"Feathers in Storms" – intelligent sensor-actuator arrays for control of turbulence and optimization of performance including fuel management

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Quantized transitions between turbulence states that are characterized by high degrees of non-linear stochastic dynamics suggests that there may be techniques for improving both the predictability and control of such states, particularly the highly critical transitions that can create extreme vehicle stress and compromise vehicle safety and integrity. Investigations into meta-stable structures within dynamic flows create limits and bounds on transitions from one behavioral condition into another, thus providing a type of "quantization" between states that are characterized by high degrees of turbulent and chaotic internal dynamics. Such flows can be detected and measured through localized, cell-like neighborhoods that comprise networks of communicating asynchronous sensor-actuator processing elements. This leads to the prospect of designing externally tunable algorithms for control systems (including both human and autonomous piloting systems) within a variety of aircraft and airborne machines. Analysis of probable interactions and consequences from interactions between an aircraft and various upcoming turbulence situations – both natural (e.g., weather formations) and man-made (e.g., intentional actions and countermeasures including incoming ballistics) – can potentially yield real-time solutions for altering an airborne vehicle's path, dynamics, or execution of effective airborne countermeasures. In addition to improving survivability and aircraft durability, this can also aid fuel efficiency. Improved understanding of how specific turbulence states can and cannot transform into different and more manageable states, or into less turbulent conditions, can be valuable in the design of diverse types of airborne vehicles and their control systems.

I. Introduction

Turbulence comes in many varieties and often without advance warning for aircraft, as many pilots and frequent travelers know from experience. Kolmogorov and Arnold studied the problem of categorization for different types of turbulence, but in the past eighty years there has been little to show how any characterization of turbulent flow types, in air or water or any other medium, could be employed in manners other than to minimize and avoid the turbulence. The question arises as to how it may be possible to achieve two seemingly diametrically opposite goals. First, one wishes to minimize negative effects of such turbulence and to stabilize a vehicle subjected to such non-linear dynamics, in its flight performance and with respect to its system consistency (e.g., its mechanical structures, engines, and that which may be inside, such as a crew and complement of passengers). Secondly, one desires to optimize the aero- or hydrodynamic flows over the body of a vehicle, extended over sufficient intervals of time, in order to optimize energy consumption and thereby even contribution to minimization of fuel consumption by the craft. Going further into the domain of what has not been tried and has been generally avoided, there appear to be few inroads made into the speculative terrain of questions regarding active uses of turbulence, for both the benefit and the disadvantage of aerospace (or aquatic) vehicles. Restricting our investigations to the former, our investigations have begun into how turbulence, both natural (e.g., weather-induced) or artificially induced by some form of technology, could be applied in the domain of both defensive and offensive measures by aircraft (manned or unmanned) or

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other support forces. In other words, turbulence phenomena may be used constructively, in a manner analogous to how auditory and electronic noise can be employed to cancel out the noise effects and produce an ambient or else an electronically secure environment.

The key to such creative uses of turbulence in any medium are linked with being able to harness the energy pattern as it is interacting with some object, such as the surface of an aircraft wing and fuselage. That ability depends upon recognition and characterization – quantification of some set of parameters within the subject system (and not only parameters concerning the turbulent media per se, by itself (e.g., air or water). Thus we are led to “square one” of the issue of modeling a system whose state-space may be vastly uncertain, fuzzy, and indeterminate, unless we can achieve some ability to model that state-space dynamic in a way that is simpler, faster, and sufficient. The argument made here in this paper is that the answer to having such an ability, in the world of vehicles operating in turbulent aerodynamic (or hydrodynamic) environments, is not in simply having bigger and faster computer engines to assimilate vaster quantities of data, but rather to radically simplify the entire process, from the data being collected to the calculations being performed as part of any modeling process.

This is radical because it goes against the generally accepted practices of engineering and information processing by the use of calculators which have “grown up” to be called computers but which are still quintessential “Turing machines” at heart (even those which strive to do their “number-crunching” in massive parallelism through the employment of arrays of qubits that can be briefly operating in a kind of lock-step dance through artificially induced quantum entanglement). So how can the modeling process, dependent upon the measurement and assignment of values to a large and potentially dynamic set of system parameters (many of which will at varying times be unobservable, uncertain or in error), get simpler even as the number of dimensions in a problem (or the number of n-axis freedom of motion robots operating in a cooperative environment) increases even exponentially? The answer may be flying around us and overhead in the wings of birds, and “feathers” in a figurative sense may be more important in the future of aerospace flight, oceanic sailing, or other robotic and robot-like activities than is likely to be imagined.

Motivations and inspirations for a new approach to understanding and harnessing turbulence originate from many sources, not the least of which are the birds and bees of the fields and skies, literally so. Once again, the focus is on aerodynamics, but many of the points about to be made here – and conducted in our experimental platform – with respect to air, apply as well to water, and to the creatures who have some hundreds of millions of years of extensive prior experience in mastering hydrodynamics under all manner of non-linear conditions, the fish and sea mammals of our world.

Here, we begin with concretely phenomenological examination of bird flight and behavior in widely different climate zones and weather conditions, one discovers that feathers are an extraordinarily unique functional surface for control on a massively parallel planar scale, beginning with sensing capabilities that are responsive to minute variations in orientation for feather stems connected with the tissue in the wing, and relying for that super-sensitivity on the basic design of a feather as a surface for reacting to the flow of air current and the changes in air pressure over small and semi-amorphous regions of the feather's surface. The covert feathers on the dorsal region of a bird's wing demonstrate a function of operating as a sensing array that will react to pressure changes and directional gusts, thereby transmitting information which results in modifications to wing geometry and changes in flight patterns.

Figure 1. Covert feather sets in eagle wings responding to varying pressures and gusts

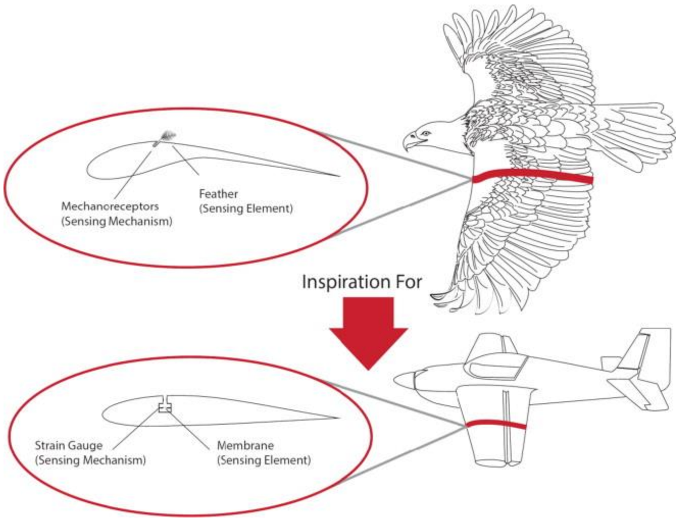

Figure 2. Pressure-actuated sensitivity within covert feather sets of bird wings (from Mohamed et al, [15])

However, in the realm of synthetic systems, machines whose designers may attempt to build in emulation of Nature, there are issues of granularity in the scale of measurement and performance in the computations. Furthermore, from the standpoint of engineering, there are immense issues of practicality – weight and cost of components, complexity in design and assembly, durability and consistency, maintenance. An airplane with feather-sensor wings is likely to never get off the ground, literally or from the perspective of system engineering and cost accounting combined.

The approach pioneered by Granichin and colleagues at Saint Petersburg State University [1-6] is based upon the mathematics underlying how turbulence can be measured and estimated in a manner that circumvents many of the problems faced by deterministically-based architectures which impose unrealistic computational requirements upon inherently non-deterministic systems. At the heart of the stochastic approximation methodology is the measurement of random parameters in local neighborhoods which may be considered as stochastic cellular automata, the boundaries of which can change dynamically and the measurements within which are focused upon boundary values with other contiguous cellular automata neighborhoods that collectively span the surface (or, extending the model the volume) of the system treated as a topological representation of a state-space.

There will be some implicit goals that can be expressed as rules governing such systems. For birds and aircraft, the simplest such system-level rules are to achieve and maintain flight and to conserve energy – or in converse terms, to use as little fuel as possible to stay aloft and mobile as long and as easily as possible. Another important principle present in biological systems and arguably required in complex machines designed and constructed by humans (and other intelligent machines) is to minimize the cost of all the information control and computation required to achieve those primal basic goals.

II. A Control Model that localizes and simplifies and makes things "safer"

The Local Voting control (LVC) protocol is based upon simultaneous perturbation stochastic approiximation (SPSA) as developed by Granichin et al [5, 6]. The LVC is one method for reducing both the size and the repetitive, uniform structure of search spaces and tests. A key element to LVC is using a non-vanishing step-size for conditions where significant uncertainty and external disturbances can be expected [14]. The objective is to search for "impending critical singularity points;" i.e., to detect changes that may be insignificant in most cases but which can be indicative of developing conditions that could have irreversible effects. A singularity within the state-space measurement process may be likened to a Thom/Zeeman catastrophe. While mathematically there may be reversibility, in many physical, biological, social and informational systems there may not be such. Figure 2 gives an illustration of the four classic Thom-Arnold catastrophe functions. [11, 12]

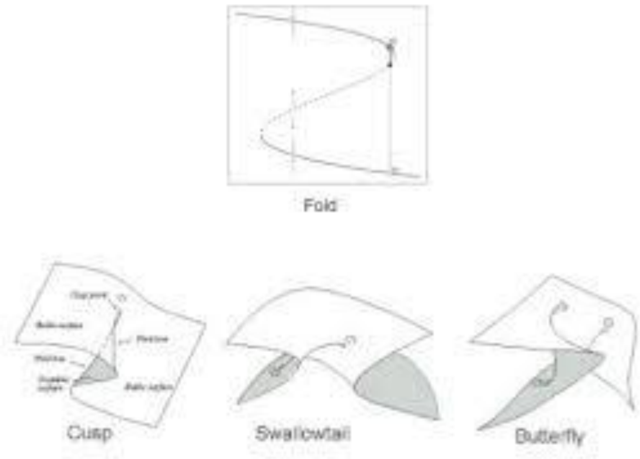

Figure 3. Four catastrophe functions (after Thom and Arnold)

The use of stochastic, randomized selection of local areas to measure and then lead into choices for the next areas in turn to measure, is based upon an important counterpart, and this is that some type of adaptive learning process is underway, built-in to the system inherently. Without some adaptive meta-level learning and retention, the randomness of selection at the lowest scale will perpetuate indefinitely and this will defeat the goal of making the system "smarter" - i.e., quicker at skipping unnecessary observables and even data sources – even regions of data points. Randomness is at the beginning, but it needs to be tempered and trained by higher-order functions that can evaluate and rearrange what should be examined in future cycles. This is where simultaneous perturbation stochastic algorithms (SPSA) [14] provide a mechanism through a descent method capable of finding global minima, sharing this property with other methods as simulated annealing. Its main feature is the gradient approximation that requires only two measurements of the objective function, regardless of the dimension of the optimization problem. Unlike Finite Differences (FDSA) and other stochastic approximation, SPSA perturbs all directions simultaneously and for any system with p components, SPSA requires p times fewer function evaluations than FDSA.

III. An experiment with wings and feathers

An experimental platform has been built in order to test the means by which LVC measurements can spread over a virtual surface such as an airplane wing. This addresses one major problem in aerodynamic stabilization during turbulence, focusing upon wing surface pressure points as the key observable parameter. This may be considered as a prototype for use of the LVC protocol to other applications including the interactivity among a group of subsystems within a single vehicle (such as an aircraft) or a group of cooperating robots (e.g., within UAV operations for agriculture or space applications) [16].

Consider the wing structure whose surface is covered with pressure sensors coupled with servo-controlled flap actuators. The actuators serve as mini-wingflaps, each coupled with a pressure sensor, such as illustrated in Figure 4. Sensor data can be directly transformed into servo-actuator commands for adjustment of the flap element, either without (bypassing) or inclusive of transmission of pressure data to a regional-cluster processor. Thus, individual sensor-flap components or arbitrary groupings (clusters) of such components can operate as independently of others on (in this case) the wing (or on any other vehicle surface).

Each sensor-actuator unit may be considered as an active agent in a computational network that is loosely and dynamically connected as cellular-automata neighborhoods. This dynamic nature of the local neighborhood sets of sensors is important for enabling the wing to "measure itself" in flight – a correspondence to the covert feather geometry and anatomy of biological birds. Sampling – and motor response – can be performed asynchronously and asymmetrically – this derives from the use of the stochastic approximation methods. This differs from other strategies employed such as in [15].

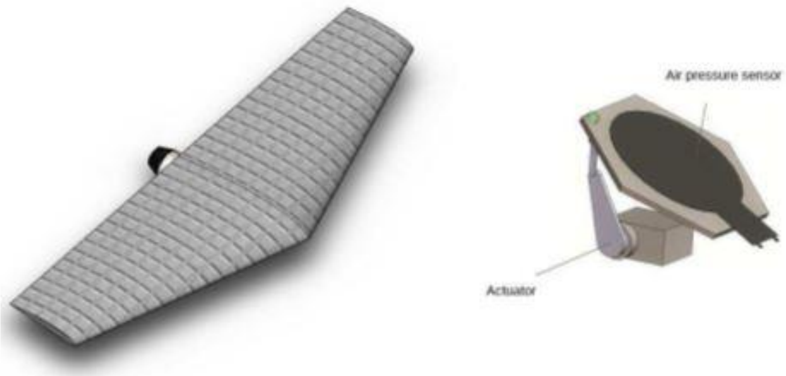

Figure 4 --- "Wings with feathers" [6]

Let x^i_k be the integrated pressure deviation for "feather" a^i – data derived from sensor measurement

Agent dynamics may be described as: $x^i_{k+1} = f\,(x^i_k, u^i_k),\ i \in N = \{1,...,n\}$

Observations: $y^i_k = x^i_k + \xi^i_k$

The Local Voting Protocol is given by: $u^i_t = \alpha \sum_{j \in N^i_k} b^{i,j}_k \,(y^j_k - y^i_k)$

Consistent behavior (consensus): $x^i_k \approx x^j_k\ ,\ i,j \in N$

In a high-turbulence flow environment, with no responsive adjustments to the sensor-actuator units, LV readings across the wing surface will resemble a "kaleidoscope" effect among the regions, as shown in Figure 5 below. All actuator units "feathers") in the wing remain unadjusted and with no change in orientation in response to changes in applied external pressures. The consensus “goal” state (illustrated in Figure 6) provides for uniform or within-threshold values from all LV “cellular regions” (clusters, neighborhoods) during turbulent conditions. This is achievable through servo-controller adjustments of the sensor-actuator “feather” units. In principal, the number of sensor-flap units on a given surface (e.g., wing or fin) is limited only by the size, weight and integration requirements for each unit.

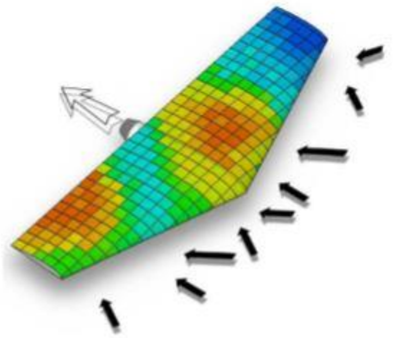

Figure 5 --- Wing sensor field (“raw”) in turbulence [6]

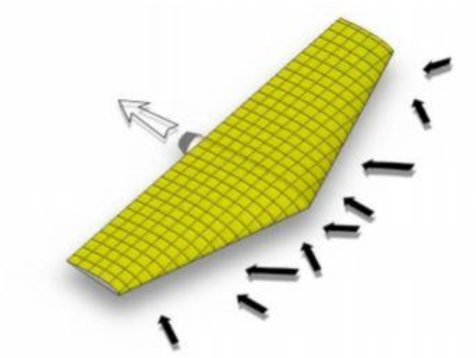

Figure 6 --- Wing consensus (stable) state [6]

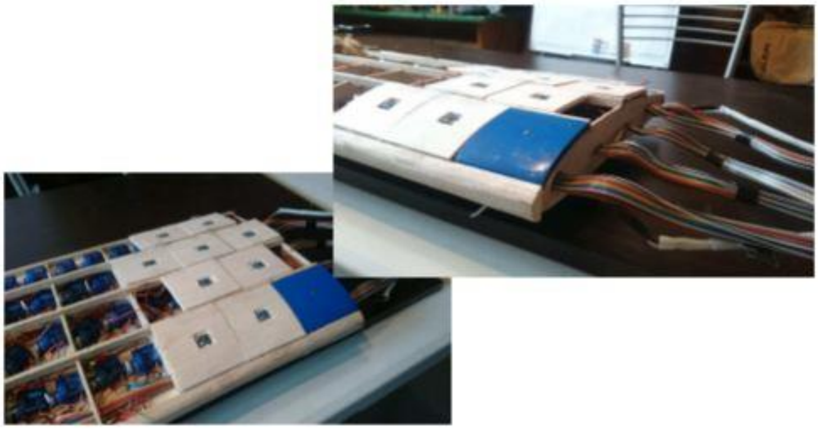

Figure 7 – Experimental Wing Sensor Platform [6]

In this given experimental case the LV clusters are statically defined by the geometry of the sensor-actuator units (Figures 4 and 7). However, stochastic approximation and randomized sampling and perturbation is not limited to a static architectural model of the given system, but quite to the contrary. A conventional aircraft wing, and the entire vessel, constitutes a static geometry – the wing has a defined and permanent geometry. In other applications and tasks the LV regions need not be uniform, nor static, in their geometry. For instance, consider cooperative agents working with interchangeable components (such as tool fittings) in physically dynamic environments with unpredictable kinetics (such as an asteroid in the process of being mined or split into fragments with the intention of reducing impact threats to Earth or some other habitation). It is possible to create different “dynamic” maps of LV cellular regions and also larger assemblies of clusters, with different geometries that correspond to how the system is being affected by its environment at any given time period.

In a real-time flight operational scenario there are critical time intervals for such adaptations that can avert an critical “singularity” event affecting the entire complex system consisting of robots and the asteroid unified within the state-space. Randomized alterations to small regions (clusters) of the system space have two unique advantages over models that attempt to comprehensively address the entire system. First, results can generally be achieved faster and with fewer computational resources. This is significant for mobile, remote and compact device platforms (such as satellites and other space vehicles, robotic or otherwise).

Secondly, and very significantly, errors in the decision process – which can be frequent in beginning stages of a cybernetic system adaptive learning process – will be more localized, more containable, and more easily correctable, than errors which affect large sectors of some system performance. Drawing from the illustration of wing adaptation to turbulence - adjustment of several “feather” actuators, in a way that has an adverse or otherwise non-beneficial effect on the overall system, will (generally) be more easily correctable and offset by other adjustments, in contrast to a system-wide adjustment that may be irreversible.

For in-flight experimentation, a commercial UAV drone is being employed. The MG-1 unit from DJI, shown in Figure 8, is employed in such commercial tasks as crop-spraying.

Figure 8 – MG-1 UAV platform for field testing

IV. Conclusion

Next stages of research will focus upon physical experimentation using the laboratory prototype (shown previously) and also a UAV drone. The latter is equipped with sensor-actuators under a variety of artificial turbulence conditions including wind tunnel operations, as well as the definition and refinement of turbulence categorization and system training.

Acknowledgments

Author thanks Mirnova Academy (http://mirnova.org) for financial support. Special appreciation is given to colleagues for insightful discussions, critiques, and pointers to new mathematical perspectives: Anna Unzhakova and Oleg Granichin (Saint Petersburg University).

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