Combined Terrain Aided Navigation based on Correlation Method and Parallel Kalman Filters

Xie Jianchun Zhao Rongchun Xia Yong
(Computer School, Northwestern Polytechnical University, Xi'an, 710072,China)

Abstract: As an important part of modern integrated navigation system, Terrain Aided Navigation (TAN) compares measured terrain height with the onboard Digital Elevation Map (DEM) to locate a vehicle's position. However, traditional TAN methods cannot work robustly when flying over flat terrain. This paper proposes a Combined Terrain Aided Navigation (CTAN) system, which incorporates the correlation method with the parallel Kalman filters. In this system, both the correlation method and the Parallel Kalman filters are utilized to calculate the position by analyzing the difference between the DEM data and the set of height measurements, which is collected in real time. Two obtained position are used to correct the possible estimation error, caused by the repetitive characteristic of terrain or the noise of measurements. Compared with the TAN system uses only the correlation method, simulation results approve the proposed system can significantly improve the navigation performance.

Keywords: Terrain Aided Navigation; correlation method; Parallel Kalman filters.

1 Introduction

Modern aircraft's navigation system usually consists of two sub-systems, the Inertial Navigation System (INS) and the Global Position System (GPS). The INS has an error, which grows with time and has to be corrected regularly. The GPS is relying on satellite signal broadcast to the aircraft. However, in a hostile situation, this signal could be deliberately jammed or even the transmitters could be destroyed. Therefore, an alternative system using other navigation principles is needed as a backup, even though the satellite system gives highly accurate position information. Terrain aided navigation (TAN) is such an alternative technique, which can autonomously update the INS. The essential idea in TAN is to acquire the position information of an aircraft through continuously measuring the terrain elevation underneath the aircraft flight track and comparing these measurements with a reference Digital Elevation Map (DEM).

In traditional TAN methods, such as TERCOM [1] and the Extended Kalman Filter [2], an aircraft measures the altitude over mean sea-level with a barometric altimeter and the ground clearance with a single altimeter sensor. Then the navigation computer gets terrain elevation by calculating the difference between these two kinds of altitude. Meanwhile, from a reference DEM, the navigation computer gets another terrain elevation, which is a function of coordinate provided by the INS. The difference between the calculated terrain elevation and the reference elevation is used to facilitate the navigation. But the nonlinearity of terrain can lead these methods to obtain only sub-optimal results. Moreover, since the sensor has to work continuously, these methods may also suffer from energy shortage [3].

This paper proposes a Combined Terrain Aided Navigation (CTAN) approach, which uses multi-sensors to simultaneously measure ground clearance on more than one point. The measurements are processed by a correlation method and parallel Kalman filters to obtain two different position fixes. The navigation is finally achieved by fusing these two results. It is demonstrated by the simulation results that the novel approach is more accurate than traditional

TAN methods.

2 Navigation method

2.1 Correlation Method

The first method is based on correlation estimation. Different from traditional TAN methods which use only one radar to measure terrain elevation [4], this method uses a radar array to measure terrain elevation under the aircraft's track. Thus at every sampling time, all the measured values from the radar array form a terrain height grid. Then the correlation of this terrain height grid with a given DEM data in larger size is calculated by moving this grid across the DEM data matrix. The correlation is calculated by the following equation.

$$T[x(t)] = \sum_{i=1}^{M}\sum_{i=1}^{N}\left(y_{i,j}(t) - h_{i,j}(x(t))\right)^2 \quad (1)$$

where $M \times N$ is the number of radars in the radar array. The correlation sum $T[x(t)]$ is calculated by comparing the measured result $y_{i,j}(t)$ at radar beam (i,j) with the corresponding DEM data $h_{i,j}(x(t))$ at position $x(t)$.

In paper [4], the likelihood function of measured value $Y(t)$ on the position $x(t)$ can be described as,

$$L(Y(t)|x(t)) = K \cdot \mathbf{exp}\left(-\frac{1}{2\sigma_e^2}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(y_{i,j}(t) - h_{i,j}(x(t))\right)^2\right) \quad (2)$$

according to equation (1), $L(Y(t)|x(t))$ can also be described as

$$L(Y(t)|x(t)) = K \cdot \mathbf{exp}\left\{-\frac{1}{2\sigma_e^2}T[x(t)]\right\} \quad (3)$$

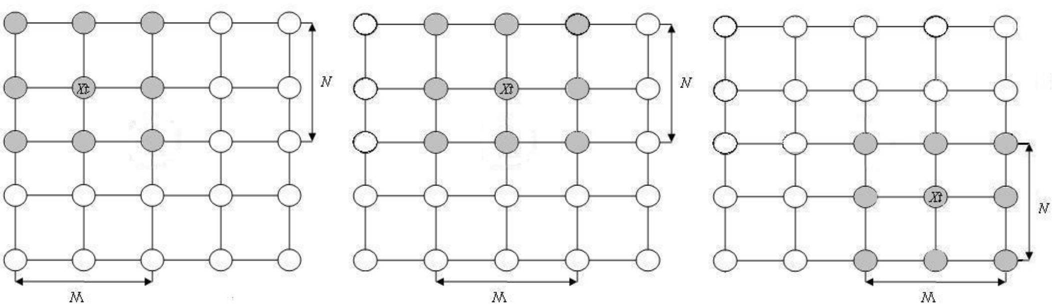
and posterior possibility density function (PDF) of the aircraft's position is proportional to

$$p(x(t)|Y(t)) \propto L(Y(t)|x(t))p(x(t)) \quad (4)$$

where $p(x(t))$ is prior possibility density function of the aircraft's position. Since $p(x(t))$ is a constant for a known aircraft's position [4], the correlation sum is inversed to $p(x(t)|Y(t))$. Therefore, the position of TAN can be estimated by the minimum of correlation sums.

$$\hat{x}(t) = arg\ \min_{x(t)} T[x(t)] \quad (5)$$

The calculation process of correlation sum is shown in Fig.1.



(a) First calculation (b) Second calculation (c) Last calculation

Figure1 Calculation of correlation sum

2.2 Parallel Kalman Filters

The other method to estimate the position fix is the parallel Kalman filers [5], which is a Multi Model Adaptive Estimation (MMAE) technique and provide measured values in a recursive manner. The MMAE composes of a bank of Kalman filters which can provide the final estimation based on the information from every Kalman filter.

Previous TAN methods like SITAN use a bank of three-state Kalman filters. Those three states respectively refer to the referenced navigation system's east, north and vertical channel bias. However, the three state filters deeply depend upon linearization of the nonlinear terrain function. If the true position does not lie within any filter's neighborhood, none of the filters can find it. In order to solve this problem, the filters are reset to the regular grid configuration in case that the fix decision rules are not satisfied after some measuring steps. The disadvantage of this method is that these intervals of measurements are highly dependent on the terrain beneath the aircraft, which may result in missing position fix.

To avoid this disadvantage, we introduce the parallel Kalman Filters with a bank of one-state Kalman filters. The single state in each filter is utilized to model the vertical channel bias. The east and north offset for each filter are set as two constants. As a result, each filter is pinned horizontally so that the filter bank is always arranged in a regular grid. Due to this simplification, Kalman filters do not migrate horizontally, and there is no need to reset them.

The discrete time process and measurement models for the vertical channel bias are assumed to be as follows:

Process Model:

$$h_t = h_{t-1} + w_t \tag{6}$$

where h_t is the vertical channel bias in sampling time t. And the w_t is white process noise, which satisfies

$$E\{w_t\} = 0\,,\ E\{w_t^2\} = qT\,, q = 3m^2 / sec \tag{7}$$

where T is the sampling interval and q is the prior assumption about the gradual change of vertical channel bias.

Measurement Model:

$$z_t = h_t + v_t \tag{8}$$

where z_t is the measured vertical bias and the white measurement noise v_t satisfies

$$E\{v_t\} = 0\,,\ E\{v_t^2\} = r\,, r = 10m^2 \tag{9}$$

where r is an prior assumption regarding the unexpected error of the measurement.

The process model indicates that the quantity of estimated vertical channel bias and the vertical channel bias is modeled as white noise. The measurement model indicates that the measurements are simply the vertical channel bias itself contaminated by additive white noise.

The number of filters in the Kalman filter bank is decided by the number of radars in the radar array. The neighborhood of each filter is defined as a rectangle region with the edge length of 30 meters. The neighborhood region of every filter is not overlapped with each other. This is because each filter occupies a different position within the bank and uses a different portion of the stored DEM to compute.

In every measurement the state space Kalman filters can be expressed as:

$$K = \hat{P}^{-} H^T \left[H\hat{P}^{-} H^T + R\right]^{-1} \tag{10}$$

$$\hat{z}_t = z_t - K \cdot \left[h_t - z_t\right] \tag{11}$$

$$\hat{P}^{+} = \hat{P}^{-} - KH\hat{P}^{-} \tag{12}$$

Where K is the Kalman gain matrix, $\hat{z}_t$ is the state vector estimate, $\hat{P}^{+}$ is the estimate of the covariance matrix of the state estimate.

2.3 Combined Method of Correlation and Parallel Kalman Filters

The different properties of the correlation method and the parallel Kalman filters allow an improvement of the navigation performance by combining both methods. Fig.2 compares the position error of the correlation method and that of the parallel Kalman filters under common condition.

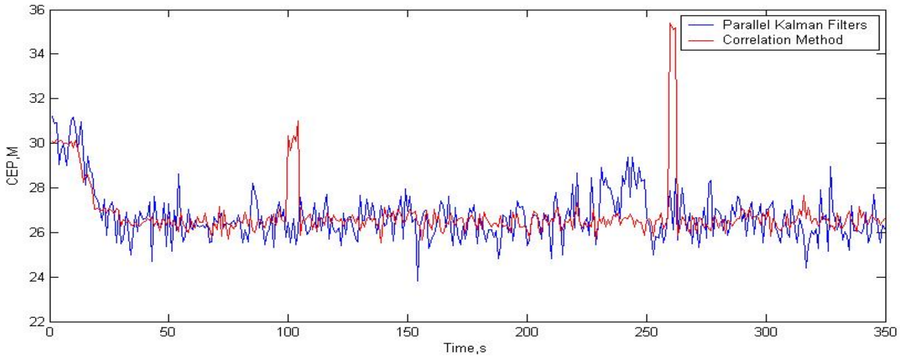


Figure 2: Comparison of Circular Error Probability (CEP) for Correlation Method and Parallel Kalman Filters

In Fig.2, we can see that the position error of the correlation method is smaller in most cases, while in some cases it is quite higher than that of the Kalman filters, which is due to the repetitive characteristic of sampled terrain under aircraft. In comparison, although the position error of parallel Kalman filters is larger in most cases, there is no sudden pulse in its data array because only vertical bias is used as state parameter of parallel Kalman filters. Therefore, it is possible to use parallel Kalman Filters to correct the error of correlation method. Meanwhile, the valid position fixes provided by the correlation can also be used to detect the parallel Kalman filters' drift.

From Fig. 1 we can also find that usually the error of the correlation method does not occur in the neighboring position. Therefore, the position error can be indicated by the abrupt change between current position estimate and that of last time.

$$d = \hat{x}_t - (\hat{x}_{t-1} + \Delta x_k) \tag{13}$$

where $\hat{x}_t$ is the estimated position by correlation method at time t and Δx_k is the horizontal distance between two measurements provided by the INS. When the calculated distance difference is larger than a predefined threshold, that is, the estimated position from the correlation method is far away from that from the parallel Kalman filters, we can conclude that a false estimation occurs

$$d > d_{lim} \tag{14}$$

Such a false estimation is invalid for the central navigation system and thus is not considered in the successive measuring process. However, if the process cannot obtain valid estimation in certain number of continuous steps, neither the parallel Kalman filters nor the correlation method can provide stable and credible estimation. Such phenomena usually happen when the airplane fly over extremely flat terrain or the waters.

3 Simulation

In this section, the performance of the two Terrain Aided Navigation algorithms and the CTAN system in simulation experiments is presented. The simulated flights have been performed over real terrain data in east longitude 1160 and north latitude 300. The real terrain data includes both rough and flat terrains. The visualization of the terrain 3D and the flight track is shown in Fig.3. The performance of the correlation method, the parallel Kalman filters and the CTAN is compared in Fig. 4.

The experimental results are obtained by performing 50 times of Monte Carlo simulation. It is demonstrated by Fig. 4 that the two invalid estimates from the correlation method have been corrected in the CTAN and at the same time the estimation error of CTAN is always smaller than that of the Parallel Kalman Filters. The CTAN combines correlation method and parallel Kalman filters and gives a reasonable improvement to the navigation system. We can conclude that the CTAN performs much better than both Correlation method and Parallel Kalman filters.

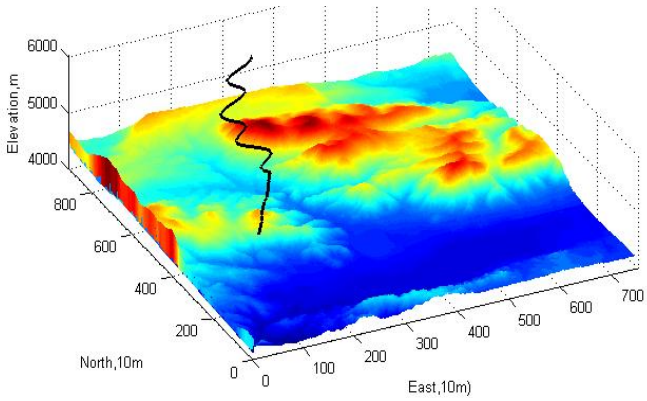


Figure3: Terrain and flight track visualization

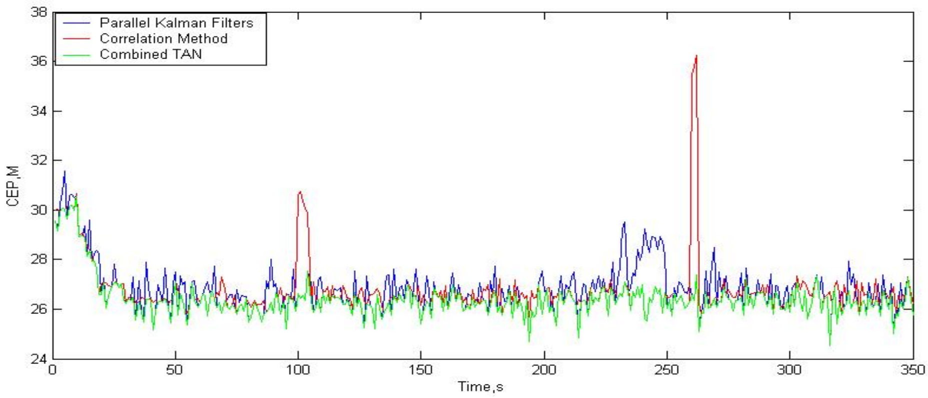


Figure4: CEP of CTAN, Correlation method and Parallel Kalman Filters

4 Summary

By using correlation method as a basic Terrain Aided Navigation module and a parallel Kalman filters as a refined module, this paper developed a Combined Terrain Aided Navigation algorithm which improves the navigation performance of the central navigation system. Simulation experiments demonstrate that the proposed approach can provide the best estimation result compared with correlation method and parallel Kalman filters, which shows a significant improvement to current systems.

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Author Biographies

Xie Jianchun was born in 1978 in Luoyang, Henan Province, China. He completed his master grade of computer science in Northwestern Polytechnic University, and currently he is working on his Ph.D student at Northwestern Polytechnic University. His research interests include computer vision, pattern recognition and Terrain Aided Navigation System.

Detail contact method:

Zhao Rongchun: received the M.E. degree in weapon control and air force engineering from PLA's Institute of Military Engineering, Harbin, China, in 1960. He was the senior visiting scholar in the department of electric and electronic, Surrey University, Britain, from 1989 to 1990.

Currently, he is working as Professor with the School of Computer, Northwestern Polytechnical University, Xi'an, China. He has been Head of the School of Computer, and is currently a member of Academic Committee of Northwestern Polytechnical University. His research interests include speech processing, image analysis and comprehension, computer vision, virtual reality and pattern recognition. He has published more than 100 scholarly research papers and two monographs.

Prof. Zhao is Founder and Director of the Provincial Key Laboratory of Speech and Image Information Processing (SIIP) at Northwestern Polytechnical University. He has also been appointed as vice president of China Society of Image and Graphics, vice president of China Society of Stereology, vice director of the Signal Processing section of Chinese Institute of Electronics, and president of Shaanxi Signal Processing Association.

Xia yong: received the B. E. degree, the M. E. degree and the PhD degree in computer application from Northwestern Polytechnical University, Xi'an, China, in 2001, 2004 and 2007, respectively.

From May 2003 to Nov. 2003, he was a research assistant in the Center for Multimedia Signal Processing, Department of Electronic and Information Engineering, Hong Kong Polytechnic University, Hong Kong. From Nov. 2004 to Jan. 2006, he was a visiting researcher in the School of Information Technologies, University of Sydney, Australia. Since Jan. 2007, he has been a postdoctoral research fellow in the School of Information Technologies, University of Sydney, Australia. His research interests include image analysis, multimedia signal processing, pattern recognition, and machine learning. He is currently an associate member of IEEE.