NON-LINEAR, NON-GAUSSIAN ESTIMATION FOR IMPROVING POSITION AND ORIENTATION DETERMINATION IN MOBILE MAPPING SYSTEM

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ABSTRACT: In a mobile mapping system, the integration of Inertial Navigation System (INS) and Global Positioning System (GPS) is widely applied for determining position and orientation. The Kalman filter or Extended Kalman Filter (EKF) is popularly used for data fusion estimation. In such those estimation strategies, linearization and assuming Gaussian distribution are utilized. However, the fact that the system model and measurement model in INS/GPS integration are originally non-linear and the noise arising during operation may be non-Gaussian distribution. These characteristics may leads to the low performance of the system utilizing KF or EKF in case of highly non-linear model and non-Gaussian noises. This paper investigates on some of non-linear, non-Gaussian estimation strategies in order to improve the performance of the system.

1. INTRODUCTION

Mobile mapping system (MMS) refers to a mean of collecting geo-spatial data using mapping sensors mounted on a mobile platform. A direct geo-referencing system is applied to transform the coordinates of objects of interest from camera frame to the mapping frame. The most common technologies utilized in that system today are satellite positioning using the GPS and Inertial Navigation System (INS) using an Inertial Measuring Unit (IMU). Due to the cost and size, the high quality IMUs is restricted to use in the commercial MMS. The advance in Micro-Electro-Mechanical System (MEMS) technology enables complete inertial units on a chip, composed of multiple integrated MEMS accelerometers and gyroscopes. In addition to their compact and portable size, the price of MEMS-based is far less than those of high quality IMUs as well, however, due to the lightweight and fabrication process, MEMS sensors have large bias, instability and noise, which consequently affect the obtained accuracy of MEMS-based IMUs (Huang, 2009). To overcome the limitation of low cost MEMS-based, main two methods are popularly investigated in the literature: Using advanced multi-sensor integration strategies and improving estimation algorithms in data fusion.

In integration strategies, commonly, loosely-coupled (LC) is applied. However, in LC, at least four satellites are required to help GPS in solving the solution and this requirement may not be satisfied in hostile environments like urban canyon areas. To overcome this limitation, tightly-coupled (TC) is investigated. In TC integration mode, GPS provide the aid measurement to the INS at observables level such as pseudo range, Doppler signal or carrier phase; so that GPS can continuously provide measurement updates even if there are less than four satellites on the sky.

For data fusion, the Kalman Filter (KF) is known as the optimal estimation tool for data fusion in most of real time tracking applications. The restriction of KF is that it can only applied on linear model and Gaussian-distribution noises. In INS/GPS integration, the system and measurement model are originally non-linear, therefore EKF is popularly applied. In principle, The EKF utilizes the first term of Taylor series expansion of the non-linear function and Gaussian noise is assumed, so that in case of highly non-linear functions and non Gaussian noise, the system utilizing EKF may perform a poor performance. To improve this situation, this research develops non-linear, non-Gaussian estimation strategies and apply them in tightly coupled INS/GPS integration in a mobile mapping system.

2. ESTIMATION ALGORITHMS.

2.1. Theory of Bayesian estimation

Bayesian estimation is the basic theory for the development of most dynamic estimation algorithms. The fundamental of Bayesian filtering theory can be described by following:

For a dynamic tracking system, generally speaking, the system model with distribution density function $P(x_k \mid x_{k-1}, z_{1:k-1})$ and aid measurement model with distribution density function $P(z_k \mid x_k)$ can be expressed by following equations

$$x_k = f_k(x_{k-1}, w_k) \tag{1}$$

$$z_k = h_k(x_k, v_k) \tag{2}$$

Where $x_k \in R^{n_x}$ is the state vector at time k. $w_k \in R^{n_x}$ is system noise. $z_k \in R^{n_z}$ is the aid measurement. $v_k \in R^{n_v}$ is measurement noises. $f_k : R^{n_x} \times R^{n_w} \to R^{n_x}$ and $h_k : R^{n_x} \times R^{n_v} \to R^{n_z}$ are non-linear function of state and measurement vectors, respectively.

The objective of estimation is to determine posterior probability density function (PDF) $P\left(x_k \mid z_{1:k}\right)$ and its inferences including estimates of state vector $\hat{x}_k$ and covariance matrix P. For this goal, due to Bayesian filter theory, there are two stages of estimation:

The prediction stage involves using the system model to obtain the prior PDF of the state at time k-1 by equation:

$$P\left(x_k \mid z_{1:k-1}\right) = \int P\left(x_k \mid x_{k-1}\right) P\left(x_{k-1} \mid z_{1:k-1}\right) d x_{k-1} \tag{3}$$

And updating stage: At time step k, aid measurements become available; the prior PDF is updated by following equation.

$$P\left(x_k \mid z_{1:k}\right) = \frac{P\left(z_k \mid x_k\right) P\left(x_k \mid z_{1:k-1}\right)}{P\left(z_k \mid z_{1:k-1}\right)} \tag{4}$$

From the fundamental of Bayesian estimation theory, several estimation algorithms have been developing and applied for INS/GPS integration.

2.2. Particle filter

Based on Bayesian estimation theory and known as Monte Carlo estimation, the principle of the generic particle filter can be described as following:

If we can sample a set of particles $\{x_{0:k}^i; i = 1, ..., N\}$ from posterior distribution $P\left(x_{0:k} \mid z_{0:k}\right)$, then the estimate of this distribution is given by

$$\hat{P}\left(x_{0:k} \mid z_k\right) = \frac{1}{N} \sum_{i=1}^{N} \delta_{x_{0:k}^i}\left(dx_{0:k}\right) \tag{5}$$

Where $\delta_{x_{0:k}^i}\left(dx_{0:k}\right)$ is Direc delta, N is number of particles.

Unfortunately, it is often not possible to sample directly from the posterior distribution, but we can use importance sampling. Instead of sampling from posterior distribution we sample from a proposal distribution $q\left(x_{0:k} \mid z_{0:k}\right)$.Then the weighted approximation posterior distribution will be

$$\hat{P}\left(x_{0:k} \mid z_k\right) = \frac{1}{N} \sum_{i=1}^{N} w^i \delta_{x_{0:k}^i}\left(dx_{0:k}\right) \tag{6}$$

Where $\{w^i; i = 1, ..., N\}$ is the weight of the particle $x_{0:k}^i$. It is proportional value of $p\left(x_{0:k} \mid z_{0:k}\right)$ to $q\left(x_{0:k} \mid z_{0:k}\right)$. This method is so called Sequential Importance Sampling (SIS). However, a common problem with the SIS particle filter is the degeneracy phenomenon (Gordon, 1993). To overcome this problem, Sequence Importance Re-sampling (SIR) particle filter is commonly applied. In this method, re-sampling is implemented in the process to check and eliminate degeneracy problem.

In general, the Particle filter has a number of advantages that make them attractive for navigation applications; they are non-parametric, can cope with nonlinearities and non-Gaussian noises, and are relatively easy to implement. However, there are some issues that make particle filter itself limited it in INS/GPS estimation: Firstly, the choice of an optimal proposal PDF to draw samples is difficult to implement; secondly, computational burden is the main disadvantages of this algorithm. In addition degeneracy and impoverishment are the other problems in particle filter.

2.3. Unscented Kalman filter

To reduce the computational burden in PF and overcome the limitations of EKF, Julier and Uhlmann (1997) proposed the Unscented Kalman Filter (UKF). In this algorithm, a fixed number of minimal points, known as sigma points are deterministically generated.

$$\chi_k^0 = \bar{x}_{k-1}, w^0 = \frac{\kappa}{(\eta_x + \kappa)}, i = 0 \tag{7}$$

$$\chi_k^i = \bar{x}_{k-1} + (\sqrt{(\eta_x + \kappa) P_{k-1}})_i, w^i = \frac{1}{2(\eta_x + \kappa)}, i = 1, \ldots, n_x \tag{8}$$

$$\chi_k^i = \bar{x}_{k-1} - (\sqrt{(\eta_x + \kappa) P_{k-1}})_i, w^i = \frac{1}{2(\eta_x + \kappa)}, i = n_x + 1, \ldots, 2n_x \tag{9}$$

Where $\bar{x}_{k-1}$, P_{k-1} are mean and covariance of state at time k-1, respectively. κ is a scaling parameter and $(\sqrt{(\eta_x + \kappa) P_{k-1}})_i$ is the i[th] row or column of the matrix square root $(\eta_x + \kappa) P_{k-1}$. w^i is the associated weight of the sigma point i[th]. These sigma points are then propagated individually through the nonlinear functions to capture posterior mean and covariance accurately. By updating step based on available aid measurements, the estimates of state vector and its covariance will be calculated.

2.4. Unscented Particle filter

One of the difficulties in generic particle filter is choosing an importance density for sampling particles. A method to overcome this problem is to use an importance density that is a Gaussian approximation to $P(x_k \mid x_{k-1}, z_{0:k})$. In this research, the proposal distribution is chosen to be the Gaussian approximation of $P(x_k \mid x_{k-1}, z_{0:k})$ using UKF, this method is so called Unscented Particle Filter (UPF). This estimation strategy is investigated in our research by the motivation from the fact that: The UKF is able to accurately propagate the mean and covariance of the Gaussian approximation to the state distribution. And the big overlap between distribution by UKF and the true posterior distribution, this make the UKF an optimal candidate for more accurate proposal distribution generation within the particle filter framework (Van der Merwe, 2000). By this algorithm, it can apply on any non-linear functions without Taylor series expansion and it may cope with any behaviors of noises without assuming Gaussian noise.

3. INS/GPS INTEGRATION

Two types of INS/GPS integration schemes, LC and TC are implemented in this research, their architectures are illustratively described in the Figure 1 and Figure 2, respectively. In general principle, the output from IMU including accelerometers and gyroscopes and the INS mechanization serve as the system dynamic model for a Bayesian-based estimation. Measurements and their basic equations from GPS help to build measurement model for the estimation tool. The data from INS and GPS is combined and processed by an estimation tool for the final solution which is much more accurate than solutions of either system in stand-alone mode. The difference between LC and TC is from aid measurements. In the LC scheme, the aid measurements are the final solutions of GPS such as positions and velocities. In TC scheme, the aid measurements are GPS raw measurements such as pseudo-ranges, Doppler signals or carrier phases.

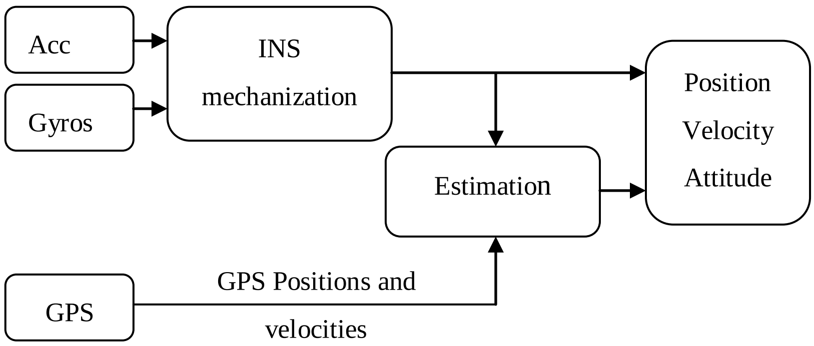

Figure 1. Loosely Coupled INS/GPS integration architectures

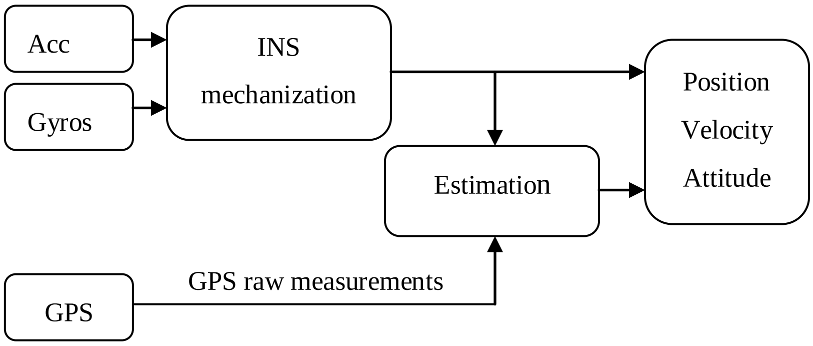

Figure 2. Tightly coupled INS/GPS integration architectures

4. EXPERIMENT

For the INS/GPS integration field test, a land-based mobile mapping van with mapping sensors mounted were employed (Figure 3). A tactical grade IMUs, SPAN-CPT and a dual-frequency GPS receiver, OEM-V were used as the reference sensors. The reference trajectory was processed based on the raw measurement of SPAN-CPT by commercial IMU/GPS processing software, Inertial Explore 8.10. The test IMU data is a low cost IMU, C-MIGITSTM III with raw GPS measurement collected by embedded receiver of SPAN-CPT. The test software is written on Matlab. The position and attitude errors were computed by the difference between the results from test IMU and the reference. The field test was implemented in Tainan city where the open area and urban canyon are included along trajectory (Figure 4).

The Figure 5, Figure 6 show the samples of comparison in positions and orientations error and Table 1 illustrate the position Root Mean Square Error (RMSE) of EKF, UKF, and UPF applied on LC scheme.

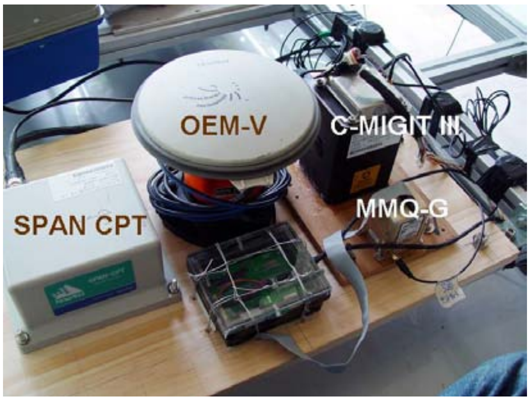

Figure 3. The experiment platform

Figure 4. Field test trajectory

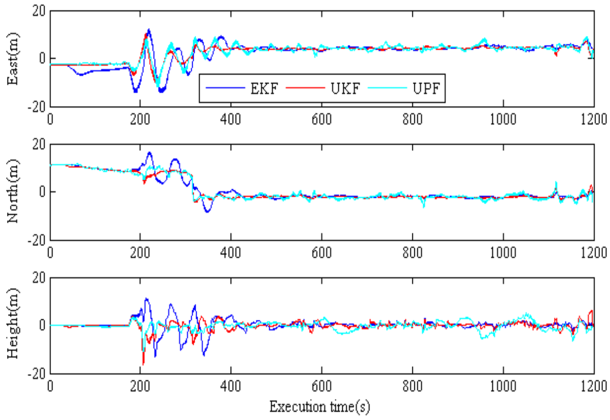

Figure 5. Samples of position errors on LC

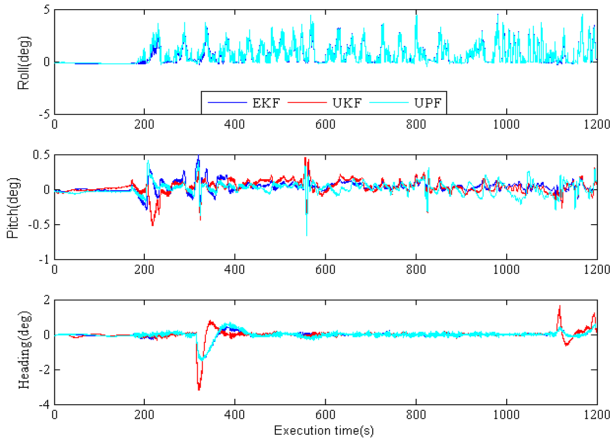

Figure 6. Samples of orientation errors on LC

Table 1. Position root mean square errors and execution time on LC

Applied method	RMSE(m)	Execution time(s)
EKF	7.44	271.41
UKF	6.69	3038.12
UPF	6.49	5769.15

Based on the results provided, it can be seen that in the LC scheme, the performance of UKF and UPF are comparable and better than EKF, the improvement in position accuracy is about 12%. However, the execution time of UKF and UPF are much longer than that of EKF. In EKF, the execution time is about 30% of operation time, while the time consuming in UKF and UPF are about 300% and 600% of operation time, respectively.

For the TC scheme, EKF and UPF are applied in the experiment, the estimation results are then analyzed by the comparison with the results estimated by LC scheme. The Figure 7, Figure 8 and Table 2 illustrate the performance.

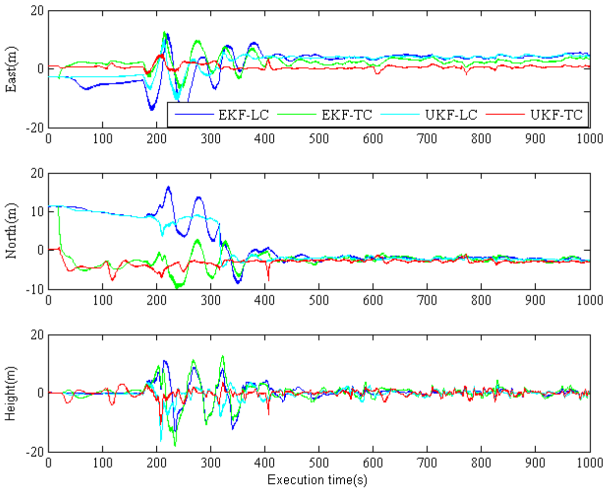

Figure 7. Samples of position errors on TC

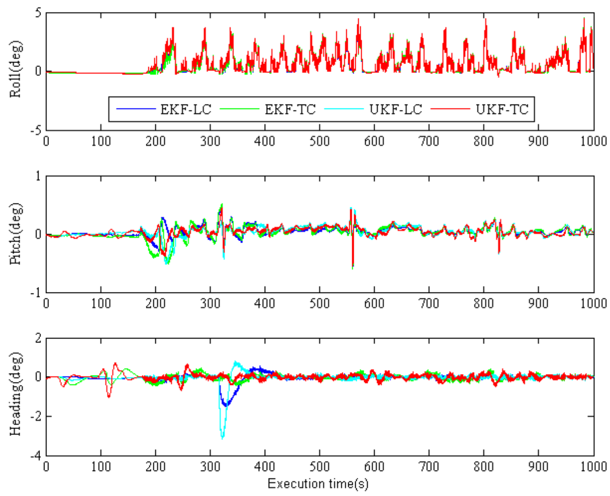

Figure 8. Samples of orientation errors on TC

Table 2. Position root mean square errors and execution time on TC

Applied method	RMSE(m)	Execution time(s)
EKF-LC	8.04	291.23
EKF-TC	4.98	293.51
UKF-LC	6.92	3038.17
UKF-TC	3.98	3278.92

The results indicate that the improvement of TC scheme compared to LC scheme is significant. With EKF, the improvement in position accuracy is about 14% and in UKF, the improvement is about 20%. In overall, the improvement of the best solution, UKF-TC over the conventional solution, EKF-LC is about 50%. In addition, it can be seen from the figures that in comparison to LC, the estimation results of TC converge faster.

5. CONCLUSIONS

The analyzed results show that in general, the performance of non-linear, non-Gaussian estimation including UKF and UPF are better than that of EKF in which linearization and assuming Gaussian noise is utilized. However, the long processing time is the disadvantage of these strategies. In term of position RMSE, UKF and UPF are comparable, however, in considering processing time, UKF is the better solution.

Generally speaking, the non-linearity of system and measurement models is at moderate level and the noise is almost Gaussian in INS/GPS integration. From these characteristics, choosing appropriate estimation algorithms for certain applications could be proposed as following: For real time navigation applications, EKF is still an optimal strategy but for post-processing mapping application, UKF or UPF are recommended.

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