Environment identification in flight using sparse approximation of wing strain

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ABSTRACT

This paper addresses the problem of identifying different flow environments from sparse data collected by wing strain sensors. Insects regularly perform this feat using a sparse ensemble of noisy strain sensors on their wing. First, we obtain strain data from numerical simulation of a *Manduca sexta* hawkmoth wing undergoing different flow environments. Our data-driven method learns low-dimensional strain features originating from different aerodynamic environments using proper orthogonal decomposition (POD) modes in the frequency domain, and leverages sparse approximation to classify a set of strain frequency signatures using a dictionary of POD modes. This bio-inspired machine learning architecture for dictionary learning and sparse classification permits fewer costly physical strain sensors while being simultaneously robust to sensor noise. A measurement selection algorithm identifies frequencies that best discriminate the different aerodynamic environments in low-rank POD feature space. In this manner, sparse and noisy wing strain data can be exploited to robustly identify different aerodynamic environments encountered in flight, providing insight into the stereotyped placement of neurons that act as strain sensors on a *Manduca sexta* hawkmoth wing.

1. Introduction

Winged flight remains one of the most successful forms of animal locomotion and one of mankind's foremost accomplishments. The aircraft of today are a direct result of centuries of fascination, inquiry and experimentation inspired by bat, bird and insect locomotion. Today's most prevalent rigid-wing aircraft perform maneuvers and functions strikingly different from that of these flexible-winged animals, and the success of these aircraft in military and transport continues to spur development of rigid-wing technology. More recently, advances in robotics, materials and high-performance computation have advanced bio-inspired flexible-wing technologies including miniaturized unmanned micro-aerial vehicles (MAVs), ornithopters, hovercraft, and drones. Suitable controllers for these small-scale autonomous technologies require extensive understanding of low-Reynolds number, unsteady aerodynamics that is often experienced by bats, insects and most birds. Of particular interest in this work is understanding the role that a limited number of sensors (e.g. neurons) play in accurately informing control decisions in this low-Reynolds number regime, thus potentially helping to reveal bio-inspired flight control principles.

While the comprehensive mechanism of wing actuation, fluid-structure coupling and response maneuvers in winged animal flight is not fully understood, biologists and engineers have nevertheless made significant progress in identifying the propulsive forces in flapping-wing flight (Ellington, 1999; Zbikowski, 2002; Tangorra et al., 2007; Dabiri, 2009). The preliminary study of these forces

Nomenclature		**t**	Vector of time t in seconds
		U_∞	Free stream velocity [10 m/s]
a	Vector of POD coefficients	**V**	Matrix of right singular vectors of **S**
b	Half-chord length of wing [.01 m]	x	Chordwise spatial coordinate [m]
c	Categories or number of environments	**x**	High-dimensional signal
$C(k)$	Theodorsen transfer function	$z(x, t)$	Transverse deflection of wing [m]
$EI(x)$	Flexural stiffness of wing [Nm^2]	α_0	Base angle of attack
f	Frequency of maneuver [Hz]	$\alpha(t)$	Angle of attack of wing
f	Vector of frequencies	ω	Angular velocity of maneuver
k	Reduced frequency [$k \triangleq 2\pi fb/U_\infty$]	μ	Linear wing density [.002 kg/m]
h_0	Initial vertical position of wing	ξ	Zero-mean sensor noise
$h(t)$	Vertical position of plate	η	Sensor noise variance
m	Spatial grid resolution	ϵ	Error tolerance parameter
N	Number of timesteps	σ	Singular values of POD decomposition
$p(x, t)$	Chordwise loading of fluid pressure	Σ	Diagonal Matrix of singular values
P	Measurement selection matrix	Φ	Basis of POD modes
r	Rank truncation parameter	Φ_r	Low-rank basis of r dominant POD modes
s	Vector of transverse strain of wing	$\widehat{\Phi}_r$	r dominant POD modes of $\hat{\mathbf{S}}$
S	Matrix of transverse strains	$\Psi, \widehat{\Psi}$	Library of multiple low-rank POD bases
$\hat{\mathbf{S}}$	Discrete Cosine Transform of **S**	Θ_r	Joint POD modes of all available data
t	Time [s]		

began with quasi-steady, inviscid assumptions from rigid-wing thin airfoil theory that proved to be inadequate at predicting the additional lift generated by insects in experiments. It was later found that the unsteady aerodynamics and added-mass of the surrounding fluid are crucial for characterizing the forces experienced by animal wings (Ellington, 1994; Sane, 2003; Wang, 2005). Although the fluid's added-mass would seem to complicate the robust generation of lift, it was discovered that animal wings rotate and flap in a manner that harness aerodynamic added-masses and leading edge vortices for additional lift in insects (Dickinson et al., 1999; Birch and Dickinson, 2001; Combes and Daniel, 2001; Song et al., 2008; Eldredge et al., 2010; Faruque and Humbert, 2010a, 2010b), birds (Spedding et al., 2003), and bats (Hedenström et al., 2007; Clark and Smits, 2006). There is evidence that wings harness low-dimensional flow structure such as leading edge vortices to maximize lift and improve stability in flight (Birch and Dickinson, 2001; Videler et al., 2004; Dabiri, 2009). This is consistent with the observation that wing motion is itself low-dimensional. It is probable that wing motions harness a low-dimensional flow structure, as the wing motion is itself low-dimensional: Proper orthogonal decomposition analysis has revealed that fin motion (Tangorra et al., 2007), bat (Riskin et al., 2008) and avian wing motion are constrained to only a few degrees of freedom. The lack of complex musculature in insect wings results in even fewer degrees of freedom. Such dimensionality reduction suggests that insects, which are constrained to small ranges of motion, capitalize on low-dimensional feature spaces to inform low-dimensional control protocols.

Wing mechanosensors in insects detect and leverage these fluid forces and accelerations for changing flight environments. Indeed, tactile sensory mechanisms have been identified on the wings of most animals - bats sense with small hairs on their wings (Sterbing-D'Angelo et al., 2011), birds sense with wing feathers (Brown and Fedde, 1993), but insects possess a small number of strain sensors on their wings called *campaniform sensilla*. The *sensilla* are strongly implicated in neurosensory flight control (Dickerson et al., 2014; Sane et al., 2007), in part because insect wings react to disturbances faster than visual stimulus transmission to the central nervous system (Collett and Land, 1975). Biological evidence shows that sensilla are stereotyped across specimens of the same species. Indeed, Cole and Palka (1982) show that the spatial distribution of sensilla are encoded in the genes of the fruit fly *Drosophila*, and sensilla determine maneuvers in flight control in locusts and *Manduca sexta* (Gettrup, 1966; Dickerson et al., 2014; Dickerson, 2009). Aerodynamic feedback is encoded within the strain signals, registering fluidic loading frequencies into the signal that can be exploited for characterizing flow environment. Evidence shows that insects exploit innate or learned knowledge of fluid environment through the strain encodings to make split-second decisions in flight. The insect nervous system has evolved specifically for the decision task, but controllers in hovercraft and MAVs require other means of exploiting point sensor feedback. Strain sensors are too sparsely distributed to fully resolve spatial flow encoding over the wing, and equation-based flow identification or prediction is expensive and difficult to generalize to different flow regimes.

In contrast, data-enabled methods for flow characterization or parameter estimation have shown remarkable promise in the analysis of complex flows. A variety of data decompositions are being applied to flow measurement data for spectral analysis, model reduction, and control of complex flows, for example, proper orthogonal decomposition (POD) (Lumley, 1970; Holmes et al., 1998), dynamic mode decomposition (DMD) (Schmid et al., 2008; Rowley et al., 2009; Schmid, 2010; Tu et al., 2014; Kutz et al., 2016), compressed sensing (Bright et al., 2013; Bai et al., 2014; Brunton et al., 2014) and sparse regression (Brunton et al., 2016b), network theoretic approaches (Nair and Taira, 2015; Taira et al., 2016), as well as many other machine learning methods for flow control, as surveyed in Brunton and Noack (2015). Broadly, these equation-free methods characterize measurements of a system to inform its state and subsequent control decisions. In addition to intriguing evidence that biological strain sensors inform reactive decisions in flight, sensors play a pivotal role in the feedback control of many complex flows.