

A FAST AND ROBUST SIMULTANEOUS POSE TRACKING AND STRUCTURE RECOVERY ALGORITHM FOR AUGMENTED REALITY APPLICATIONS

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ABSTRACT

A robust simultaneous pose tracking and structure recovery algorithm based on the Interacting Multiple Model (IMM) for augmented reality applications is proposed in this paper. A set of three extended Kalman filters (EKFs), each describes a frequently occurring camera motion in real situations (general, pure translation, pure rotation), is applied within the IMM framework to track the pose of an object. Another set of EKFs, one filter for each model point, is used to refine the positions of the model features in the 3D space. The filters for pose tracking and structure refinement are executed in an interleaved manner. The results are used for inserting virtual objects into the original video footage. The performance of the algorithm is demonstrated with both synthetic and real data. Comparisons with different approaches have been performed and show that our method is more efficient and accurate.

1. INTRODUCTION

The research work presented in this paper falls into the category of structure and motion (SAM) in computer vision. The goal is to reconstruct a 3D structure and its pose from a sequence of 2D images. A major stream of the solutions is to tackle the problem in a batch. Factorization [2] and bundle adjustment [4] are common approaches. Besides, there are solutions that deal with the problem in a recursive way. Most of them are based on Kalman filtering. The work in [1] adopts iterated extended Kalman filter (IEKF) for structure updating. The series of methods in [5] [6] [7] recover both the structure and motion. The work in [7] is the ancestor of this series of researches. The authors apply a single IEKF to recover the structure and pose of an object. Azarbayejani and Pentland describe a method in [6] that improves [7] by making an extension in recovering the camera focal length and the representation of the 3D model. The most recent recursive method is by Chiuso et al [5]. Similar Kalman filtering techniques in SAM have also been applied to simultaneous localization and map-building for robot navigation [8].

The Interacting Multiple Model (IMM) based algorithm presented in this paper aims to solve the problem of structure and pose ambiguities encountered in most of the existing SAM algorithms, which has been reported by Szeliski and Kang in [9]. Inaccuracy due to the ambiguities can be minimized if prior information about the structure or motion is utilized. In our algorithm, the three extended Kalman filters (EKFs) for pose estimation embedded within the IMM framework describe three different motion dynamics that represent frequently occurring camera motions in real situations. The IMM [10] provides a mechanism to “select” suitable filters automatically in order to set constraints on the camera’s motion once prior information is available. With the constraints, the total number of parameters to be estimated is reduced and the accuracy can be improved. In addition, the problem of motion discontinuity in real image sequences can be handled properly with the IMM.

Our structure and motion algorithm consists of $N+3$ small EKFs. This arrangement has the advantage of avoiding tripling the computation time. Indeed, it reduces the time complexity from quadratic to linear compared to the approaches that use a single full covariance EKF. It is necessary since the computation speed is crucial for augmented reality applications. The rigidity of the object under reconstruction is maintained by expressing the 3D point features in terms of the first images that they appear. Experimental results show that our IMM-based approach can resolve the ambiguities among the Yaw angle, Pitch angle and the structure notably. Our method also has higher computation efficiency than the interleaved bundle adjustment method [4] and the EKF by Azarbayejani and Pentland [6]. We have tested our algorithm by tracking the pose of a real scene. The recovered pose sequence has been applied to produce an augmented reality video.

2. PROBLEM MODELING

Figure 1 shows the geometry of our system. $X_i^O = [x_i^O, y_i^O, z_i^O]^T$ and $X_{i,t}^C = [x_{i,t}^C, y_{i,t}^C, z_{i,t}^C]^T$ denote the coordinates of the point X_i with respect to the object and the camera coordinate frame respectively. $p_{i,t} = [u_{i,t}, v_{i,t}]^T$

$$X'_{i,t} = X'_{i,t-1} + \gamma_t$$

$$\varepsilon_{i,t} = h_t(X'_i) + v_t$$

γ_t and v_t are the zero mean Gaussian noise. $\varepsilon_{i,t}$ represents the real measurements from the image sequence. $h_t(X'_i)$ is the projection function, which can be found by substituting X'_i into equation (3) (1) and then (2). X'_i is a scalar that represents a model point:

$$X'_i \circ + T^c = \begin{bmatrix} x_i^s \\ y_i^s \\ z_i^s \end{bmatrix} = \begin{bmatrix} u_{i,1} \\ v_{i,1} \\ 0 \end{bmatrix} + \frac{X'_i}{f} \begin{bmatrix} u_{i,1} \\ v_{i,1} \\ f \end{bmatrix} \quad (3)$$

Intuitively, the 3D coordinates of the points are expressed in terms of the first images that the features appear. This measure reduces the required computation time and maintains the rigidity of the object under the assumption that the measurements acquired are non-biased. Again, the implementation of EKF in this step is standard and the formulation is not repeated here.

6. EXPERIMENTS AND RESULTS

6.1. Experiments with synthetic data

An object with 300 random feature points in 3D within a cube of volume of 0.13m^3 , centered at a place 0.33m away from the camera, was generated. The motion of the object was composed of three different segments, a pure translation section, a pure rotation section and a general motion section. The sequence of occurrence of the sections was by random. The motion parameters were generated randomly from 0.05 to 0.15 degrees per frame for Yaw, Pitch, Roll angle and 0.0005 to 0.0015 meters per frame for t_x , t_y and t_z . The length of each synthetic sequence is 60 frames. A total of ten independent tests were carried out. Our IMM-based algorithm, the interleaved bundle adjustment method [4] and the EKF by Azarbajani and Pentland [6] were tested and compared.

Figure 3 shows the average total rotation and translation errors of the three approaches under the ten test cases. For the plots in figure 3 to 5, the line with asterisk (*), triangle (\blacktriangle) and circle (O) markers are for our IMM-based approach, the interleaved bundle adjustment method and the EKF by Azarbajani and Pentland respectively. These three algorithms were implemented in Matlab with a Pentium III 1GHz machine and the time measurement is in seconds. In figure 3, the total rotation error is calculated by using the axis-angle representation to reduce the Yaw, Pitch, Roll angle into a single angle. The total translation error is computed by Pythagoras theorem. Our approach has errors lower than the other two methods most of the time. It is obvious that our approach can recover a more accurate pose.

Figure 4 shows the time for the three algorithms to optimize the image residual error of the back-projected

model. Our algorithm falls to the lowest errors at the earliest time among the three methods. It can resolve the structure and pose ambiguities to at least a certain extent and thus avoids the poor local optima.

Figure 5 shows the time needed to reconstruct a model when extra frames were added sequentially to the image sequence. The first step in creating this plot was to reconstruct a model with the first 10 frames. The succeeding 50 frames were sequentially fed to the algorithm as the new measurements of the scene. You can see that our approach outperformed the other two algorithms. Our algorithm takes only 0.79 seconds to update the structure of the scene for every extra frame added to the image sequence. The EKF by Azarbajani and Pentland takes 2.60 seconds while the interleaved bundle adjustment method takes at least 4.55 seconds.

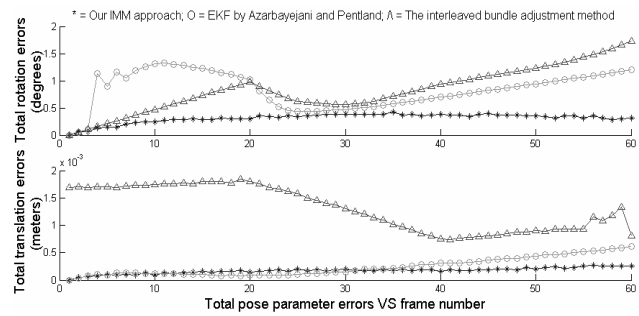


Figure 3. The average total rotation error (top, in degrees) and total translation error (bottom, in meters) versus frame number of the 3 algorithms.

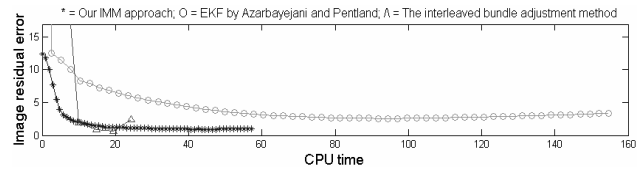


Figure 4. The relationship between the CPU time and the image residual error.

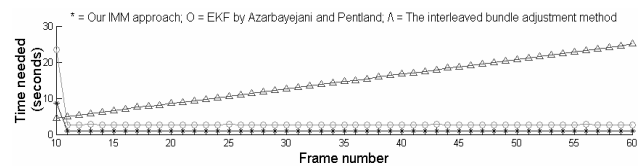


Figure 5. A graph showing the time needed for the 3 algorithms to reconstruct the model and pose when extra frames are added to the image sequence.

6.2. Experiments with real scene

An experiment using real scene images was also performed. The test image sequence was captured by translating the camera sideways on a rig. The length of the image sequence is 100 frames. Our IMM-based algorithm was applied to track the camera motion while reconstructing the scene's structure. The recovered pose

sequence was used to produce an augmented reality video, in which a synthetic car was put onto the yellow box in the real scene.



Figure 6. Results of inserting an artificial object into the real scene. First row: The first and the last image of the laboratory sequence. Second row: A synthetic car, which is drawn by wire-frames, was inserted into the real scene. Demonstration video can be found at <http://www.cse.cuhk.edu.hk/~khwong/demo/>

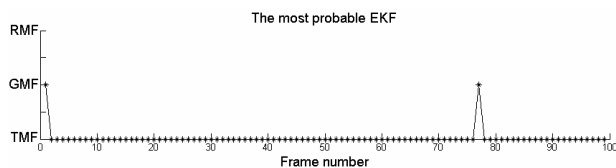


Figure 7. A plot showing the most probable EKF for pose estimation against frame index in the process of tracking the camera motion of the real image sequence.

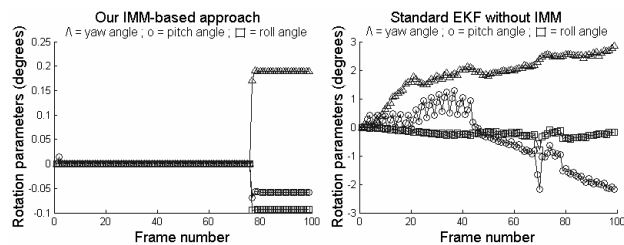


Figure 8. The rotation parameters recovered from the real scene with our IMM-based approach (the left one) and with a standard EKF with no IMM (the right one).

Figure 6 shows the results. An augmented reality video has been made successfully. The orientation of the synthetic car is consistent with the real scene. Figure 8 shows a comparison of the rotation parameters acquired with and without the IMM. The pose recovered with our IMM-based algorithm is smooth with no ambiguities among the Yaw and Pitch angle. The small jump in the rotation angles at the 76th frame is due to the vibration of the camera. On the other hand, the pose recovered using a

standard EKF with no IMM (i.e. A 2-step EKF in which one GMF is for pose estimation and N EKF's are for structure updating) is fluctuating and has an error about 2 degrees for the Yaw and Pitch angle.

7. CONCLUSION

The ambiguities between pose and structure have been solved by our IMM-based structure and motion algorithm under the following frequently occurring camera motions: pure translation, pure rotation or motion discontinuity. Our approach outperformed two other existing SAM algorithms in both the accuracy of the recovered pose and computation speed. Our algorithm also achieves a linear time complexity in terms of the total available point features, which suits the real-time requirement for many of the augmented reality applications.

8. REFERENCES

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