ABSRTACT: IN-SITU UNMANNED AERIAL VEHICLE (UAV) SENSOR CALIBRATION TO IMPROVE AUTOMATIC IMAGE ORTHORECTIFICATION

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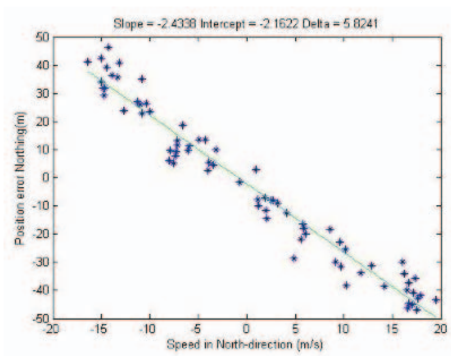
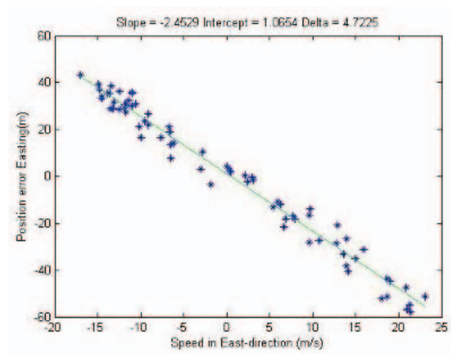
1. INTRODUCTION

Small, low-altitude unmanned aerial vehicles (UAV)s can be helpful as remote sensing platforms; they can be low-cost, easy-to-use, quick to deploy and have high spatial resolution. AggieAir, a unmanned aerial system (UAS) developed at Utah State University (USU), has shown the effectiveness of a UAV as a remote sensing platform [1]. Even though the UAV itself is inexpensive, conventional post processing and georeferencing of the imagery can still take significant time and resources due to the small image footprint and the high number of images needed to cover an area. For example, it may take 100 images to cover a two kilometer squared area. One could georeference all of the images using a basemap and common features in each image. However, this could be very time consuming and costly, making the UAV platform less competitive with conventional remote sensing platforms. In addition, many cases lack the necessary features in each image to georeference them to a basemap. Another quicker and less expensive approach to georeferencing the images would be to orthorectify them based on the position and orientation of the camera at the time the image was taken; this can be done completely autonomously. The problem with this method is that the low-cost sensors which measure position and orientation of the aircraft have some inherent errors, and these errors are projected onto the ground with the image. Depending on the altitude, this can cause up to 60m of error on the ground. Some have addressed this issue and have improved the location accuracy of a ground target by loitering above it, sampling the location many times, and filtering the data [2]. Others improved the location accuracy of a ground target using multiple UAVs [3]. Since they are applied to a single ground target, these methods might not work for creating maps of an area. The best solution to the errors in the aircraft sensors may be to quantify them by in-situ calibration of the system [4]. This includes setting up ground control points (fig. 1a) with defined geodetic positions measured by a precise GPS receiver, taking aerial photographs of the control points, and using the control points to inverse orthorectify the images to find the actual position and orientation of the camera when the picture was taken. The method used by Jensen et. al. [4] to inverse orthorectify the images only found the position, altitude and yaw of the UAV. The inability to find roll and pitch also decreased the accuracy of the position estimation. This paper describes a different, more accurate method which also finds the roll and pitch of the aircraft. This more accurate pose estimation allows us to characterize not only the position and orientation, but also the delays caused by the GPS receiver and the synchronization between the datalog and the cameras. With this method, the control point errors are reduced from less than 60m to less than 1.5m.

(a) Ground control targets



(b) Speed vs. GPS error in North Component



(c) Speed vs. GPS error in East Component

Fig. 1. Results from a test flight.

2. CALIBRATING AIRCRAFT SENSORS

To calibrate the aircraft sensors, the real position and orientation of the UAV needs to be compared with the measured position and orientation from the sensors. The algorithm that is used to find the real position and orientation of the UAV is called General Procrustes Analysis (GPA). GPA uses least-squares fitting to find the transform matrix between two 3D point sets [5]. For this application, GPA will be used to find the transformation matrix between the ground control points on the image and their geodetic positions. This transformation matrix is then converted to the position and orientation of the camera. For a sample of images, comparing the position and orientation found by GPA with the sensor data that was logged in synchronization with the cameras allows us to find, quantify and correct many features of the sensors: the biases in the altitude, yaw and position, the misalignment of the cameras with the aircraft coordinate system, and the time delays caused by the GPS receiver and the synchronization between the datalog and the cameras.

Figures 1b and 1c show some of the results obtained from a test flight. Both of these graphs display the relationship between a component of the UAV speed versus a component of the error in the measured UAV position. They both show a linear relationship with a slope of -2.4, which represents a time delay. This time delay occurs both in the GPS receiver and in the synchronization error between the datalog and the cameras. More results will be shown in the final paper.

3. REFERENCES

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