \begin{bmatrix} \frac{1}{\hat{R}_m + \hat{h}} & 0 & 0 \\ 0 & \frac{1}{(\hat{R}_t + \hat{h})\cos\hat{L}} & 0 \\ 0 & 0 & -1 \end{bmatrix} \hat{C}_b^n \Delta\tilde{r}^b \tag{3}$$

$$\begin{aligned}
&= r_{im} + \delta r_{im} - (\Xi + \delta\Xi)(\mathrm{I} - \Psi) C_b^n (\Delta r^b + \delta\Delta r^b) \\
&= r_{im} + \delta r_{im} - (\Xi + \delta\Xi)(\mathrm{I} - \Psi)(C_b^n \Delta r^b + C_b^n \delta\Delta r^b) \\
&\approx r_{im} + \delta r_{im} - (\Xi + \delta\Xi)(C_b^n \Delta r^b - \Psi C_b^n \Delta r^b + C_b^n \delta\Delta r^b) \\
&\approx r_{im} + \delta r_{im} - (\Xi C_b^n \Delta r^b + \delta\Xi C_b^n \Delta r^b - \Xi\Psi C_b^n \Delta r^b + \Xi C_b^n \delta\Delta r^b) \\
&= r_{im} + \delta r_{im} - \Xi C_b^n \Delta r^b - \delta\Xi C_b^n \Delta r^b + \Xi\Psi C_b^n \Delta r^b - \Xi C_b^n \delta\Delta r^b
\end{aligned}$$

By arranging and neglecting above terms, we can simply represent the measurements errors as follows.

$$\therefore \hat{r}_{IMU} - \tilde{r}_{IMU} = \begin{bmatrix} \delta L \\ \delta\ell \\ \delta h \end{bmatrix} + \begin{bmatrix} 0 & \frac{-\Delta r^n(3)}{R_m + h} & \frac{\Delta r^n(2)}{R_m + h} \\ \frac{\Delta r^n(3)}{(R_t + h)\cos L} & 0 & \frac{-\Delta r^n(1)}{(R_t + h)\cos L} \\ \Delta r^n(2) & -\Delta r^n(1) & 0 \end{bmatrix} \begin{bmatrix} \phi_N \\ \phi_E \\ \phi_D \end{bmatrix} + v_{im} \tag{4}$$

*B. Measurements Refinements*

Considering lens distortion parameters, the collinearity equations are expanded as

$$f_1 = S \cdot x_a - x_p + dx + c\,\frac{U}{W}$$

$$f_2 = S \cdot y_a - y_p + dy + c\,\frac{U}{W}$$

Because of strong correlation between interior and exterior orientation parameters, singularity problem in a least square estimation approach is aroused. To eliminate this dilemma, we separately calculate exterior and interior orientation parameters. We define $f_{ex} = (\omega, \theta, \kappa, X, Y, Z)$ for exterior orientation parameters and $f_{in} = (x_p, y_p, c, dx, dy)$ for interior orientation parameters. For given value of $f_{in}$ and coupled of image coordinates, $f_{ex}$ are directly determined by a least square solution which is so called "space resection" in photogrammetry.

However, while processing image data, faulty selection is primary culprit to choose the same feature points appeared in consecutive two frames. To alleviate and compensate the errors of several pixels problem, motion estimation scheme applied to determine inter-frame image motion and estimate camera motion. Inter-frame motion is determined by matching technique as shown in Fig. 3. By applying this skill successfully, the refined measurements can be combined with a Kalman Filter.

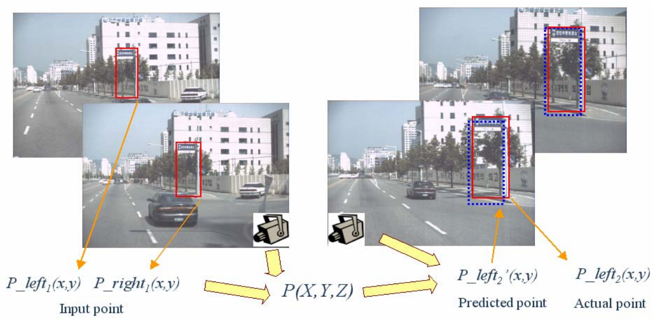


**Fig. 3.** faulty pixel selection and correction

## IV. PRELIMINARY EXPERIMENT AND ANALYSIS

In order to verify the reliability of multi-modal approach integration, field test was performed for 1 hour in a trajectory chosen from a suburb of DaeJeon. Fig. 4 shows a vehicle trajectory used for the validation of integration approach. During the experimental test, there were more than 6 visible satellite signals available. One of the advantages of multi-modal approach is during GPS signal outages. From its operation viewpoint, this integration is desirable to keep IMU performance from degrading. In this section, we simulated non-GPS area and analyzed the INS estimated position. Two periods of interesting path were selected to analyze this approach as labeled case I and II since GPS/IMU integration information is still available and it could be used as reference trajectory for comparisons with multi-modal approach. For the tests, we placed an assumption as previous approach [1]. First, the vehicle should move slower to be present the same features in consequent two image frames. This guarantees locating the known 3D point in the next frame, allowing the system to estimate the vehicle's 3D location by photogrammetric approach. Second, there exists a rectangular area in which a feature point lies within a certain error boundary.

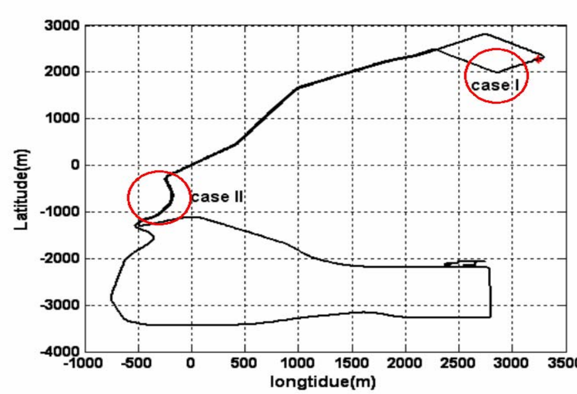


**Fig. 4. Test Vehicle trajectory**

For performance analysis, we compared the result of commercial post processing S/W POSPac™ because post-processing smoother trajectory is known to provide smoother best estimates [4].

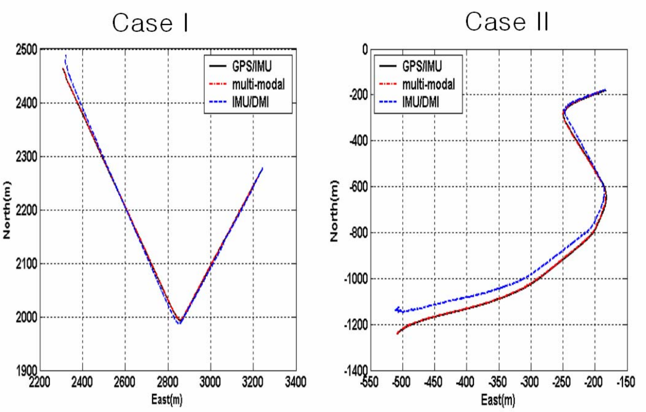


**Fig .5.Vehicle trajectory with GPS outage simulation**

Multi-modal approach has shown significant improvements in positioning error accuracy in horizontal plane as shown Fig 5. Mean positioning errors are shown in Fig 6. The results are represented in horizontal geodetic (North, East) reference frame. The results show that multi-modal approach was more accurate than IMU/DMI integration approach in loosely coupled scheme and worse than post-processing smoothing results. Based on vehicle dynamic environments, the performance of the proposed algorithm in the case I is more accurate than the case II. Overall, the positions on errors are suppressed below 0.5 meters.

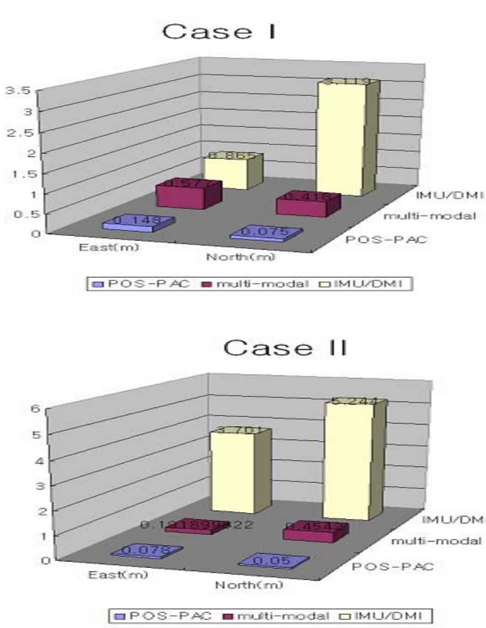


**Fig .6. Positioning error in Case I and II**

Therefore, our multi-modal approach verified that this approach could meet the requirements of land vehicle geo-location around sub-meter level. So, our new proposed approach provides more precise navigation trajectory than general loosely coupled approach in which IMU/DMI integration is performed. Therefore, we successfully demonstrated the robustness of this advanced approach and overcame poor performance of low cost IMU. The contribution of this paper is that we introduce alternative approach to integrate low cost IMU and GPS for land vehicle applications and refine such one, even though further simulations and algorithm refinements are required.

## V. CONCLUSION AND REMARKS

This paper presents reliable geo-localization of a land vehicle using multi-modal approach, based on the GPS/IMU/DMI/Image sensor integration. The performance analysis was carried out to show the effectiveness and robustness of this multi-modal approach. Under GPS unfavorable environment, decimeter accuracy has been achieved under different vehicle dynamic cases. Using this multi-modal approach can pave the way of overcoming general loosely coupled drawbacks. The main purpose of this study is to introduce another modality to overcome low cost IMU performance and achieve the high position accuracy. The test demonstrates that multi-modal approach shows promising result for geo-localization of a land vehicle. Provided algorithms refinements and further developments, precise land vehicle localization will come true.

## REFERENCES


[1] S. B. Kim et al.,"A Bimodal Approach for GPS and IMU Integration for Land Vehicle Applications", *porc. of IEEE VTC Fall 2003*, orlando, october 2003

[2] Eun H. S, Accuracy Improvement of Low Cost INS/GPS for Land Applications, UCGE Reports Number 20156, Dept. of Geomatics Engineering, Calgary, Canada.

[3] R. Tsai and T. Huang, "Estimating Three-Dimensional Motion Parameters of a Rigid Planar Patch I," *IEEE Transactions of Acoustics, Speech, Signal Processing*, vol. ASSP-29, pp. 1147-1152, Dec , 1981.

[4] Q.A. Abdullah, M.A., "Integrated GPS-inertial measurement solution as an alternative to aerial triangulation: a case study, Proceedings",*ASPRS Annual Convention*, Baltimore, 1999, pp. 867- 876.

[5] K.P. Schwarz, , M.A. Chapman, M.E. Cannon and P. Gong, "An Integrated INS/GPS Approach to the Georeferencing of Remotely Sensed Data", *Photogrammetric Engineering & Remote Sensing*, Vol 59.No.11, pp. 1667-1674.

[6] M. Moffit, E. M., Mikhail, Photogrammetry. Harper and Row, New York, 1980. pp.37-40.

[7] R.G. Brown and P.Y.C. Hwang, Introduction to Random Signals and Applied Kalman Filtering, 3rd ed, John Wiley & Sons, 1997.

[8] C.Jekeli, Inertial Navigation Systems with Geodetic Applications, Berlin: Walter de Gruyter, NewYork, 2001.