A MULTI-PARAMETER MEASUREMENT SYSTEM FOR MEMS ANEMOMETERS FOR DATA COLLECTION WITH MACHINE LEARNING OUTCOMES

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ABSTRACT - In order to generate consistent and comprehensive datasets for the application of machine learning algorithms to MEMS thermal flow sensors, a measurement set up was created. This system allows automatic data collection of large datasets involving parameters such as the angle of attack, humidity, temperature and flow speed. The electrical output signals in both the time and frequency domain can be measured for both AC and DC actuation. The setup has been able to fully characterize an anemometer by exposing it to flows of 0 to 5 m/s in steps of 0.02 m/s under angles from -45 to 45° in steps of 5° at a constant temperature of 25 °C and humidity of 30 %RH and complete the measurement in 8 hours.

Key Words – MEMS, Machine Learning, thermal, anemometer, microfluidics, flow sensor.

INTRODUCTION

The measurement of flow through the use of MEMS thermal anemometers is a well-established field [1]. Thermal anemometers measure the heat transfer rate from a heat source to a fluid as a measure of the flow rate. Provided the fluid is cooler than the heat source, heat flux increases with higher flows. A hot-wire anemometer is perhaps the simplest example of this type of device. Another family of thermal sensors uses at least one sensing element placed downstream from the heat source to measure the heat transfer from the heater, through the fluid, and back to the sensing element. These types of sensors are known as calorimetric anemometers [1].

Superficially both types of sensors are simple, however there are many physical principles that make determining the flow velocity from sensor data more complicated. Some of these complicating factors include thermal inefficiencies such as heat flux into the mechanical scaffolding of the heater, temperature variations of the fluid, or changes in gas composition which leads to different thermal diffusivities and heat capacities [2]. There might also be heat leaking into the sensing elements through other means or condensation on the sensing element surface if there is a condensable gas present.

It is often the case that these practical complications are circumvented by measuring the device response to changing flow experimentally and calculating a calibration curve in very specific conditions such as at room temperature, low humidity and perpendicular flow conditions [3]. Though this is not necessarily a bad practice it does limit the scope of the device. On the other hand it is also nigh impossible to make a fully comprehensive theoretical model from which to develop a set of equations which perfectly model the device.

To relate sensor signals to specific flow speeds in varied conditions one could train a machine learning (ML) model. This has indeed been done before, and has shown to be better at characterizing measurements than traditional calibration curves [4].

To be able to train a ML model well, a common approach is to provide a complete and comprehensive learning and test set for all the conditions in which the device should be able to measure accurately. The larger and more complete the learning set, the more accurate the models tend to be. In order for it to be a comprehensive dataset many combinations of different physical conditions should be applied to the sensor.

This work aims to make the collection of such a large dataset in the context of applying ML to thermal MEMS anemometers more achievable for research labs. Testing time in commercial wind tunnels can be expensive and limited, meaning that a smaller lab-based system should be produced. A small wind tunnel has the added benefit of being highly customizable and able to apply more physical conditions than a commercial one.

This system has several important requirements. It should be highly automated in order to prevent excessive time use for the researchers and eliminate user error. It should also be able to provide consistent conditions including ambient temperature and humidity as well as constant heater temperatures or powers.

Additionally the system should also be able to apply different independent variables, which for these types of sensors would be the magnitude (0-2.3 ms^{-1}) [5] and angle of attack (AoA) (±45°) of the flow velocity. Some of the control variables could also become independent variables for multi-parameter devices including the ambient temperature and humidity as well as the gas composition.

The system should be able to simultaneously measure as many dependent and independent variables as possible for each datapoint. It should also be able to resolve different sensor signals in the time and frequency domains as additional information could be stored in either domain.

MACHINE LEARNING BENEFITS

There are several types of devices that can have ML applied to them in order to provide more accurate measurement results, as well as testing and characterizing multi-parameter chips.

Improved Accuracy

Machine Learning has shown to improve measurement accuracy for MEMS thermal anemometers already. In a paper by J. Amaral *et al.* K-nearest neighbor regression (KNNR) was able to reduce the maximum error from 20.4% to 1.7%, while measuring water flow with a central heater and thermocouple measuring elements [4].

This approach could also be applied to non-thermocouple based thermal flow the sensor presented in Alveringh *et al.* where resistors are used as the measuring elements has previously been measured in a similar set-up [6].

Multiple parameters

Devices like the one presented in Azadi *et al.* would benefit from using a measurement system capable of providing varied conditions as humidity, gas composition and temperature can have negative effects on the accuracy of results [7]. The gas independent sensor presented in the work would be easily characterized in the system.

Sensors that have structures to decrease their dependence on external conditions as well as devices without these additions could potentially reveal information about the external conditions with the aid of a properly trained model, which indeed requires a larger data set than a single variable model due to the increased complexity.

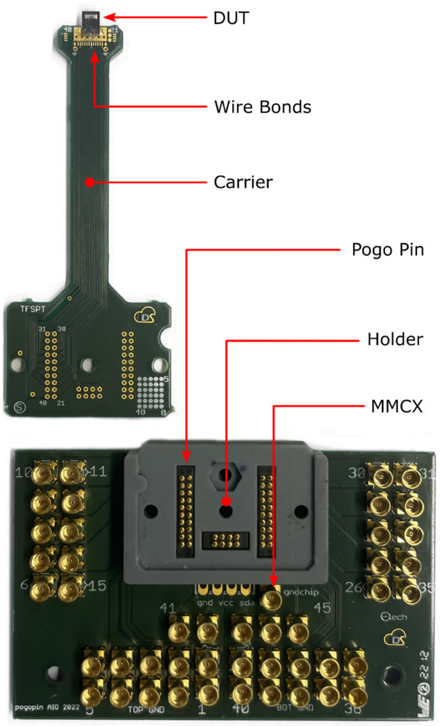

Figure 1: The carrier and holder PCBs used to place the DUT in the stream of the wind tunnel.

MEASUREMENT SYSTEM

The device under test (DUT) is held near the center of the wind tunnel using a custom built PCB which allows for the DUT to stick out 5 cm from the side wall through an elongated carrier PCB shown in Figure 1.

The DUT can be interfaced through the use of wire bonds from the DUT to the carrier PCB. The carrier PCB is affixed to the holder PCB using a 3D printed mounting system, which uses some screws to press the carrier to the holder's pogo pin connectors. These then connect through to MMCX connectors allowing the DUT to interface with the electronics outside of the climate cabinet.

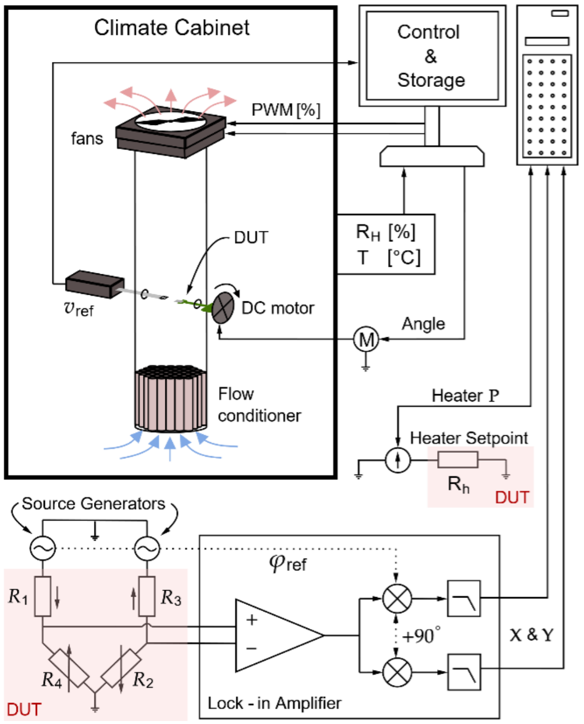

Figure 2: A schematic of the measurement system in the case of a calorimetric anemometer with a Wheatstone bridge readout.

The holder is mounted on a DC servo motor (Newport M-495 ACC) which using its controller (Newport ESP 300) is able to rotate the holder, carrier and DUT within a precision of 0.001°. The MMCX connections to the holder PCB can be put under strain when the DC motor rotates the DUT more than 45°, in order to prevent this the cables were affixed to the rotating portion of the set-up with ample of leeway.

The wind tunnel itself is a 1.5 m long PMMA tube with an inner diameter of 114.5 mm. The bottom of the wind tunnel has a flow conditioner and a dust filter to make sure that the incoming velocity profile is flatter and free of any debris that could damage the DUT. The flow conditioner consists of 292 parallel tubes, 10 cm in length with an inner diameter of 5.55 mm and outer diameter of 5.95 mm.

At the other end of the wind tunnel are two pulse-width modulated (PWM) fans that draw air through the wind tunnel. The first fan (Scythe SU1225FD12MR-RHP) is able to provide a lower range of flow speeds between 0.02 and 0.4 m s^{-1} while the second fan (Delta Electronics PFR1212UHE-SP0) can provide higher flow speeds of 0.4 to 5 m s^{-1}. Both fans are controlled via an Arduino UNO from the LabVIEW program.

To measure the reference flow velocity at the DUT a reference flow meter is placed symmetrically opposite the DUT through a small hole in the wind tunnel (Voltcraft PL-135HAN) around 2 cm away from the DUT.

An seal is required at the point of entry of the carrier PCB and the reference sensor into the wind tunnel to minimize air leakage. The noise in the reference flow measurement decreases significantly when no flow enters the wind tunnel from the side. Additionally the flow velocity range within the tube at the measurement height increases when the seal is made better, as higher flow speeds can be achieved.

The entire wind tunnel is placed within a climate controlled cabinet (ESP PRC 1200 WL) which is able to vary the temperature and humidity effectively in the ranges of 10-50 °C and 20-80 %RH. These values are measured using a reference sensor (Dracal USB-PTH-450) placed in the cabinet.

Though the DUT can vary the holder has many possible MMCX connectors that allow for multiple electronic configurations to be tested. As an example Figure 2 shows a DUT consisting of 4 measuring resistors placed in a Wheatstone bridge and one heating resistor.

The system has two in phase signal generators (Agilent 33220A) that allow for any fabrication related asymmetries in the bridge to be compensated. In case of DC measurement these can also be set as DC voltage sources. The bridge is measured using a lock-in amplifier (Stanford Research Systems SR830) locked into to the phase of the source generators. The X, Y, R and θ of the lock-in amplifier are recorded in the LabVIEW program.

The heating resistor is powered by a source measurement unit (Keithley 2400) which can be run in two modes using the LabView program. Constant power, which can sweep a given set of powers, or constant temperature, which works to keep the temperature of the heating element constant.

The LabVIEW program is able to automatically record and sweep over the flow velocity (v), AoA (θ), heating power supplied (P), while measuring the lock-in's in phase (X), quadrature (Y), amplitude (R), and phase (φ), the heater's volage (V) and current (I), and the climate cabinets temperature (T) and humidity (%RH). All of the variables above are recorded as one data entry in a CSV file for easy post processing, while being shown live during the experiment.

Simulation

The flow velocity profile in the wind tunnel must be as flat as possible to allow for reproducible measurements. This is because small variations in the flow velocity profile could result in incongruent results due to small misalignments within the wind tunnel. This can be simulated for by using COMSOL Multiphysics®.

The expected flow speeds induced by the dual fans is around 0.04 to 4 m s^{-1} and with the inner diameter of the wind tunnel being 114.5 mm the Reynolds number is given by the equation below [8]:

$$\mathrm{Re} = \frac{uL}{\nu}$$

Where u is the flow velocity, L is the tube diameter and ν is the kinematic viscosity. The resulting Reynolds number is between 310 and 31,000 assuming a kinematic viscosity of 1.83E-5 m s^{-2} at room temperature, meaning that the flow regime spans from laminar to turbulent [9].

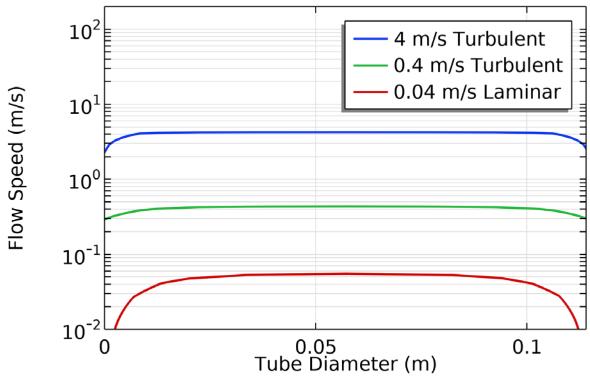

Figure 3: Simulated velocity profiles within the laminar and turbulent flow physics modules.

Turbulent flow velocity profiles tend to be quite flat, while laminar flow profiles are parabolic [10]. This is confirmed by the simulation results shown in Figure 3. The COMSOL Multiphysics® laminar flow module was used for flows with $Re < 1000$ while the turbulent flow module was used for flows with $Re > 1000$.

The inlet of the wind tunnel is given a flat flow profile boundary condition due to the flow conditioner. Figure 3 shows the flow velocity profiles at 50 cm from the flow conditioners given by the laminar flow physics module in COMSOL Multiphysics®.

The central 6 centimeters of the flow velocity profile vary by about 1% for flows of 0.4 m s^{-1}. This allows for some tolerance with regards to the placement of the DUT in the wind tunnel without loss of accuracy.

Measurement Protocol

The most efficient order of measurement is to first vary the flow speed, followed by the angle, temperature, and finally humidity, since the latter variables require a longer time to adjust compared to the flow rate.

Due to the length of the wind tunnel it takes time for the flow velocity of a PWM set point to be achieved. This takes longest (60 s) when doing a zero flow measurement as it can take up to a minute before the flow is fully stopped. Therefore it is good to include a stability control script, which can start a measurement while the reference flow is consistently within a range of ±0.01 m/s from the last 20 measurement values.

A further stability control script can be used for any heating elements in the sensor. This is because the element must also compensate for heat flow away from the chip into the PCB. Furthermore using a proportional integral control for the heater set point is recommended in order to maintain consistent heating conditions.

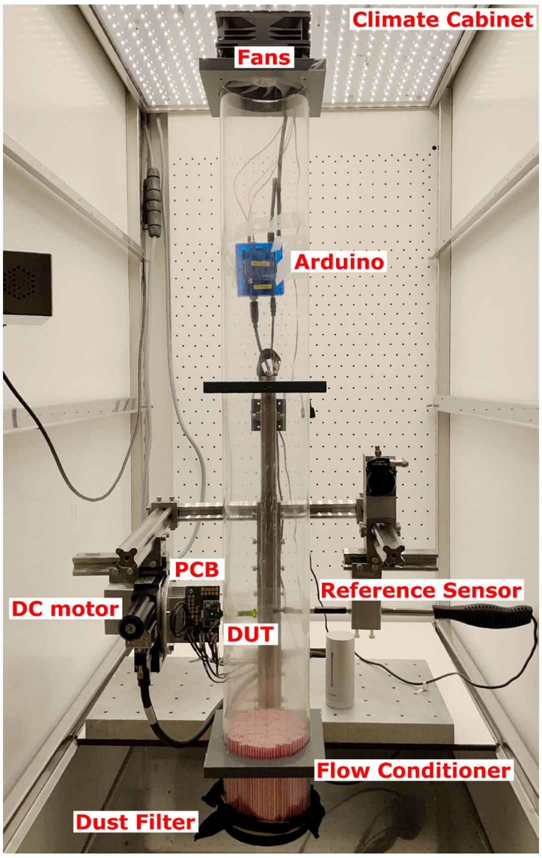

Figure 4:The system as placed within the climate cabinet, with a the DUT placed within the wind tunnel.

Integrating these stability arrays and PI controllers into the same program used for data collection allows for more control over the experiment including the step sizes for each variable as well as the amount of measurements per specific condition.

RESULTS

The measurement system was built and run in the climate cabinet as shown in Figure 4. The system is able to produce very large datasets without supervision. A continuous measurement of 24 hours can be run without issue. A typical measurement takes around 12 hours and will yield a large enough dataset for ML purposes.

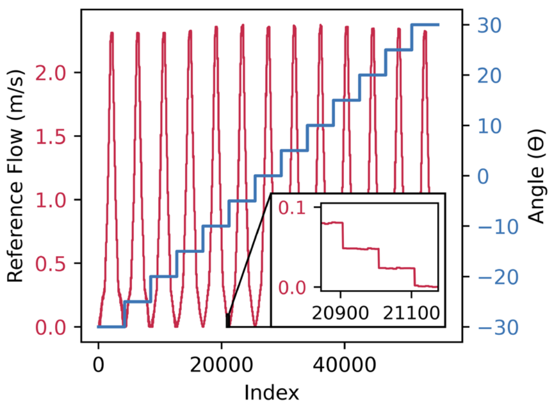

Figure 5: Data from a test run taking 8 hours.

As shown in Figure 5, a measurement at one temperature and humidity set point with 13 individual angles and 5% changes in PWM with 100 measurements per condition would yield 54,600 datapoints. If this was also done for 5 humidities and 5 temperatures this number reaches above the 1.3 million. The chips presented in Azadi *et al.* [7] and chips similar to the one presented in Alveringh *et al* [6] were successfully measured in the wind tunnel, providing a dataset over 10 million datapoints for future ML research and publication.

CONCLUSION

The system provides reliable and automated datasets with high controllability of physical conditions. An anemometer was automatically measured over a range of flows (0 – 5 ms^{-1}) over 90° of AoAs and in several humidities (30-80 %RH) at a controlled temperature (20 °C). Different types of hot wire and calorimetric sensors have been tested in it automatically each with large datasets containing more than 1 million datapoints. These large datasets allow for the next step in the development of these devices as there is plenty of data for both learning and testing sets for all devices. Both single and multiple parameter chips can also be characterized for non ML purposes as an added benefit.

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