Mono-Vision Corner SLAM for Indoor Navigation

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***Abstract*—We present a real-time monocular vision based range measurement method for Simultaneous Localization and Mapping (SLAM) for an Autonomous Micro Aerial Vehicle (MAV) with significantly constrained payload. Our navigation strategy assumes a GPS denied manmade environment, whose indoor architecture is represented via corner based feature points obtained through a monocular camera. We experiment on a case study mission of vision based path-finding through a conventional maze of corridors in a large building.**

I. Introduction

The complexity of urban environments poses unique challenges and risks for the military forces to conduct urban operations. The capability of vision based SLAM in an autonomous MAV can provide vital information for situation awareness. A vision-based solution does not emit light or radio signals, it is portable, compact, cost-effective and power-efficient. Such a platform has a broad range of potential military applications including navigation of robotic systems and soldier position localization with wearable or helmet-mounted devices. Moreover, an MAV with the ability to hover can play a key role in Intelligence, Surveillance and Reconnaissance missions held at GPS denied environments which are not suitable for fixed wing flight.

Nonetheless, the limitations on payload, size, and power, inherent in small MAVs, pose technological challenges due to the direct proportionality in between the quality and the weight of conventional sensors available. Under these circumstances, a theory for developing autonomous systems based on the information gathered from images is appealing, since a camera possesses a far better information-to-weight ratio than any other sensors available today. On the other hand, it breeds another rich kaleidoscope of computational challenges. For instance, there is no standard formulation of how a particular high level computer vision problem should be solved, albeit a plethora of the methods proposed for solving well-defined application specific problems that can seldom be generalized.

Indoor flight of a rotorcraft MAV, where no GPS signal is available, is a collective effort of two main challenges; platform attitude management, and path planning. The former is straightforwardly automated via lightweight sensors such as gyroscopes and with minimal information about the environment, or even lack thereof. Whereas the latter requires gathering and aggregation of excessive amounts of information about the surroundings, particularly true for a vehicle that would be destroyed upon the slightest impact with the surroundings. The stringent weight requirements of MAVs prevent the use of standard obstacle sensing mechanisms such as laser range-finders, and parabolic cameras [1], [2]. However, the machine vision technology has evolved so as to allow for cameras less than an ounce in weight with a decent picture quality, and such a video stream includes more information about the surrounding environment than other sensors alone can provide.

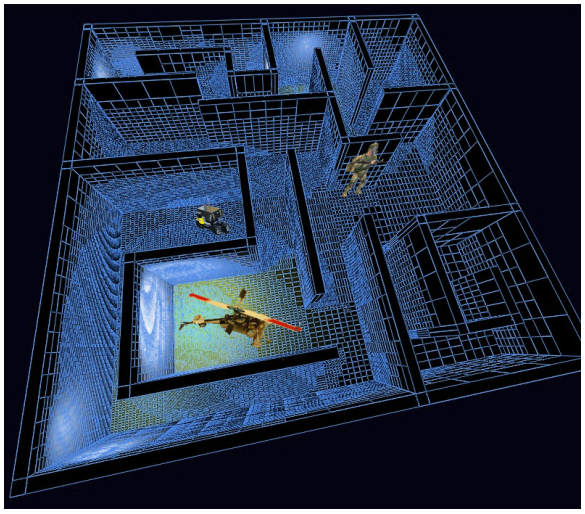

Fig. 1. Potential applications of vision-based navigation in GPS denied environments.

Nevertheless, this information comprises a surpassingly high level of abstraction and redundancy, which is particularly aggravated in cluttered environments. Therefore it requires acutely specialized knowledge to interpret. Ironically, the lack of such knowledge is often the main motivation behind conducting a reconnaissance mission with an MAV. Therefore the technique used in navigating an MAV by vision alone must assume minimal a priori knowledge, while it still provides reliable results. The MAV needs to construct a collective view of its unknown environment in order to navigate through it. Nevertheless, even after three decades of

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research in machine vision, the problem with "understanding" sequences of images stands bordering on being uninfluenced.

We propose a method for gathering useful landmarks from a monocular camera for SLAM use. We make use of the corners by exploiting the architectural features of the manmade indoors. Our decision to use corners is particularly due to the level of the consistency that corners can offer for the purpose of understanding the surrounding environment. A corner is a consistent feature for a variety of reasons, but the following three are particularly important. First, corners are unlikely to change their position in three dimensional space. Second, corners are relatively convenient to detect and track. Third, the positions of corners can be further exploited to infer about the location and size of surrounding walls. The contribution of this paper is a new absolute range and bearing measurement algorithm using a monocular camera. Such measurements can be used for a vision-based navigation and SLAM problem in an unknown indoor environment.

A. Related Work

There are two main technological challenges associated with the mono-vision based SLAM problem: the lack of absolute depth information, and the development of robust SLAM algorithms. Since an image is a projection of a three dimensional world on a two dimensional surface, it is merely a shadow. Hence it contains no depth information to those without extensive knowledge pertaining to its content. To mitigate the complications entailed by the absence of direct depth information, some alternative approaches have been tried involving the attachment of additional sensors to a camera, such as laser range finders [3] and cross validating the precise depth information provided by the laser range finder with the interpretations from the camera. However, such a technological advantage is a luxury for an aircraft of miniature proportions, it is more appropriate for a land based robot with no practical weight constraints. Even if a laser range finder could be designed as light as a camera, they have a shorter range than cameras, and they make a one dimensional slit through the scene versus the two dimensional signal created by a camera.

Using a camera with an adjustable focus via moving lenses have been discussed in the literature [4] owing to the depth-of-field effect and the Scheimpflug Principle [5], in which the distance in front of and beyond the particular subject in front of a camera appearing to be out of focus when the lens axis is perpendicular to the image plane. Therefore, the distance of a particular area in an image where the camera has the sharpest focus can be acquired. Nonetheless, the focus of interest may not be an useful feature to begin with. The other reasons rendering these methods far from practical for our application include calibration issues specific to different cameras and lenses, and limitations of cameras currently available that are suitable for MAV use. In addition, unless the lenses can be moved at approximately 30 Hz, this approach will significantly reduce the sensor bandwidth.

Binocular cameras for stereo-vision have been promising tools for range measurement for purposes of path planning and obstacle avoidance where the computer compares the images while shifting the two images together over top of each other to find the parts that match. The disparity at which objects in the image best match is used by the computer to calculate their distance. Nonetheless, binocular cameras are heavier and more expensive than their monocular counterparts. Moreover, stereo-vision has intrinsic limitations in its ability to measure the range, particularly when large regions of the image contain a homogeneous texture such as a wall or a carpet. Furthermore, human eyes change their angle according to the distance to the observed object to detect different ranges, which represents a significant mechanical complexity for a lens assembly and a considerable challenge in the geometrical calculations for a computer.

The literature recognizes MonoSLAM [6] an elegant approach to vision based SLAM with minimum assumptions about the free movement of the camera, it may be summarized in three steps as follows, detect and match feature points, predict motion via analyzing feature points with error estimates, and update a map with locations of feature points. This results in "a probabilistic feature-based map, representing at any instant a snapshot of the current estimates of the state of the camera and all features of interest and, crucially, also the uncertainty in these estimates"[6]. These error estimates mentioned, along with the map containing all known feature points, allow the algorithm to correct for drift when a feature point is rediscovered, providing a precise tracking system in which other than a standard initialization target defining the origin and orientation of the world coordinate frame. However, MonoSLAM assumes an extensive feature initialization procedure, and is not meant to leave the immediate vicinity of the starting position. In case it did so, with so many new features being introduced, using "image patches" as feature points, in which, small portions of the scene are stored in the memory for later reference via correlation, the increasing number of possible feature points would quickly become overwhelming for the computer mounted on an MAV with limited power and system resources. In addition, corners are better (i.e. more rigid) features in overall, considering the features used in MonoSLAM experiments. Moreover, MonoSLAM assumes a hand-held camera with a limited range but in contrast, the camera in this paper should be able to move through, for instance, an entire floor of a building, and still be able to maintain the track of its relative position. We address these issues in the next sections.

II. The Platform

As a test platform, we are using an electric powered MAV. Fully loaded weight is 2lbs, with up to 10 minutes endurance, and 1 mile of effective combat range. Mechanically identical to her full size counterparts the MAV features true-to-life

collective pitch helicopter flight dynamics. The flight stability and control is handled via an on-board IMU and autopilot unit from Micropilot[8] that uses two yaw gyroscopes, two roll and pitch gyroscopes, planar accelerometers, barometric and ultrasonic altimeters, and a magnetic compass to achieve flight control.

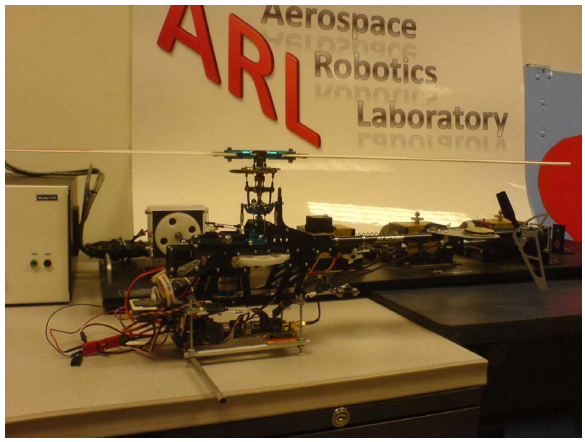

Fig. 2. The MAV used in our experiments

Since the MAV does not have any GPS reception indoors, the autopilot is merely responsible for governing the PID loops aileron from roll, elevator from pitch, and collective (mixed with throttle via a quadratic function specific to aircraft) from altitude to keep the MAV at hover. In other words the autopilot is *flying* the MAV but not *navigating* it, since it has no way of measuring the consequential results of its actions. Navigation, including obstacle avoidance and Simultaneous Localization and Mapping (SLAM) are to be performed by vision.

III. Feature Extraction from Live Video Stream

In order to produce a reliable solution for tracking motion and trajectory, it is essential to have a reliable method for feature extraction in which feature points are consistently extracted from an environment whenever a feature is in the field of view of the camera. Furthermore, the set of features selected should be large enough to allow for accurate motion estimations, but at the same time, sparse enough so as not to create a negative impact on the system performance. [10] has addressed several different approaches as to what constitutes to a "better" feature and what not, such as texturedness, dissimilarity, and convergence. According to Shi and al. sections of an image with big eigenvalues are to be considered "good" features. The general method involves calculating the minimal eigenvalue for every source image pixel in the image, followed by a non-maxima suppression in 3x3 neighborhood remain. The features with minimal eigenvalue less than a threshold value are rejected, leaving only stronger features.

Although a promising method, there are a few pitfalls to its operations. For instance, the method will get attracted to a bright spot on a glossy surface, which will perhaps be the reflection of ambient lightning, therefore an inconsistent, or worse, deceptive feature. Considering indoor environments of manmade architectures, corners of the architecture provide a rigid single point of identification which makes the comparison of features scalable. Corners are also consistent about their location in space, that is to say it is unlikely to find the corner of a wall move to a different location. Corner detection works on the principle that if a small window is placed over an image, and if that window is placed on a corner, then if it is moved in any direction there will be a large change in intensity. If the window is over a flat area of the image then there will be no intensity change when the window moves. If the window is over an edge there will only be an intensity change if the window moves in one direction. If the window is over a corner then there will be a change in all directions. This well established probabilistic technique for identifying corners in an image is the Harris - Stephens - Plessey Corner Detection Algorithm [7]. The Algorithm-1 describes our implementation and use of this method.

Algorithm-1: Harris Corner Detection Algorithm

```
I = CaptureFrame().
I = rgb2gray(I).
Consider an image patch over the area (u, v), shifted by (x, y).
Calculate sum of square difference between (u, v) and (x, y).
A = approximate S with a 2nd. order Taylor series expansion.
Express A in derivatives of I. (angle brackets denote averaging)
Determine eigenvalues of A.
IF(both eigenvalues remain nearly zero)
THEN, There is no feature of interest at this pixel.
IF(eigenvalue[1] ≃ 0 AND eigenvalue[2] ≫ 0)
THEN, An edge is found.
IF(both eigenvalues are distinct positive values)
THEN, A corner is found.
```

IV. Motion and Mapping Estimation

After the corner extraction process is complete for the current set of feature points (i.e. corners) within the field of view of the camera, the next step is to exploit the relative point locations in response to the movement of the MAV and attempt to determine the structure of the elements that may lay ahead, such as walls and corridors. Other relevant information to be extracted in this step includes the speed, direction and degree of motion.

Nevertheless, this set of corners is likely to have redundant features in it, such as corners that do not belong to the boundaries of the architecture. We are more interested in corners that provide hints about the shape and structure of the architecture the MAV is flying through, particularly those that we refer to as the "golden four". The golden four is the four particular corners that indicate a wall or an opening (e.g. door) approximately perpendicular to the pitch axis of the MAV, so we can we adjust the attitude and position with respect to those four corners, which ensures the MAV is always flying at the middle point of the hallway. Edge

detection and analysis helps reveal the likelihood of detected corners being a golden four. The MAV features an onboard digital magnetic compass which measures the bearing of the MAV in degrees along the yaw axis with respect to the magnetic North. The computed heading of the MAV is cross validated with the true heading from the compass.

A. Range Measurement in a Hall Way

We begin the range and bearing measurement by assuming that the height of the camera from the ground, H, is known a priori, which equals the altitude of the MAV, and is conveniently and precisely measured using the ultrasonic altimeter onboard. For another application, where a human carries a helmet-mounted monocular camera (see Fig 1), obtaining such height information is trivial. The camera is pointed at the far end of the corridor, but slightly tilted down with an angle β, which is measured by the tilt sensor on the MAV. And X denotes the distance from the normal of the camera with the ground, to the first detected corner (see Figure 3). The two lines that define the ground plane of the corridor are of particular interest, indicated by blue arrows in Figure 4. By applying successive transformations [23], [25] among the camera image frame, the camera frame, and the target corner frame, we can compute the slope angles for these lines, denoted by ϕ in Figure 5.

$$\tan\phi_1 = \frac{H}{W_l\cos\beta} = L_1, \quad \tan\phi_2 = \frac{H}{W_r\cos\beta} = L_2 \tag{1}$$

Using the (1) we determine the individual slopes, L_1 and L_2. If the left and right corners coincidentally have the same relative distance, $W_r + W_l$ gives the width of the corridor as shown in Figure 4. Equation (2) shows how these coordinates are obtained for the left side of the hallway.

$$u_L = u_o + \frac{\alpha(W_l)}{\cos\beta x + \sin\beta H} \qquad v_L = v_o + \frac{\cos\beta H - \sin\beta x}{\cos\beta x + \sin\beta H} \tag{2}$$

where (u_L, v_L) and (u_R, v_R) denote the perspective-projected coordinates of the two corners at the left and right side of the corridor. It should be mentioned that we wrap (u, v) with a radial distortion [6] to find a more accurate location of the corners on the image frame. In addition, the ratio of the camera focal length to the camera pixel size is given by

$$\alpha = \frac{f}{d} \tag{3}$$

From the two equations given in (2), we can solve for H in (4).

$$H = \frac{\alpha W_l}{u_L - u_o}\sin\beta + \left(\frac{v_L - v_o}{u_L - u_o}\right) W_l\cos\beta \tag{4}$$

For the sake of simplicity, we can introduce C as follows.

$$\begin{aligned} \left(1 - \tfrac{v_L - v_o}{u_L - u_o}\tfrac{1}{L_1}\right) H &= \tfrac{\alpha W_l}{u_L - u_o}\sin\beta \\ C &= \left(1 - \tfrac{v_L - v_o}{u_L - u_o}\tfrac{1}{L_1}\right) \end{aligned} \tag{5}$$

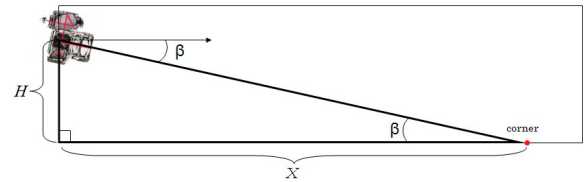

Fig. 3. The image shows a conceptual cutaway of the corridor from the left.

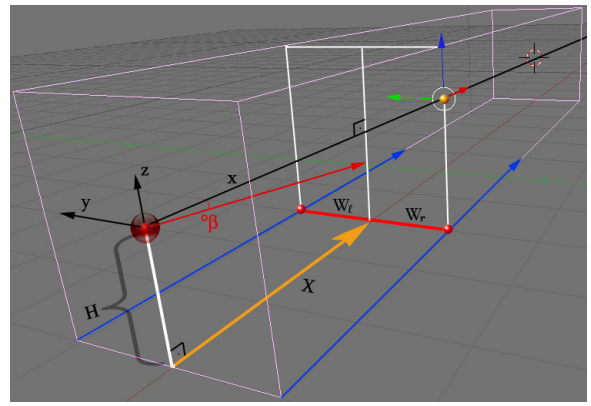

Fig. 4. The image shows the three dimensional representation of the corridor and the camera.

Finally, we solve for the longitudinal distance X and the transverse distance W_l, by combining the preceding equations:

$$\begin{aligned} W_l &= \tfrac{(u_L - u_o)H}{\alpha}\sqrt{C^2 + \tfrac{\alpha^2}{(u_L - u_o)^2 L_1^2}} \\ &\text{assume that, } u_L > u_o \\ \cos\beta &= \tfrac{H}{W_l L_1} \\ X &= \left(\tfrac{\alpha W_l}{u_L - u_o} - \sin\beta H\right)\tfrac{1}{\cos\beta} \end{aligned} \tag{6}$$

The same process can be repeated for any number of corners, including the corners on the other side. In essence, exploiting the certain geometry of the corners present in the corridor, we can compute the absolute range and bearing of the features (corners) needed for the SLAM formulation.

B. Corner SLAM formulation

Let us consider one instantaneous field of view of the camera, shown in Figure 6, in which the center of the four corners (shown in red) is shifted. Note that the proposed method uses only the ground corners (corners 3 and 4 in the figure). From the distance measurements in (6), we can derive the relative range and bearing of a corner of interest as follows

$$\mathbf{y} = \mathbf{h}(\mathbf{x}) = \begin{pmatrix} \sqrt{X^2 + W^2} \\ \tan^{-1}(\frac{\pm W}{X}) \end{pmatrix}, \tag{7}$$

which can be related with the states of the vehicle and the i-th corner (landmark)at each time stamp (k) as follows

$$\mathbf{y}_i(k) = \begin{pmatrix} \sqrt{(x_r(k) - x_{ci}(k))^2 + (y_r(k) - y_{ci}(k))^2} \\ \tan^{-1}(\frac{y_r(k) - y_{ci}(k)}{x_r(k) - x_{ci}(k)}) - \theta_r(k) \end{pmatrix} + w(k) \tag{8}$$

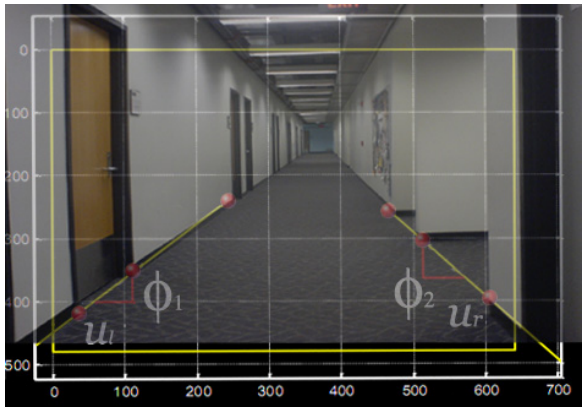

Fig. 5. The image plane of the camera.

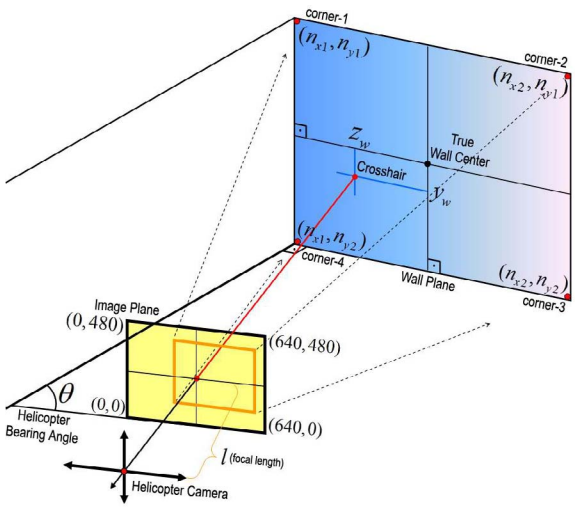

Fig. 6. 3D representation of an instantaneous shot of the MAV-camera flying through a corridor towards a wall, with bearing angle θ.

For simplicity, we focus on the two-dimensional car-like vehicle model [13], [14] as our vehicle dynamics. Indeed, the dynamic model of MAVs with an autopilot system that takes care of the altitude hold resembles a car-like kinematic model.

The extended Kalman filter (EKF) [13] based SLAM formulations can be used to simultaneously estimate the vehicle pose and the location of the corners. In particular, we make use of the compressed EKF SLAM algorithm, presented in [22], that can significantly reduce the computation requirements when the vehicle navigates for a long period of time. A more sophisticated method such as FastSLAM [14] is a subject of the future work. Since the Kalman filters of the autopilot system, which incorporates the IMU/gyroscope and electronic compass measurements, output the heading information, we are only concerned about providing the global metrology system in the absence of the GPS signal. We have to simultaneously locate

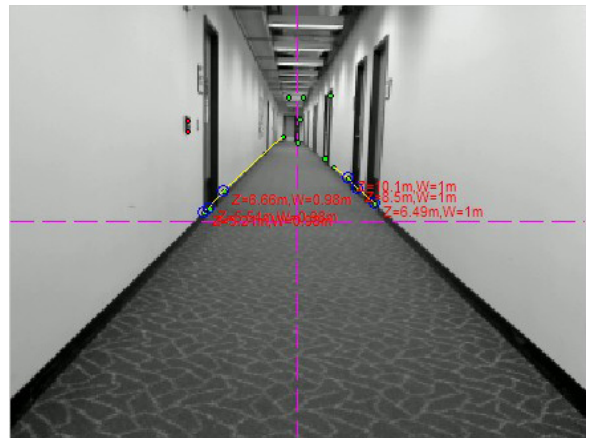

Fig. 7. The world as seen from the MAV. Green dots represent useful corners, blue circles represent corners that are currently considered for measurement. The yellow lines represent the slope measurements.

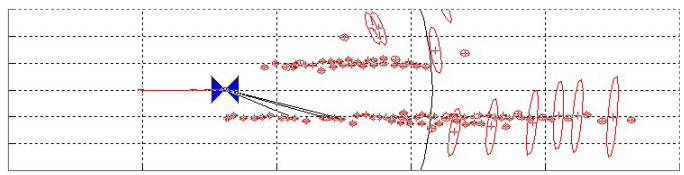

Fig. 8. The visual radar that displays the MAV, and features used for SLAM calculations. An elliptical feature represents the uncertainty in the ellipse direction. Therefore a large ellipse represents an inconsistent feature. Such features are introduced when external disturbances are present. The arc represents the current range of the visual radar, which is is a variable we adjust based on the resolution of the camera such that features at very far distances where the resolution is inadequate for a high quality feature detection are disregarded. As illustrated in the figure, our system has correctly located the corner locations.

the landmarks (corners shown in red in Fig 5), as well as the vehicle states x_r, y_r, θ_r described by

$$\mathbf{x}(k+1) = \begin{pmatrix} \cos\theta_r(k)u_1(k) + x_r(k) \\ \sin\theta_r(k)u_1(k) + y_r(k) \\ u_2(k) + \theta_r(k) \end{pmatrix} + \gamma(k) \tag{9}$$

where the linearized input signal noise $\gamma(k)$ can be represented by [22]

$$\gamma(k) = \frac{\partial F}{\partial u}|_k \gamma_u(k) + \gamma_f(k) \tag{10}$$

The standard EKF routines iterate the prediction step and measurement update step using the Jacobian matrices obtained from (8) and (9). Care must be taken to determine if the detected corners exist and can be associated with the existing corners in the map. This data association problem also decides if a new corner is sufficiently different from the existing ones to warrant a new land mark. For the data association, the measure of the innovation is written as

$$I_v = (\mathbf{y}(k) - \mathbf{h}(\mathbf{x}(k)))^T \mathbf{S}^{-1} (\mathbf{y}(k) - \mathbf{h}(\mathbf{x}(k))) \tag{11}$$

and the innovation covariance $\mathbf{S}$ is given by

$$\mathbf{S} = \frac{\partial \mathbf{h}}{\partial \mathbf{x}} \mathbf{P} \frac{\partial \mathbf{h}}{\partial \mathbf{x}}^T + \mathbf{R} \tag{12}$$

where $\mathbf{P}$ is the error covariance matrix, and $\mathbf{R}$ is the covariance matrix of the measurement noise. As a result, the preceding formulation solves the SLAM problem, thereby simultaneously estimating the pose and orientation of the MAV with respect to the corners as well as the location of the corners. Our preliminary experiments with a 2 mega-pixel web camera with $\alpha = 281.49$ achieved accurate range measurement as depicted in Figs. 7 and 8.

C. The Mapping Function

As the MAV moves through the scenery, every incoming video frame is processed for presence and behavior of good corners, which are then passed as landmarks to the SLAM algorithm to calculate and return motion parameters to the radar screen, which is a six degree-of-freedom description that includes information about pitch, roll, and collective actions of the MAV. Mapping function uses these parameters to plot the detected motion trajectory, with the assumption that the MAV is a unit sphere, initially centered at origin, $C(x, y, z)$. A vector starting at the center of this sphere with unit magnitude and a direction represents the gimbal angle where the camera is pointing. Every time the MAV makes a move a corresponding motion parameter is generated, the direction of the vector changes accordingly, therefore a new intercept point is calculated. Every time the MAV moves the sphere center is moved accordingly to this new interception point.

V. Conclusion

This paper introduced the implementation of a vision based SLAM and navigation strategy for an autonomous indoor MAV, and tested it in a vision based path-finding mission through hallways of a building as an indoor airborne navigation and mapping system. Since our system uses a light-weight monocular camera, able to measure ranges to ggod features, and does not depend on GPS coverage, a practical solution is born for autonomous indoor flight and navigation. Our design is also robust in the sense it does not depend on extensive feature finalization procedures. Airborne SLAM is still at its infancy, nevertheless its capabilities over conventional sensors stimulates future research. Our system is only limited by the capabilities of the camera and the availability of good corners. Many of the current limitations in airborne SLAM are also governed by the computational power-per-ounce ratio of computers which affects the real-time quality of service of any algorithms involved. This problem can be addressed by by removing the computer from the helicopter and processing video on the ground control center, which brings a limit to the effective range of the aircraft as a compromise.

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