Sensor Fusion Method Using GPS/IMU Data for Fast UAV Surveillance Video Frame Registration

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Abstract

This paper proposes an innovative framework for fast image registration of UAV surveillance video frames by fusing the data from a GPS receiver high-frequency IMU sensor (Piccolo autopilot) and a feature-domain registration method through a non-linear filter. The high-frequency imprecise data from the Piccolo autopilot is refined by the low-frequency precise data from our feature-domain based random M least squares (RMLS) method. The projective transformation model is chosen to achieve high precision. The state and measurement models are non-linear to approximate the real-world imaging dynamics. A periodic hybrid particle filter (PHPF), composed of extended Kalman filter (EKF) and unscented Kalman filter (UKF), is proposed to minimize running time while maintaining accuracy. Both the efficiency and effectiveness of the proposed algorithm will be evaluated through our experiments.

Keywords*: Registration, Sensor Fusion, Periodic Hybrid Particle Filter*

1. Introduction

In modern surveillance systems, a real-time analysis requirement has become more and more important in recent years. Image registration is the basis for advanced image post-processing (e.g,mosaicking, de-noising, tracking and super-resolution). Primitive registration methods such as the block-matching [1] and frequency-domain registration [2] suffer from drawbacks such as operation time or model limitations. The feature-based random M Least squares [3] (RMLS) Method can significantly improve the precision of the registration; however, due to the computation required for locating and matching feature points, the RMLS still has room for significant time-efficiency improvement. In our experiments, it usually costs about 0.8-1.5 seconds, depending on the precision requirement, to register one frame by RMLS. Thus, running-time becomes a bottleneck for registration without extra knowledge. Fortunately, UAV autopilots are typically equipped with GPS and IMU sensors, which can provide flight information such as position and angle speed. In our experiments, the Piccolo autopilot from Cloud Cap Tech. [4], which has a kalman GPS/IMU built-in filter, is adopted to obtain the flight data of our customized UAV. Then the flight data can be utilized to calculate the transformation matrix between two frames (Which we named direct piccolo registration (DPR)). Since the input data of piccolo is from the GPS/IMU, which is imprecise because of the loss of GPS signal and inertial oscillation, the DPR is treated as measurements/observations in our algorithm. Comparatively, the RMLS registration method is much more accurate, and is chosen as the initial state for each loop.

The extended Kalman particle filter(EPF) [5] and unscented Kalman particle filter (UPF) [5] are popular candidates to to solve the non-Gaussian/non-linear estimations. Generally, the EPF can provide equal precision as the UPF when dealing with linear-like, non-linear system, which requires less running-time. While dealing with the typical non-linear system, the UPF's accuracy dominates the EPF. Synthesizing the benefits of the two filters, we propose a robust and fast particle filtering method with a hybrid Kalman filter to update the particles. Meanwhile, incorporated with the periodic correction by RMLS, we can avoid the augmentation of estimation bias. To achieve both accuracy and time-efficiency, we choose 10 frames in one group, applying the RMLS method with sufficient iterations on the first two frames as initialized state, and recursively recover the transformation matrix from the direct Piccolo registration (DPR).

This paper is organized as follows. Section 2 will introduce DPR the RMLS methods, while Section 3 will cover the state/measurement model with our periodic hybrid particle filter (PHPF). Section 4 describes the experimental results and conclusions.

2. Frame Registration

The Piccolo autopilot is sophisticated equipment that provides flight data for the aircraft. These data can be used to calculate the parameters of the transformation matrix. The random M least squares feature-based registration [3] method adopts the scale invariant feature transformation [6] to process an iterative non-linear least squares optimization. For higher precision, we adopt the homography transformation (1) in our algorithm. Section 3.1 explains the direct piccolo transformation (DPT), and Section 3.2 describes the RMLS method.

$$\begin{bmatrix} x' \\ y' \\ p \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{1}$$

2.1 Direct Piccolo Registration

The Piccolo autopilot is mounted on the UAV airframe to provide flight information, such as the latitude, longitude ,altitude ,roll, pitch and yaw. According the multi-view geometry model, we can project the Piccolo parameters to the homography matrix according to the following equations:

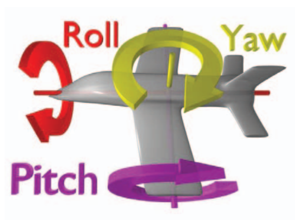


Figure 1. Dynamics of Aircraft

$$\left(\begin{array}{c} h_{11} = \frac{H_2}{H_1} cos(\theta_1 - \theta_2) \\ h_{12} = \frac{H_2}{H_1} sin(\theta_1 - \theta_2) \\ h_{13} = LO_1 - LO_2 \\ h_{21} = -\frac{H_2}{H_1} sin(\theta_1 - \theta_2) \\ h_{22} = \frac{H_2}{H_1} cos(\theta_1 - \theta_2) \\ h_{23} = LA_1 - LA_2 \\ h_{31} = \frac{sin(\gamma_1 - \gamma_2)}{H_1} \\ h_{32} = \frac{sin(\alpha_1 - \alpha_2)}{H_1} \\ h_{33} = 1 \end{array} \right) \tag{2}$$

Here, the H_1, LO_1, LA_1, θ_1,γ_1 and α_1 are the altitude, longitute, latitute, yaw, pitch and roll of Frame 1, respectively. Meanwhile, the same symbols apply to Frame 2.

2.2 Feature-Based Registration by Random M Least Sqaures

The scale-invariant feature transformation [6] approach is used to detect the local feature points, which are invariant to rotation, noise, illumination, and scaling. Once the feature points are found, they are merged into a k-d [7] tree. The four nearest neighbors are found with a computational complexity of $O(NlogN)$. Next, a standard RANSAC [8] routine is chosen to reject the feature points outside the overlapping region. The homography transformation model is then adopted as in equation (1) and (1) can be rewritten as (2) for least-square solution.The algorithm of feature-based registration is summarized in Table [1].

Table 1. Procedure of Random M-Least Square Algorithm for Image Registration

1. Using all of the match pairs in the match set, generate A_{total} according to the matrix on the lefthand side of equation (3) and B_{total} according to the vector on the righthand side of equation (3) and then assign the accepted error according to the desired precision, ϵ.
2. Randomly Choose M (approximately one quarter of the total number of matched pairs, based on our testing results) points from the match set, generate the matrix A_M and vector B_M , calculate the transformation matrix using the least squares fit and the total tolerance : $h = LeastSquareSolve(A_M, B_M)$ $tol = \|\|A_{total}h - B_{total}\|\|$
3. Use the parameters derived by Step 2 to fit all of the elements in the match set and find the total fitted number less than the accepted error: $Total_{num} = Count(\Sigma(A_{total}h - B_{total})^2 < \epsilon^2)$
4. Repeat the above steps a suitable number of times, updating the transformation matrix when the following condition is satisfied: $\|\|tol_{new}\|\| < tol$ and $Total_{numnew} > Total_{num}$

Equation (1) can be rewritten as

$$\begin{bmatrix} x & y & 1 & 0 & 0 & 0 & -\frac{xx'}{p} & -\frac{yx'}{p} \\ 0 & 0 & 0 & x & y & 1 & -\frac{xy'}{p} & -\frac{yy'}{p} \\ .. & .. & .. & .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. & .. & .. & .. \end{bmatrix} \begin{bmatrix} h_{11} \\ h_{12} \\ h_{13} \\ h_{21} \\ h_{22} \\ h_{23} \\ h_{31} \\ h_{32} \end{bmatrix} = \begin{bmatrix} \frac{x'}{p} \\ \frac{y'}{p} \\ .. \\ .. \\ .. \\ .. \\ .. \\ .. \\ .. \end{bmatrix} \tag{3}$$

From this representation, we see that if we have more than four matching pairs, this problem is overdetermined, and we use the algorithm described in Table 1 to derive the required transformation matrix from coarse to fine.

3 Periodic Hybrid Particle Filter

3.1 State and Measurement Model

Although the Piccolo autopilot has a built-in INS/GPS filter, it has unavoidable measurement error caused by two factors, the inertial oscillation and the loss of GPS signal. As a robust motion estimation method, RMLS registration can provide more accurate transformation parameters. The drawback of the RMLS method is relatively expensive computation. In the proposed framework, to utilize the benefits of high accuracy by RMLS and high speed of DPR, the state vector X, measurement vector Z, processing noise N, and measurement noise V are defined as follows:

$$\left(X_k = f(X_{k-1}) + g(N_{k-1}); Z_k = l(X_k) + V_k;\right) \quad (4)$$

From a Bayesian perspective, the estimation problem is to calculate the X_k at time k from observations $Z_{1:k}$. Thus, to reconstruct the pdf $p(X_k|Z_{1:k})$ is important. Since Z_0 can be replaced by the RMLS registration X_0, the $p(X_0|Z_0) = p(X_0)$. Therefore the $p(X_k|Z_{1:K})$ could be obtained recursively by equations (5), (6), and (7).

$$p(X_k|Z_{1:k}) = \frac{p(Z_k|X_k)p(X_k|Z_{1:k-1})}{p(Z_k|Z_{1:k-1})} \quad (5)$$

$$p(X_k|Z_{1:k-1}) = \int p(X_K|X_{K-1})p(X_{k-1}|Z_{1:k-1})dX_{k-1} \quad (6)$$

$$p(Z_k|Z_{1:k-1}) = \int p(Z_k|X_k)p(X_k|Z_{1:k-1})dX_k \quad (7)$$

3.2 Filtering Method

Particle Filtering (PF) [9] is the sequential Monte Carlo method for simulation-based estimation, which replaces the integrals of equations (6) and (7) with sums of random samples (particles). Therefore, the posterior distribution can be constructed from the following equation:

$$\hat{p}(X_{0:t}|Z_{1:t}) = \sum_{i=1}^{N} \tilde{w}_t^{(i)} \delta_{X_{0:t}^{(i)}}(dX_{0:t}) \quad (8)$$

The normalized importance weights $\tilde{w}_t^{(i)}$ can be calculated from:

$$\begin{pmatrix} w(X_t^{(i)}) \propto \frac{p(Z_t|\hat{X}_t^{(i)})p(\hat{X}_t^{(i)}|X_{t-1}^{(i)})}{q(\hat{X}_t^{(i)}|X_{0:t-1}^{(i)}, Z_{1:t})} \\ \tilde{w}_t^{(i)} = \frac{w_t^{(i)}}{\sum_{j=1}^{N} w_t^{(j)}} \end{pmatrix} \quad (9)$$

$q(\hat{X}_t^{(i)}|X_{0:t-1}^{(i)}, Z_{1:t})$ denotes the arbitrary probability distribution from the generated samples. After the importance weights are drawn, N random samples (particles) $X_{0:t}^{(i)}$ are selected by multiplying the samples $\hat{X}_{0:t}^{(i)}$ with the high importance weights $\tilde{w}_t^{(i)}$. Then, the re-sampled particles are applied to equation (6) to obtain the posterior distribution.

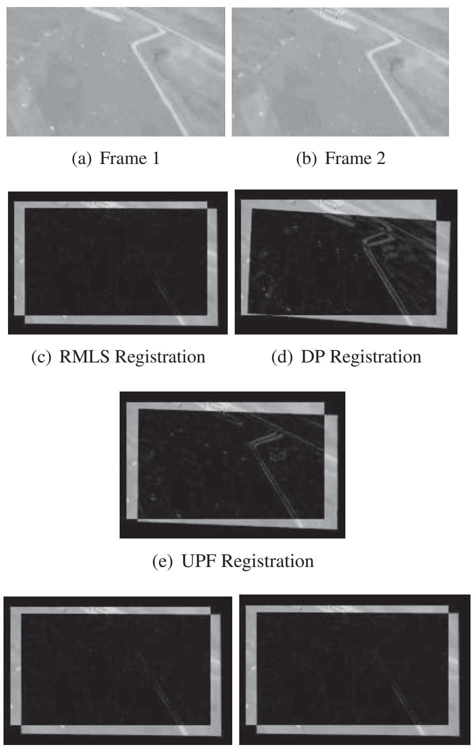
The update of the particles is particularly important in the PF method. Since our state and measurement model are assumed non-linear, the extended Kalman filter(EKF)[5] and unscented Kalman filtering (UKF) [5] methods are the reasonable candidates. Basically, the EKF is the first order series Taylor approximation of nonlinear equations and UKF is a non-linear recursive minimum mean-square-error (MMSE) estimator in itself . By dealing with the linear-like, nonlinear system, the EKF can provide equal precision as UKF with much less run-time. While there is no significant change of pitch and yaw, the state and measurement model could be treated as linear-like. Thus, a hybrid particle updating method is proposed to guarantee precision while improve the timing efficiency. Meanwhile, utilizing the re-correction by RMLS, we propose our algorithm called periodic hybrid particle filter (PHPF), which is summarized in the Algorithm 1. The threshold for switching between the UKF and EKF is 0.0007, according to our experiments.

Algorithm 1 Periodic Hybrid Particle Filter

- **for** $t = 1 : T : \infty$ **do**
  - Register the first two frames by RMLS and apply the direct Piccolo registration to every frame
  - **if** $\Delta\gamma < Thresh_1$ and $\Delta\alpha < Thresh_1$ **then**
    - **for** $i = 1, ..., N,$ **do**
      - $Initialization$: Draw the particles $x_0^{(i)}$ from the $p(x_0)$
    - **end for**
    - **for** $t = 1 : T$ **do**
      - **for** $i = 1, ..., N$ **do**
        - 1. Update the particles with EKF
        - 2. Evaluate and normalize the importance weights by equation (9)
      - **end for**
      - Select the N particles and obtain the posterior distribution by equation (8)
    - **end for**
  - **else**
    - **for** $i = 1, ..., N,$ **do**
      - $Initialization$: Draw the particles $x_0^{(i)}$ from the $p(x_0)$
    - **end for**
    - **for** $t = 1 : T$ **do**
      - **for** $i = 1, ..., N$ **do**
        - 1. Update the particles with UKF
        - 2. Evaluate and normalize the importance weights by equation (9)
      - **end for**
      - Select the N particles and obtain the posterior distribution by equation (8)
    - **end for**
  - **end if**
- **end for**

4. Experimental Results

The PHPF algorithm was applied to our real UAV data, and experimental results were generated to verify its efficiency and effectiveness. As a comparison, 40 frames are registered utilizing the RMLS method, direct Piccolo registration (DPR), unscented particle filter (UPF), periodic unscented particle filter (PUPF), and the periodic hybrid particle filter(PHPF), respectively. Figures 2 (c)-(g) show the absolute differential image in the overlapped region after we register Frame 31 to Frame 30 by these methods. From Figure 2, we can see the DPR and the UPF will produce apparent registration error, while the RMLS, PUPF and PHPF generate similar outputs. Figure 3 provides the comparison of quantitative precision, which is based on the mean of absolute error (MAE). It is reasonable the RMLS can provide higher precision, as it is adopted as the State Correction Factor (SCF) in our algorithm. The PUPF and PHPF methods provide the similar precision, which elaborates for linear-like, non-linear system, the EKF does perform a accurate approximation. The Time-efficiency is elaborated in table 2, which shows if there is linear-like transformation existing in the system, the PHPF does improve time-efficiency. And the time-efficiency improvement is increased with the linearity of the system.



(a) Frame 1 (b) Frame 2

(c) RMLS Registration (d) DP Registration

(e) UPF Registration

(f) PUPF Registration (g) PHPF Registration

Figure 2. Precision Comparison

Table 2. Time-efficiency of Registration (Unit: seconds/ten frames)

RMLS	PUPF	PHPF	UPF	PD
9.126	5.339	4.043	4.478	0.5
8.714	5.008	3.746	4.213	0.5
7.368	3.747	1.978	3.085	0.5
7.795	4.627	2.321	3.953	0.5

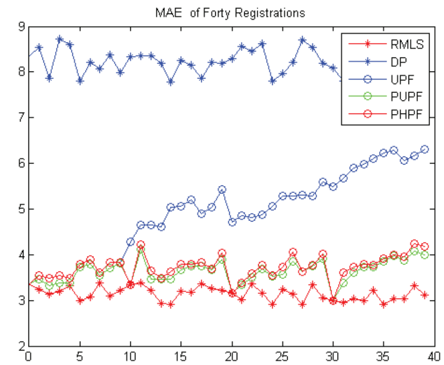


Figure 3. Precision Comparison

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