

Distributed Pressure Sensing for Enabling Self-Aware Autonomous Aerial Vehicles

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Abstract—Autonomous aerial transportation will be a fixture of future robotic societies, simultaneously requiring more stringent safety requirements and fewer resources for characterization than current commercial air transportation. More robust, adaptable, self-state estimation will be necessary to create such autonomous systems. We present a modular, scalable, distributed pressure sensing skin for aerodynamic state estimation of a large, flexible aerostructure. This skin used a network of 22 nodes that performed *in situ* computation and communication of data collected from 74 pressure sensors, which were embedded into the skin panels of an ultralightweight 14-foot wingspan made from commutable, lattice-based subcomponents, and tested at NASA Langley Research Center’s 14X22 wind tunnel. The density of the pressure sensors allowed for the use of a novel distributed algorithm to generate estimates of the wing lift contribution that were more accurate than the direct integration of the pressure distribution over the wing surface.

I. INTRODUCTION

The introduction of robotics into mainstream society has the potential to enhance safety while increasing mobility for under-served people through autonomous transportation [1]. There is significant interest and investment into the development of personal air vehicles (PAVs) and various other forms of vertical take-off and landing (VTOL) aircraft, which will need to leverage the current advances in unmanned aerial vehicles to achieve full autonomy [2], [3]. One of the mechanisms to allow for such fully autonomous vehicles is the creation of a self-aware aerial vehicle [4]. The creation of self-aware vehicles would allow for scenarios described in [5] where the combination of knowledge of the vehicle’s internal state and external environment allow for graceful degradation of performance as the aircraft ages. This mechanism is especially important for PAVs because there will be no single ideal configuration for the wide variety of missions that these vehicles might undertake and the market for them is predicted to be unable to bear the intensive testing regime that commercial aircraft require to safely transport people [6]. The creation of a self-aware vehicle could help to address these constraints while simultaneously helping to reduce the accident rate for current general aviation vehicles.

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The ability of a fully-autonomous aerial vehicle to have a robust estimation of itself and its environment is critical for the vehicle to be able to adapt its behavior, and current research has made progress on this capability with terrestrial robots [7]. This paper introduces a novel distributed sensing system composed of many imprecise pressure sensors that, when their data are fused together, can provide high-level insight into aerodynamic state, providing the first required level for vehicle self-awareness. The modular, robust, mass-producible skin introduced here shares many of the same goals as previous work by Buchan et al. [8], where the authors showed the robustness of a properly-designed distributed architecture for an insect robot. Other work has focused on similar modular sensing modules on humanoid robots in order to provide better environmental interaction through tactile sensing. This work extends these lines of enquiry by focusing on the aerodynamic equivalent in the form of air pressure sensors.

In addition to enabling autonomy, aerodynamic state estimation through distributed sensing in aircraft has been performed for gust load alleviation and drag reduction. NASA’s SensorCraft model utilized accelerometers, strain gauges, and leading-edge stagnation point sensors, which are typically sets of Pitot tubes or pressure sensors that are used to identify the stagnation point, to perform gust load alleviation in a wind tunnel [9]. Bio-inspired hair sensors developed by the Air Force Research Lab (ARFL) have been designed using carbon nanotubes to estimate airflow [10]. Similar artificial hair concepts have been proposed using silicon-based MEMS techniques for lateral line flow sensing in marine robots[11], and the lateral line flow sensing problem space and various solutions bear an intellectual similarity to the proposed method for circulation calculations presented in this paper. The use of potential flow fields and Bayesian filtering has been shown to be an effective means for estimating flow conditions [12]. These solutions require either a relatively simple airfoil geometry for which closed-form solutions exist or extensive testing, which might preclude its use for autonomous aerial transportation systems.

We introduce a modular and distributed pressure sensing skin that is capable of real-time aeroelastic state estimation. The distributed MEMS-based pressure sensors, in conjunction with their localized collection and processing boards, allow for *in situ* information processing and selective loading of the network with useful information instead of unprocessed data. Other work has used similar sensors as a means of aerodynamic state estimation [13], [14] and found them to be satisfactory. This work extends this approach by focusing

on mass-manufacturable hardware, flexible architecture, and algorithmic solutions that allow for the distributed information fusion of networks with much higher sensor density.

The mass producibility and flexibility of the system makes it capable of being applied to any arbitrary aircraft design making it especially well suited to the aforementioned PAVs. This flexibility of the algorithms via the distributed knowledge of the aerodynamic pressure field could enable the much sought after “fly by feel” [15], where the primary feedback mechanism is real-time estimates of aerodynamic states. The best implemented example of this mechanism is in biology, where birds like the steppe eagle are hypothesized to have automatic aeroelastic responses due to pressure changes at high angle of attack without the need for centralized decision making.[16] Such behaviors are thought to be part of what is missing for full-scale robotic autonomy, and are motivation for how our proposed sensor networks are applicable to flexible aeroelastic aircraft.

The unique requirements of such an instrumentation approach push the limits of conventional wireless sensor networks. Such networks (e.g. [17]) typically operate on much larger scales (10^1 - 10^3 m node separation), with a corresponding increase in network latency (~ 1 s) and sampling period (~ 15 min/sample). Recent work, such as TinyNet [18], has focused on networking protocols that use stateless routing to provide connectivity guarantees that align with this work’s focus on scalability and fault-tolerant data transfer.

Further details of the hardware development and estimations techniques will follow. Section 2A describes the hardware and network design decisions that went into the construction of the distributed sensor network. Section 2B describes the operation of the experiments that tested the prototype sensor network, and details the component selection and programming of the sensor nodes for this experiment. Section 3 examines the collected data and assesses whether it was able to satisfy the criteria described in Section 2A. Section 4 describes a few estimation algorithms used on the collected data set, and compares the results of these algorithms to global values measured over the course of the experiment. Finally, Section 5 assesses the success of the system’s high-level goals and suggests next steps for future systems.

II. METHODOLOGY

A. Design

The distributed instrumentation network described here was composed of two parts: 74 pressure sensors embedded in the skin of a shape-morphing wing, and 22 sensor nodes that collected sensor data, packaged these data with timekeeping and ID information, and routed these packets to a central sink. The questions this network sought to answer were as follows:

- 1) What insights into flow behavior could be deduced from imprecise, low-cost pressure sensors?
- 2) Could many such sensors sufficiently match existing methods of aerodynamic state estimation?

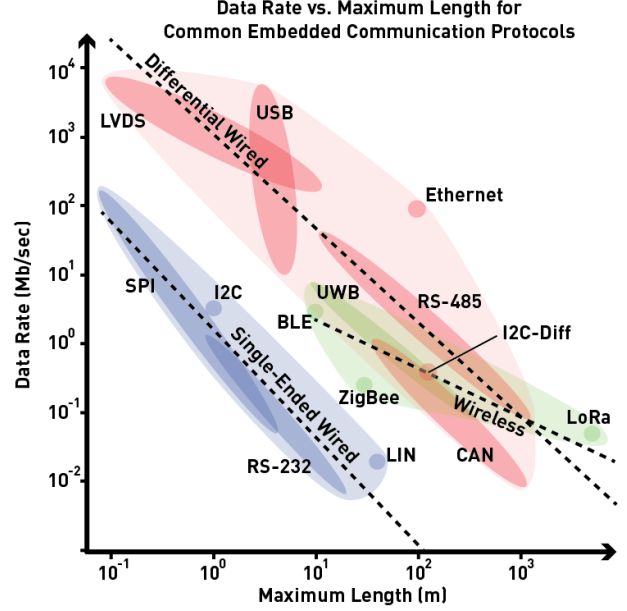


Fig. 1. Plot showing maximum datarate versus maximum length for many common embedded communication standards. Standards vary in power consumption, topology, and complexity. The primary source for estimates is Table 14.3 of [19]. Other sources include: LVDS [20], UWB [21], LoRa [22], and differential I2C [23].

- 3) Could such parameter estimation occur with sufficient speed to be useful in aerodynamic control applications.

We identified the high-level requirements of a system that could answer these questions. These requirements were as follows:

- 1) The system needed to sample the flow at a sufficient rate to capture interesting flow information
- 2) The data logs produced by the network needed to be able to reconstruct collected information
- 3) Hardware designs needed to reasonably scale to many hundreds of nodes and thousands of pressure sensors

Given these requirements, a few major design decisions defined the configuration of the sensor network. The first and most critical was that the network would deliver full sensor data to a central sink rather than attempting *in situ* information fusion. This decision stemmed from the observation that the test of the sensors as an effective state estimator was independent of their ability to perform this fusion. Despite this decision to use a central sink, we still gave special focus to the scalability of the system, preferring to make hardware decisions that could feasibly service many orders of magnitude more elements even if the firmware used for this particular experiment could not.

This scalability requirement became critical in the design of the network architecture. While a conventional system of this size might use a single bus communication standard such as EtherCAT or RS-485 to address each node, such a bus would rapidly become infeasible as the number of nodes becomes very large. Other alternatives exist, including point-to-point serial such as RS-232 or USB, or wireless

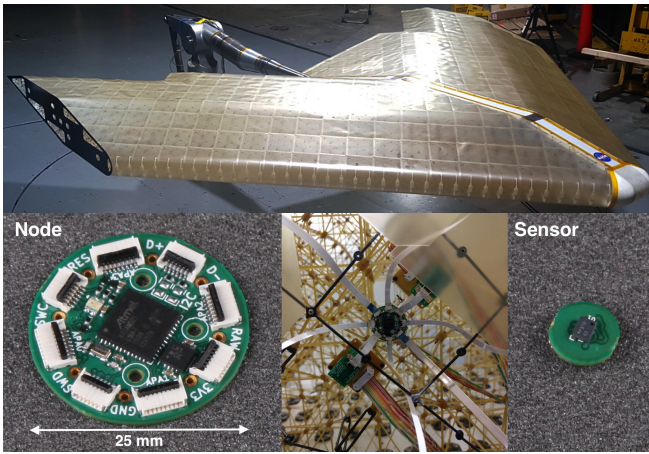


Fig. 2. TOP: The MADCAT wing as assembled in the 14x22 Wind Tunnel at Langley Research Center in Hampton, VA. BOTTOM LEFT: The sensor node, with scale bar for reference. BOTTOM CENTER: A node installed in the substructure of the wing, with FFC connections. BOTTOM RIGHT: The DPS310 sensor and mounting PCB. The FFC connector is located on the opposite side of the board. Size is to scale with the node scale bar.

protocols like Ultrawideband (UWB) and Bluetooth. In order to understand the diversity of choices in selecting a proper communication protocol for embedded applications, Figure 1 shows data rates versus maximum length of various common embedded communication standards. From this chart, we make a few observations:

- 1) Most embedded communication standards follow a distinct negative trend between maximum transmission distance and data rate, due to resonance caused by self-capacitance of the wires
- 2) Adding differential signaling can increase the transmission distance of a protocol by two orders of magnitude. This comes at the cost of additional components and wires
- 3) Higher bandwidth communication is possible, especially in the wireless regime, but not without significant infrastructural/energy requirements

Additionally, the choice between wired vs. wireless communication standards was made to maximize the simplicity of setup, configuration, and debugging. A wired system also consumes less power and needs less code overhead to run. For instance, a typical UART peripheral requires about 1/100th the power of a BLE system [24], and hard-coded connections between nodes were simpler to set up, since most commercial microcontrollers come with configurable serial interfaces and the routing table is effectively the network topology. With all this said, future work will examine the impacts and performance of wireless technology versus wired for such sensor skins, in particular when on-board information fusion is used.

B. Implementation

The sensor network that was produced from these design decisions was integrated into the MADCAT aeroelastic structure experiment. This experiment investigated a novel, building-block based approach to the creation of aeroelastic structures. It consisted of 14-ft span swept wing constructed

from these building-blocks with a segmented Ultem 1000 skin. the experiment was performed at the NASA Langley Research Center 14x22 wind tunnel and was designed to test the feasibility of passive structural deformation under aeroelastic load.

The sensor network was embedded in one half-span of the MADCAT wing and consisted of 22 nodes that collected and routed sensor data and 74 sensors that polled the environment for these data. The primary sensor used was a commercial off-the-shelf capacitive pressure sensor, the DPS310. Typically used in cell-phones as an altimeter, this sensor provided absolute pressure measurements over a range of 300-1200 hPa with a precision of 5 Pa_{RMS} at the maximum datarate of 128 Hz with a current consumption at this rate of 268 μ A [25]. Each node consisted of a SAMD21G18A Cortex M0+ microcontroller, a step-down voltage regulator, a status indication LED, a 32.768 kHz oscillator, and 8 flat flexible cable (FFC) ports that connected nodes with their neighbors or nodes with nearby sensors. Four of the FFC ports connected to separate dedicated UART peripherals on the microcontroller. Both node and sensor are shown in Figure 3.

The four UART ports on the node were configured to run at a 1 Mbit data rate with a frame size of 8 bits, no parity, and 1 stop bit with hardware flow control. The other four FFC ports were all connected to a single configurable peripheral that could use either the I2C or SPI protocol. Each of these FFC ports was routed to a dedicated GPIO pin that acted as chip select for the sensors connected over the SPI bus. Using this configuration, it was possible to use the same node to connect to four pressure sensors, reducing the number of nodes on the network. Finally, the 32 kHz watch oscillator was connected to an on-board 32-bit real time counter, configured to increment at a rate of 1024 Hz. This counter provided node-level timestamping for collected data.

The MADCAT experimental article was mounted to a central sting that allowed the automated testing of different angles of attack for the structure. This sting also supplied standard power and ethernet data connections. As a result, all data were transmitted to two dedicated central nodes that were identical to the sensor nodes except they were connected to no sensors. These nodes then connected over USB to a Startech USB 2.0 over Ethernet extender and transmitted the data at a maximum bandwidth of 480 Mbps to a laptop in the control room. Power for the entire sensor network came from one of these USB ports (max. 2.5 W).

Each sensor was attached to a skin panel on the wing using a piece of double-sided tape, and the panel had a small window cut to accommodate the pressure port. FFC cables then connected the sensor to the nearest node, which mounted directly onto the substructure, as shown in Figure 3

The sensors were configured into eight chord-wise sections located at important transition sites in the wing profile, as identified in an XFOIL simulation of the airfoil [26]. These sites were the leading edge (nodes 5 and 6 in Figure 4), the transition between the front facets on the top and bottom

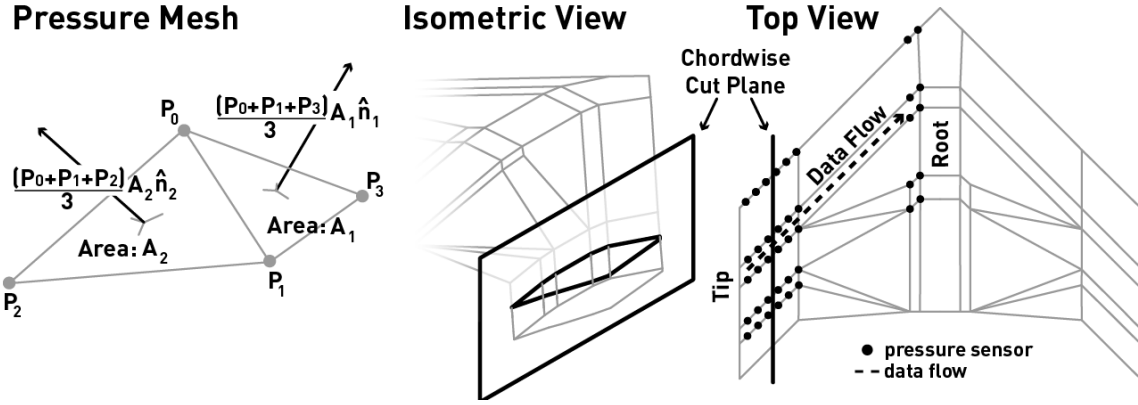


Fig. 3. LEFT: Illustration of the pressure mesh calculation, for two facets of the mesh formed by the graph of the pressure sensors' locations. The force over the n -th triangular facet is the average pressure of the three sensors at each of the three vertices, multiplied by the area A_n and the unit normal $\hat{n}$ vector. The sum of the vectors from all of the facets, projected along the perpendicular to the free stream flow, produces the total lift. RIGHT: Two schematic views of the MADCAT wing, with the sensor locations on the top surface shown. The nodes that route the collected sensor data are not shown, but the general direction of the spanwise data flow from the wing tip to the centerbody is illustrated with the dashed line. The chordwise cut plane is to illustrate the airfoil section used in the Bernoulli Circulation Calculation.

faces the wing (Nodes 3,4,7, and 8), and the transition between the rear facets on the top and bottom faces of the wing (nodes 1,2,9 and 10). Sensors were placed before and after these transitions to help mitigate the effect of their sharpness on the measured pressure distribution.

Along the span, most sensors were concentrated at the tip of the wing, since it was determined through simulation that the most interesting aeroelastic behavior would be present there. 20 of the sensors were placed at the root of the wing, to provide a baseline comparison to the tipward sensors.

In order to transmit information to the sink, the nodes in the network were configured into five spanwise strings of five sensors apiece. Three of these strings connected one of the routing nodes and two connected to the other to reduce the load on any one router. Nodes collected 24-bit pressure data from the sensors connected to it, packaged the data with a timestamp and a node ID, and transmitted the packet to a rootward node so it could be transmitted to the sink. At the sink, a script running on the computer transferred the incoming data to a text file and added a UTC timestamp every second of operation. This stamp allowed drift in the node RTCs to be corrected.

Each node was connected to its nearest neighbors along the string using a point-to-point serial connection. For connections that were longer than the maximum length of the FFC cables (approximately 25 cm), a twisted-wire ribbon cable was used to extend the cable, as seen in Figure 3. An equivalent bus over the space of the entire wing would have required a minimum datarate of 240 kHz and an overall length of 14 m. Using point-to-point serial connections with the network topology chosen reduced the datarate to 48 kHz and the maximum cable length to 1.5 m. From Figure 1, it is apparent that the total length and speed requirements of the bus topology put it outside what a single-ended bus could feasibly accomplish without investing in additional hardware to upgrade to a differential bus. Using point-to-point connections therefore reduced hardware requirements by reducing both the required communication distance and datarate.

The sensor nodes used a simple state machine and a semaphore on the transmitter resource to route data packets from the tipward nodes to the rootward nodes. Use of interrupts to handle receiving packets and the Direct Memory Access (DMA) Controller for transmitting packets ensured that no polling occurred at the byte level for transmitting data, freeing up CPU time for data collection tasks and maximizing bandwidth.

C. Experiments

The wind tunnel tests of the MADCAT test article consisted of varying the angle of attack of the wing relative to the flow, while the dynamic pressure of the flow Q was held constant at 2 pounds per square foot (psf), or approximately 100 Pa. The range of the angle of attack sweep was -4 degrees to 18 degrees in increments of 1 degree. This sweep began and ended with a tare run, where the article proceeded through the same set of angles with the wind off in order to establish a baseline. At each angle of attack, the article was held steady until the measured force at the wind-tunnel balance converged, a process that took between 30 and 60 seconds. We removed these transition periods and took an average of the values in the converged region, in order to find a single pressure value for each angle of attack.

III. RESULTS

In total, approximately two gigabytes of data were collected during the testing. The network successfully transmitted 96% of the data, with three of the sensors on the underside of the wing not being polled due to an address collision on the I2C bus that connected them.

The raw data files produced during the experiment consisted of unordered lists of data packets containing a node ID, node-time of the collection, and the 24-bit pressure values collected by that node.

Each sensor had a slightly different baseline owing to defects in the manufacturing and calibration process. We removed this baseline variation by zeroing the value of the measured pressure to the pressure measured during the tare

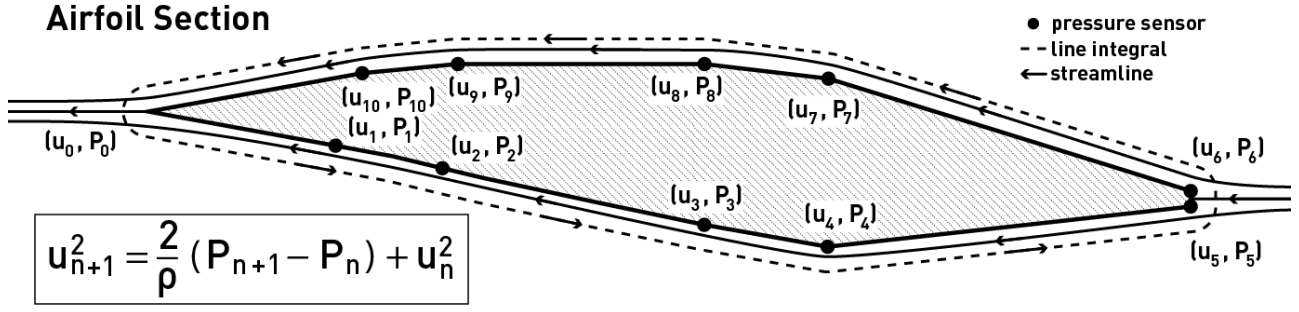


Fig. 4. A sample airfoil section of the MADCAT wing, with the locations of the pressure sensors and the three closest streamlines. The Incremental Bernoulli Algorithm calculates the lift using a line integral along the dashed contour. The direction of integration is indicated on the contour.

run (when the air in the wind tunnel was off). In addition, all of the sensors exhibited a drift in the measured pressure. This was evident when the experiment ended and the final tare run values were approximately 100 Pa higher than the initial tare values. The change in barometric pressure over the course of the morning of the tests accounted for the variation, and inserting the correction from historical data taken at Langley Air Force Base removed this drift [27].

A critical state parameter that can be derived from pressure data is the net lift imparted to the wing by the flow. We calculated this value in two ways: first, by integrating the pressure over the entire surface of the wing, and second, by calculating the circulation around each wing section and integrating those values along the entire span of the wing.

For both methods, knowledge of the location each sensor's physical location was required. The CAD model of the entire wing provided the rough location of each skin panel that hosted a sensor, and the CAD model of the panel itself provided the precise location of the sensor. Combining these two values together produced a three-dimensional point cloud of values.

A. Pressure Mesh Calculation

The direct pressure calculation used the sensor point cloud to generate a mesh with Delaunay Triangulation [28]. With this mesh, each vertex corresponded to a sensor location with a pressure value, and each facet provided an area and a normal over which the average pressure could be integrated to produce a net force vector. This pressure was found by taking the mean of the three pressure sensors which formed the vertices of the facet. Figure 3 shows an example mesh formed from four pressure sensors, and shows how the area of the facet, the surface normal, and the average pressure are combined to find a facet force vector. Summing these force vectors produced the total force vector, and the component of this vector normal to the free stream flow was the net lift.

B. Bernoulli Circulation Calculation

The second method involved partitioning the network into sections with near-equal span, producing chord-wise airfoil slices. The sensors in each section sampled the pressure at several points on this airfoil slice with sufficient density that they could approximate the pressure distribution over the entire airfoil. By assuming that the airflow was smooth over this foil, Bernoulli's method could be used to calculate the total

local stream velocity at each sensor location [12]. Integrating these velocities around the foil produced an estimate for the total circulation, which was then used to calculate the total lift. Each of these lift values were integrated over the length of the span to produce the total lift for the wing.

Figure 4 shows a sample airfoil with these sensor locations, as well as three of the streamlines for the flow and the direction of the line integral used for calculating the circulation. Given an initial value for u_0 and P_0 (the free stream flow and ambient pressure, respectively), the velocity at an adjacent sensor can be calculated using the pressure measured at that point:

$$u_n^2 = \frac{2}{\rho} (P_n - P_0) + u_0^2 \quad (1)$$

Where n can be either 1 or 10, since those sensors are the closest to the trailing point where value 0 is located. Integration of these velocities then involved performing a line integral of the velocity on the dashed line contour C in Figure 4:

$$\oint_C v(s) \cdot \hat{s} ds = \sum_{n=0}^m \frac{1}{2} (u_{n+1} + u_n) [(\vec{x}_{n+1} - \vec{x}_n) \cdot \hat{s}] \quad (2)$$

The continuous version of the integral is the left and side of the equation, and the linear approximation provided by the sensors is shown on the right. The vector $\vec{x}$ is the physical position of the sensor. Since the flow is assumed to be smooth, the velocity at each point is parallel to the surface of the foil, so that the dot product $(\vec{x}_{n+1} - \vec{x}_n) \cdot \hat{s}$ is positive on the top of the foil, and negative on the bottom. The location of the stagnation point decided the transition between "top" and "bottom", and was assumed to be located between nodes 5 and 6 regardless of the angle of attack of the section.

C. Centerbody Correction

The measurements from the wind tunnel balance represent the total lift and be viewed as the sum of the left and right wings as well as the centerbody section. The spanwise lift was simulated using Dynamic Tornado [29], a MATLAB implementation of the vortex-lattice method that has been validated for flexible aircraft [30]. The full span lift of the simulation matched the balance data from the wind tunnel allowing for the contributions of the left wing and center

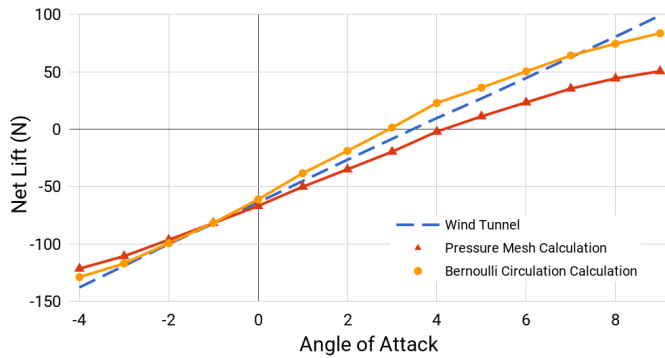


Fig. 5. Comparison of the lift force measured by the wind tunnel balance and the two different methods for calculating lift from the collected data.

body to be estimated and removed from the load balance data as a correction.

IV. DISCUSSION

Figure 5 shows the two methods described above alongside the wind tunnel measurements for lift, over an angle of attack range from -4 to 9 degrees. As the figure shows, the pressure mesh calculation consistently underestimates the lift force, for angles of attack greater than 2, while the expected force from the Bernoulli circulation remains close to the measured wind tunnel response. This is likely due to the pressure mesh being sensitive to the undersampled midspan of the wing. While the Bernoulli calculation only interpolates the lift distribution in this midspan, the pressure mesh calculation interpolates the raw pressure values, decreasing the accuracy of the estimation.

A. Scalability

While the modest number of sensors in this experiment allowed the use of a central sink with *post facto* reconstruction, future applications that require real-time analysis or use many times the number of sensors will need to have a strategy for locally collecting and processing data. For the pressure mesh calculation, existing research into power-efficient transmitting in wireless sensor networks has found near-optimal solutions for information fusion over arbitrary networks [31], [32].

For the Bernoulli Circulation calculation, the physics of the algorithm can provide insight into the data flow. Namely, optimal solutions for information fusion will naturally fall along trajectories that are parallel to the free stream flow, since the direction of the line integral and the streamline will be near-parallel. In addition, the Bernoulli Circulation calculation requires external information, in the form of u_0 , the free stream flow velocity and P_0 , the ambient pressure. These values are usually consistent across the wing, and can therefore be measured using a single sensor at the body of the vehicle [33]. These values can then be transmitted along the trailing edge of the wing to each airfoil section, where the top and bottom nodes of the airfoil can simultaneously calculate their circulation contributions, and the nodes at the leading edge then fuse the result to get a complete estimate of the circulation.

V. CONCLUSIONS

We have shown that a distributed network consisting of low-cost sensors can accurately extract high-level information about aerodynamic state. We have introduced two algorithms for calculating this information, and have shown that the version that uses information about the physics of the flow produces more accurate results than the naive approach for small angles of attack. We have also shown that the spatial distribution of the sensors provides insight into the lift distribution that would otherwise not be possible to extract from the wind tunnel balance, and have used this information to identify areas to sense in order to improve the accuracy of the system at high angles of attack. Finally, we detailed how such approaches could be extended to large and/or real-time control networks by intelligently fusing the data at the site of collection.

A. Future Work

Future work will involve extending this approach in two ways: first, by analyzing the captured data to find algorithms for other flow feature identification tasks, and second, by implementing the algorithms introduced here and found later *in situ*, and possibly combine them with actuation for distributed feedback-control of the wing.

The first task involves examining the existing data to find other useful flow features that the network can identify. Some assumptions regarding the flow- for instance, that it was laminar, entirely attached to the foil, and the stagnation point did not move- simplified calculations but could be explicitly identified with the pressure sensors.

The second task involves changing the software present on the network so that nodes can perform more complex operations on collected data than routing it to the sink. Examples include the lift calculation discussed before, where the addition of distributed actuation can optimize wing shape to maximize lift or reduce drag. Accurately finding the chord-wise lift would be a critical parameter in such a feedback control calculation, and, because of the design decisions made in the architecture of the network, adding such capability is a matter of replacing the firmware running on the nodes, and not completely redesigning the system.

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