Proceedings of the 2012 2nd International Conference on Computer and Information Application (ICCIA 2012)

Vision Algorithms for UAVs Aerial Refueling Using Probe-drogue

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***Abstract*—A critical limitation for the current use of Unmanned Aerial Vehicles (UAVs) is represented by the lack of aerial refueling capabilities. This paper describes the results of an effort on the modeling of the refueling soft hose realized by FEM techniques and on the algorithms of the docking control. The algorithms of the docking maneuver is based on Machine Vision (MV).The simulation results with a vision technique capable of estimating the drogue position is presented. Simulation results suggest the proposed algorithm performs the same accuracy with extremely fast speed compared with the current employed algorithms.**

Keywords-UAV; Autonomous Aerial Refueling; Drogue; Machine Vision; Pose estimation

I. INTRODUCTION

The biggest limitation of the current use of UAVs is their limited voyage. Autonomous Aerial Refueling (AAR) is the best solution to increasing the rang of Unmanned Aerial Vehicles (UAVs). To achieve these capabilities specific technical challenges need to be developed. The level of accuracy and precision for the final phase of the 'tanker-UAV' docking is such that the use of Machine Vision (MV) technology. Currently there are two different hardware set-ups for manned aerial refueling. The first method is based on a refueling boom; the second method is based on a probe-drogue approach. This research effort focuses on the probe-drogue method for the AAR of UAVs. For the specific problem of the probe-drogue refueling method a MV system has been proposed in [1] using the general approach used for spacecrafts [2]; the methodology features optical markers [3].In this paper, a Algorithms based on MV for UAVs aerial refueling using probe-drogue is presented.

II. THE DESCRIBING OF AUTONOMOUS AERIAL REFUELING(AAR)

A system of the AAR refueling problem using the probe-drogue method, relevant reference frames and distances is shown in Fig. 1. It is assumed that both the UAV and the tanker are equipped with GPS systems and a functional communication link; for simplicity, it is assumed that the GPSs provide measurements with respect to Obo and Ob respectively. It has been reported that GPS sensors might not be able to provide the required attitude information due to signal distortion caused by the tanker proximity or instrumental errors. Therefore in this work, a novel algorithm based on MV is proposed.

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• GPS-based relative distance vector *dG*:

The UAV, exploiting the shared GPS measurements, can evaluate the relative distance between the points *Obo* and *Ob*. Additionally, since the camera is located at a fixed position, it is also possible to infer the distance vector *dG*.

• GPS-based "nominal" drogue distance *dDn*:

Vector *dGno* represents the nominal position of the drogue. The corresponding position in the *Obo*-RF is measured by the vector dDn = *dG - dGno*

• Drogue "real" distance vector *dD*:

Vector *dD* provides the measurements of the relative camera-drogue distance.

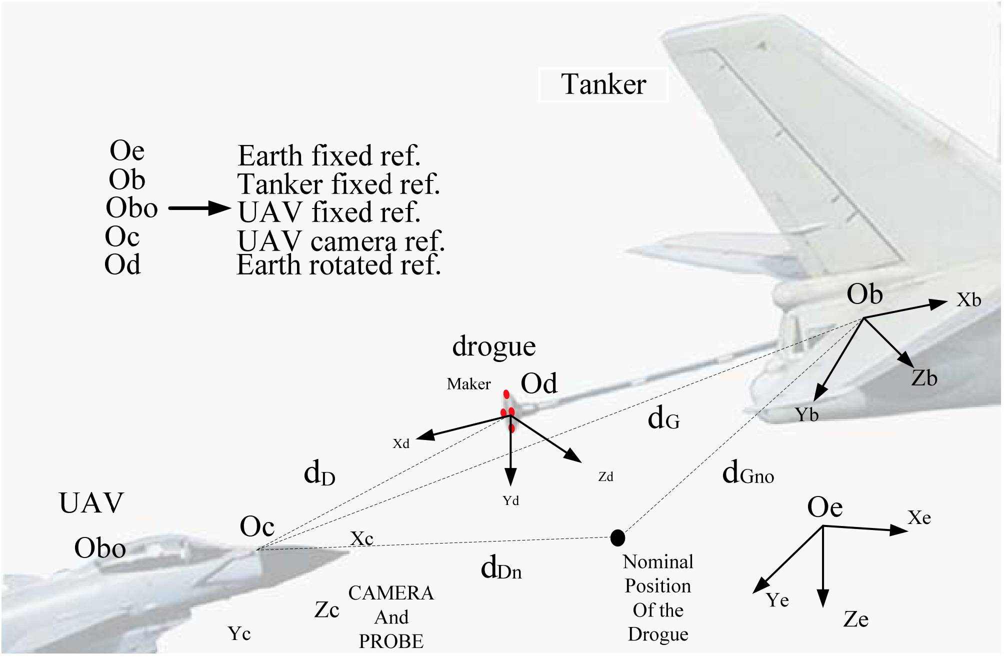

Figure 1. Schematization of the AAR Problem

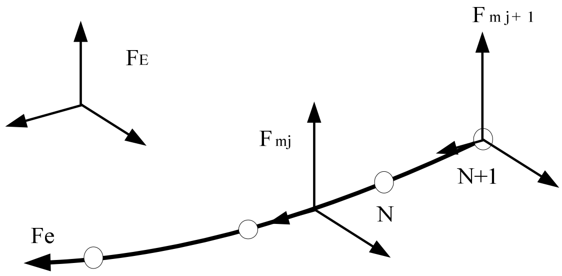

Figure 2. Tanker and Cable Reference Frames

IV. MODEL OF THE DRAGGING HOSE

The dragging hose is modeled as a system of N massless inextensible segments. The segments are connected by spherical hinges, with their mass concentrated at the end where all forces act. An external force Fe is applied at the end of the cable; it can be used to model contact force with the UAV. For the purpose of modeling the cable trail by the tanker, the tanker is modeled as a point mass system. We use the following notation: node 1 is the one where Fe is applied, node N+1 is the one constrained to the tanker. Two reference systems are used, an inertial reference FE and a local reference Fmj for each mass mj+1, as shown in the fig. 2.

The orientation of the j-th segment with respect to FE is defined by two angles θ1j, θ2j, yielding the transformation matrix LmiE :

$$L_{miE} = \begin{bmatrix} \cos\vartheta_{2i} & \sin\vartheta_{1j}\sin\vartheta_{2i} & -\cos\vartheta_{1i}\sin\vartheta_{2i} \\ 0 & \cos\vartheta_{1i} & \sin\vartheta_{1i} \\ \sin\vartheta_{2i} & -\sin\vartheta_{1j}\cos\vartheta_{2i} & \cos\vartheta_{1i}\cos\vartheta_{2i} \end{bmatrix} \quad (1)$$

For the generic mass mj, the kinematic relationship for position, velocity, and acceleration are found in standard form:

$$\begin{cases} (P_j - O_e) = (P - O_e) + \sum_{K=J}^{N} \underline{r}_K \\ \underline{v}_j = \underline{v}_p + \sum_{K=J}^{N} \underline{v}_{rk} \\ \underline{a}_j = \underline{a}_p + \sum_{k=j}^{N} \underline{\dot{v}}_{rk} \end{cases} \quad (2)$$

A detailed information of the numerical aspects of the hose simulation can be found in[4].

V. VISION ALGORITHMS OF DROGUE POSITION AND ATTITUDE

The objective of the vision problem is to estimate the relative displacement and rotations of the drogue respect to the UAV. A Camera is mounted onboard the UAV and it captures images of the drogue. Determining the rigid transformation relating 2D images to known geometry is one of the central problems in computer vision.

The mapping from 3D reference points to 2D image coordinates can be formalized as follows: Given a set of non-collinear 3D coordinates of reference points with expressed in an object centered reference frame, the corresponding camera space coordinates are related by a rigid transformation as:

$$q_i = Rp_i + d \tag{3}$$

where are the rotation matrix and the translation vector of the object frame respect to the camera frame, respectively. In computer graphics, the camera reference frame is chosen so that the center of projection of the camera is at the origin of the axis and the optical axis points in the positive direction. The reference points pi are projected to the plane with , referred to as the normalized image plane, in the camera reference frame.

Let the image point be the projection of on the normalized image plane. Under the idealized pinhole imaging model, and the center of projection are collinear. This fact is expressed by the following equation:

$$w_i = \frac{1}{r_3^t + d_z}(Rp_i + d) \tag{4}$$

Given observed image points , the pose estimation problem is formulated as the problem of minimizing the sum of the squared error

$$E(R,d) = \sum_i^n \|e_i\|^2 \tag{5}$$

It does this minimization solving first the absolute orientation problem, determining an estimated rotation matrix for step; then, from Eq. 1 estimates the translation vector and then iterates. This algorithm has been proven to be globally convergent, that , and has shown that in few iterations: 4 to 11, it reaches the solution.

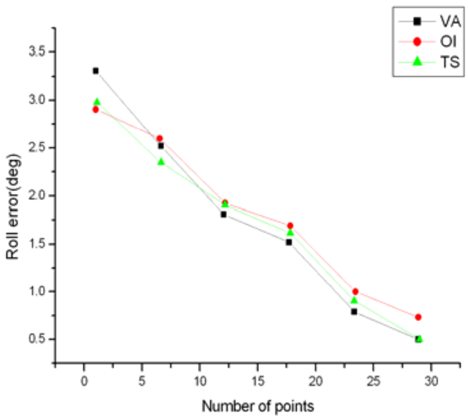

Figure 3. Rotation error against number of points.

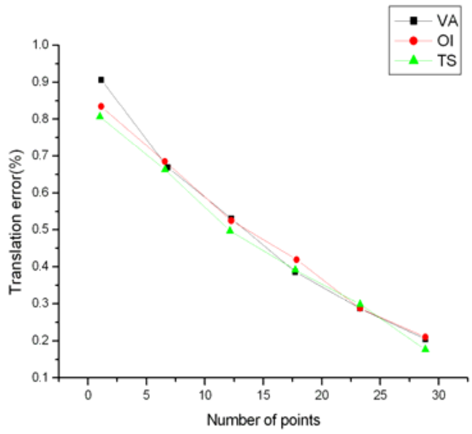

Figure 4. Translation error against number of points.

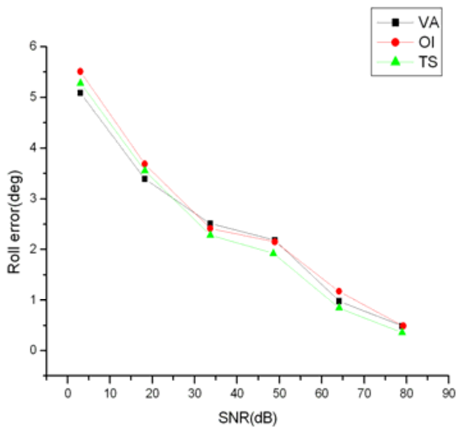

Figure 5. Rotation error against SNR.

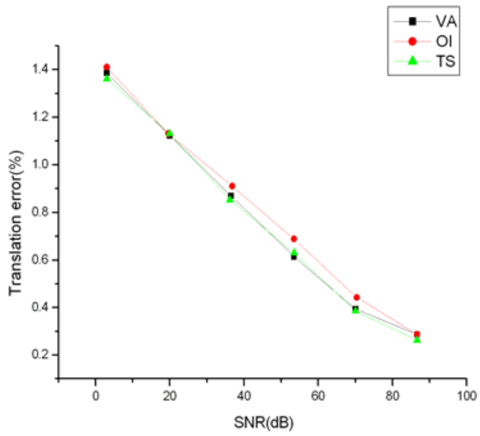

Figure 6. Translation error against SNR.

VI. SIMULATION AND COMPARING

The proposed algorithm is compared with Lu's OI algorithm[5] and Zhang's two-stage algorithm[6] in accuracy and noise-resistance. The vision algorithms have been executed both in Matlab 6.5 and VC++ 6.0 with linear algebra package. And the computer was a Lenovo PC with clock frequency 2.4 GHz and with 2 GB of random access memory. The operating system was Microsoft Windowsr XP Professional.

The initialization of data is as follows:

The coordinates of the feature points , = 1, 2, . . ., n are generated randomly distributed within [−4,4]×[−4,4]×[−4,4] in the object coordinate frame. The rotation matrix R is generated randomly by the Euler angles: yaw, pitch and roll within (−90, 90)×(−90, 90)×[0, 360) degree. The translation vector d is generated randomly distributed within [4,16]×[4,16]×[20,200] in the camera coordinate frame.

The coordinates of the image points are generated by , R and d, then Gaussian white noise is added to to generate the observed points . The noise is related to the (signal-to-noise ratio) by . 1000 sets of is generated for each selected set of , R and d, and the computation results are averaged as one result of the selected set.

Simulation 1. Set n = 15, SNR = 30 dB–80 dB by step of 10 dB, record the errors of Euler angles and translation vector. The result of each step is the average value of 400 sets of , R and d.

Simulation 2. Set SNR = 55, n = 5 – 40 by step of 5, record the running time, the errors of Euler angles and translation vector. The result of each step is the average value of 400 sets of , R and d.

In Figs. 3–6, we can infer the accuracy and noise-resistance of three algorithms. We denote VA as our proposed "Vision algorithm", OI as Lu's orthogonal iterative algorithm, and TS as Zhang's two stage algorithm. As shown in Figs. 3–6, three algorithms have almost the same accuracy and noise-resistance.

VII. CONCLUSION

In this paper, we have builed a model of the dragging Hose and have presented a fast vision iterative algorithm. Because of the new absolute orientation method, in which complicated SVD operation is replaced by the Fobenius norm, determinant and adjoint of matrix, the proposed algorithm is much faster and no less accuracy and noise-resistance than the best current algorithms. The vision algorithm should be relevant for many applications in real-time vision servo missions. In addition, there is no configuration requirement of feature points used in our algorithm, thus we will focus on the design and configuration of feature points in future research.

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