Acquisition of Aerial Light Fields

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Abstract: Since its inception in computer graphics community light field has drawn a lot of attention and interest. By densly sampling the plenoptic function light fields present an alternative way to represent and produce a faithful reconstruction of 3D scenes. But acquisition of densely sampled light fields require camera arrays, robotic arms or newly developed plenoptic cameras. The light fields captured using the existential technologies are limited to scenes containing limited complexity. In this paper we propose to use unmanned aerial vehicle for acquisition of larger unstructured aerial light fields. We aim to capture light fields of larger objects and scenes which are not possible by traditional light field acquisition setup. We combine the data from IMU and state estimated using homography with a Kalman filter framework. Frames which gives a minimum error (approximation of free form camera surface to traditional parameterization) are selected as perspective images of light fields. Rendering algorithm is devised to support the unstructured camera surface and to avoid rebinning of image data.

1 INTRODUCTION

In recent times image based rendering (IBR) has become a popular alternative to traditional 3D graphics in representing visual aspects of 3D scenes. In contrast to traditional polygonal rendering pipeline IBR algorithms uses a collection of pre-acquired views to generate new virtual views. Mostly this algorithms do not depend on the scene depth information and it's complexity, which makes IBR a great technique to realize photo-realistic image synthesis. Light field (one of IBR techniques) has become increasingly practical since its inception in computer graphics community. Light fields densely sample the plenoptic function and thus presents an alternative way to represent and produce a faithful reconstruction of 3D scenes.

Acquisition setup required to capture light fields varies with the parameterization with which the light field is represented. In 1996 Levoy and Hanharan (Levoy and Hanrahan, 1996) and Gortler et al. (Gortler et al., 1996) implemented 2PP (Two plane parameterization). Levoy (Levoy and Hanrahan, 1996) acquired light fields using a standard camera array setup implemented in Standford University. While Gortler (Gortler et al., 1996) used a video camera along with depth information of the scene which is difficult to acquire. Since then various other alternate parameterization such as spherical light fields by Ihm et al. (Ihm et al., 1997), cylindrical parameterization(Indrajit et al., 2014), two sphere parameterization (Camahort et al., 1998) and sphere plane parameterization by Camahort et al. (Camahort et al., 1998) have been proposed. But this parameterization also requires complex robotic arm setup for acquisition of light fields. Though nowadays various light field cameras (eg. Lytro and Raytrix) are commercially available. But this cameras has very limited field of view. Due to the complexity involved with acquisition of light fields most of the work in light fields has been focused on capturing of scenes with limited complexity. The existential acquisition setup are limited by its dimension and provides limited scene coverage.

Light field photography have various advantages compared to digital photography, such as synthetic refocusing, multi-perspective recording, depth-variant filtering, and much more. But the complexity involved in the acquisition of light fields has constrained its application to scenes with limited complexity. A simple way to acquire light fields will open up its application to various different fields such as scene reconstruction of a complex and detailed environment for movie production.

Recent times has also seen tremendous development in unmanned aerial vehicles. This has resulted in capturing of scenes which were not possible long before. UAVs can be remote controlled aircraft (e.g.

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flown by a pilot at a ground control station) or can fly autonomously based on pre-programmed flight plans or more complex dynamic automation systems. UAVs have been employed in surveying of objects and ground on the basis of orthographic photos to generate point clouds, volume calculations, digital height and 3D models.

In this paper we propose to use UAVs to capture unstructured light fields as an approximation to traditional light field parameterizations. For acquisition of light fields, data from IMU and state estimated using homography are combined with a Extended Kalman filter framework . Frames which gives a minimum error (approximation of free form camera surface to traditional parameterization) are selected as perspective images of light fields. The rendering algorithm is devised to support the free from camera surface.

The rest of the paper is organized as follows. Section 2 presents related work to acquire light fields. Section 3 presents our proposed system to capture light fields using UAV.

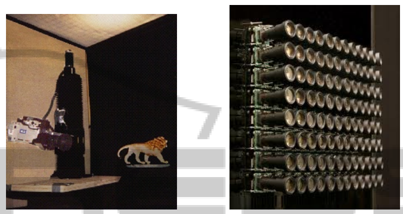
2 BACKGROUND AND RELATED WORK

Most of the works in light fields has been focused on acquisition of light fields of simple scenes. Here we discuss some of the acquisition setups employed to capture light fields. To our knowledge, acquisition of light fields using UAVs has not been attempted. Here we will also discuss some of works in which state of UAVs have been estimated.

2.1 Light Field Acquisition

The light field rendering system utilizes a computer controlled camera gantry such as shown in Figure 1(a) and 1(b), which is based on a modified motion platform with additional stepping motors. The setup, in Figure 1(b), was later utilized for light field rendering and consists of 128 camera array. The cameras are mechanically setup and they are placed at a distance from each other such that the whole set up works as a multiple-center-of-projection camera to capture the light field. Any displacement between cameras will alter the sampling density and hence has to be carefully setup mechanically.

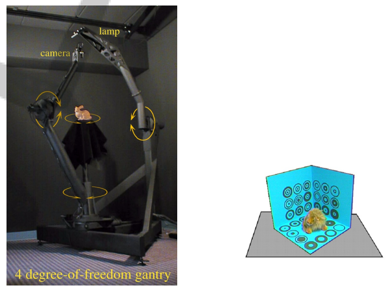
The lumigraph system follows a very inexpensive but a complex approach. They capture the scene by moving a handheld video camera through the scene. Therefore, the cameras pose need to be estimated for each frame. For finding the camera pose for each frame, they use calibration markers in a specially designed data capturing stage (Figure 2(b)). This also presents an additional problem of interpolation of the 4 dimensional lumigraph from scattered data because of the unstructured input. Gortler et al. (Gortler et al., 1996) store a rough approximation of the object for allowing depth corrections in the later stage. To recover a geometric model of the scene, however, additional effort has to be spent. 3D scanning technology as well as sophisticated stereo vision and image based feature extraction methods are applied to extract the geometric representation.



(a) Setup for Light field rendering (lev, 1996)

(b) 128 camera array built by Stanford graphics laboratory (sta, 2004)

Figure 1: Light field acquisiton setup.



(a) Spherical gantry (Sph, 2002)

(b) Setup used for lumigraph aquisition (Gortler et al., 1996)

Figure 2: Different acquisiton setup.

In (Davis et al., 2012) the authors generate unstructured 4D light fields by capturing views on and around a sphere containing the desired object using a hand held camera. But the scenes which can be captured are limited by our capability to form a bounding sphere around the desired object. For other scenes a complex, detailed and densely sampled light field acquisition is impracticable.

Hence we propose to use UAVs to capture images which can be employed as perspective images for light fields. This system provides capability to capture detailed and densely sampled light fields for various different complex scenes which were not possible previously. UAVs can be automatically guided or manually driven which provides an option for acquisition of aerial light fields.

2.2 UAVs State Estimation

The pose and position of the UAVs can be estimated accurately and rapidly. The regular approach is to apply sensor fusion to the data from the inertial sensors and other sensors. Some of the other sensors used for this purpose are the Global positioning sensor (GPS), inertial measurement unit (IMU), altitude sensors (ALS) and speedometers. But all this sensors have their individual limitations. For example, GPS sensor data are unavailable at some locations or the data is prone to error. Data error from IMU tends to accumulate and hence proves disadvantageous when used individually. The main reasons for the inaccuracies are gravity modeling, external disturbances and sensor malfunctions.

Vision-based navigation approaches have been developed to overcome these limitations. These approaches can be used where GPS systems are not available. The vision based algorithms (Roumeliotis et al., 2002), (Lobo and Dias, 1998) and (Laboratoire et al., 2002) can be used with other sensors to obtain better state and position estimation. State of UAV X is denoted as

$$X = [X, Y, Z, V_x, V_y, V_z, \omega_x, \omega_y, \omega_z, \theta, \psi, \phi] \quad (1)$$

where X, Y, Z are vehicle position; V_x , V_y , V_z are linear velocities; ω_x , ω_y , ω_z are angular velocities; θ, ψ, ϕ are Pitch, Roll and Yaw. This algorithms (Roumeliotis et al., 2002), (Lobo and Dias, 1998) and (Laboratoire et al., 2002) are estimating either complete vehicle state or some of the vectors of vehicle state by combining the inertial measurements either with bearings to known fiducials or from optical flow data from different video algorithms. Diel (Diel et al., 2005) presents a variant in which he uses epipolar constraints for vision-aided inertial navigation. (Soatto et al., 1996) derived the implicit extended Kalman filter (IEKF) for estimating displacement and rotation that incorporates an implicit formulation into the framework of the IEKF on the random walk model. The IEKF implementation was applied on the non linear space to characterize the motion of a cloud of feature points about a fixed camera. While Marks (Marks, 1995) demonstrates real time navigation using camera as the primary sensor. A sonar proximity sensor is employed to obtain distance from nearest planar surface. And position offsets relative to a reference image is obtained using texture correlation. This capability has been adapted to enable underwater station keeping (Leabourne et al., 1997) and has been extended to incorporate additional sensors (Richmond, 2009).

(Grabe et al., 2012) had use continuous homography constraint (Ma et al., 2001) for linear velocity estimation, integrated with the IMU for full state estimation, i.e they partially estimated state using computer vision. (Dusha et al., 2007) proposed algorithm based on Kalman filter and optical flow for state estimation. Their algorithm is not suitable for real world scenario. Amidi (Amidi, 1996) describes vision aided navigation for an autonomous helicopter where a stereo pair is used to aid in station keeping. Sinopoli (Sinopoli et al., 2001) describe a system that uses data from fused GPS/ INS and a digital elevation map to plan coarse trajectories which are then refined using data from a vision system. Roberts (Roberts et al., 2003) describes a flight control system for a helicopter that uses a stereo pair to determine altitude and optical flow to determine ground speed.

In our formulation a complete UAV state is estimated. The position and pose is computed by fusing the Measurements from IMU and visual odometery in a extended kalman filter framework.

3 LIGHT FIELD ACQUISITION USING UAVs

Our acquisition system is as depicted in Figure 3. The system contains a flight path planner which can be done automatically or manually, a state estimator which estimate position and pose of each frame of the video acquired. To improve the accuracy of position and pose estimated we combine the state estimated using IMU and videos using a kalman filter framework. Once the position and pose of each frame is estimated, we select the frames which lowers the error in position difference between an approximated free form camera surface and a traditional light field parameterization. The frame position and pose data is also given to the Flight path planner where it shows the coverage of the scenes for each frames. Using this coverage data the flight path planner can decide the path which takes images from an undersampled area. Once the whole scene is densely sampled we render virtual views from the frame selected using our rendering algorithm.

3.1 Flight Path Planner

The flight path planner can be automatically or manually controlled. An user interface shows the scene to be captured. Once the scene to be captured is selected by the user an appropriate approximation of the camera surface is overlayed on the scene. This overlayed camera surface will demonstrate the state of the frame

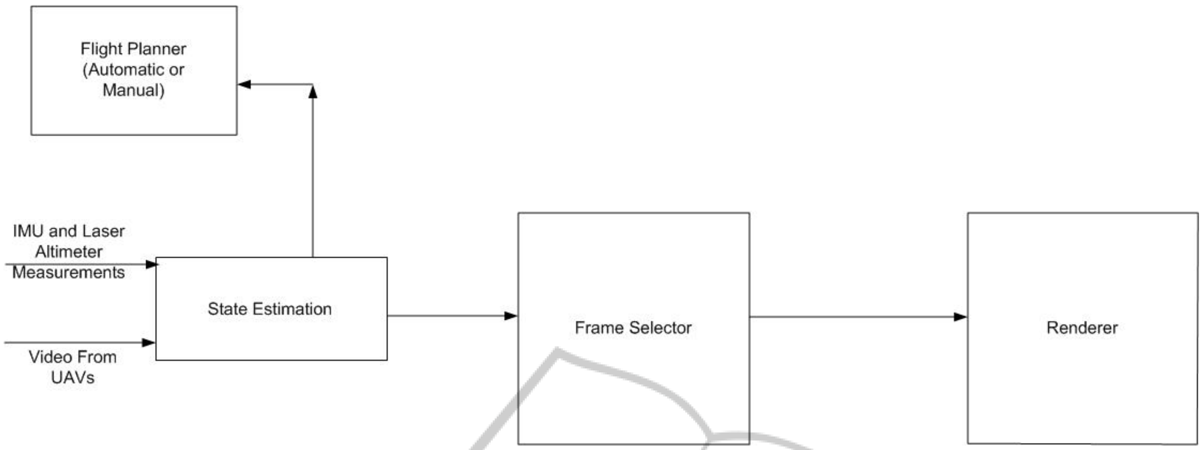


Figure 3: Acquisition System To Capture Light Fields Using UAVs.

captured. The aim of flight planner is to make assure that the UAV traverse along the camera surface. This is demonstrated on the overlayed camera surface with colour coded information. As the UAV deviates from the surface the state estimates turns red and as soon as the UAV is on the overlayed camera surface the state estimates turns green. This will help the user to control the UAV when flight is manually controlled. While manually controlling the user also needs to make sure that the states estimated are uniformly distributed. An automatic flight controller continuously monitors the UAVs state information and tries to plan the flight path to minimize the error in the UAVs current state estimate and the desired state.

3.2 State Estimation using IMU and Camera

The system combines visual odometry with data from IMU to estimate the state (position and attitude) of the vehicle. Our solution is designed to take advantage of complimentary IMU and camera sensor characteristics. Rapid changes in angular rotation rates and linear accelerations are accurately measured by IMU. But measurement from IMUs are subject to unbounded low-frequency drift. Contrastingly estimates obtained from Visual sensors are generally more accurate when the cameras field of view changes relatively slowly. By fusing their output, each sensor is able to compensate for the weaknesses inherent in the other.

Many visual odometry implementations use stereo cameras, as stereo allows the depth of landmarks to be calculated directly from known camera geometry. In (Amidi, 1996), Amidi et al. present a visual odometer designed specifically for an autonomous helicopter. They estimate vehicle attitude using gyroscopes and vehicle position by tracking ground targets with stereo cameras. However our system operates with either monocular imagery. An EKF is used to fuse monocular camera, laser altimeter, and IMU data. In our system we track point landmarks across image frames, and find the incremental change in camera pose by aligning corresponding sets of landmark positions. Visual and inertial measurements are fused in an extended Kalman filter (EKF) to produce an estimate of the vehicle state. We use the continuous discrete formulation of the EKF, in which the state estimate is propagated according to the underlying continuous-time non-linear system dynamics, while measurement updates are made at discrete time steps. Our state vector includes the position of the UAV in the global frame, the velocity of the helicopter in the body frame, the attitude of the helicopter. Further details on the EKF implementation are available in(Saripalli et al., 2003).

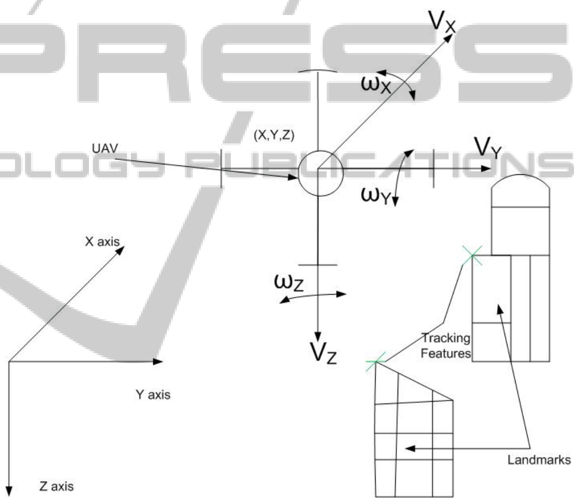


Figure 4: State estimation of UAVs.

3.3 Frame Selector

Once all the frame position and pose is estimated, frames which gives a minimum error(approximation of free form camera surface to traditional parameterization) are selected as perspective images of light fields.

$$min \sum (A_{position} * Error_{position} + A_{pose} * Error_{pose}) \quad (2)$$

$$Error_{position} = A_X * E_X + A_Y * E_Y + A_Z * E_Z \quad (3)$$

$$Error_{pose} = A_\theta * E_\theta + A_\psi * E_\psi + A_\phi * E_\phi \quad (4)$$

The weightage A given to each error E is decided after performing an error analysis. For example, error in measurements of X, Y coordinates E_X, E_Y will result in less error overall than error E_Z in measurement of Z. Similarly the pose errors E_θ, E_ψ and E_ϕ weightage A_θ, A_ψ and A_ϕ will increase substantially once error increase certain threshold angles. A detailed error analysis is required to assign the weightage to each error in measurement.

3.4 Renderer

Our system proposes a light field rendering technique that directly renders views from an unstructured collection of input images. Along with the unstructured collection of source images, their associated camera position and pose estimates are applied as input to our renderer. A camera blending field is evaluated at a set of vertices in the desired image plane and this field is interpolated over the whole image. A simple blending field is not sufficient for unstructured light field. Hence, for constructing pixels of virtual views different weights is assigned to the different source cameras. The blending field describes how the weight has been assigned to each cameras. Factors related to ray angular difference, estimates of undersampling, and field of view are also considered while calculating the blending field.

A threshold is set over the ray angular differences. As the angle differences increase from the threshold the blending weight will decrease from one to zero. We employ and adaptive way to compute the blending weight. We consider the closest k source cameras with smallest angle difference. In this case we must take care that a particular cameras blending weight falls to zero as it leaves the set of n closest cameras. This is accomplished by combining the criterion of n closest cameras and the angular threshold.

To reconstruct a pixel, we do not want to use source cameras that significantly under sample the observed point p. Since we know the positions of the cameras and their fields of view we compute an accurate prediction of the degree of undersampling at observed point p. Similarly we do not want to select cameras in n closest cameras, for which the ray from which pixel to be reconstructed falls out of the cameras field of view. Hence we create a weight function which changes from one to zero as the camera selected undersamples the point or ray fall outside its field of view.

4 CONCLUSIONS

We have presented a system to unstructured aerial light fields as an approximation to the traditional light field parameterization using UAVs. Acquisition of light fields using UAVs presents tremendous opportunities to capture aerial light field of scenes. The presented system calculates the UAVs state using an EKF framework. The framework combines the data from the IMU, laser altimeter and measurements obtained using camera. An autonomous flight planner is presented to reduce the error by maintaining the state of UAVs close to the overlayed camera surface. The presented frame selector assigns different weights to different measurement according to the error analysis. We are currently simulating the conditions in C++ and OpenGL Platform for error analysis. Following the simulation we are aiming to capture aerial light fields using the presented system.

There are also other challenges in capturing larger aerial light fields such as caching or compression of light field data while rendering, which we have not addressed here. The future work will also involve developing a caching or compression algorithm pertaining to unstructured aerial light fields.

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