# A Comparison of two Adaptive Control Architectures for Disturbance Canceling

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*Abstract :* - Adaptive control is often used to control systems subject to unknown external disturbance and whose parameters may be uncertain and/or time-varying. In this paper, two adaptive control architectures, featuring both real time plant modeling and disturbance canceling, are compared. The two adaptive control architectures include (a) self-tuning regulator and (b) plant disturbance canceler with two methods for controller tuning and three dithering schemes for plant identification. A linear mass-spring-damper system of two DOF is chosen for comparing performances of these adaptive control systems for vibration isolation. Numerical simulation results show that the self-tuning regulator outperforms the plant disturbance canceler in terms of much faster convergence rate and much more amount of vibration isolated.

Key-Words: self-tuning regulator, plant disturbance canceler, recursive least square, filtered-x LMS Proc.pp..1441-1448

### **1** Introduction

Feedback control with a fixed controller has been of popular interest for a long time and its successful applications can be found in a wide variety of engineering disciplines. The controller is usually designed based on the model of the controlled process (plant) and known operating conditions. However, control with a fixed controller may not always give satisfactory performance as is designed. The difficulty arises because of the possible changing properties of controlled processes and their signals, parameter uncertainty, and/or existence of Adaptive control is unknown disturbances. therefore needed in such systems to modify their behavior in accordance with the aforementioned An adaptive control system is conditions. characterized by the two complementary processes of identification and control. In the process of identification a suitable model is developed online that exhibits the same input/output characteristics of the controlled process. Based on the identified model and control/performance objective, the controller is updated and a control action is generated and tested on the plant in the control process. In other words, the adaptive control system can be viewed as an automation of plant modeling and controller design, in which the plant model and controller are updated at each sampling period.

In this paper two types of adaptive control architectures are to be compared for disturbance canceling of a disturbed system with uncertain and/or time-varying parameters. More specifically, the adaptive control system should perform two functions: it learns about the controlled process online whilst, at the same time, controlling its behavior (disturbance canceling in this case). Among the various types of adaptive control architectures that can do the job are the self-tuning regulator (STR) of Astrom and Wittenmark [1,2] and the adaptive plant disturbance canceler (PDC) derived from Widrow and Walach [9] and Shaw [7]. The self-tuning regulator is the best-known and most popular adaptive control method, which is just a direct integration of an identification and a controller design algorithm in such a manner that the two processes proceed sequentially. The adaptive plant disturbance canceler has various forms of structures due to the three dithering schemes for real-time plant identification and an offline (Widrow and Walach [9]) and an online (Shaw [7]) process for the controller tuning. Though the adaptive PDC has a quite different control architecture as the STR, it functions much the same as the STR, i.e., real-time plant modeling and disturbance canceling. Therefore it is of interest to compare performances of the two adaptive control systems in canceling the plant disturbance.

The paper is organized as follows: in the next section the self-tuning regulator and adaptive plant disturbance canceler are briefly introduced. Adaptive algorithms for real-time controller tuning (offline and online) and plant modeling are also given, where three dithering schemes for online plant identification of the PDC are employed. In the third section both adaptive control architectures are evaluated for vibration isolation of a linear mechanical system by numerical simulations. Conclusions of the paper are presented in the fourth section.

## 2 Self-Tuning Regulator and Plant Disturbance Canceler

In this paper, a linear system disturbed by an unknown external disturbance d(t) and controlled by an actuating signal u(t) with uncertain-but-fixed system parameters is considered. The two adaptive control architectures are employed for plant disturbance canceling. Figure 1 depicts the first adaptive control architecture employed for disturbance canceling, which is a generic diagram of the self-tuning regulator of Astrom and Wittenmark [1,2]. The STR works in the following way. The plant output y(t) contains a response to input u(t), plus a response to plant disturbance d(t). A plant estimator, receiving both the signal input and signal output of the plant, estimates the plant parameters. These estimates are then fed to an automatic design algorithm that sets the parameters of the controller. Note that many different identification schemes have been used. Among these the recursive leastsquares (RLS) [5] algorithm has proved to be the most useful and practically successful self-tuning Note also that it is possible to identifier. parameterize the plant directly in terms of the control law parameters. If this is done, the design calculation necessary to determine the control law becomes essentially trivial. That is, a direct adaptive algorithm is adopted.

In this paper, the plant is described by an ARMAX model [5] (i.e., a stochastic auto-regressive moving-average model) whose output is, in the discrete-time domain,

$$\hat{y}(t) = \phi(t-1)^T \theta(t-1)$$
 (1)

Note that

$$\theta(t-1) = [\alpha_1(t-1), ..., \alpha_n(t-1), \beta_1(t-1), ..., \beta_m(t-1)]^T (2)$$

and

$$\phi(t-1) = [y(t-1), \dots, y(t-n), u(t-1), \dots, u(t-m)]^T \quad (3)$$

are the estimated system parameter vector and regression vector composed of the selected plant output and input variables, respectively. The RLS algorithm for plant parameter estimation is adopted as follows:

$$\theta(t) = \theta(t-1) + \frac{P(t-2)\phi(t-1)}{1 + \phi(t-1)^T P(t-2)\phi(t-1)} [y(t) - y(t)]$$

$$P(t-1) = P(t-2) - \frac{P(t-2)\phi(t-1)\phi(t-1)^{T}P(t-2)}{1+\phi(t-1)^{T}P(t-2)\phi(t-1)}$$

(4)

with initially

$$P(-1) = \delta I, 0 < \delta < \infty.$$
<sup>(5)</sup>

For the controller of the STR, the minimum variance controller [3] is adopted. The basic idea behind the controller is to form an adaptive prediction of the plant output and then to determine the input by setting the prediction output equal to the desired output. This is essentially the same philosophy as the one-step-ahead controller. For the one-step-ahead controller, the control law based on minimum variance is

$$\phi(t)^T \theta(t) = y^*(t+1),$$
 (6)

from which the control input is obtained:

$$u(t) = \frac{1}{\beta_1(t)} [y^*(t+1) - \alpha_1(t)y(t) - \dots - \beta_2(t)u(t-1) - \dots]$$
(7)

The desired output  $y^*(t)$  is of course identically zero if disturbance canceling is desired. Note that there is a remote possibility of division by zero in Eq. (7), which can be avoided by imposing constraint on the size of  $f_1(t)$ . This is done as follows, with knowledge of the sign and lower bound on the magnitude of  $f_1$ :

$$\beta_1(t) \operatorname{sign} f_1 < |\beta_1|_{\min} \tag{8}$$

then

$$\beta_1(t) = | f_1|_{\min} \operatorname{sign} \beta_1.$$
(9)

Another important practical point is that the control input in Eq. (7) can call for large input signal due to any large change in system parameters or in  $y^*(t)$ . In this case, the control law can be modified as follows:

If 
$$u(t) > u_{\text{max}}$$
, then  $u(t) = u_{\text{max}}$  (10)  
If  $u(t) < u_{\text{min}}$ , then  $u(t) = u_{\text{min}}$  (11)

where  $u_{\text{max}}$  and  $u_{\text{min}}$  are the specified maximum and minimum input levels.

Another adaptive control architecture that can cancel plant disturbance is the plant disturbance canceler by Widrow and Walach [9], as shown in Figure 2. Online plant modeling is achieved by introducing an external dither  $\delta(t)$  to the system and controller tuning is accomplished by an offline adaptive algorithm (requiring another dither signal). Widrow and Walach have shown that no other linear system, regardless of its configuration, can reduce the variance of the plant disturbance to a level lower than that of Figure 2. In fact, it can be readily shown [7] that the transfer function from disturbance d(t) to system output response y(t) is identically zero if the plant model and controller exactly match the plant actuation dynamics (from u(t) to y(t)) and its inverse, respectively. More specifically, the system output response subtracted from the plant model output represents response of the system due to disturbance only. By utilizing this response, the controller is then used to compute the negating force u(t) to negate effects of the disturbance on the system. Complete plant disturbance canceling is thus achieved.

There are, however, other forms of adaptive plant disturbance canceler due to the three dithering schemes for plant modeling [9] and an online controller tuning method [7]. These are shown in Figures 3-5, which are just the combinations of the three dithering schemes for plant modeling [9] and the online controller tuning method of filtered-x LMS algorithm [7]. Of the three dithering schemes for plant modeling, scheme A (see Figure 3) has the simplest form which is effective when the controller output is a stationary stochastic process and the independent dither is added to achieve a desired spectral character for plant input u(t). However, when the controller output is nonstationary (which is truly the case with the adaptive plant disturbance canceler architecture), one may be better off not including it at all in the plant modeling process. This is when dithering schemes B and C (see Figures 4 and 5) come to play, both of which using dither exclusively in effecting the adaptive plant modeling process. The purpose is to assure known stationary statistics for the input modeling signal. Using scheme B with a white dither, the mean square error will be minimized when the impulse response of the adaptive plant model exactly matches that of the plant over the duration span of the model's impulse response. Note that dithering scheme B has larger minimum mean square error at the adaptive plant model output than scheme A has, due to the additional power of the controller output after propagating through the plant. To compensate for this power, an extra plant model with controller output as the input signal needs to be included, as shown in scheme C. Scheme C thus has all the good features of scheme B and overcomes the drawback of having an increased minimum mean square error, with the cost of a somewhat increased system complexity.

To have a common base for the purpose of comparing the two adaptive control architectures, the plant model in the adaptive plant disturbance canceler of Figures 2-5 is chosen the same as in the STR with the same number of auto-regressive (n) and moving-average (m) coefficients. In addition, the RLS algorithm of Eqs. 4 and 5 is also used for tuning its coefficients online. For the controller model in the plant disturbance canceler, a finite impulse response (FIR) filter with length  $\ell$  is The usual least mean square (LMS) adopted. algorithm [6] is used for offline tuning the controller weights in Figure 2, while the filtered-x LMS algorithm is employed online in Figures 3-5 which has the following weights updating algorithm [7]:

$$g_{j}(t) = g_{j}(t-1) + \eta(y^{*}(t) - y(t))x(t-j), \quad j=0, 1, ...,$$
  
 $\ell - 1$  (12)

where  $\eta$  is a learning rate controlling the rate of convergence of the adaptive algorithm.

#### **3** An Example for Vibration Isolation

A linear mass-spring-damper system with an attached active dynamic isolator [8] is taken as the plant under study and is shown in Figure 6. An

unknown external disturbance d(t) applies at the main mass of the system and causes vibratory oscillation at the secondary mass. The attached mass-spring-damper-actuator system acts as a vibration isolator if the control goal is to minimize the vibrational amplitude at y(t), namely, the undesirable vibration originated from the main mass is isolated from reaching to the secondary mass. The power source injected into the actuator for providing control force can be either hydraulic or electromagnetic power source. For numerical simulations of the system, the following parameters are assumed:

$$m1 = 1, m2 = 0.2, k1 = k2 = 1, b1 = b2 = 0.1$$
 (13)

For the plant model, an ARMAX model with n = m = 11 is taken in both adaptive control architectures. An FIR filter with  $\ell = 150$  is chosen as the controller model in the adaptive plant disturbance canceler. The sampling period set at  $\Delta T = 0.05$  second and the unknown disturbance d(t) for the first mode excitation are used for all the following numerical simulations for disturbance canceling. Note that zero initial coefficients (or weights) for the plant and controller models are adopted in accordance with the presumed uncertain system parameters.

The two adaptive control architectures of Figures 1-5 are employed for vibration isolation of the system. Figure 7 to Figure 11 are the corresponding results for vibration isolation. It is clearly seen that the STR of Figure 1 has the fastest convergence rate for disturbance canceling, while the PDC of Figure 2 has the worst performance. Note also that dithering schemes B and C have better overall performances over scheme A in the PDC, as clearly seen in Figures 9-11. This is due to the fact that the controller output is nonstationary resulting in ineffective plant modeling for dithering scheme A. Table 1 summarizes the final amounts of vibration amplitude isolated from reaching to the second mass of the five adaptive controllers at the end of 10,000 time-steps running.

Table 1: vibration isolations

STR	PDC	PDC	PDC	PDC
Fig. 1	Fig. 2	Fig. 3	Fig. 4	Fig.5
99.9%	37.4%	76.5%	92.2%	88.2%

### 4 Conclusion

In this paper the STR and the adaptive PDC are evaluated for plant disturbance canceling of a

disturbed system with uncertain-but-fixed system parameters. It is noted that the two adaptive control architectures can also be applied to a time-varying system since both plant modeling and controller tuning can be carried out online in a real-time scale. From numerical simulations of the mechanical vibration system, the STR outperforms the adaptive PDC in terms of much faster convergence rate and much more amount of vibration isolated. For the adaptive PDC, online fine-tuning of the controller with the filtered-x LMS algorithm seems superior than using the offline tuning process by the direct LMS algorithm. The reason is that the online filtered-x LMS algorithm aims to directly minimize the plant output for disturbance canceling, while the offline process for tuning the controller aims to converge to the inverse plant model. For the plant modeling process, dithering schemes B and C, having somewhat complex though system configuration, improves on scheme A for the case when the controller output is nonstationary. For the example studied, the adaptive PDC of Figure 4 with the filtered-x LMS algorithm for controller tuning and scheme B for plant modeling gives the best performance over other PDC configurations. Such online controller tuning by the filtered-x LMS algorithm and plant modeling by scheme B had also been successfully employed by Eriksson and Allie [4] for active noise control in a duct in a feedforward control configuration.

Finally, it should be point out that the adaptive PDC can obtain the least variance of the plant disturbance than any other linear system (as has been verified by Widrow and Walach [9]), regardless of its configuration including the STR. For instance, if system identification of the actuator dynamics (the plant model) has been conducted beforehand by the ARMAX model using least square method (see Yang, et al. [10] for example) and if the adaptive tuning is applied only to the controller in the PDC, Figure 12 shows the resulting vibration isolation of the PDC (and STR for comparison). It is clearly shown that, though the PDC has a much slower convergence rate at the beginning of simulation than the STR, it has however much reduced variance of the disturbance in the long run.

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Fig. 1 The STR control architecture.



Fig. 3 The PDC with online controller tuning and scheme A



Fig. 4 The PDC with online controller tuning and scheme B



Fig. 2 The PDC with offline controller tuning and scheme C



Fig. 5 The PDC with online controller tuning and scheme C



Fig. 6 A mass-spring-damper system.



Fig. 7 Vibration isolation by STR.

Fig. 8 Vibration isolation by PDC with Figure 2 architecture.

Fig. 9 Vibration isolation by PDC with Figure 3 architecture.

Fig. 10 Vibration isolation by PDC with Figure 4 architecture.

Fig. 11 Vibration isolation by PDC with Figure 5 architecture.

Fig. 12 Vibration isolations by PDC (solid line) and STR (dotted line).

