

Unsteady Pressure Sensitive Paint Camera Calibration Improvements

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New challenges have arisen in processing a significantly increased volume of data collected during recent large-scale demonstrations of unsteady pressure-sensitive paint. Techniques designed for several thousands of images collected in a lab do not necessarily scale to tens of millions collected in a large-scale test. New techniques are needed to meet the tighter requirements on robustness and accuracy that accompany larger wind tunnel models, higher camera resolution, and more run conditions per test. This paper outlines several such techniques and improvements in regard to the camera calibration process.

I. Introduction

Over the past two decades, pressure-sensitive paint (PSP) has become a powerful technique to measure surface pressure of a wind tunnel model with high spatial density [1–5]. An important step in the PSP processing pipeline has always been the camera calibration which allows for a point on the 3D model to be mapped to a point in the 2D image. Camera calibration is composed of an internal calibration, the process that maps 3D points relative to the camera to 2D image points, and an external calibration, the process that determines relative position and orientation between the camera and model.

In the most recent large-scale wind tunnel tests with unsteady PSP (uPSP) in the Unitary Plan Wind Tunnel (UPWT) complex at NASA Ames Research Center [2,4], data was collected for the Space Launch System (SLS) on a model that was nearly 8 ft. long. These tests presented challenges as the large SLS wind tunnel models necessitated wide fields of view and exhibited significant model motion at high Mach numbers. Additionally, the amount of data was greatly increased as tens of thousands of frames were collected for hundreds of run conditions.

Typically, the internal calibration was performed with a calibration board that covered a significant portion of the field of view. With the wide fields of view, it was not reasonable to scale the calibration board as it would be unwieldy in the confined UPWT test section. This complicated the internal calibration process and required a new approach.

Previously, the external calibration was performed for only one frame of a run condition. This was sufficient because either only one frame was collected [6], or model motion between frames was assumed to be small [4]. One method of mitigation was to perform an external calibration for the first frame, then use image registration to warp subsequent frames into the perspective of the first frame [4]. However, between the increased number of frames collected, the wide field of view, and the high model motion, stricter requirements had to be imposed on the external calibration. The image registration technique was particularly troublesome as it was computationally expensive, had complicated effects on pressure signal, and did not lend itself to generating additional useful data products such as uncertainty quantification or node-to-pixel mapping for successive frames.

To overcome these issues, improvements have been made to the operational procedures and processing algorithms for internal and external camera calibration. These improvements have created a more robust and more accurate pipeline while having minimal impact on the tunnel setup time and the required computational expenses.

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II. Internal Calibration Improvements

A. New Internal Calibration Procedure

Previously, internal calibration for uPSP at Ames utilized a large and cumbersome board and specified 5-8 positions for the calibration board per camera. This procedure worked well for applications where the calibration board covered a significant proportion of the field of view but did not scale to applications with a wide field of view and wide depth of field. As shown in Fig 1, when applied to one SLS wind tunnel test configuration, the procedure led to node-to-pixel mapping errors greater than 1 pixel. This error was the largest source of uncertainty in the camera calibration pipeline but could be mitigated with minimal added costs and without increasing the overall tunnel setup time.

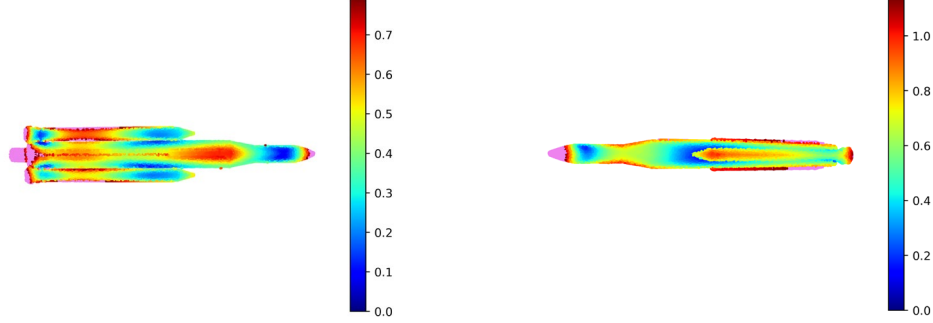


Fig 1: Heatmap of Node-to-Pixel Mapping Uncertainty (in Pixels) for Old Procedure, maximum error less than one pixel. Left image is side view of model. Right image is top view of model. Pink Represents Oversaturated Error

A major issue with the previous calibration procedure was moving the large calibration board around the wind tunnel model, other setup equipment, and other personnel involved in setup. The previous board was 48" x 48" and required at least 2 people to manipulate in the tunnel. To overcome this, the previous board was replaced with a smaller board that is 31.5" x 23.5" and is manufactured by Calib.io [7] on their standard aluminum substrate. Since the new board is made from aluminum rather than wood, it is flatter and stiffer than the previous one which additionally improves the calibration quality. One drawback is that the smaller board has fewer calibration targets. The new board has a 14 x 20 hexagonal circle grid pattern whereas the previous board had a 24 x 24 rectangular circle grid pattern. Fewer targets on the new board means it requires more images for the same calibration quality, but an accurate calibration can still be performed with a reasonable number of images.

With 500 images distributed throughout the field of view and depth of field, the new calibration procedure reduces the internal calibration contribution to the node-to-pixel error to 0.1 pixels or less. These images can be collected in parallel to other setup steps and the process does not significantly increase the overall setup time. The new error distribution is given in Fig 2 and has a similar shape as before but is reduced by an order of magnitude. The internal calibration uncertainty can be reduced further with more images and is inversely proportional to the square root of the number of images. The calibration board size and number of calibration images can be scaled to accommodate different fields of view, environments, or uncertainty tolerances.

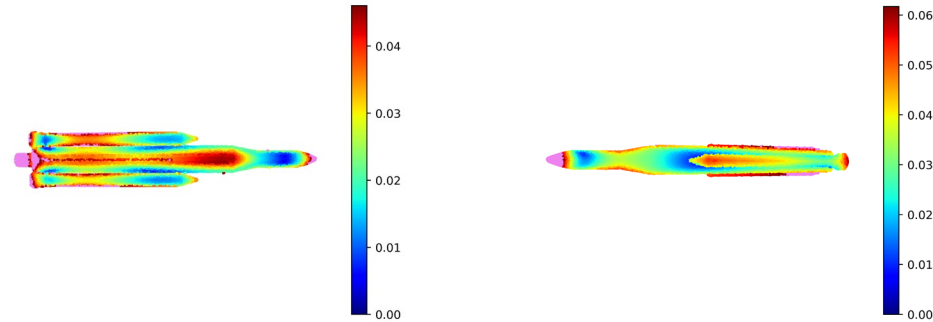


Fig 2: Heatmap of Node-to-Pixel Mapping Uncertainty (in Pixels) for New Procedure, maximum error less than 0.1 pixel. Left image is side view of model. Right image is top view of model. Pink Represents Oversaturated Error

To ensure that the internal calibration is accurate, it is important that the calibration board is imaged across the entire field of view of the camera [8]. It can be difficult to collect calibration points very close to the edge of the field of view, so care must be taken to ensure that area is filled. The area of the image where calibration points are collected can be referred to as the calibration area. Points near the center of the image are relatively sensitive to lower order radial distortion terms ($K1$ and $K2$) while points near the edge of the image are relatively sensitive to higher order radial distortion terms ($K2$ and $K3$). Neglecting points near the image boundary can lead to high uncertainty in the higher order terms. As a result, points far outside the calibration area should not be used during data processing as their uncertainty may be higher than tolerated.

B. Improved Internal Calibration Software

For the camera intrinsic parameter estimation, we used Calib.io's Calibrator software application [7]. It uses well-established algorithms such as Zhang's method [9], Tsai's method [10], and autocalibration [11,12]. It has demonstrated robustness against false positives in target detection and provides built-in uncertainty quantification and visualization tools.

False positives in the detection of calibration board targets have been a major hurdle in the automation of the internal calibration for uPSP tests. In the UPWT these false positives are primarily due to background artifacts such as the corrugated section of the tunnel wall or other setup equipment. Blob detection using OpenCV [13] was tested, but changes to the environment, lighting, or camera lens would often require manual tuning of detection algorithm parameters. Previously, the PSP software sidestepped this issue by requiring manual input to define the position of the calibration board in each image. The Calib.io's Calibrator application is robust against these false positives and requires little-to-no manual input.

The Calib.io software provides several visualizations as to the quality of the internal calibration. These visualizations are useful for identifying the occasional frame with a mis-localized target, as well as more global biases such as regions missing in the calibration area. The Calib.io software also provides uncertainty estimates for the calibration parameters which provide a quantitative measure of the calibration quality.

III. External Calibration Improvements

A. External Calibration with RANSAC

The final improvement was to the external calibration pipeline and applied RANdom Sample Consensus (RANSAC) [14] to the Perspective-n-Point (PnP) problem. PnP is the problem of estimating the relative pose (3D position and orientation) between a calibrated camera and an object given a set of n visible 3D points and their corresponding 2D projected image points [15]. For this application, the object is the wind tunnel model, and the points are the targets. RANSAC ensures with a high degree of probability that even if there are incorrect matches between 3D targets and image locations, the final PnP solution will be correct. The RANSAC algorithm is extremely robust to mismatch errors and is used in many other computer vision and machine learning applications. This increased robustness is an important step of automating the camera calibration process, as well as performing external calibration on every frame collected during a test to mitigate the effect of model motion between frames.

An example of a case where this implementation of RANSAC improved the robustness of the external calibration is given in Fig 3. In the example used for Fig 3, a single mismatch (out of 21 total matches) occurs near the aft of the model. The distance between the mismatched 3D target's projected position and the detected image location was at the upper end of, but still within the typical matching tolerance of, 6 pixels. With RANSAC, this mismatched target is flagged as an outlier since the reprojection error becomes 10 pixels after the external calibration is performed. The results of the external calibration with RANSAC are shown in the bottom image of Fig 3 in blue. The calibration with RANSAC has relatively low reprojection error and can be viewed as a 'ground truth' with which to compare the calibration without RANSAC. The calibration without RANSAC is shown in red. The single mismatched target degrades the calibration such that the reprojection error of targets toward the aft of the model is 1.5 - 2.4 pixels.

For this application, RANSAC is applied after the 3D targets have been matched to their image locations. RANSAC is applied in that a subset of 4 of the matches are used to solve the PnP problem. If most of the other matches agree with the solution found using the subset, then that solution is kept. Agreement is defined by some threshold on reprojection error between the 3D target and image location. This method is implemented by OpenCV with the *solvePnPRANSAC* function.

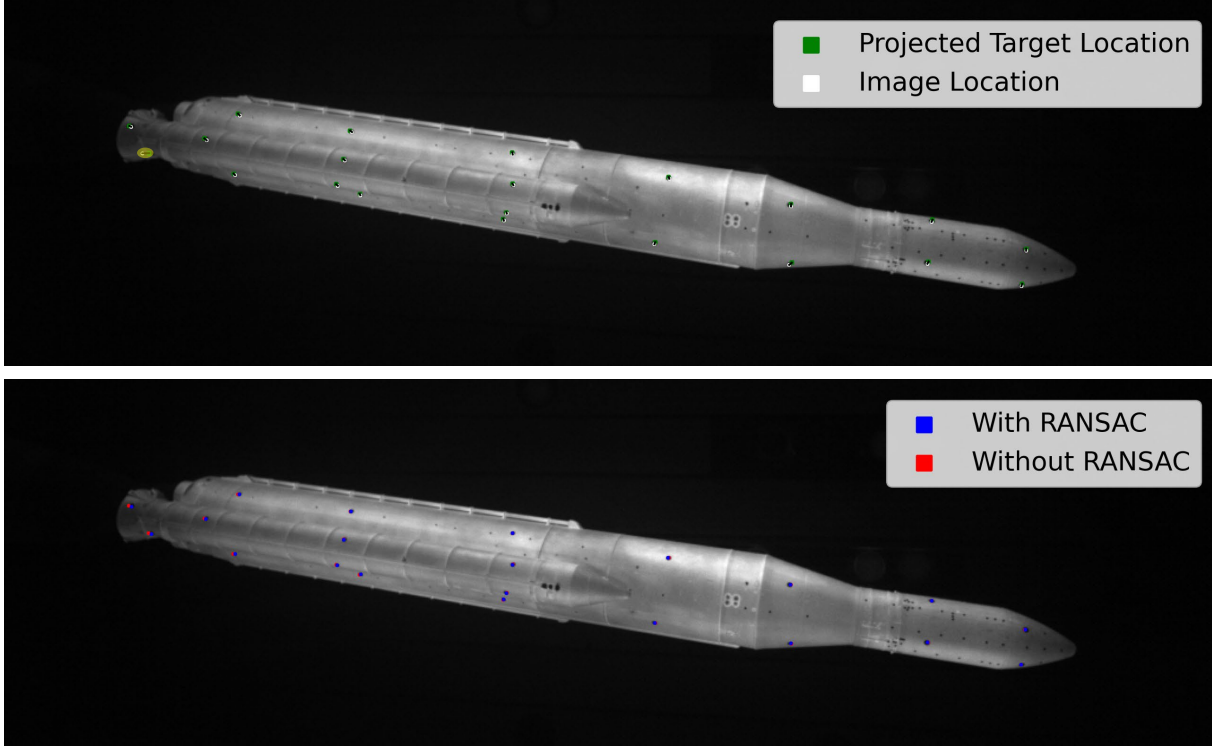


Fig 3: Comparison of External Calibration with and without RANSAC

Top Image: Initial Matching between Projected 3D Targets (white) and Image Locations (green). There is a single mismatch highlighted in yellow.

Bottom Image: Comparison of results with RANSAC (blue) and without RANSAC (red). External Calibration with RANSAC had a mean reprojection of 0.4 pixels with a max single error of 0.7 pixels. The calibration without RANSAC had a mean of 0.9 pixels and a max single error of 2.4 pixels.

RANSAC has been applied in similar ways [16,17], but the implementation for this paper is the more traditional approach to PnP with RANSAC. Unlike [16] and [17], it is relatively simple in the UPWT to start with an accurate initial guess for the camera-to-model pose based on the commanded model position and an estimate of the sting deflection. Using an initial guess has several benefits for our application such as reduced optimization computation, and the ability to flag instances where the external calibration deviates from the initial guess by a large margin. The method used in [16] and [17] was implemented to find the initial camera-to-model transformation since its main advantage is it requires no manual input as to an initial guess of the transformation. There are several drawbacks that make the method used in [16] and [17] a poor match for application in the UPWT for general use.

First, it requires target detection over the entire image rather than small regions around the projected target locations. Over hundreds of datapoints each with tens of thousands of frames, the increased computation cost for target detection becomes significant. This also leads to more false positives since the entire image must be searched rather than small regions around the projected target positions. False positives increase the potential for a bad external calibration, as well as significantly increased computation time when using RANSAC.

Second, the most recent test with uPSP had roughly 50 3D targets with roughly 20 visible to each camera. Assuming no false positives or incorrect image locations, that puts the odds of a correct calibration at roughly 1 in 100,000 iterations. In testing this, the average runtime per frame was on the order of 5 minutes but varied from 30 seconds to 20 minutes based on random selection.

Finally, the method of [16] and [17] can create a large consensus from a wrong external calibration if the targets are rotationally symmetric or if the targets form a repeating pattern. The method has no external knowledge, so any fold of the rotationally symmetric case produces the same sized consensus. With a repeating pattern, the method can be off-by-one in the pattern and still have a relatively large consensus. In both those cases, the targets need not be perfectly rotationally symmetric or in a perfect repeating pattern as a reasonable reprojection error tolerance is allowed. For a small number of external calibrations these types of failures can be checked for manually. However, that is not reasonable for the amount of data collected in recent tests.

IV. Conclusion

Several improvements have been made to the camera calibration pipeline for uPSP in the UPWT at NASA Ames. The improvements required only small changes to the tunnel setup procedure and processing algorithms but made significant improvements to the robustness and accuracy of the camera calibration pipeline.

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