

Surface Flow Visualization via Tuft-Tracking on Transonic Truss-Braced Wing Configuration

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A wind tunnel test of the NASA-Boeing 4% full span Subsonic Ultra Green Aircraft Research (SUGAR) Transonic Truss-Braced Wing (TTBW) was conducted at the 12-Foot Low-Speed Tunnel (12-Ft LST) at NASA Langley Research Center (LaRC). The test aimed to understand flight behavior of TTBW configurations at edge-of-envelope stall/post-stall conditions and to further advance tools to ensure satisfactory aircraft dynamics at high angles of attack. Surface flow visualizations were implemented using strips of tufts along areas of interest. Improvements on traditional qualitative assessment of tuft videos at various flow conditions are presented to identify separated regions on the aircraft body. Computational Fluid Dynamics (CFD) simulations were performed for selective cases to compare with the qualitative tuft analysis. The qualitative enhancement tuft-flow techniques prove to be useful for non-optimal lighting conditions that arise in a wind tunnel environment and show agreement with CFD results.

I. Nomenclature

<i>SUGAR</i>	=	Subsonic Ultra Green Aircraft Research
<i>TTBW</i>	=	Transonic Truss-Braced Wing
<i>AATT</i>	=	Advanced Air Transport Technologies
<i>CFD</i>	=	Computational Fluid Dynamics
<i>FFTT</i>	=	Frame-by-Frame Tuft Tracking
<i>UV</i>	=	Ultra-Violet
α	=	Angle of Attack, degrees
β	=	Sideslip Angle, degrees
x_c	=	Cartesian X-Coordinate Within Image Frame
y_c	=	Cartesian Y-Coordinate Within Image Frame
x_1	=	X-Coordinate of Identified Object Root
y_1	=	Y-Coordinate of Identified Object Root
xy_{tail}	=	Index of Pixel Corresponding to Object Tail
x_2	=	X-Coordinate of Identified Object Tail
y_2	=	Y-Coordinate of Identified Object Tail
θ	=	Instantaneous Tuft Angle, degrees
<i>rms</i>	=	Root-Mean-Square

II. Introduction

The Subsonic Ultra Green Aircraft Research (SUGAR) project is an ongoing NASA/Boeing collaborative effort to advance commercial subsonic aircraft to meet NASA defined systems-level metrics and goals for 2030-35 entry into service [1]. These metrics reflect key technological benefits such as reduced noise, emissions, and energy/fuel consumption to increase the efficiency, environmental compatibility, and economic impact of future subsonic commercial aircraft. During the SUGAR study, the Transonic Truss-Braced Wing (TTBW) configuration was identified as a promising aircraft concept due to its potential fuel burn benefits. Preliminary research into the design has shown a clear

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advantage over a conventional tube-and-wing configuration, allowing hope in achieving the US Aviation Climate Action Plan's goal of net-zero greenhouse gas (GHG) emissions by 2050 [2]. The SUGAR TTBW is a Boeing-developed N+3 aircraft configuration funded by the NASA Aeronautics Research Mission Directorate (ARMD) Advanced Air Transport Technologies (AATT) project. The aerodynamic efficiency of the aircraft stems from its high aspect ratio ($AR = 19.55$) wings, significantly greater than traditional cantilever wing transport configurations ($AR = 9-15$). The increase in aspect ratio requires additional support to compensate for the elevated wing-root bending moment, thus the need for the truss-bracing from which the aircraft derives its name. This design isn't completely new to the world of passenger aircraft; high aspect ratio trussed-braced wings have existed since the 1950's, beginning with the French-made Hurel-Dubois HD-31, possessing an AR of 20.2 and carrying up to 36 passengers at speeds of Mach (M) = 0.2 [3]. The modern adaptation of this configuration is designed for a nominal cruise Mach number of 0.8 carrying 150+ passengers [4]. Figure 1 shows a rendering of the SUGAR TTBW $M = 0.8$ design with key features labeled.

This paper focuses on experimental efforts to assess this design within a set of wind tunnel tests performed at the NASA Langley Research Center (LaRC) 12-Foot Low-Speed Wind Tunnel. The tests were aimed at exploring the flight behavior of TTBW configurations at edge-of-envelope stall/post-stall conditions and to further advance tools to ensure satisfactory aircraft dynamics at high angles of attack. A secondary objective of the tests, and the subject of this paper, was to use the unique flow physics of this complex configuration to refine flow visualization techniques and compare results with relevant computational fluid dynamics (CFD) cases.

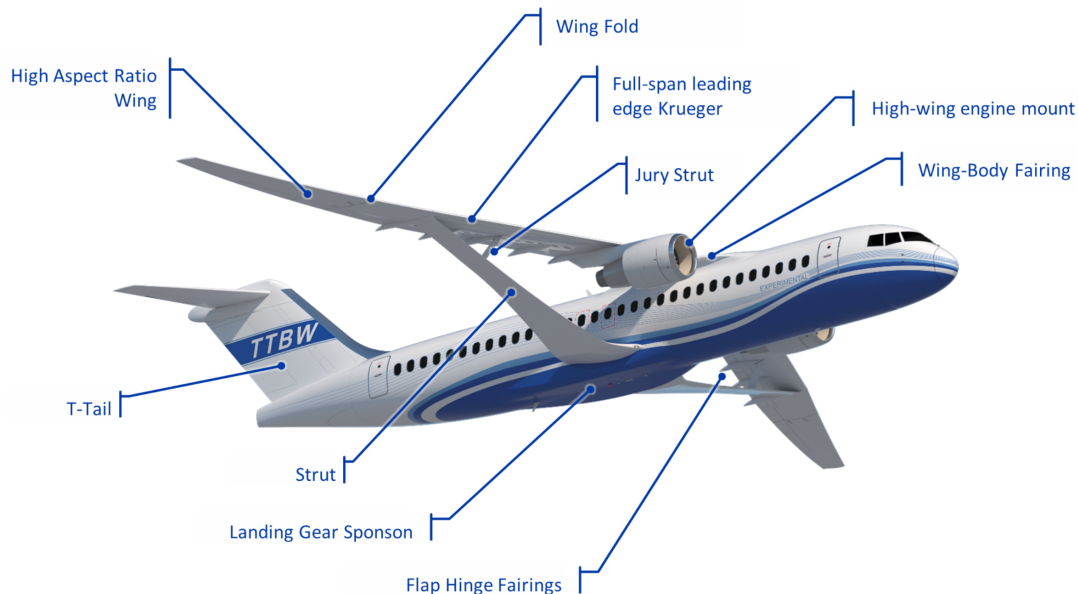


Fig. 1 SUGAR TTBW Mach 0.80 Configuration [4].

A. NASA Langley 12-Foot Low-Speed Tunnel

The NASA Langley 12-Foot Low-Speed Tunnel began operations in 1939, originally designed to explore aircraft stability and control characteristics using free-flight testing techniques. The test section had the ability to rotate about the pitch axis to match the flight path angle of a free-flying remote controlled model. The octagonal test section, with a height and width of 12 feet and a length of 15 feet, is enclosed in a sphere to allow for air recirculation as the test section is rotated. In the early 1950's, free-flight testing moved to the larger 30-by-60 foot Full-Scale Tunnel and the 12-Foot test section was horizontally fixed where it remains to this day [5], until the completion of its replacement, the Flight Dynamics Research Facility (FDRF) [6]. The 12-Foot Tunnel is now used for exploratory research and low-speed stability and control data. Figure 2 shows the 12-Foot Tunnel exterior (2a) and a schematic of the tunnel's current configuration (2b). The tunnel operates at atmospheric pressure with a maximum freestream dynamic pressure (Q) of 7 psf, driven by a 6-bladed, 15.8-foot diameter fan. For data presented in this paper, the testing was conducted at $Q = 4$ psf, corresponding to a freestream velocity of roughly 60 ft/s.

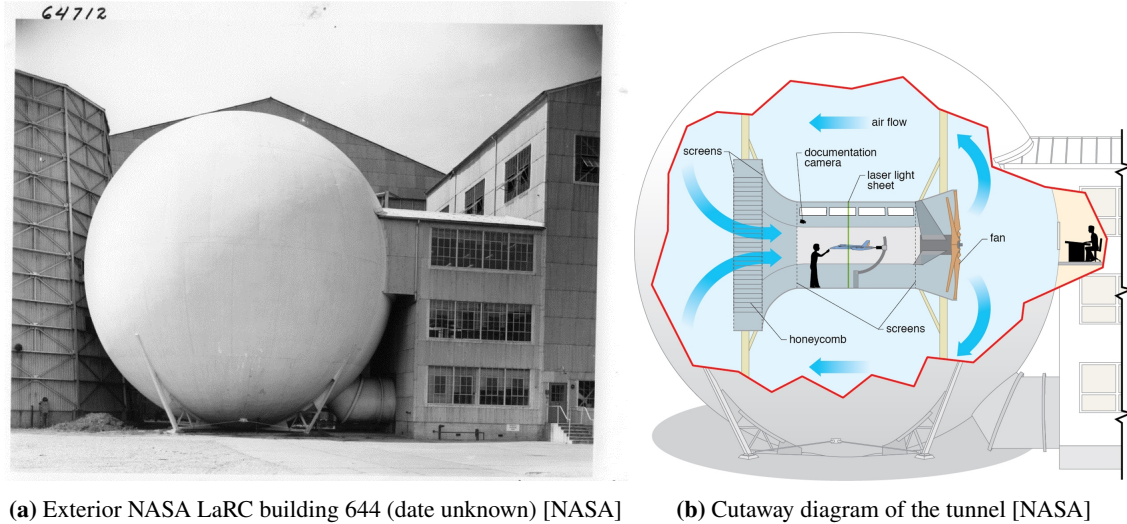


Fig. 2 NASA Langley 12-Foot Low-Speed Tunnel.

B. 4%-Scale SUGAR TTBW $M = 0.8$ Model

The model used in these experiments is a 4%-scale model of the SUGAR TTBW made of polycarbonate 3D-printed material. The model is mounted to the tunnel C-strut system with a moment reference center (MRC) at $\frac{1}{4}$ mean aerodynamic chord (MAC). Figure 3 shows the model mounted in the wind tunnel during the preliminary testing phase. The original model was painted white, it was later painted matte black for the test entries that had more of a focus on flow visualization. This change sought to maximize contrast with tufts on the model.

The tufts used during the flow visualization runs were polyester/cotton sewing thread attached to strips of Kapton tape. This stripping method allowed for rapid manufacturing and application/removal of a large number of tufts onto the models surface. Figure 3 also shows an example of the tufts on the model fuselage. An optimization of the lighting setup was performed during the experimental campaign, with the goal of reducing glare on the model in areas of interest to allow for tuft tracking. The images analyzed in the results section utilized matte black Kapton tape for the tufting strips and a pair of Ultra-Violet (UV) lights to enhance tuft-model contrast.

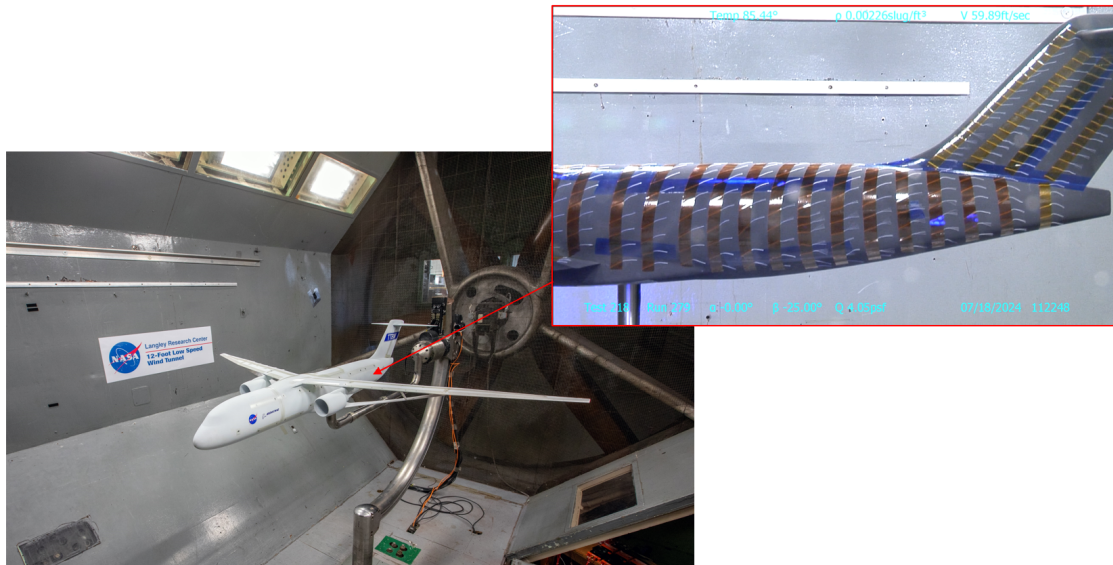


Fig. 3 4%-scale model of the SUGAR TTBW $M = 0.8$ configuration mounted in the test section of the 12-Foot Low-Speed Tunnel, and an example of tuft strip application to the side of the fuselage [Photos: NASA].

C. Tuft Flow Visualization Overview

Arrays of tufts have long been utilized as a simple and effective means to observe flow over bodies of interest. Traditionally, still photographs are used to identify the position of tufts in varying flow conditions [7]. Modern methods supplement high-quality still photographs with video recordings, allowing for the observation of tuft motion and resulting in identification of attached, unsteady, and separated flow regions. Video recordings also allow for the computation of mean tuft angles via the averaging of successive frames, which can be achieved with the still photographs by adjusting the camera's exposure time. As is often the case during a wind tunnel test, a sweep through various flow conditions is performed and a long video recording is produced. Researchers can immediately recognize the inefficiency of qualitatively observing and making note of tuft motion during this lengthy recording. Despite this inefficiency, simply watching the videos or comparing snapshots are still highly effective methods to extract relevant information of a given flow field. Recent NASA experimental campaigns have demonstrated this: Andino et al. [8] used qualitative observations of tuft patterns on the vertical tail of a Boeing 757 wind tunnel model to assess the efficacy of different flow control devices; Koklu et al. [9] supplemented tuft snapshots with relevant pressure and force measurements to identify separated and attached flow regions on an aircraft wing; Mears et al. [10] used tuft video as a diagnostic tool to complement Particle Image Velocimetry (PIV) measurements and identify different flow states on a launch vehicle model.

However, with more tufts on a surface and more flow conditions of interest, the inefficiency of qualitatively assessing video becomes even more glaring. Many papers have sought to remedy this by automating the process of tuft recognition and attempting to gain quantitative data from the tuft's behaviors. Before highlighting the methods used here to parse through terabytes of tuft flow videos, the following paragraphs highlight some current work tackling this problem.

Vey et al. [11] applied quantitative tuft tracking to the real world (i.e., in-the-field) flow of wind turbines. Mean tuft angles and per-tuft statistics were computed to recognize separated regions and specialized filters were developed to account for bi-modal flow states. Swytink-Binnema et al. [12] similarly investigated tufts on wind turbine blades; rather than computing instantaneous tuft angles they fit an ellipse around each recognized tuft and determined the flow state (attached/separated) of each tuft based on the eccentricity of the minimum ellipse that can be drawn around each recognized tuft.

Further application of quantitative tuft flow visualization has been applied to the flow around cars. Weiser et al. [13, 14] tracked each individual tuft in a photo series. The images were pre-processed using registration markers (colored dots) within the field of view to correct image displacements (due to camera vibration). The roots of tufts were deliberately marked by different colored stickers to allow for easy tracking, endpoints were identified in the vicinity of these roots and angles were computed. The standard deviation of the fluctuating tuft angles was utilized to identify separated regions in the flow and comparisons were made with CFD data.

Within wind tunnels, where more control over the measurement environment is achievable, tuft post-processing methods have yielded even more insight into flow physics. Steinfurth et al. [15] proposed Tuft Deflection Velocimetry (TDV) methods that involved the extraction of tuft edges and Hough transforms of these edges to extract distinct lines with discrete angles. They also performed a parametric study of different tuft sizes and materials. They concluded that short tufts are not well suited for low-speed applications, due to small deflection angles with large uncertainties relative to the small resultant angles. Cotton tufts were found to have desirable high visibility and response to flow angularity with minimal variance. The visibility of tufts is highly influenced by the ambient lighting of the test area. Some researchers utilized UV lighting setups and fluorescent tufts that glow to increase the contrast between the model and tuft. Chen et al. [16] applied fluorescent mini-tufts to the well-studied transient flow field of a backwards facing step. Quantitative information was extracted from the tufts using instantaneous and averaged images with angles computed over the time series allowing for spectral information to be obtained from each tuft. Ma and Chen [17] identified fluorescent mini-tufts in a 3D flow field based off of brightness level. They identified the root of each tuft then proceeded in a pixel-by-pixel manner, stepping along the tuft by searching for the brightest pixel within a half circle stemming from the previous point with a prescribed radius. Though more computationally expensive than other methods, this technique yielded highly accurate data on the orientation of each tuft.

All of these methods rely on some computational approach to identify tufts within an image based on the contrast between the tuft edge and background such as the edge detection algorithm by Prewitt [18], a frequent citation in the aforementioned papers. Recently, there has been a movement towards the application of machine learning methods to improve tuft post-processing. Amjoud and Amrouch [19] provided a review of recent advancements in deep learning and Convolution Neural Networks (CNN) for the purpose of object detection and recognition. In short, instance segmentation, feature extraction, and classification is something that machine learning algorithms excel at, particularly CNN's, given high-quality training data. Tsalicoglou and Rösigen [20, 21] utilized a mask Region-based Convolutional

Neural Network (R-CNN) to identify, segment, and classify tufts as being attached or separated. The Mask R-CNN was trained on fully synthetic data representing the shape of tufts in various states with noise, intensity variations, random objects, and additional blurriness added to help make the model robust against variations and imperfections. The use of synthetic training data allowed the model to learn from thousands of images without the need to manually label the flow state of experimental images. Lee et al. [22] forwent the use of synthetic training data for tuft recognition in videos obtained for helicopters and unmanned aerial vehicles (UAV) in flight. Given the real world application scenario, the authors train their models with semi manually generated training data, only using the labeling of a few bounding boxes to reduce the computational costs and apply probabilistic approaches to facilitate the learning process without requiring any manual annotations of semantic segmentation masks. Whether the machine learning models are trained on synthetic data or cleverly annotated experimental data, the result is similar in that these approaches are more robust than traditional edge detection algorithms with recognizing the state of a given tuft in non-optimal conditions (i.e. imperfect lighting).

The method presented in the following section attempts to replicate the robustness of the machine learning methods utilizing only simple object recognition algorithms. The object detection is coupled with the use of multiple masks with discrete binarization levels to account for inconsistent lighting conditions. The main goal with the techniques presented in this paper is to develop a methodology that can be applied to a full-scale wind tunnel test environment where optimal lighting is not possible, while maintaining a relatively simple mathematical process that does not require the generation of extensive training data.

III. Methods

A. Tuft Processing

The method of tuft analysis used to understand the complex flow features of the TTBW configuration can be separated into a pre-processing and post-processing element. An overview of the pre-process, deemed Frame-by-Frame Tuft Tracking (FFTT), with the built-in MATLAB [23] functions used at each step, is as follows:

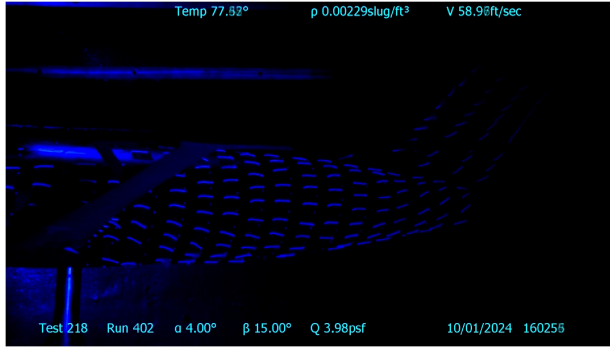
1. Pre-Processing

- 1) Import clipped video of specific flow conditions and display the average frame.
- 2) Convert average frame to grayscale (RGB2gray).
- 3) Convert grayscale image to binary (imbinarize). Adjust binarization threshold to allow for tufts to be visible.
- 4) Apply mask to region of interest (saving the binarization threshold associated with this mask).
- 5) Adjust binarization threshold and applying more masks as needed to observe all tufts on the model.
- 6) Identify objects within the resultant image (bwboundaries).
- 7) Filter objects based on a minimum and maximum number of pixels (this removes adjacent tufts that are stuck together and small objects that are not tufts).
- 8) Identify root of tuft based on the pixel with the minimum x-value within each object (X-values in the frame are defined from left to right, in these experimental images the flow also is directed from left to right).
- 9) Compute the tail (end point) of tuft based on Equation 1. The tail is defined as the pixel who is the maximum Euclidian distance away from the root within the same object.

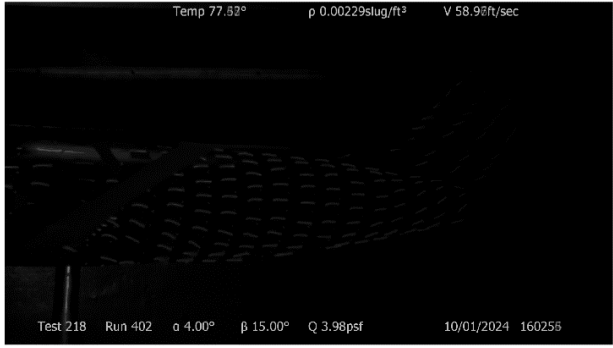
$$xy_{tail} = MAX \left(\sqrt{(x_c - x_1)^2 + (y_c - y_1)^2} \right) \quad (1)$$

Where, xy_{tail} is the index within the object of the coordinates of the tail of the tuft, x_c and y_c are the candidate x and y values of each pixel assessed and x_1 and y_1 are the x and y coordinates of the root of the tuft.

Figure 4 shows the first step in the pre-processing procedure where the video is averaged in time to produce a mean frame (4a) and then converted to grayscale (4b). It is immediately apparent that the lighting is not consistent across the entire model; tufts on the fuselage near the wing-strut root are easier to observe than those on the vertical tail. This lighting inconsistency is what drives the need for multiple masks with varying binarization thresholds. Figure 5 shows four images that each have different binarization thresholds. In this step, all grayscale pixel values in the image are mapped between 0 and 1; all pixel values at or above the threshold become 1.0 (white) and all below become 0.0 (black). Figure 5 illustrates the effect of altering the binarization threshold. The tufts on the fuselage can be properly resolved with the binarization level in Figure 5c so a mask is drawn around these tufts on the fuselage (Mask 1). The tufts on the vertical tail can be better seen with the level of 5d (Mask 2). In practice, even worse lighting conditions often necessitate more than two masks.

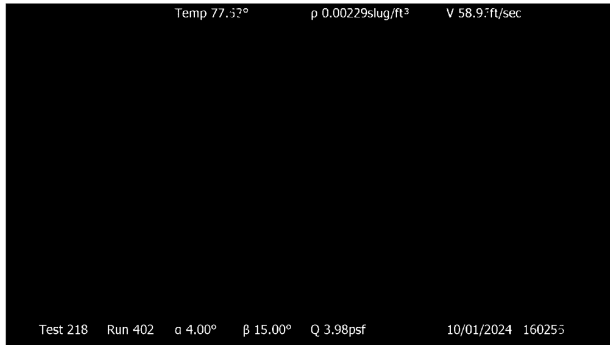


(a) Mean RGB image.

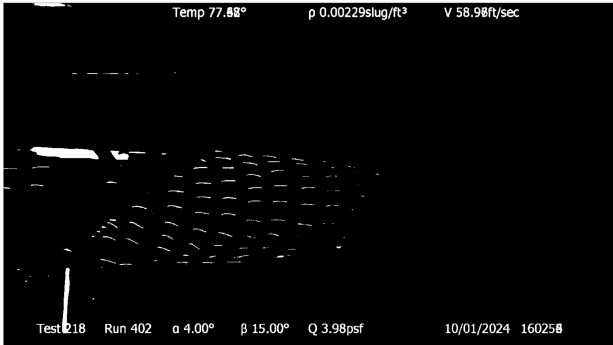


(b) Converted to grayscale.

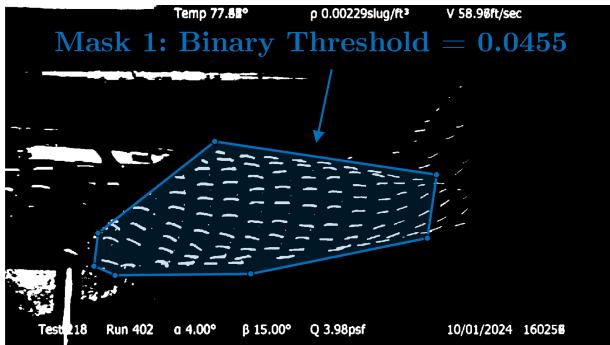
Fig. 4 Pre-processing procedure steps 1+2: Create mean frame and convert to grayscale.



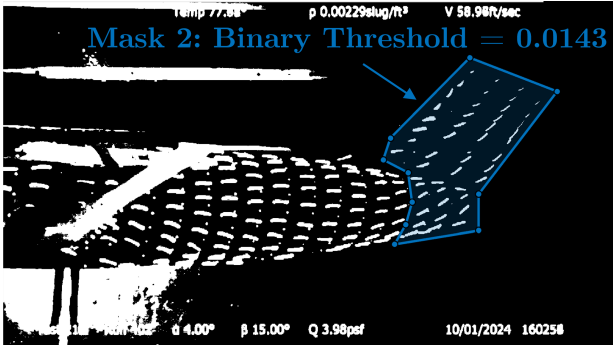
(a) Binary Threshold = 0.5



(b) Binary Threshold = 0.1

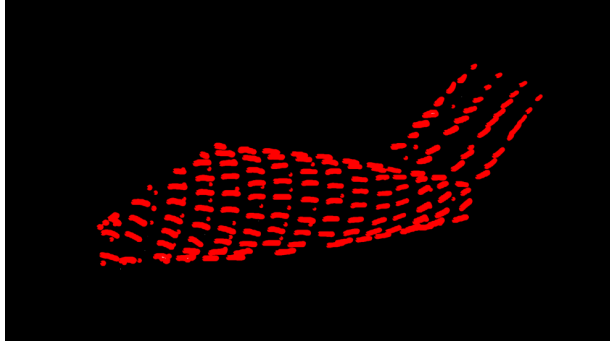


(c) Binary Threshold = 0.0455

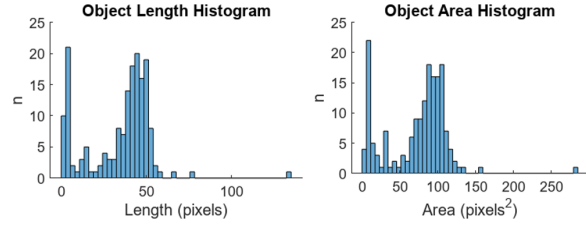


(d) Binary Threshold = 0.0143

Fig. 5 Pre-processing procedure steps 3-5: Example binarization thresholds applied to image: (a) 0.5, (b) 0.1, (c) 0.0455 - with masked region around fuselage, (d) 0.0143 - with masked region around vertical tail



(a) All identified objects.



(b) Histograms of identified objects lengths and areas.

Fig. 6 Pre-processing procedure steps 6+7: Binarization thresholds applied within masked regions.

Following the application of masks with sufficient binarization thresholds to the frame, all objects within the frame can be identified. In this context, objects are any cluster of white pixels. All identified objects can be seen in Figure 6a, Figure 6b shows histogram distributions of the identified objects length and area. It is observed that there is often a bi-modal distribution of object lengths and areas. The first peak is near zero in both metrics where small non-tuft objects are picked up.* The second peak in the distributions is almost always a normal-like distribution of tuft specific lengths and areas. Filters can be applied by prescribing a minimum and maximum length/area to ensure that only the tufts are identified for analysis. For this example, a band-pass filter for length can be applied between 20-60 pixels and for area between 50-120 pixels².

This results in only singular tufts being identified as objects in the frame. Figure 7 shows the identified objects with the filters applied. Notice, sometimes when two tufts overlap or touch they are recognized as a single object. The band-pass filtering removes these instances from the analysis - carefully applying more masks with proper thresholds can ensure that all tufts are recognized.

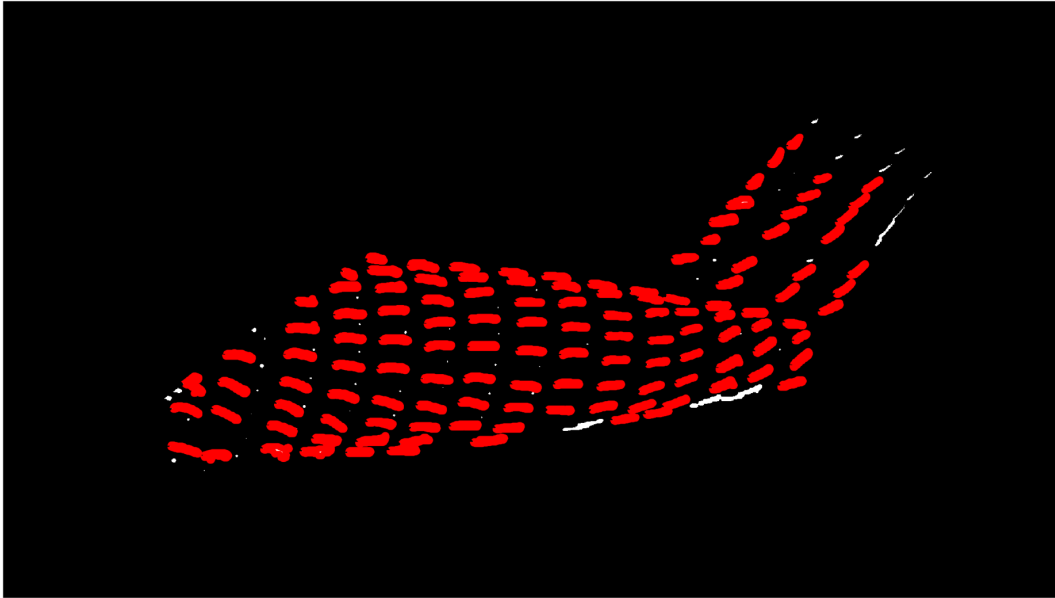


Fig. 7 Objects filtered by length and area leaving only individual tufts.

Now that the masks, binarization thresholds, and correct object filters have been applied to a single frame, the same

*The method of applying the tufts with strips of tape results in a small bit of the tuft material poking out from underneath the tape on the opposite side of the tuft due to the way in which they were cut. These small end pieces account for a majority of the objects in the peaks around 0 length and area.

analysis can now be applied to every frame in the video sequence. This step begins the post-processing phase.

2. Post-Processing

For the results shown in this paper, the pre-processing steps are applied to 300 frames for 10-second video clips at condition (camera recording at 60 fps). Figure 8 shows a zoomed in example of an object identified to be a tuft with the root and tail points marked. A vector is shown corresponding to these points with the instantaneous angle θ defined in Equation 2, where the index 1 denotes the root and the index 2 denotes the tail. For simplicity in analysis the tufts are treated as 2-dimensional in the video frame, and 3-dimensional effects due to curvature of the model are not accounted for. Future improvements to the processing will address this issue.

$$\theta = \tan^{-1} \left(\frac{y_2 - y_1}{x_2 - x_1} \right) \quad (2)$$

Figure 8c shows how the data is organized in the form of an $n \times m \times 5$ matrix with n being the number of tufts and m being the number of frames. For every tuft, in every frame, the coordinates of the root and tail are recorded and stored along with the instantaneous angle. This data matrix results in a time series of the tuft angle permitting the computation of statistical information about the tuft's behavior. The post-processing involves a checking algorithm that compares the root location in every successive frame to the known root locations of previously identified tufts to ensure that the information stored in the different rows of the matrices correspond to individual tufts. This accounts for the common situation where a tuft is not recognized in some frames. For those cases, the cells are occupied by empty values. Once the tufts are properly organized in the matrices, statistical information of each tuft's time series of data can be computed, such as the root-mean-square (*rms*) of the fluctuating tuft angles. This term allows for quick identification of tufts whose motion is more apparent, and a correlation can be drawn from this motion and the separated regions of the flow. Mean tuft locations can be interpolated on a grid drawn on the model to generate streamlines to provide additional information on flow directionality.

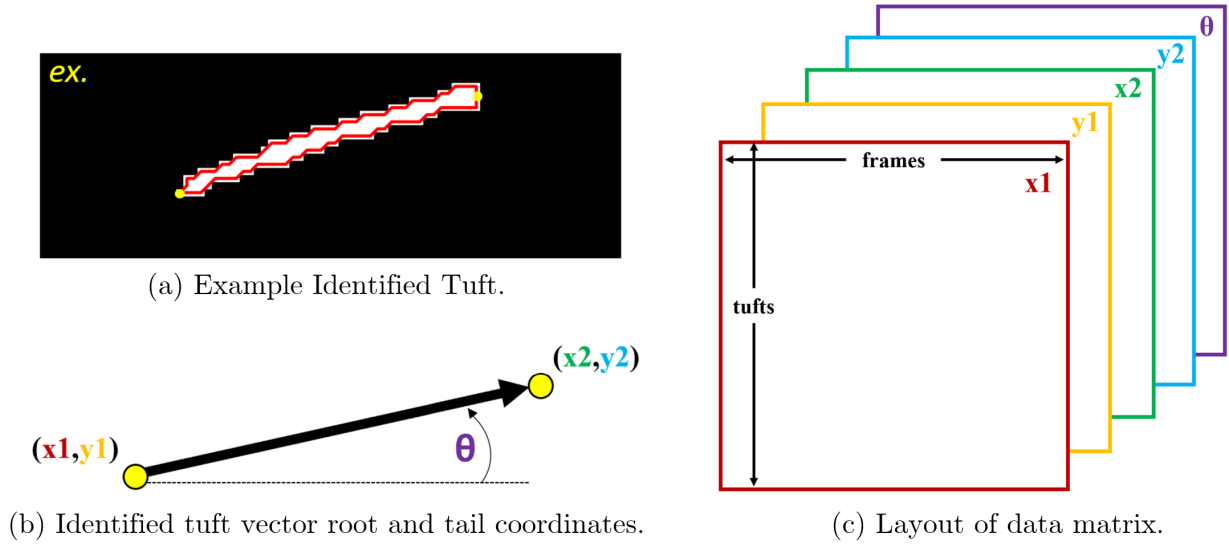


Fig. 8 Pre-processing procedure steps 8+9: Data organization.

B. CFD Setup

Reynolds-averaged Navier Stokes (RANS) simulations for the TTBW were carried out using USM3D-ME [24–26], a cell-centered, finite volume solver (see Jamal et al. [27] for additional info). USM3D-ME utilizes unstructured mixed element grids with triangular prismatic cells inside the boundary layer, tetrahedral cells outside the boundary layer, and pyramid cells to transition between different cell topologies. USM3D-ME uses the Hierarchical Adaptive Non-Linear Iteration Method (HANIM) [28] which is a strong solver that improves computational robustness, efficiency, and automation of the RANS solutions. HANIM uses a matrix-free linear solver for the exact linearization of the RANS equations and a non-linear control method to update the solution. Additional features of the USM3D-ME solver include the utilization of an automated adaptive pseudotime-step, line-implicit preconditioner, and optimized parallelization to maximize solution throughput.

A 50.28 million cell unstructured grid was generated using Heldenmesh [29] with the first cell having a non-dimensional height (y^+) value of 1.0 based on freestream Mach number $M = 0.052$ and for a Reynolds number $Re = 0.136 \times 10^6$ per mean aerodynamic chord (MAC) (matching the experimental runs). Steady-state TTBW configurations were solved using the SA-Neg-QCR-2000 [30] turbulence model with rotation and curvature correction [31] for the conditions shown in Table 1.

Table 1 CFD flow conditions.

Angle of Attack (α)	4°	12°
Sideslip Angle (β)	0°, 15°	0°, 15°

The CFD simulations were performed in a free-air environment absent of any tunnel mounting effects. Convergence was determined based on mean-flow residual and standard deviation of C_L , C_D , and C_m values. Once the convergence criteria were satisfied, solutions were then exported and analyzed using Tecplot360 [32].

IV. Results

A. Force and Moments

Before presenting the results of the tuft processing, it is necessary to show that the tufts have little effect on the aerodynamic characteristics. This paper is not meant to focus on the aerodynamic effects of the TTBW configuration, rather it stands to use the unique flow field that arises around the TTBW as a test bed for flow visualization methods. Still, for the tufting methods to be as useful as possible, they must be non-intrusive to an extent to provide the valid acquisition of force and moment data alongside the flow visualization measurements. To highlight the minimal effects of the presence of tufts on the aerodynamic characteristics of the configuration of interest, Figure 9 shows a comparison between a repeatability run done during the experimental campaign. Both runs involve an α sweep at $\beta = 0^\circ$.

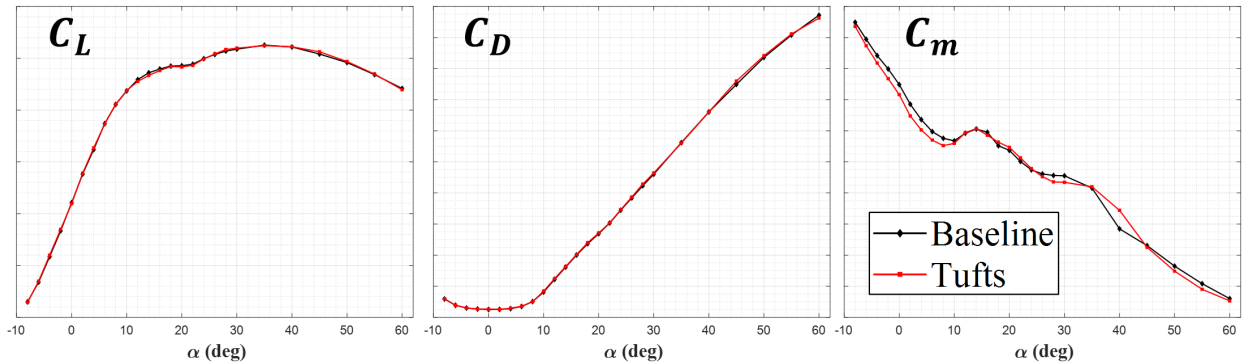


Fig. 9 Comparison between C_L , C_D , and C_m curves with and without tufts on the model (Y-axis values not shown due to data restrictions).

For the all angles of attack, the difference in the force and moment measurements with the tufts on and off is within the run-to-run uncertainty. The largest discrepancy occurs at low α 's where the signal-to-noise ratio is low at the low wind speeds involved in this test, this is most apparent in the C_m curve.

B. FFTT-CFD Comparisons

Qualitative comparisons are made between CFD cases and resultant streamlines from the FFTT methods. A small subset of the experimentally tested conditions are presented to show validity of the FFTT methods. The different flow conditions, shown in Table 1, represent a low and high angle of attack with zero sideslip, and a high sideslip condition. Note that for all the experimental runs, the camera was in a fixed position on the port side of the model. Figure 10 shows a schematic of the model in the test section with the camera position shown, and terminology definition for a positive sideslip case. The high sideslip experimental results are data from different runs. The CFD cases are from a single sideslip condition but showing the windward/leeward side of the model where necessary.

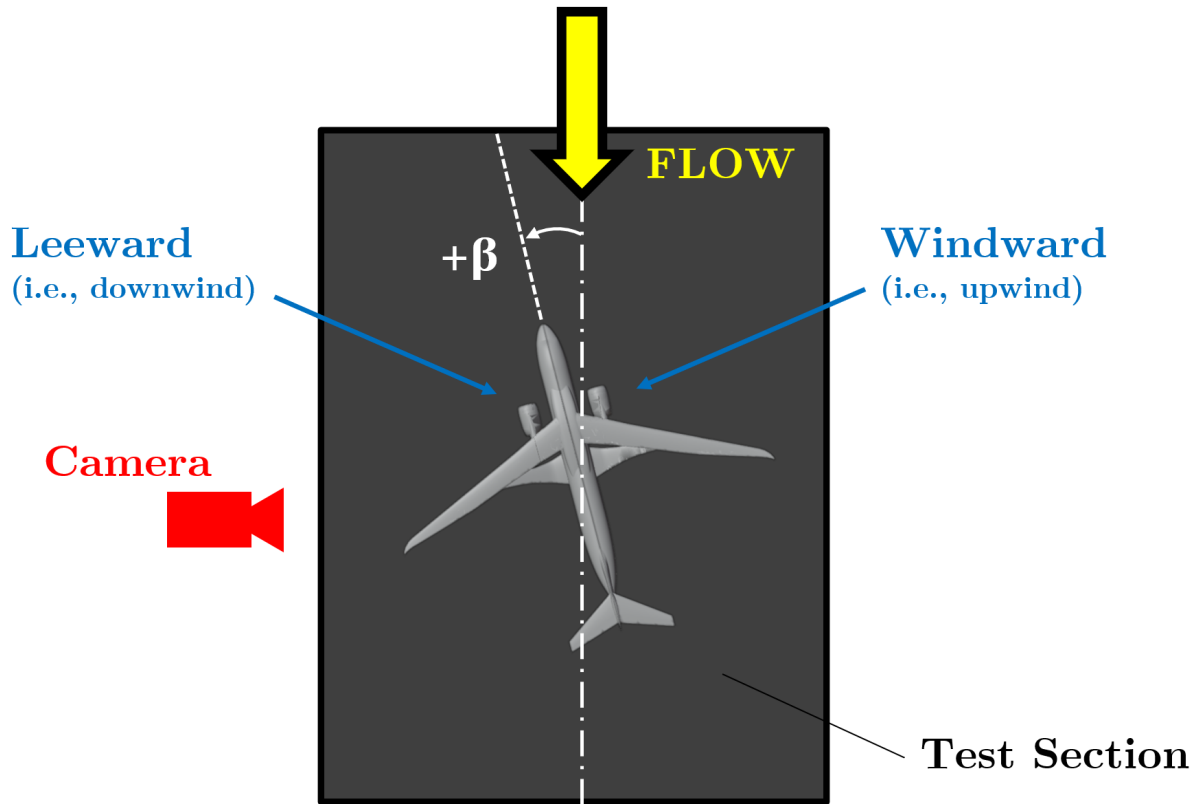
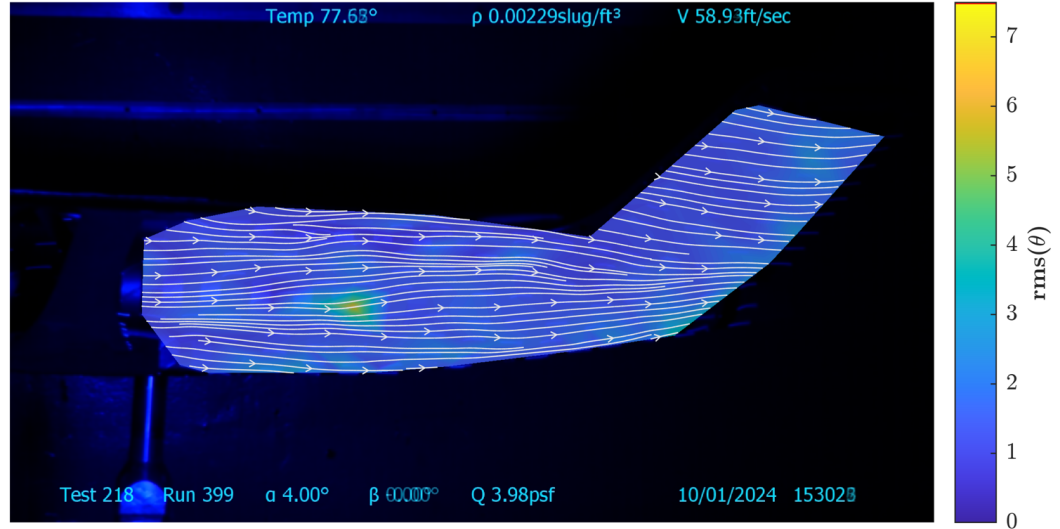
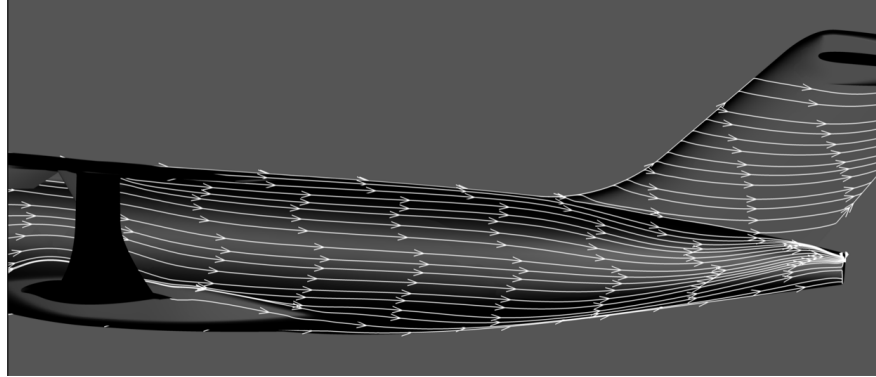


Fig. 10 Test Section schematic with camera location and positive sideslip (β) terminology definition.

Figure 11 shows the results for angle of attack $\alpha = 0^\circ$ and sideslip angle $\beta = 0^\circ$. The top image (11a) shows the experimental output after the FFTT processing, where streamlines are generated based off the mean position of each tuft over the acquisition window. The colored contour represents the root-mean-square (*rms*) of each tuft's angle (θ). For all the *rms* contour plots presented, the same scale is used with an arbitrarily chosen limit of 7.5 (chosen to qualitatively show high *rms* regions across all cases). Any value above 7.5 is shown as red on the contour plots (seen in Figures 12 and 13). Figure 11 does not show much difference nor any clear similarity between the experimental and simulated results. The no-sideslip low α case does not have the most interesting flow pattern. Differences between the two cases can likely be attributed to the lower resolution of the experimental results due to the spacing of the tufts on the model, or the lack of accounting for 3-D effects.



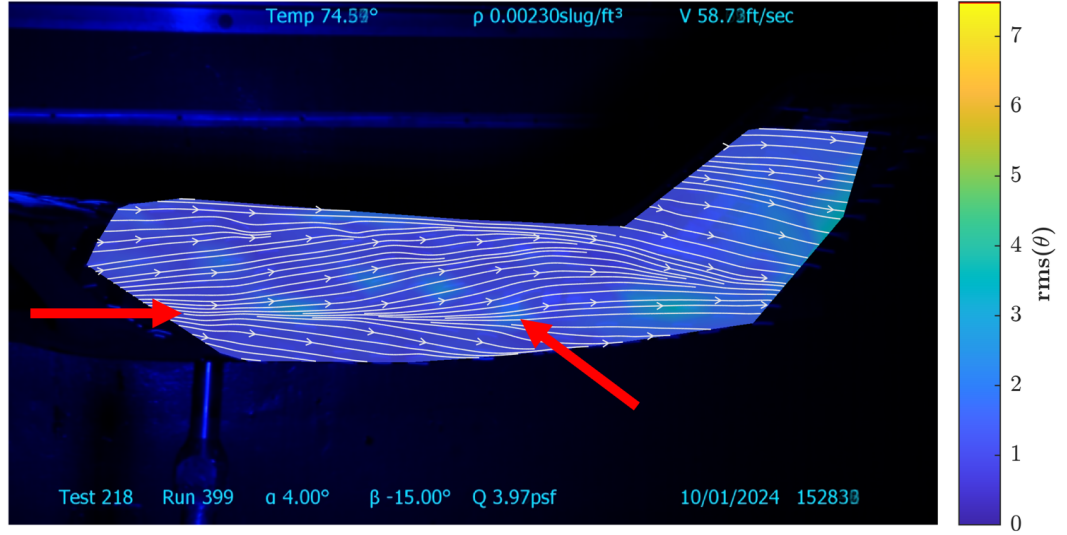
(a) Experimental streamline and *rms* of $\theta(t)$ contour from experimental FFTT methods.



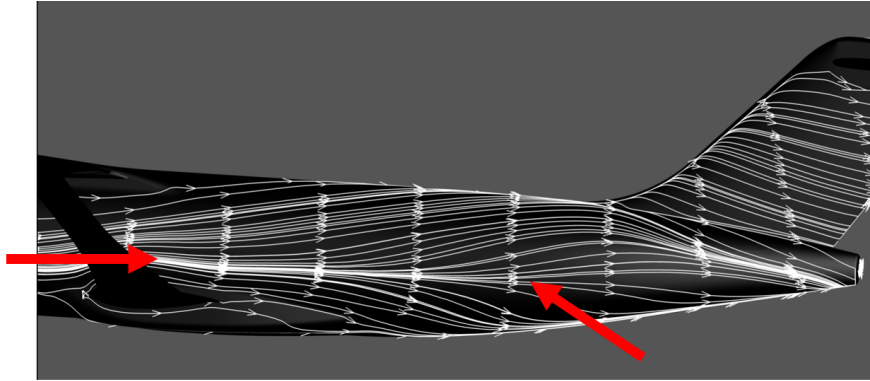
(b) CFD streamlines.

Fig. 11 FFTT and CFD comparisons at $\alpha = 4^\circ$ and $\beta = 0^\circ$.

Figures 12 and 13 show comparisons for the $\alpha = 4^\circ$ cases at the high sideslip ($\beta = \pm 15^\circ$) conditions. Red arrows are drawn on the figure to draw attention to similar features in the flow. Observing the negative sideslip case, where we see the windward side of the fuselage in Figure 12, there is a clear similarity between the experimental and computational flow-fields. The left-most red arrows show a convergence line of the streamlines that exists about 1/3 up the height of the fuselage in both results. The convergence line in both cases begins to spread apart around the same area as the flow moves downstream towards the end of the fuselage.



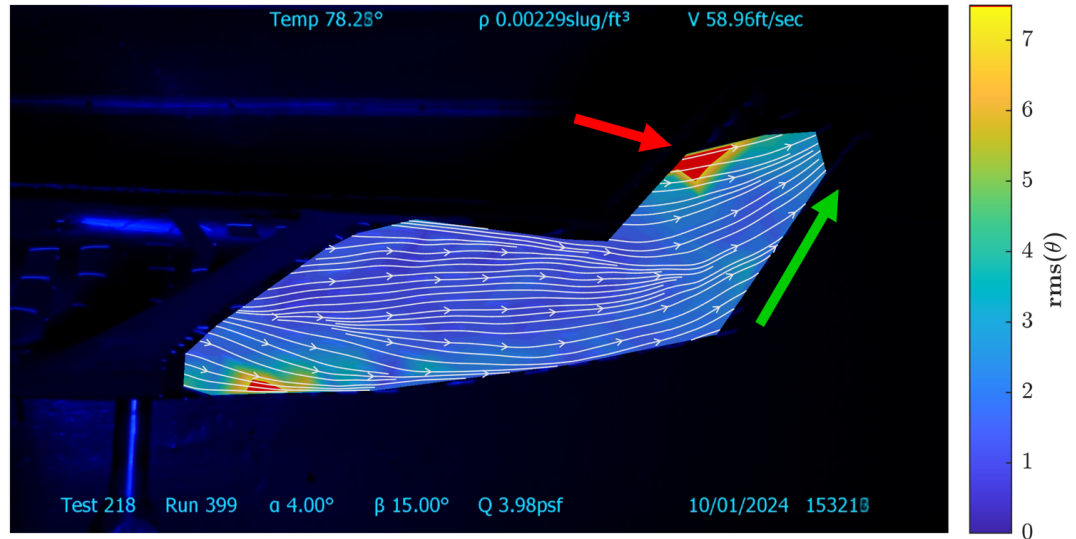
(a) Experimental streamline and rms of $\theta(t)$ contour from experimental FFTT methods.



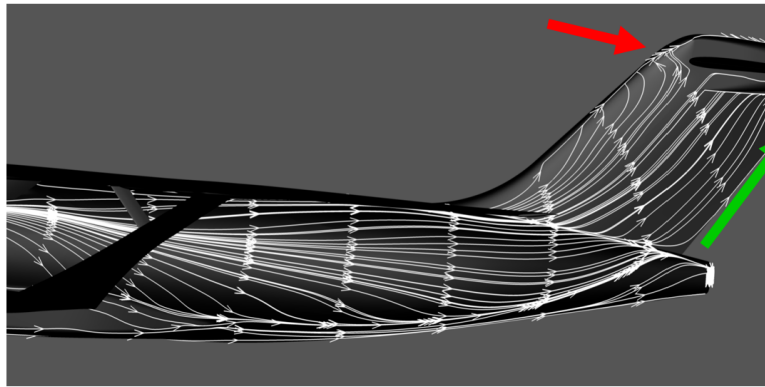
(b) CFD streamlines.

Fig. 12 FFTT and CFD comparisons at $\alpha = 4^\circ$ and $\beta = -15^\circ$ (windward).

Figure 13 shows a similar comparison for the leeward side of the high sideslip case. Once again there is qualitative agreement in the results. The FFTT methods identify two regions of flow separation indicated by high rms values. One aft of the strut-fuselage junction and the other on the leading edge of the vertical tail. In both of the red regions there is a corresponding disturbed streamline pattern in the CFD result, especially in the tail region where the CFD streamlines have their direction reversed. Furthermore, both results capture a change in flow directionality along the vertical tail indicated by the green arrow. The upward trajectory is much more apparent in the CFD case, though still captured by the tuft streamlines.



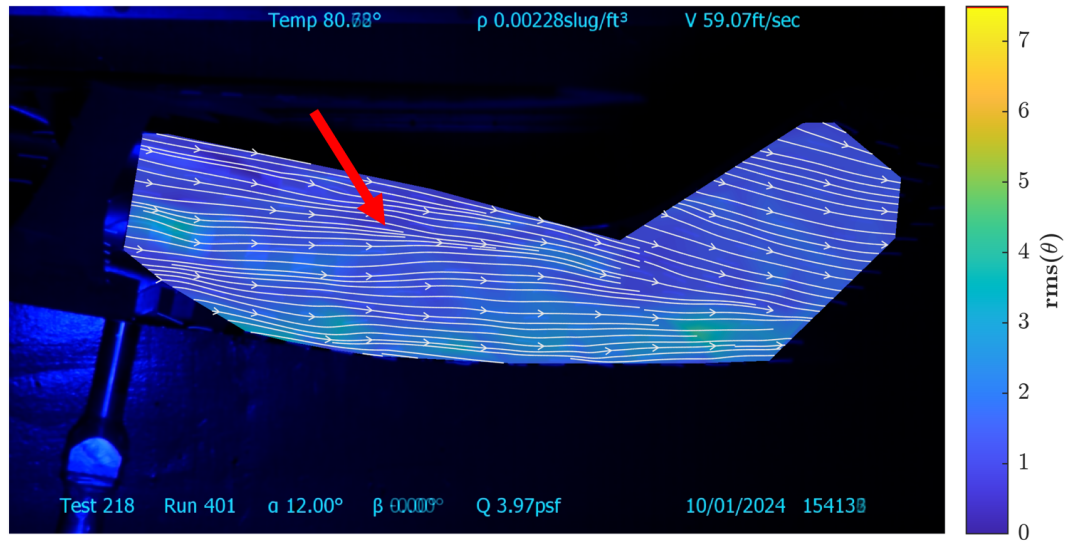
(a) Experimental streamline and rms of $\theta(t)$ contour from experimental FFTT methods.



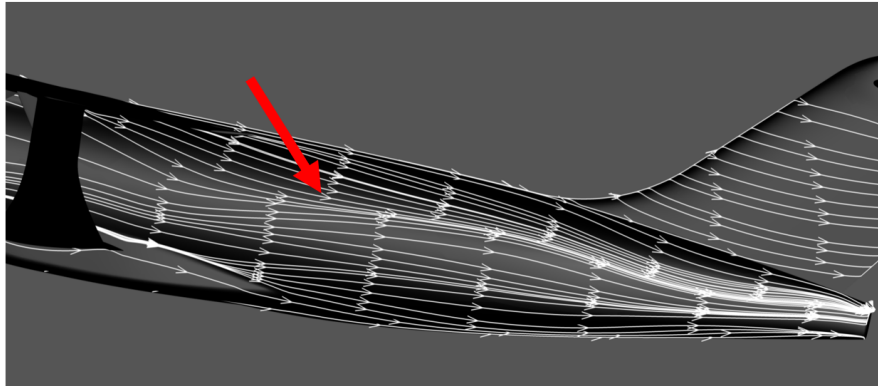
(b) CFD streamlines.

Fig. 13 FFTT and CFD comparisons at $\alpha = 4^\circ$ and $\beta = 15^\circ$ (leeward).

Figure 14 shows the zero sideslip comparison for the high angle-of-attack condition ($\alpha = 12^\circ$). The red arrow on this figure shows an area of common streamline convergence between the cases occurring at similar locations on the fuselage.



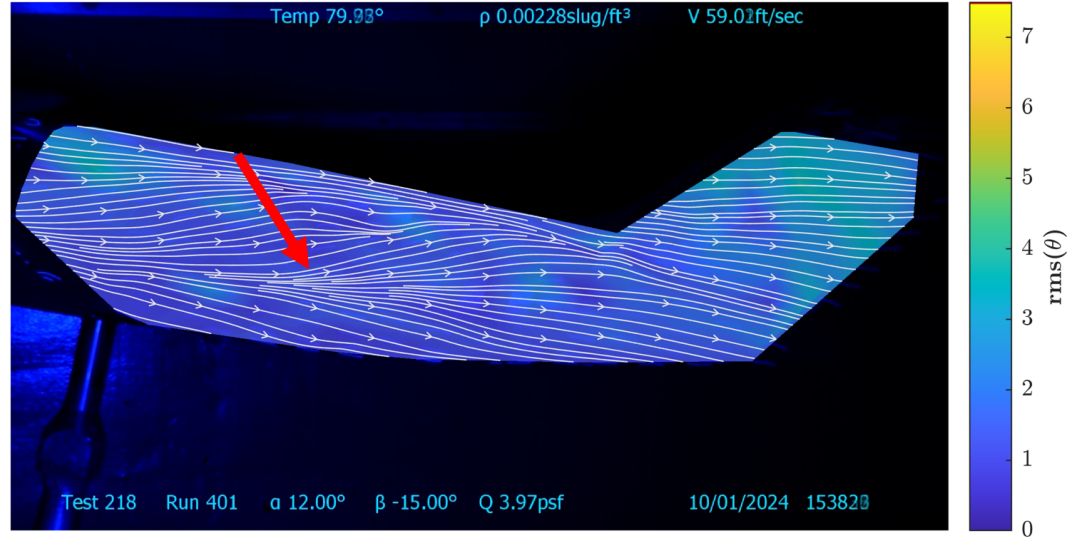
(a) Experimental streamline and rms of $\theta(t)$ contour from experimental FFTT methods.



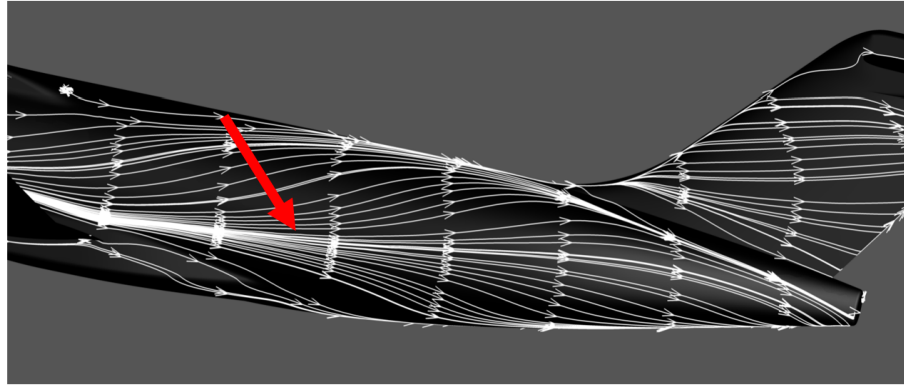
(b) CFD streamlines.

Fig. 14 FFTT and CFD comparisons at $\alpha = 12^\circ$ and $\beta = 0^\circ$.

Figures 15 and 16 show the comparisons for the high α , high β cases looking at the windward and leeward views respectively. In Figure 15, the windward view, there is a similar streamline convergence and divergence region seen in both results. The red arrow points to the region where the streamlines diverge. This is a similar flow pattern to that observed in Figure 12 at the lower angle of attack.



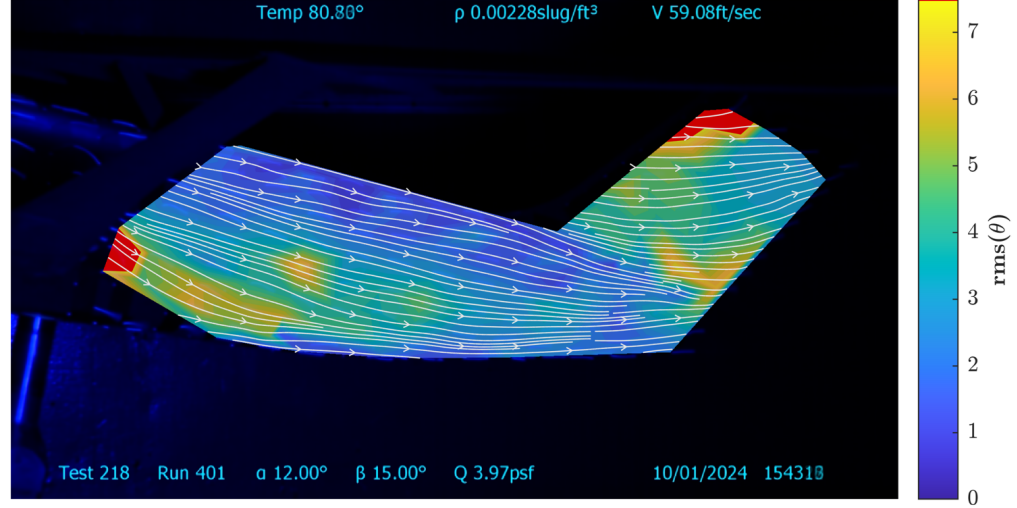
(a) Experimental streamline and rms of $\theta(t)$ contour from experimental FFTT methods.



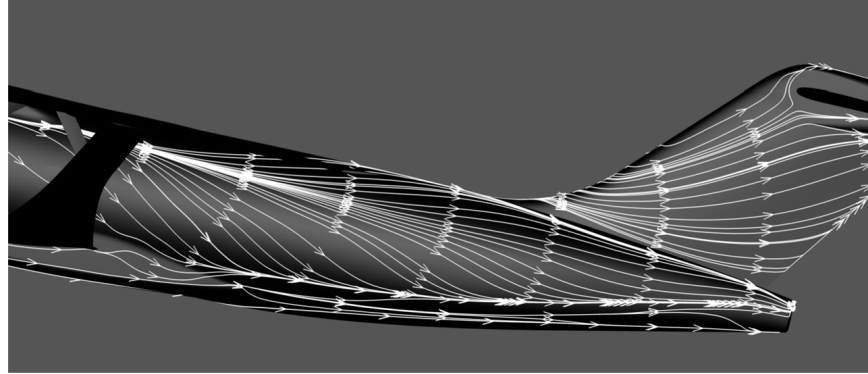
(b) CFD streamlines.

Fig. 15 FFTT and CFD comparisons at $\alpha = 12^\circ$ and $\beta = -15^\circ$ (windward).

The leeward side comparison shows less of a clear similarity (Figure 16). The experimental streamlines do not show much of a clear pattern, especially when compared with the CFD results. There is a slight convergence of the streamlines on the bottom of the fuselage in the experimental case that is much more prominent in the CFD result. There is slight agreement with the upflow on the vertical tail (once again similar to that seen at the lower angle of attack). The experimental result also has two distinct separated regions at the leading edge of the vertical tail and aft of the fuselage-strut junction.



(a) Experimental streamline and rms of $\theta(t)$ contour from experimental FFTT methods.



(b) CFD streamlines.

Fig. 16 FFTT and CFD comparisons at $\alpha = 12^\circ$ and $\beta = 15^\circ$ (leeward).

Unfortunately the CFD results do not provide time accurate information so a direct comparison for $rms(\theta)$ cannot be made (such as using the fluctuating wall normal velocity to compare with tuft data like in Koklu et al.[9]). Instead, vorticity contours can be used to gain insight into flow features and add additional context to the surface streamline patterns. Figure 17 shows the normalized vorticity magnitude at different cross-stream slices for the high angle of attack, high sideslip case. Two distinct vortical structures can be observed in the aft-fuselage region on the leeward side of the aircraft: one emanating from the wing-fuselage junction (I) on the starboard wing, and the other emanating from the strut-fuselage junction (II) on the port side. For discussion these will be referred to as the top and bottom vortex streets respectively. Comparing back to the experimental results in Figure 16a the high rms region on the left of the image is due to the lower vortex street's impingement on the fuselage in the region immediately behind the strut. This same feature is also seen for the lower angle of attack case in Figure 13a.

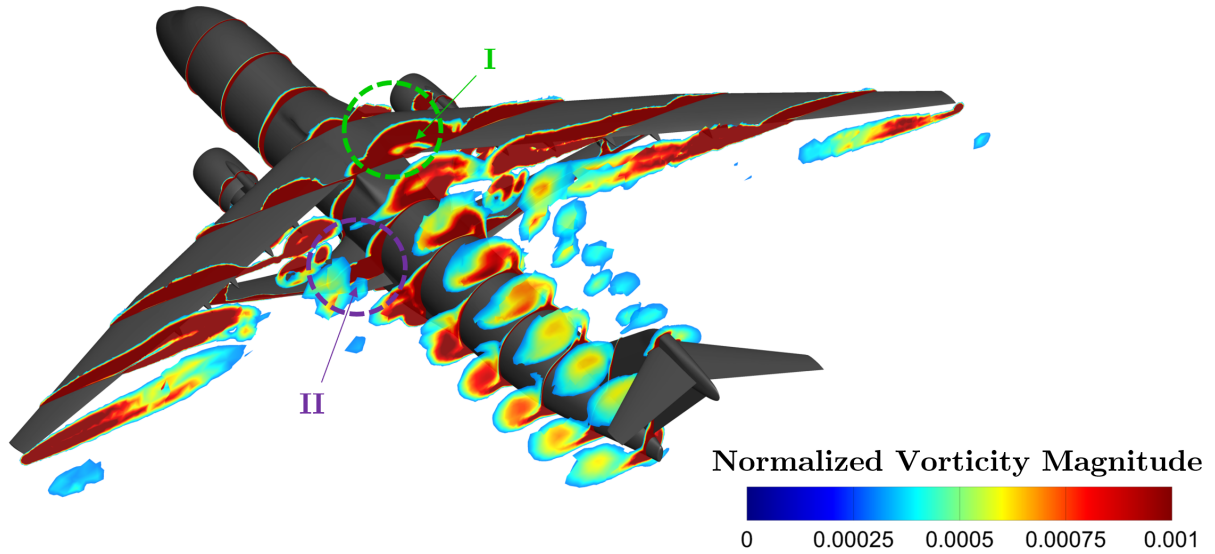


Fig. 17 CFD normalized vorticity magnitude at different cross-stream slices at $\alpha = 12^\circ$ and $\beta = 15^\circ$.

A more distinct flow feature can be observed on the windward side of the fuselage at the high-sideslip condition, the vorticity contours reveal the source of the converging-diverging streamline patterns seen in Figures 12 and 15. Figure 18 shows the windward side of the model (note, looking at Figure 17, this would be the starboard side of the aircraft that cannot be seen. The view has been rotated to be consistent with the experimental view of Figures 12 and 15), the equivalent "lower" vortical structure that emanates from the strut-fuselage junction is observed to be the driver of the diverging streamline pattern. Figure 19 isolates this vortical structure to allow for a clearer view.

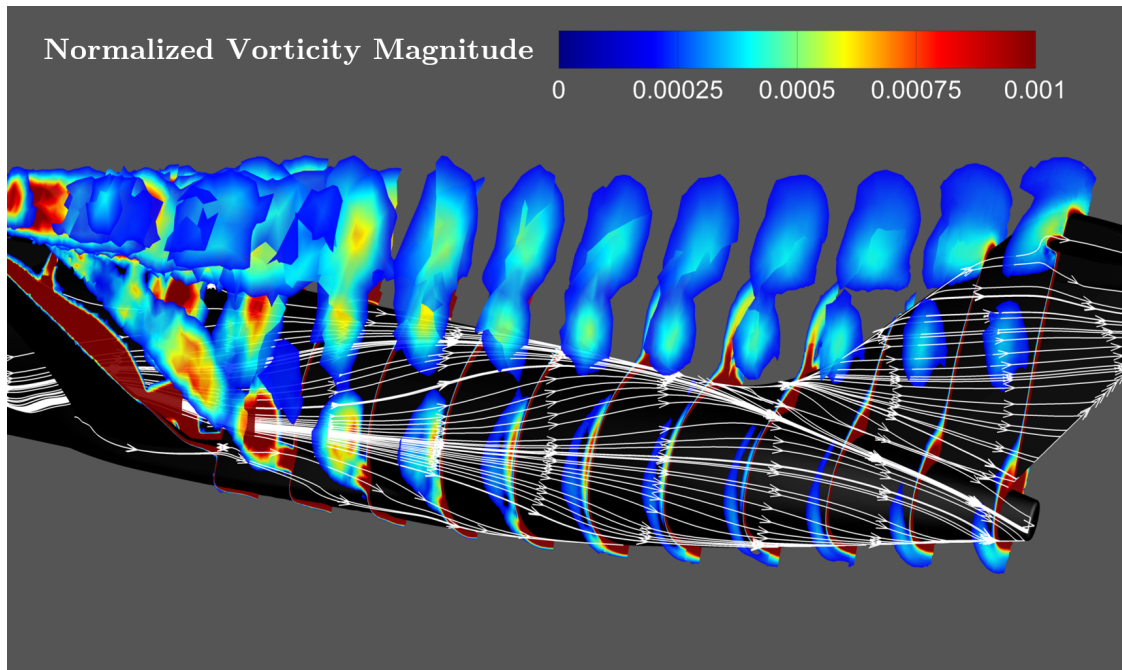


Fig. 18 CFD normalized vorticity magnitude at different cross-stream slices (windward side of aft-fuselage) at $\alpha = 12^\circ$ and $\beta = -15^\circ$.

In addition to the vortices of interest being isolated, Figure 19 also has a label for the struts trailing edge (yellow dashed line) and numerical labels for the first six axial slices (white text below). At station 1 a vortical structure is formed as the flow moves over the strut, it holds its shape through station 2. As it moves downstream it moves closer to the fuselage, and impingement seems to occur somewhere between stations 3 and 4 (indicated by the red arrow). For stations 4-6 the flow pattern flattens out along the fuselage and causes the divergence of streamlines. This phenomena was accurately captured by the tufts for both of the windward high sideslip cases ($\beta = -15^\circ$).

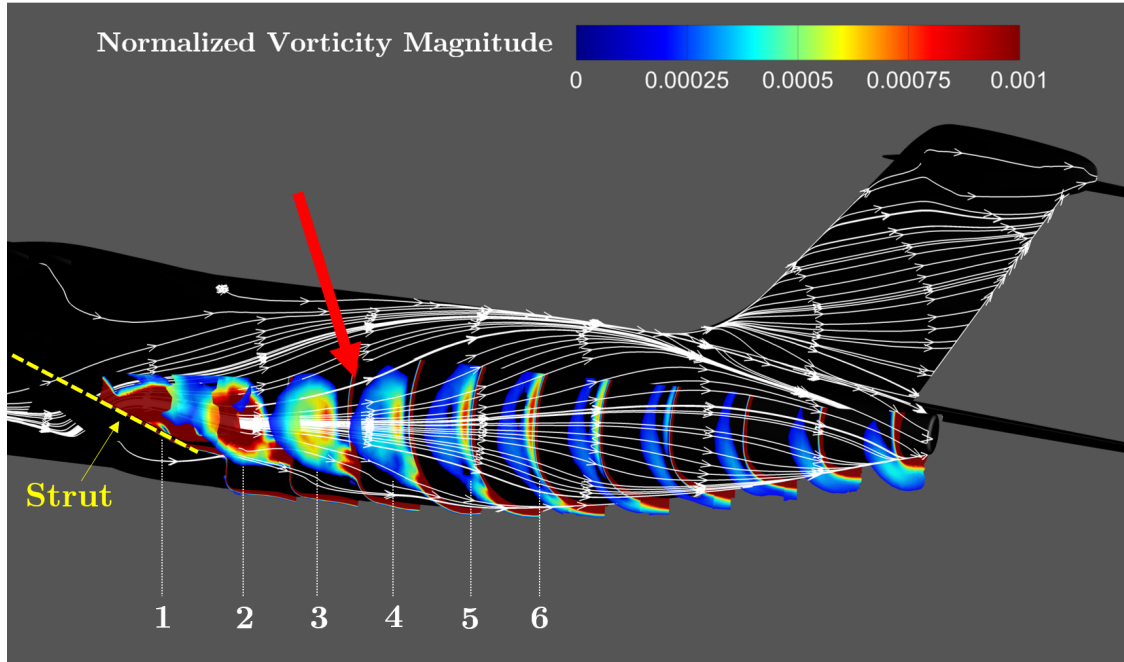


Fig. 19 CFD isolated normalized vorticity magnitude in region of interest at different labeled cross-stream slices (windward side of aft-fuselage) at $\alpha = 12^\circ$ and $\beta = -15^\circ$.

V. Conclusions

This paper presents a means for extracting information from qualitative tuft flow visualization methods given poor lighting conditions. The technique is unique in the application of multiple masked regions with different binarization thresholds in order to overcome varying light conditions along the tufted area of interest. The result is a set of qualitatively enhanced images of the Transonic Truss-Braced Wing aircraft configuration in a low speed wind tunnel test environment. Comparisons are made between the tuft processing results and relevant computational fluid dynamics cases. Flow directionality agreement and identification of separated/unsteady zones have been shown between the experimental and simulated methods.

Six different flow conditions were analyzed involving a low ($\alpha = 4^\circ$) and high ($\alpha = 12^\circ$) angle of attack, with no sideslip ($\beta = 0^\circ$) and high sideslip ($\beta = \pm 15^\circ$) flow conditions. Key aerodynamic features were captured with the tufts as well as the CFD analysis. At the high sideslip conditions for both angles of attack there was a distinct diverging streamline pattern on the windward side of the fuselage captured in the experimental and computational measurements. The CFD provided further context to this feature indicating the vortex emanating from the strut and impinging on the fuselage was the cause. On the leeward side of the model at high sideslip, a similar strut-related vortex caused separated regions on the fuselage in the region just aft of the strut-fuselage junction; this was captured by the tuft time series analysis and visualized with contours of the fluctuating tuft angles. Flow moving upwards along the vertical tail was also qualitatively observed with both methods for the leeward high sideslip case at both angles of attack.

Improvements are still being made to the tuft processing technique with plans to implement the procedure into a MATLAB based graphical user interface (GUI) for release. In its current state, the FFTT algorithm was able to accurately capture flow features unique to the TTBW configuration in a larger-scale wind tunnel environment and utilize CFD cases for additional context in understanding the relevant complex fluid dynamics problem.

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