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Gradient-based machine learning control for the stabilization of the fluidic pinball and the open cavity experiment

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Abstract

We optimized control laws for stabilization of two shear flows: a DNS of a flow past a cluster of three rotating cylinders—the fluidic pinball—and the cavity flow experiment. The fluidic pinball is stabilized in increasingly reached control law spaces employing 9 sensors downstream and 3 actuators (the cylinders). As for the cavity, two regimes are controlled in single-input single-output manner: a single-mode driven regime and a mode-switching regime. Key enablers are automated machine learning algorithms augmented with gradient search: explorative gradient method for the open-loop parameter optimization and a gradient-enriched machine learning control (gMLC, [1]) for the feedback optimization. For both plants, the need of feedback for control is demonstrated. gMLC learns the control law significantly faster than previously employed genetic programming control both in DNS and experiment.

Keywords: Flow control; wake stabilization; fluidic pinball; machine learning control; cavity flow, gradient.

1. Introduction

Flow control is at the heart of many engineering applications. However, control design is challenged by the high-dimensionality, the inherent nonlinearities with many frequency crosstalks and time-delays between actuation and sensing. Hence, most closed-loop control studies of turbulence resort to a model-free approach. Genetic programming control (GPC), pioneered by Dracopoulos (1997) over 20 years ago, has been proven to be particularly successful for nonlinear feedback turbulence control in many experiments [2]. GPC has a powerful capability to find new mechanisms (exploration) and populate the best minima (exploitation). Yet, the exploitation is inefficient leading to increasing redundant testing of similar control laws with poor convergence to the minimum. This challenge is well known and is addressed in this study with a gradient augmented algorithm. The methodology is applied to two shear flows: a cluster of three rotating cylinders—the fluidic pinball—at Reynolds number $Re=100$ and the cavity flow for two regimes: a narrow-bandwidth and a mode-switching regime; the flow is forced with a DBD actuator and monitored by a hot-wire sensor.

2. Methodology

The control problem is formulated as an optimization problem where a cost function J characterizing the performance is minimized. The cost functions associated with the stabilization problems are: For the fluidic pinball, the residual fluctuation energy of the actuated flow field with respect to the symmetric steady flow. For the cavity, the PSD maximum peak for the streamwise velocity measured downstream plus an actuation penalization term. For both cases, the cost function J are values averaged over the whole evaluation time. The control objective is then to derive the optimal control law K^* that minimizes J :

$$K^* = \arg \min_{K \in \Lambda} J(K) \quad (1)$$

with Λ being the space of control laws and K a function of the plant's sensor signals. In general, equation (1) is a challenging non-convex optimization problem presenting, a priori, several local minima.

The employed algorithms are the Explorative Gradient Method (EGM) [3] for parametric optimization and the gradient-enriched Machine Learning Control (gMLC) for control law optimization. Starting point is machine learning control (MLC, [4]) based on linear genetic programming. The gradient-enriched version combines the evolutionary iterative process for exploration of the search space and intermediate gradient descent steps with downhill simplex to exploit local gradient information for a fast convergence towards the minima. The gradient-descent is performed in a subspace defined by the most performing control laws (Figure 1a).

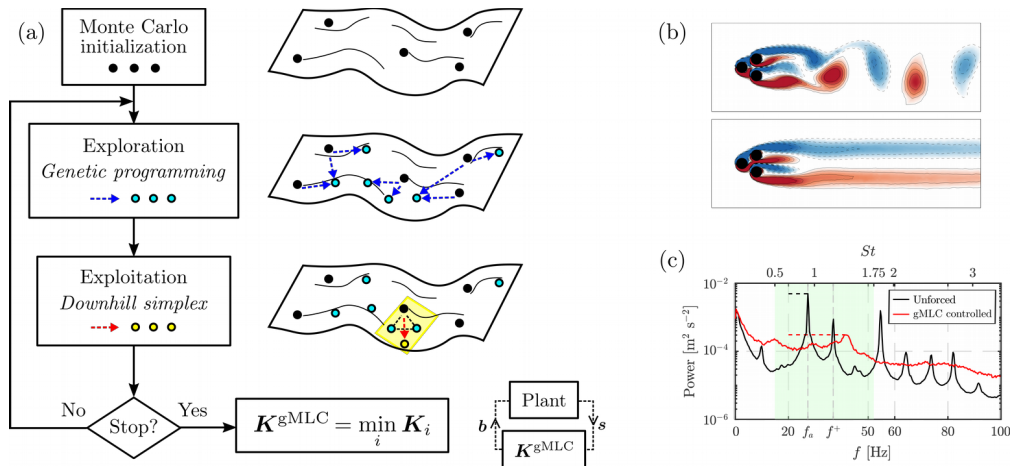


Figure 1 gMLC methodology and results. (a) gMLC algorithm steps and conceptual progress in the search space. (b) Fluidic pinball vorticity fields for the unforced flow (top) and the gMLC controlled flow (bottom). (c) PSD of the downstream velocity for the mode-switching regime of the cavity: unforced flow (black) and gMLC controlled (red).

3. Results and discussion

For the fluidic pinball, the control laws are optimized in three successively richer search spaces. First, stabilization is pursued with steady symmetric forcing, achieving a 51% reduction of the cost function. Second, we allow for asymmetric steady forcing, reducing the cost by 72%. And third, we determine an optimal feedback controller employing nine velocity probes downstream and reduces the cost by 80%. As expected, the control performance increases with every generalization of the search space. Surprisingly, both open- and closed-loop optimal controllers include an asymmetric forcing, which surpasses symmetric forcing. Intriguingly, the best performance is achieved by a combination of phasor control and asymmetric steady forcing. The resulting mean flow looks similar to the optimal asymmetric steady forcing (Figure 1b). For the cavity, first, steady forcing is employed to stabilize the two regimes, revealing that a strong enough blowing kills the main frequencies of the cavity and increases the background noise. Second, feedback laws are optimized reducing the cost by 98% for the narrow-bandwidth regime and 94% for the mode-switching regime (Figure 1c) and with less than 2% of the maximum actuation power. Expectedly, the law learned in the simpler regime is only able to partially control the complex one. Surprisingly, the law learned in the most complex regime is able to control even better the simpler regime than the law learned in the same condition. Finally, like for the fluidic pinball, the need of feedback has been demonstrated to be an essential feature to mitigate the oscillations of the cavity.

4. Conclusion

The presented stabilizations are expected to be independent of the employed optimizer. The chosen optimizers balance exploration (search for better minima) and exploitation (downhill descent of found minima). The search has been significantly accelerated both in DNS and by intermittently adding gradient-based descends. The resulting EGM and gMLC algorithms are proved to be efficient for both exploration and exploitation. Building on this success, we foresee that gradient-enriched MLC will greatly accelerate the optimization of control laws for MIMO control as compared to linear genetic programming control. Recent experimental applications of gMLC include successful drag reduction of a generic truck model under yaw and lift increase of a high-Reynolds number airfoil.

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