A Position Based Iterative Learning Control Applied to Active Flow Control

Zhonglun Cai, Peng Chen, David Angland and Xin Zhang

Abstract— **In this work, active flow control by using pulsed air jet was investigated in order to delay flow separation on a two-element high-lift wing. The method was validated experimentally. A novel iterative learning control (ILC) algorithm was presented which uses position based pressure measurements to update the actuation. The method was experimentally tested on the wing model in the 0.9 m $\times$ 0.6 m wind tunnel at the University of Southampton. Compressed air and fast switching solenoid valves were used as actuators to excite the flow and the pressure distribution was measured as a feedback control signal for the ILC controller. Experimental results showed that the actuation was able to delay the separation and increase the lift by approximately 20%. By using ILC algorithm, the controller was able to find the optimum control input and maintain the improvement despite sudden changes of separation position.**

NOMENCLATURE

c_f	Flap chord length
c_m	Main element chord length
e_k	Tracking error for k^{th} iteration
k	Iteration or trial number
L	Proportional learning gain
r	Reference signal
U_∞	Free stream velocity
u_k	Control input for k^{th} iteration
x_e	Position of actuation
y_k	Output for k^{th} iteration

I. INTRODUCTION

Active flow control technique has become more important in modern aerodynamic research and aircraft design phase. During take-off and approach-to-landing phases of aircraft operation, high-lift devices, e.g. slats and flaps, are often deployed to provide extra lift. Under changeable oncoming flow condition and configurations, flow separation could appear, with detrimental effect on performance, e.g. lift loss and noise emission. Control of flow separation on high-lift devices such as flaps is therefore an important topic of research. Over the recent years, active flow control techniques have attracted increased attention in aerodynamic flow control application [1]. In the current study, we study the active control of flap flow separation on a two-element wing configuration. The aim is to avoid and/or attenuation the turbulent flow separation on the suction surface of the flap at a deployed flap angle. There were a number of investigations on active flow control of airfoil and wing flows using different approaches. It was experimentally demonstrated that periodic excitation on a single airfoil is effective to delay boundary layer separation [1], [2], [3]. It has been shown by using alternative blowing and suction through a span-wise oriented small slot is able to enhance shear layer mixing and transfer high momentum flow from the shear layer to the wall, thus preventing boundary layer separation. Furthermore the method increases the overall lift as the separation position is shifted towards the trailing edge of the airfoil. As an important area of interest, active control of flow separation can be useful in many other applications of fluid dynamics research. For example, methods of active control have been used for jet vectoring [4], [5], engine performance improvement [6], [7], and wing tip/flap side edge vortex breakdown control [8].

Zhonglun Cai, Peng Chen, David Angland and Xin Zhang are with Aeronautics, Astronautics and Computational Engineering, Faculty of Engineering and the Environment, University of Southampton, Southampton, SO17 1BJ, UK.

Corresponding authors: Zhonglun Cai (`z.cai@soton.ac.uk`) and Xin Zhang (Airbus Professor of Aircraft Engineering, Airbus Noise Technology Centre, `xzhang@soton.ac.uk`)

Motivated by human learning activities, iterative learning control (ILC) is a technique for controlling systems operating in a repetitive (or pass-to-pass) mode with the requirement that a reference trajectory $r(t)$ defined over a finite interval $0 \leq t \leq T$ is followed to a high precision. It uses the tracking error information from previous trials to update the control input for the next iteration, and by repeating this process iteratively, a perfect or desired control input can be learnt. Examples include robotic manipulators that are required to repeat a given task, chemical batch processes or, more generally, the class of tracking systems. Since the original work on ILC [9], the general area of ILC has been the subject of intense research effort. Initial sources for the literature are the survey papers by Bristow et al. [10] and Ahn et al. [11]. Since the basic ILC algorithms do not need any information of the plant model which benefits the flow control process as it is very difficult to obtain an accurate mathematical model because there are too many configuration parameters and each of them can lead to very large difference. Although other control techniques have been tried and found effective, for example, extremum seeking method [12], the focus on this paper is on using a novel ILC algorithm only.

The application of ILC algorithms on aerodynamic research or active flow control area is new and novel. In this study, a positional based iterative learning control algorithm is employed, which uses the surface pressures alongside the wing and flap surface to update the actuation, in order to maximise the improvement of lift and delay boundary layer separation. The ILC algorithm is also able to minimise the energy consumption of the actuators.

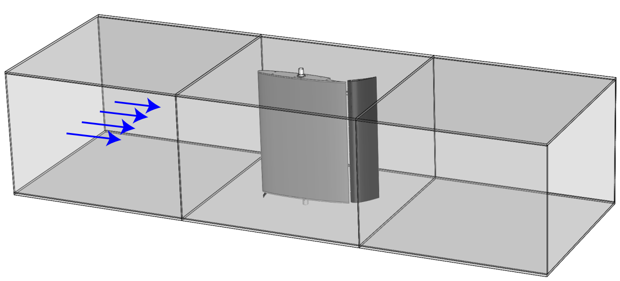
II. Experimental Facilities

A. Wind tunnel

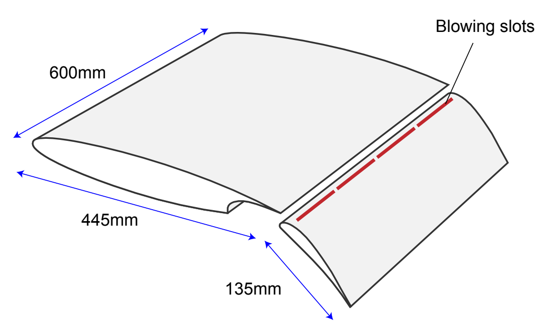
The experiments were conducted in the University of Southampton 0.9 m $\times$ 0.6 m low speed wind tunnel. The tunnel has an open loop circuit with a closed cross section of 4 m in length. The freestream turbulence was less than 0.2 % at the maximum tunnel speed of 25 m/s. The baseline test conditions were defined as a freestream velocity of 20 m/s, corresponding to a Reynolds number of 5.5 $\times$ 10^5 based on the chord of the retracted configuration. The exact separation on the high-lift device i.e. the flap is sensitive to how the flow is tripped. In order to obtain the correct flow conditions, the boundary layer was tripped to ensure the boundary layer was turbulent before it separated from the flap.

B. High lift wing model

The wing model used here is a two-element high-lift configuration consisting of a main element and a trailing edge flap. It is an 80% scaled version of the DLR F15 wing model. The chord length in clean cruise condition is $c_m = 445mm$ and the span is 600mm. Figure 1 shows the diagram of the wing model mounted in the wind tunnel as well as the dimensions. A set of holes with 2 degree between each other are placed on both end plates for enabling the angle of attack to be changed from 0 to 12 degrees. A set of adjustable brackets are made to enable tuning of the flap gap and overlap as the flap gap and overlap are crucial parameters in determining the flow separation on the flap.



(a)



(b)

Fig. 1. (a) Wing model mounted in wind tunnel, (b) Wing model dimension

C. Actuators

There are 4 actuator segments designed and positioned alongside the span of the wing model. Each segment is approximately 120mm wide and includes a FESTO MHE2 series fast switching solenoid valve and a chamber. All segments are supplied with high pressure compressed air. The valves are supplied with a high frequency periodic pulse signal at the desired frequency and the duty cycle of the pulse can be tuned as a control input. The position of the excitation is located at $x_e/c_f = 0.1$ on the upper side of the flap. The jet direction is normal to the surface. Figure 2 shows the actuator setup inside the model. Because of the limited space in the flap, the fast switching valves are mounted inside the main element and connected to the chamber inside the flap. Since the connecting tube is short, the frequency and strength of pulsed jet can be maintained.

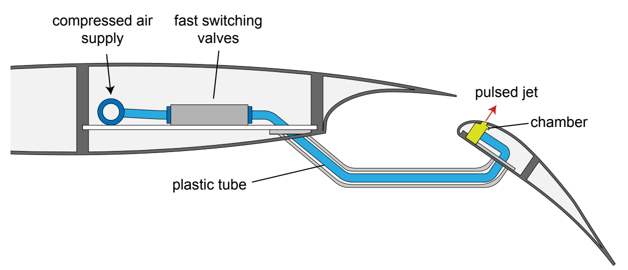


Fig. 2. Diagrams of the actuator setup inside the wing model

It is found experimentally that tuning the duty cycle (pulse width) of the switching pulses for the valves is able to change the effect of the flow excitation. To maximise the improvement, feedback control is needed with tuning of the duty cycle as control input. Figure 3 shows the pulses which are fed into the actuators and the response which are measured by using hot wires at the exit of a blowing slot.

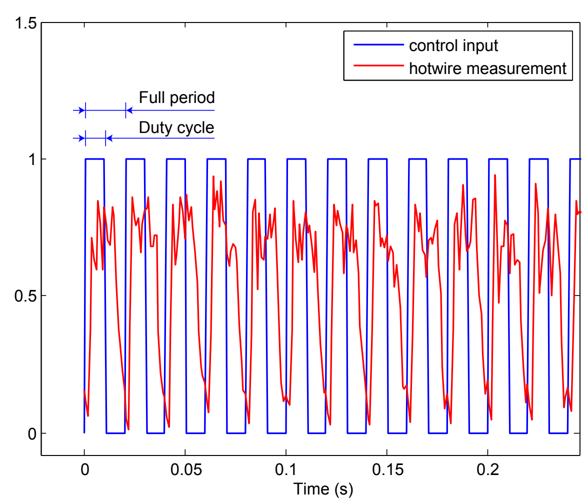


Fig. 3. Pulses input and the hot wire measurement

D. Pressure scanner

A total of 20 pressure taps are placed on the suction and pressure surfaces of the flap on the centre line of the span. The pressure taps are connected to a Scanivalve ZOC33 pressure scanner by using tubes with an inner diameter of

1.98mm. The length of the connecting tubes are less than 1m long in order to maximise the response that the pressure scanner can obtain. The particular pressure scanner has a very high scanning rate of 40kHz, so over the used 20 channels, the maximum scanning frequency can be 2kHz. In the tests, a scanning frequency of 100Hz is used to ensure that there are multiple points can be measured and averaged for better quality.

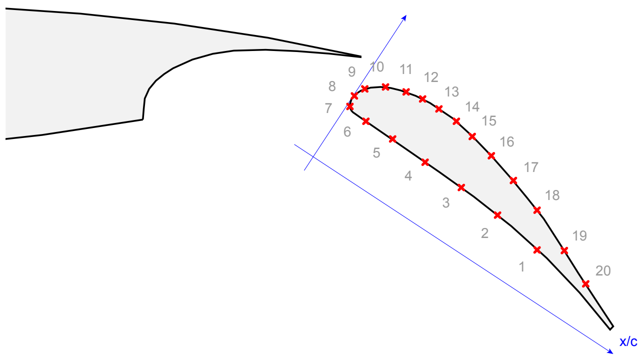


Fig. 4. Pressure taps positions on the flap surface

In the study, two-dimensional flow control is considered as the pressure measurements are taken from the centre line of the wing model span. All 4 span-wise of actuators are using the same control input.

E. Experimental Setups

A number of tests were conducted in the wind tunnel. The control of actuators and pressure measurements were completed by a dSPACE (DS1006) system with multi-channel A/D and D/A boards. Table I shows the configuration that was used to obtain all experimental results.

TABLE I
CONFIGURATION USED IN THE WIND TUNNEL TESTS

Parameter	**Value**
Free stream velocity	20 m/s
Angle of attack α	2°
Flap deflection δ_f	40°
Flap gap	13.0 mm
Flap overlap	3.5 mm
Blowing pressure	4 Bar
Blowing frequency	20 Hz

III. OPEN LOOP CONTROL

Open loop studies were conducted to test the controller with a series of fixed control inputs. The open loop tests were conducted in order to make sure the actuators were working in the area that improvement could be obtained and that also it was able to setup the reference for ILC algorithm by using the open loop test results. Each test with one fixed control input lasted a duration of 10 seconds in order to ensure enough data will be measured and all pressure measurements can be averaged. Figure 5 shows two sets of results, each includes the pressure measurements using different duty cycles ranging from 10% to 80%. The improvement of lift can be seen by comparing to the results without any actuation. The flow separation appeared at around 20% of flap chord and it was shifted downstream towards the trailing edge of the flap. It was found out in [3] and [13] that there was not too much influence of the jet frequency on the performance of actuation. Therefore in the current study only one frequency of excitation was tested.

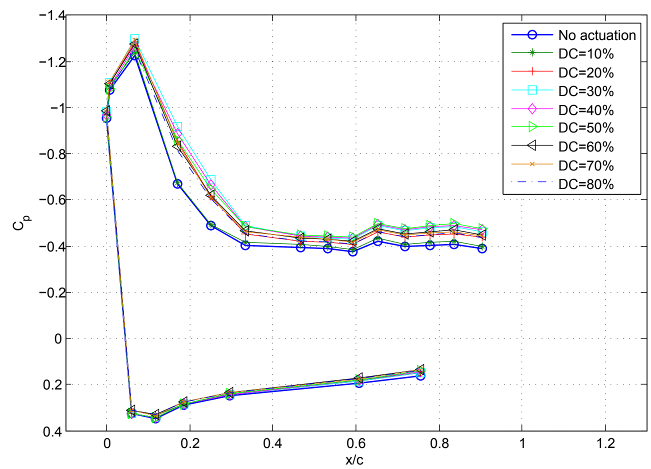


Fig. 5. Pressure measurements from open loop tests

The relationship between the lift improvement and the control input are shown in Figure 6. It is obvious that there are optimum duty cycle between 20% and 30%. The aim of the ILC controller is to find the optimum control input accurately and keep the performance.

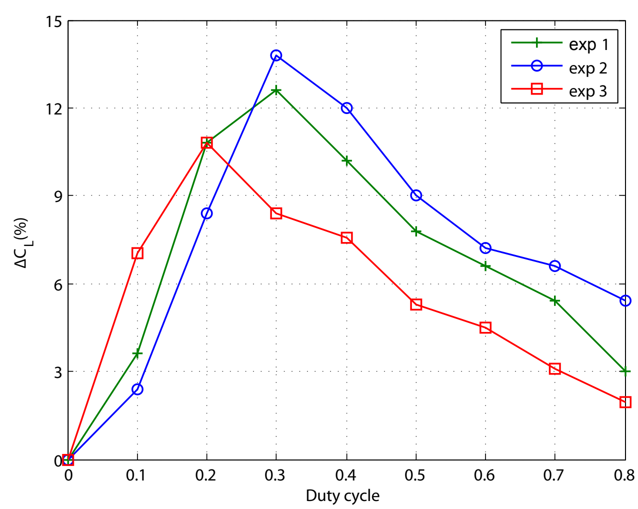
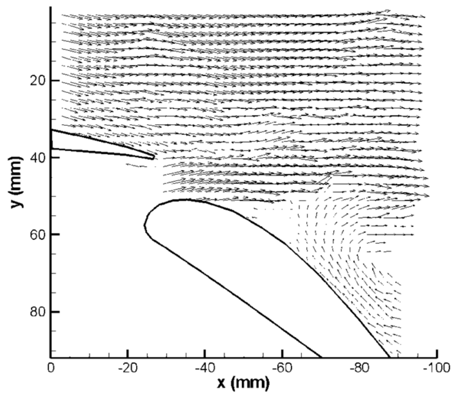
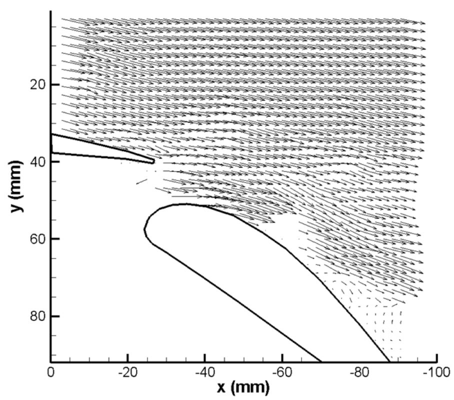


Fig. 6. Improvement vs duty cycle

Particle image velocimetry (PIV) tests were also conducted as well to verify the effects of the actuation. Figure 7 shows the comparison of flow with and without the actuation. Clearly, with the actuation, the flow was attached so that separation was delayed.



(a) Baseline



(b) Actuation ON

Fig. 7. Velocity fields around the flap measured by PIV

IV. Iterative Learning Control

A. Position based ILC

The fundamental algorithm of iterative learning control given by Arimoto et al [9] was a continuous time derivative type (D-type) ILC which uses the derivatives of the tracking error with a learning gain to update control input. It can be written as:

$$u_{k+1}(t) = u_k(t) + L\dot{e}_k(t), 0 \leq t \leq T \tag{1}$$

where k denotes the iteration number (or trial number), $u_k(t)$ is the control input for the k^{th} iteration. L can be a simple gain or a vector or a matrix depending on different sub algorithms. $e_k(t)$ is the tracking error of the k^{th} iteration and

$$e_k(t) = r(t) - y_k(t)$$

where $y_k(t)$ denotes the measured output of k^{th} iteration. Theoretically, $e_k(t)$ will converge to zero where the trial number k approaches infinity, and at the mean time $u_k(t)$ converges to a constant value or vector $u_d(t)$, the ideally desired input for the plant to produce the reference output $r(t)$. That is also the numerical solution to the plant model with the given reference if it can be described by a mathematical equation. The algorithm is later simplified into a proportional type (P-type) ILC by Arimoto et al [14] because the derivatives sometimes bring uncertainty and would make the learning process unstable especially with the discrete measurement when there is noise inherently in the signal.

$$u_{k+1}(t) = u_k(t) + Le_k(t) \tag{2}$$

Figure 8 shows the block diagram of the normal ILC process.

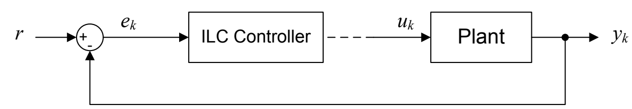


Fig. 8. Block diagram of basic ILC algorithm

In this work, t is the time step and T represents the finite time interval. All signals in the setup are time based or sample based in the case of discrete time. Now the time step t can be replaced with p — a position index of measurement alongside the chord length of the flap (as shown in Figure 4). Therefore within the trial, the controller will scan all the positions and get the pressure measurements as plant output $y_k(p)$. The error $e_k(p)$ is still the difference between the reference $r(p)$ and the output. Hence the ILC law will become:

$$u_{k+1}(p_u) = u_k(p_u) + Le_k(p_y) \tag{3}$$

where p_u and p_y are the positional indexes of the control input and output, respectively. Here it is not necessary for the control input to have one-to-one mapping with the output and the tracking error. Since there is only one actuator placed along the chord length in this particular configuration, the l_2 norm of the error is used to update of the control input iteratively. Thus the ILC updating law can be written as:

$$u_{k+1} = u_k + L||e_k(p)|| \tag{4}$$

where L is the learning gain and it can be tuned to alter the converge speed.

The measurement of one trial will collect all the static pressure data on the flap surface for a fix duration and at each point the measurements will be averaged. Therefore all the measurement should be a steady state measure of the flow behaviour. At this stage, no time dynamic is considered because the generation of turbulent flow is considered random, so that time dynamic on a fix point is not useful and important for the controller to control the overall flow separation.

B. Reference signals

The reference signal is one of the essential conditions that ILC requires to perform. However, unlike the typical tracking control problem (e.g. robot arms trajectory control), the controller here is used to maximise the improvement of the actuation. From the results of the open loop control study, it is known that at a certain duty cycle range, the improvement can be maximised. The maximum results from the open loop tests can be used for the reference signal and an additional offset was added on the top of the reference to ensure the controller was able to maximise the improvement. Figure 9 shows an illustration of the pressure measurement and the defined reference. In this case an extra algorithm is

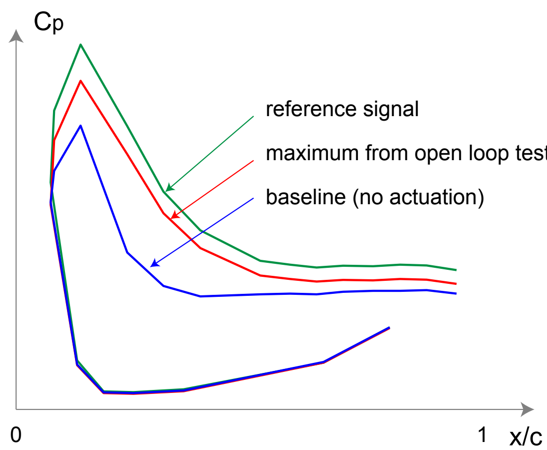


Fig. 9. Reference signal defined by the maximum output from open loop tests.

developed to enable the convergence

$$u_{k+1} = u_k + D_k \cdot L \cdot ||e_k(p)|| \tag{5}$$

where D_k refers to the direction of learning at the kth iteration, and

$$D_k = \begin{cases} D_{k-1}, ||y_k|| > ||y_{k-1}|| \\ -D_{k-1}, ||y_k|| < ||y_{k-1}|| \end{cases} \tag{6}$$

where the initial direction $D_0 = 1$.

Since the reference r is set to beyond the reach of plant output y_k as

$$\lim_{k\to\infty} y_k < r$$

The computed error is not able to converge to zero.

$$\lim_{k\to\infty} e_k \to r - y_{max}$$

Therefore if the normal ILC setting in either (1) or (2) was used, the learnt input would not be bounded with a fixed positive learning gain L as

$$\lim_{k\to\infty} u_k = \lim_{k\to\infty} (u_{k-1} + L \cdot e_{k-1}) \to \infty$$

This means the control input will be unstable and no optimum input can be learnt to maximise the improvement.

The learning direction is defined in (6) because there exists an ideal input u_d where the maximum output can be obtained. Initially the controller will make u_k converge towards u_d. When the learnt input u_k is greater than u_d, the output is going away from the optimal values, therefore the controller needs to change its direction. And with a carefully selected learning gain L, although the reference r can not be reached, the output y_k is converging towards the maximum value y_{max}.

C. Experimental results

The ILC controller is tested using a learning gain $L = 0.2$. The iteration length T is set to 5 seconds in order to get enough data for accurate pressure measurements. Figure 10 shows the pressure measurement of 100 completed iterations in one set of results. Figure 11 shows the improvement along the iterations. Here the term ΔC_L is computed by using integration of the pressure coefficients C_P in each trial. The pressure distributions are significantly improved comparing to the one without any actuation. At the 94^{th} and 95^{th} iterations there appeared to be some sudden flow separation, however, the controller reacted and recovered an optimum within 2 trials. After only 5-10 iterations, the improvement of lift can be maintained at between 10% - 15% all the time throughout the test except for the sudden change of separation. This reflected the performance and robustness of the ILC controller.

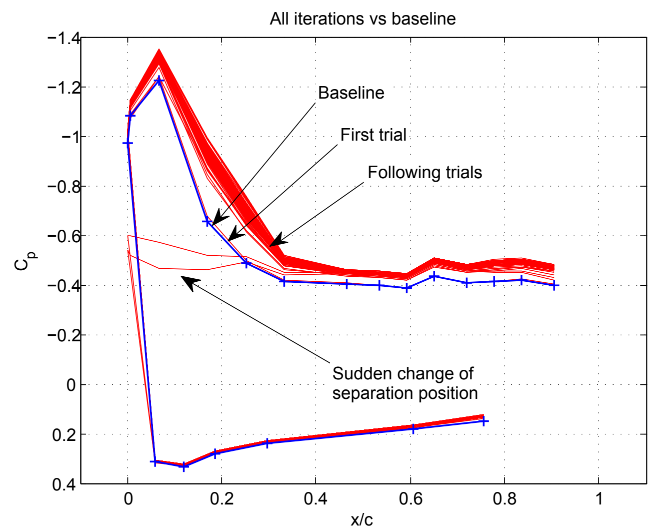


Fig. 10. Pressure distribution of all 100 iterations in one experiment.

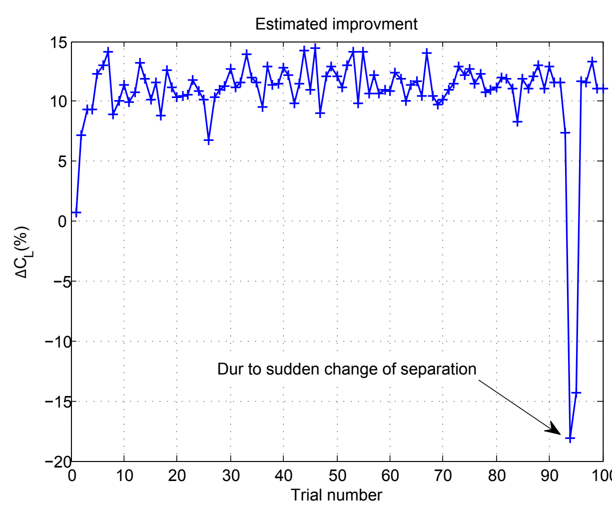


Fig. 11. Improvement over 100 iterations in one experiment.

Figure 12 shows the recorded control inputs over all iterations. The learning process in the initial iterations is clearly visible. The benefit from the actuation is obvious as shown in Figure 13, where the best output are selected and overlapped. The best results from a series of tests are very similar even though some of the control parameters were different. The parameter tuning affects only the overall performance of the control. Using larger learning gain will not only increase the convergence speed but also the fluctuation of the input around the optimum value. Using smaller learning gains will slow down the learning progress. The trial length will affect on measurement accuracy as a shorter trial makes the controller respond faster but degrade the measurement accuracy.

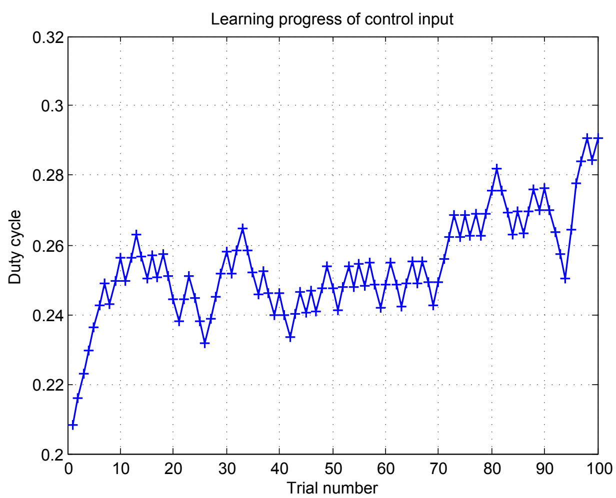


Fig. 12. Control inputs evolution for all 100 iterations.

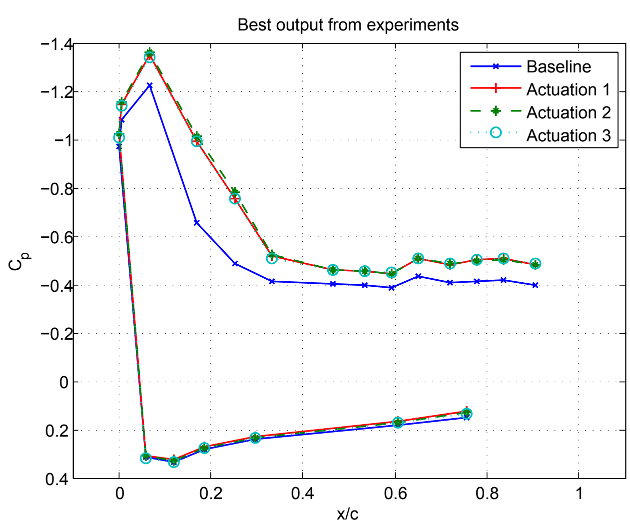


Fig. 13. Benefit of the actuation.

V. Summary and Future Work

The paper presented an iterative learning control algorithm with the aim to use the periodic blowing at 10% chord length from the leading edge of the flap to excite the flow and delay flow separation. A conventional ILC algorithm has been modified by replacing the time stamp with a set of position indices. During each iteration, the controller scans all positions and obtains the surface pressure measurement. A reference was set by using the results from open loop results. ILC controller uses the difference between reference and output to update the control input iteratively. The method is implemented and tested on a two-element wing model with a flap, mounted in a low speed wind tunnel. The results show that significant improvement was achieved and the ILC controller is able to keep the performance even with sudden change of separation.

Future work will include more data measurements, such as pressure distribution on the main element, lift and drag coefficients, lift-to-drag ratio, etc. Moreover, more ILC control algorithms are yet to be tested and compared to other approaches.

References

[1] D. Greenblatt, D. Neuburger, and I. Wygnanski, "Dynamic stall control by intermittent periodic excitation," *Journal of Aircraft*, vol. 38, no. 1, pp. 188–190, 2001.

[2] A. Nishri and I. Wygnanski, "Effects of periodic excitation on turbulent flow separation from a flap," *AIAA Journal*, vol. 36, no. 4, pp. 547–556, 1998.

[3] R. Petz and W. Nitsche, "Active separation control on the flap of a two-dimensional generic high-lift configuration," *Journal of Aircraft*, vol. 44, no. 3, pp. 865–874, 2007.

[4] L. G. Pack and A. Seifert, "Periodic excitation for jet vectoring and enhanced spreading," *AIAA Paper 99-0672*, Jan 1999.

[5] B. L. Smith and A. Glezer, "Jet vectoring using synthetic jets," *Journal of Fluid Mechanics*, vol. 458, pp. 1–34, 2002.

[6] W. K. Lord, D. G. MacMartin, and T. G. Tillman, "Flow control opportunities in gas turbine engines," *AIAA Paper 00-2234*, June 2000.

[7] D. E. Culley, M. M. Bright, P. S. Prahst, and A. J. Strazisar, "Active flow separation control of a stator vane using surface injection in a multistage compressor experiment," *NASA TM-212356*, 2003.

[8] D. Greenblatt, "Management of vortices trailing flapped wings via separation control," *AIAA Paper 05-0061*, Jan 2005.

[9] S. Arimoto, S. Kawamura, and F. Miyazaki, "Bettering operations of robots by learning," *Journal of Robotic Systems*, vol. 1, pp. 123–140, 1984.

[10] D. A. Bristow, M. Tharayil, and A. G. Alleyne, "A survey of iterative learning control a learning-based method for high-performance tracking control," *IEEE control systems magazine*, vol. 26, no. 3, pp. 96–114, 2006.

[11] H.-S. Ahn, Y. Chen, and K. L. Moore, "Iterative learning control: brief survey and categorization 1998–2004," *IEEE Transactions on Systems Man and Cybernetics Part C*, p. In Press, 2007.

[12] R. Becker., R. King, R. Petz, and W. Nitsche, "Adaptive closed-loop separation control on a high-lift configuration using extremum seeking," *AIAA Journal*, vol. 45, no. 6, pp. 1382–1392, 2007.

[13] F. Haucke, I. Peltzer, and W. Nitsche, "Active separation control on a slatless 2d high-lift wing section," Anchorage, Alaska, USA, September 2008.

[14] S. Arimoto, F. Miyazaki, S. Kawamura, and S. Tamaki, "Learning control theory for dynamical systems," in *Proceedings of the 24th Conference on Decision and Control*, Fort Lauderdale, Florida, 1985, pp. 1375–1380.