Novelty Detection in Laminar and Turbulent Flows

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**1. Introduction**

This paper presents a novelty-based approach for autonomous underwater locomotion, based on highlighting and characterizing changes in the sensing picture of steady and altered flows. Inspired by the lateral line of fish, arrays of flow and pressure sensors have been progressively gaining attention in underwater robotics, as means to complement vision and sonar systems with flow-related information [1, 2]. Research in literature has mostly focused on performing low-level processing and on characterizing signals generated by a sinusoidally-vibrating sphere placed in still water [3]. In this work, we progress to more complex flow regimes. On the grounds that adaptation to environmental changes is key for autonomy, we propose a signal processing method that can be summarized as follows: first derive a description, through hydrodynamically significant signal features, to capture steady-state flows; then, exploit such features to highlight and characterize transitions, whenever flows deviate from their steady states. We focus on laminar flows and Kármán vortex streets (KVS) as representative regimes; KVS form due to the presence of objects in the flow and appear as columnar arrays of vortices, shed alternately and in a periodic fashion.

**2. Approach**

The degree of turbulence in flow is evaluated using the Reynolds number $Re$, defined as the ratio of inertial to viscous forces. Laminar flows correspond to low $Re$; with increasing $Re$ flow gets progressively more turbulent, usually coupled with high vorticity throughout the flow. A second independent measure to evaluate unsteadiness concerns fluctuations in velocity. In laminar flows, the signal at any point in space is nearly constant in time; on the other hand, turbulent flows come with wide and unpredictable fluctuations [4]. We evaluate steadiness through the turbulence intensity $\tau_s$ – the ratio of the standard deviation $\sigma_s$ of sensor readings $s_n$ over the mean value $\bar{s}$ calculated over a fixed period with order of magnitude 1 ($\tau_s = \sigma_s / \bar{s}$). The higher the $\tau_s$, the more turbulent the flow. KVS are sometimes categorized as organized turbulence, as they exhibit high $\tau_s$, due to the alternately shed vortices, but also maintain an aspect of predictability. KVS are periodic phenomena characterized by the vortex shedding frequency $f_{vs}$, the number of vortices shed per second and the wake wavelength $\lambda$, defined as the downstream distance between centers of two consecutive vortices.

We recognize KVS from laminar flows or (disorganized) turbulence by evaluating to what degree the temporal behaviour of the sensor signal is representable through a periodic function. To this end, we use sensor readings as input to an adaptive frequency Hopf oscillator, proposed in [5]. In the absence of input, the Hopf oscillator has an asymptotically stable harmonic limit cycle with an intrinsic frequency $f_o$. When there is an input signal, the oscillator frequency $f_h$ synchronizes with the frequency of the input signal $f_s$. We evaluate the relationship (starting from the correlation $C_s$), between input signal and the oscillator output. If the relationship is close, we consider the input signal as “mostly periodic”.

We employ the hydrodynamic features $\tau_s$, $f_h$ and $C_s$ to model the flow’s steady-state and highlight when transitions occur away from such state. To this purpose, we present an
online novelty detection mechanism that tracks the current state vector \((\tau_s(t), f_h(t), C_s(t))\) at time stamp \(t\) and highlights when it differs from values observed at \(t - T\). The mechanism also enables classifying the changes and recognizing into which flow regime the environment is transitioning: the filter responds to laminar flows with \(f_h = f_o\) and by outputting a label \textit{laminar}, whereas it reacts to KVS with \(f_h \approx f_s\) and the label \textit{KVS}.

3. Materials and Methods

Experiments were conducted in a flow pipe with a working section of of \((0.5 \times 0.5 \times 1.5)\) m\(^3\). A bio-mimetic robot was placed parallel to the incoming flow and harnessed rigidly with a vertical rigid rod, which in turn was attached to a force plate at the bottom of the test space. The force plate reads the resultant up/down-stream \((F_x)\) and lateral forces \((F_y)\) acting on the robot due to the flow. We also mounted three pressure sensors on the (rigid) head of the robot – one at the nose \((p_n)\), one on the right \((p_r)\) and one on the left side of the head \((p_l)\); pressure can be measured within 700 kPa absolute range. The robot was not actuated during experiments; we recorded pressure and force readings every 0.02 s (50 Hz). We tested our method to detect changes in laminar flows and KVS. In this abstract we limited our analysis to KVS transitions, starting with still water (for 30 s) and applying a step-wise increase in the flow speed, so as to generate two KVS (recorded for 90 s) at 31 cm/s and 48 cm/s. We then switched off the water pump and continued recording for another 60 s. The diameter of the cylinder used to generate the KVS was 10 cm, resulting in \(f_{vs}\) of 0.7 and 1.2 Hz. The robot was aligned with the center of the cylinder, at a distance of 26 cm.

4. Results

Figure 1 illustrates \(\tau_s, f_h\) and \(C_s\) values for the pressure difference, \(P = p_r - p_l\) (1st row) and the lateral force \(F_y\) (2nd row). In each plot, the red and blue lines indicate respectively the past \((P(t-T), F_y(t-T))\) and present \((P(t), F_y(t))\) values, whereas the green line shows the difference signal. Peak values in the green highlight the transitions. In still water, \((\tau_{P}, \tau_{F_y})\) is low and there is no correlation between the oscillator and the input signal; \(f_h\) follows the intrinsic frequency of the oscillator. In both KVS, we observe a significant increase in \((\tau_{P}, \tau_{F_y})\) and \((C_{P}, C_{F_y})\). The oscillator successfully synchronizes in frequency with the vortex shedding frequency. A higher \((\tau_{P}, \tau_{F_y})\) in the second KVS is to be expected as flow is faster. Once the engine is turned off, \((C_{P}, C_{F_y})\) and \((\tau_{P}, \tau_{F_y})\) decrease to the levels observed in still water.

5. Further scope of this research

We evaluate the performance of our approach across flow regimes and across the specific methods with which the filter is configured, characterizing its operational limits along the way (response time, adaptation rate and range of frequency adaptation). We also test the generalizability of the approach to multimodal flow-related data, acquired from flow/pressure sensors, CFD simulations and DPIV flow imaging. The rationale is that, if representative
Figure 1: The trends in hydrodynamic features of \((\tau_P, \tau_Fy), f_h\) and \((C_P, C_Fy)\) across flow regimes: still water (30 s), KS1 (60 s), KS2 (60 s) and still water (60 s). Our novelty detection mechanism compares the present values (blue line) with the values 7 s before (red line). The peaks on the difference signal (green line) highlight the transitions. We computed the features at each instant based on a 7 s observation window.

features of the phenomenon have indeed been captured, the method is applicable across sensing modalities. In this respect, the method paves the way for data fusion in hydrodynamic settings. Non-linear oscillators have already been successfully applied to autonomous locomotion [6]; there is potential to adapt our novelty approach as a component of sensory-motor mapping to govern the swimming gait of the robot in the presence of flow changes.

References