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Improving the Transient Performance of Unfalsified Adaptive Control with Modified Hysteresis Algorithms ⋆

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Abstract: The controller switching algorithms of Unfalsified Adaptive Control (UAC) is investigated. Two modifications of the Morse-Mayne-Goodwin hysteresis switching algorithm are used and associated convergence theorems are proved. Simulations illustrate that the two modified algorithms can improve the transient performance. Further theoretical analysis show that in UAC, decreasing the total number of controller switches is a promising approach to achieve better transient performance.

Keywords: unfalsified adaptive control, hysteresis algorithm, modifications, transient performance, controller switching

1. INTRODUCTION

The Morse-Mayne-Goodwin ϵ-hysteresis switching algorithm (HSA), see Morse et al. (1992); Weller and Goodwin (1994), plays an important role in adaptive control. Recently, HSA is widely used in the studies of Unfalsified Adaptive Control (UAC), a real-time data-driven switching control approach. UAC adaptively chooses a controller online from a set of candidate controllers and evaluates the performance of each candidate based on the real-time data. With HSA, UAC guarantees closed-loop stability if the adaptive switching control problem is feasible in the sense that there exists a robustly stabilizing controller in the candidate controller set and the employed cost function is cost-detectable (Wang et al. (2007); Stefanovic and Safonov (2008); Battistelli et al. (2010)).

However, HSA in UAC may result in transient performance problems (Engell et al. (2007); Dehghani et al. (2007)). In Dehghani et al. (2007), the authors present an academic example, in which a destabilizing controller is repeatedly inserted into the loop by HSA and the magnitudes of the control signal and output signal increases to an unacceptable level before the plant is stabilized finally. Throughout the paper, we refer to the phenomenon in this example as the Dehghani-Anderson-Lanzon (DAL) phenomenon.

DAL phenomenon has stimulated new research directions of UAC. Chang and Safonov (2008) tried to improve the transient performance of UAC with filters. Anderson and Dehghani (2008); Dehghani et al. (2009) investigated how to guarantee that only stabilizing candidate controllers can be switched online. Baldi et al. (2010, 2012) introduced multi-model in UAC. In Battistelli et al. (2013); Jin et al. (2014), fading memory data are used in UAC to improve the ability to detect instability timely. To attenuate the DAL phenomenon, Wonghong and Engell (2012) designed a new fictitious reference signals and cost functions, while Jin and Safonov (2012) designed new controller switching algorithms. All these results enrich the methods of UAC and deepen the understanding of data-driven control.

This paper investigates how to improve the transient performance of UAC with two modifications of HSA. The first modification gives a threshold and the controller switching is executed by HSA only if the current active controller's cost function value is greater than the threshold. The second modification is well known Scale-Independent HSA (SIHSA)(Hespanha et al. (2003)), in which the additive hysteresis constant is replaced by a multiplicative one. As HSA, the two modifications can stabilize the closed-loop in UAC subject to feasibility of the adaptive stabilization problem and cost-detectability of cost function.

Simulations illustrate that both modifications can attenuate the DAL phenomenon and improve the transient performance of UAC. Moreover, our simulations show that it is possible to simultaneously have better transient performance and a bigger value of the active controller's cost function. This implies that, in UAC, the use of HSA with a small ϵ to guarantee a small upper bound of the active controller's cost function may not be necessary. It

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may result in more controller switches and worse transient performance. A more efficient approach is to minimize the total number of controller switches, for example, to use THSA, SIHSA, or HSA with a larger ϵ.
This paper is organized as follows. Section II introduces the background of UAC and HSA. Section III gives the two modifications of HSA and their converge theorems. Then in section IV, theoretical analysis and simulations illustrate that the two modifications can improve the the performance of UAC by lessening the controller switches.

2. BACKGROUND OF UAC AND HSA

2.1 Background of UAC

The set of natural numbers, real numbers, and non-negative real numbers are denoted by $\mathbb{N}$, $\mathbb{R}$, and $\mathbb{R}_+$ respectively. For a given $x \in \mathbb{R}_+$, $\lceil x \rceil$ denotes the smallest integer greater than or equal to x. For a given $\tau \in \mathbb{R}_+$, the truncation of a signal $y(\cdot)$ is defined as

$$y_\tau(t) \triangleq \begin{cases} y(t), & 0 \le t \le \tau \\ 0, & \text{otherwise} \end{cases}$$

and the truncated $\mathcal{L}_2$-norm of $y(\cdot)$ is defined as $\|y\|_\tau \triangleq (\int_0^\tau y(t)^T y(t) dt)^{1/2}$. If $\|y\|_\tau$ exist for any finite $\tau \in \mathbb{R}_+$, we say the signal $y(\cdot)$ belongs to the linear space $\mathcal{L}_{2e}$.
UAC is an approach to adaptively control a plant without *a priori* model of the plant. It merely depends on real-time data measurement and can avoid the chance that a model is unreliable(Safonov (2012)). UAC considers the switching adaptive control system Σ shown in Fig.1. In the system Σ, the plant $\mathcal{P}$ is assumed unmodeled. A finite candidate controller set $\mathbb{K} = \{K_1, K_2, \cdots, K_N\}$ and a supervisor are used to stabilize the plant $\mathcal{P}$. The signals r,y and u are the reference signal, output signal, and control signal respectively. For brevity, let $d(t) = [u(t), y(t)]'$. At each time, one and only one candidate controller is active and the active controller at time t is denoted as $\hat{K}(t)$.
So, $\Sigma(\hat{K}, \mathcal{P})$ denotes the closed-loop system with the switching active controller while $\Sigma(K_i, \mathcal{P})$ denotes a closed-loop system in which K_i is the only active controller for all time. The supervisor monitors the performance of the system based on measured data and switches controller if necessary. The supervisor consists of a cost function used to order candidate controllers based on accumulated data and a controller switching algorithm that determines how the cost function is used to switch controllers.
In this paper, the primary performance goal is stability, which is defined with the input-out data because we do not have the mathematical model of the plant $\mathcal{P}$.

Definition 1. (**Stability**) Consider a system $T : \mathcal{L}_{2e} \to \mathcal{L}_{2e}$ with input r and output $y = Tr$, where r and y may be vectors. System T is said to be *stable* if for every input $r \in \mathcal{L}_{2e}$ there exist constants $\alpha, \beta \ge 0$ such that

$$\|y\|_t \le \beta \|r\|_t + \alpha, \forall t \ge 0.$$

Otherwise, T is said to be *unstable*.$\diamondsuit$

We assume:
A1 There exists at least one candidate controller K in set $\mathbb{K}$ such that $\Sigma(K, \mathcal{P})$ is stable.
A2 Each candidate controller is LTI and has all zeros in open left-half s-plane.
The basic idea of UAC is *unfalsification*, which means the collected data have not shown an assumption is false.

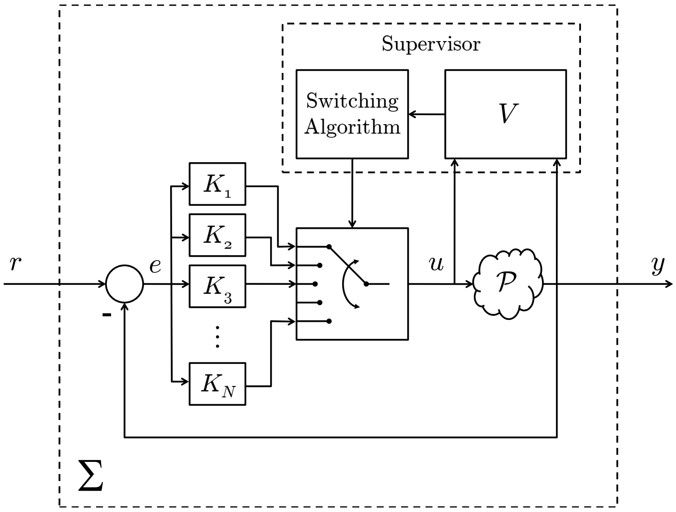

Fig. 1. The switching adaptive control system.

Otherwise, the assumption is said *falsified*. For the stability defined above, the two concepts are defined as follows.

Definition 2. (**Unfalsification of stability**) Consider a system $T : \mathcal{L}_{2e} \to \mathcal{L}_{2e}$. Suppose we have a pair of input-output data (r_1, y_1), where $y_1 = Tr_1$. We say that the stability of T is *unfalsified* by the data pair (r_1, y_1) if there exist constants $\alpha_1, \beta_1 > 0$ such that

$$\|y_1\|_t \le \beta_1 \|r_1\|_t + \alpha_1, \forall t \ge 0.$$

Otherwise, we say the stability of T is *falsified* by (r_1, y_1).$\diamondsuit$
By A2, we can generate the *fictitious reference signal* of each controller $K_i \in \mathbb{K}$ with equation

$$\tilde{r}_i = y + K_i^{-1} u.$$

Here, $\tilde{r}_i$ is a hypothetical reference signal with which the closed-loop $\Sigma(K_i, \mathcal{P})$ would have exactly generated the data d which are generated by the closed-loop $\Sigma(\hat{K}, \mathcal{P})$ with the real reference signal r. Then, for each $K_i \in \mathbb{K}$, we can define its corresponding *cost function* with

$$V(K_i, d_t, t) = \max_{\tau \le t} \frac{\|\tilde{r}_i - y\|_\tau^2 + \|u\|_\tau^2}{\|\tilde{r}_i\|_\tau^2 + \gamma}, \quad (1)$$

where γ is a positive constant.
It is easy to verify that for each $K_i \in \mathbb{K}$, the cost function (1) is bounded if and only if the stability of $\Sigma(K_i, \mathcal{P})$ is unfalsified by the input-output data pair $(\tilde{r}_i, d)$. And, the pair $(V, \mathbb{K})$ has the following property (Wang et al. (2007); Stefanovic and Safonov (2008)).

Definition 3. (**Cost detectability**) Consider the switching adaptive control system in Fig.1. Suppose $\hat{K}(t) \in \mathbb{K}, \forall t \in \mathbb{R}_+$. The cost function and controller set pair $(V, \mathbb{K})$ is said to be *cost detectable* if for every $\hat{K}(t)$ with at most finitely many switches, the following statements are equivalent:
(1) Stability of the $\Sigma(\hat{K}(t), \mathcal{P})$ is unfalsified by (r, d);
(2) $V(K_f, d_t, t)$ is bounded as $t \to \infty$, where K_f is the final active controller.$\diamondsuit$

Remark 4. A1 is called *feasibility.* A controller $K \in \mathbb{K}$ is said to be a *feasible controller* if $\Sigma(K, \mathcal{P})$ is stable.

Remark 5. A2 guarantees all candidate controllers are *stably causally left invertible (SCLI).* However, this assumption can be removed with the approach in Dehghani et al. (2007) and Manuelli et al. (2007). In this paper, we focus on the controller switching algorithm and use A2 for brief.

2.2 HSA used in UAC

If the switching adaptive control problem is feasible, UAC can guarantee the closed-loop system stability with the cost-detectable cost function (1) and a suitable controller switching algorithm. One of the most widely used switching algorithm in UAC is HSA, whose continuous-time version is described as follows.

Algorithm I: Continuous-time HSA
Constants
ϵ: hysteresis constant;
dt: infinitesimal time increment.
variables
t: time;
$\hat{K}(t)$: active controller at time t.
Algorithm
(1) Initialization: $\epsilon > 0, t \leftarrow 0, \hat{K}(t) \in \mathbb{K}$;
(2) $t \leftarrow t+dt$, collect data r, u, y, update $\tilde{r}_i$ and calculate $V(K_i, d_t, t)$;
(3) IF
$$V(\hat{K}(t-dt), d_t, t) > \epsilon + \min_{K_i \in \mathbb{K}} V(K_i(t), d_t, t) \quad (2)$$
THEN
$$\hat{K}(t) \leftarrow \arg\min_{K_i \in \mathbb{K}} V(K_i(t), d_t, t);$$
ELSE
$$\hat{K}(t) \leftarrow \hat{K}(t-dt);$$
ENDIF
(4) Go to step (2).

Remark 6. The convergence theorem of Algorithm I used in UAC can be found in Wang et al. (2007) and Stefanovic and Safonov (2008).

Remark 7. If inequality (2) holds, we say the controller $\hat{K}(t)$ is *interfalsified* at time t by data d_t (Jin and Safonov (2012)). "Interfalsified" means it is falsified by another candidate controller.

2.3 DAL phenomenon

As pointed out by Anderson and Dehghani (2008), HSA used in UAC may cause a bad transient performance. The flowing is an academic example (Dehghani et al. (2007)).

Example 1 Consider the switching adaptive control system Σ shown in Fig.1. Let $\mathcal{P} = \frac{1}{s-1}$, $K_1 = 2, K_2 = 0.5$, $\mathbb{K} = \{K_1, K_2\}$, and $r(t) = \sin(t) \cdot 1(t)$.

In Example 1, it is clear that K_1 stabilizes $\mathcal{P}$ while K_2 does not. But with cost function (1) and Algorithm I, the supervisor repeatedly inserts the destabilizing controller K_2 into the loop. When ϵ is small, the overshoots of the control u and the output y may be too high to be accepted. This is referred to as DAL phenomenon.

3. TWO MODIFICATIONS OF HSA

In this section, two modifications of HSA are used in UAC. Their convergence theorems are proved. The first modification is named Threshold Hysteresis Algorithm (THSA) because it gives HSA a threshold. The second is the Scale-Independent Hysteresis Algorithm (SIHSA) proposed by Hespanha et al. (2003).

3.1 THSA

Algorithm II: Continuous-time THSA
Constants
ϵ: hysteresis constant;
M: threshold;
dt: infinitesimal time increment.
variables
t: time;
$\hat{K}(t)$: active controller at time t.
Algorithm
(1) Initialization: $\epsilon > 0, M > 0, t \leftarrow 0, \hat{K}(t) \in \mathbb{K}$;
(2) $t \leftarrow t+dt$, collect data r, u, y, update $\tilde{r}_i$ and calculate $V(K_i, d_t, t)$;
(3) IF
$$(V(\hat{K}(t-dt), d_t, t) > \epsilon + \min_{K_i \in \mathbb{K}} V(K_i(t), d_t, t)$$
$$\textbf{AND} \;\; V(\hat{K}(t-dt), d_t, t) > M) \quad (3)$$
THEN
$$\hat{K}(t) \leftarrow \arg\min_{K_i \in \mathbb{K}} V(K_i(t), d_t, t);$$
ELSE
$$\hat{K}(t) \leftarrow \hat{K}(t-dt);$$
ENDIF
(4) Go to step (2).

The difference between THSA and HSA is (3). In THSA, the controller switching takes place not only when the active controller is interfalsified but also when its cost function value is greater than the threshold M. The following is the convergence theorem of THSA.

Theorem 8. Suppose A1-A2 hold and cost function (1) is used. Then, with THSA, the switching control system $\Sigma(\hat{K}(t), \mathcal{P})$ in Section 2.1 is stable.

Proof. First, with the definition of stability and unfalsification, it is clear that if a controller $K_i \in \mathbb{K}$ stabilizing the plant $\mathcal{P}$, then the stability of $\Sigma(K_i, \mathcal{P})$ is unfalsified for each possible data pair $(\tilde{r}_i, d)$ and its cost function $V(K_i, d_t, t)$ is uniformly bounded for all $t \geq 0$. Let $\mathbb{D}$ be the set of all possible data d. Define the *true cost* of controller K_i as
$$V_{true}(K_i) = \sup_{d \in \mathbb{D}, t \in R_+} V(K_i, d_t, t),$$
and the *robust optimal controller* in $\mathbb{K}$ as
$$K_{RSP} = \arg\min_{K_i \in \mathbb{K}} V_{true}(K_i).$$
With assumption A1, we have $V_{true}(K_{RSP}) < \infty$.
Second, similar to Lemma 4 of Stefanovic and Safonov (2008) and Lemma 1 of Battistelli et al. (2013), we can prove for each reference r, the controller switching stops and the final controller's cost function is bounded. Suppose the final is the f-th switch, which takes place at t_f, and the final active controller is K_f, we have:
(1) If $M \geq V_{true}(K_{RSP})$, then
$$f \leq N - 1,$$
$$V(K_f, d_t, t) \leq M + \epsilon;$$
(2) If $M < V_{true}(K_{RSP})$, then
$$f \leq N(\lceil \frac{V_{true}(K_{RSP}) - M}{\epsilon} \rceil + 1),$$
$$V(K_f, d_t, t) \leq V_{true}(K_{RSP}) + \epsilon, \quad \forall t \geq 0.$$
Third, with the cost-detectability of $(V, \mathbb{K})$, we conclude that for each reference r, the stability of $\Sigma(\hat{K}, \mathcal{P})$ is unfalsified by (r, d). That is the definition of stability. □

Remark 9. The terms "true cost" and "robust optimal controller" are cited from Stefanovic and Safonov (2008).

3.2 SIHSA

Algorithm III: Continuous-time SIHSA
Constants
h: multiplicative hysteresis constant;
dt: infinitesimal time increment.
variables
t: time;
$\hat{K}(t)$: active controller at time t.
Algorithm

(1) Initialization: $h > 0, t \leftarrow 0, \hat{K}(t) \in \mathbb{K}$;
(2) $t \leftarrow t + dt$, collect data r, u, y, update $\tilde{r}_i$ and calculate $V(K_i, d_t, t)$;
(3) IF

$$V(\hat{K}(t-dt), d_t, t) > (1+h) \min_{K_i \in \mathbb{K}} V(K_i(t), d_t, t) \quad (4)$$

THEN

$$\hat{K}(t) \leftarrow \arg \min_{K_i \in \mathbb{K}} V(K_i(t), d_t, t);$$

ELSE

$$\hat{K}(t) \leftarrow \hat{K}(t-dt);$$

ENDIF
(4) Go to step (2).

The difference between SIHSA and HSA is (4). The following is the convergence theorem of SIHSA.

Theorem 10. Suppose A1-A2 hold and cost function (1) is used. Then, with SIHSA, the switching control system in Section 2.1 is stable.

Proof. The proof is also in three steps. The first step and the third step are similar to the proof of Theorem 8. For the second step, we have:
(1) If there exists $K_i \in \mathbb{K}$ such that $V(K_i, d_t, t) \equiv 0$, then we have $f \leq N-1$ and $V(K_f, d_t, t) = 0$.
(2) Otherwise, let t_0^1 be the first instant such that

$$V(\hat{K}(t), d_t, t) > 0. \quad (5)$$

If at $t = t_0^1$ we have

$$V(K_i(t), d_t, t) > 0, \forall K_i \in \mathbb{K}, \quad (6)$$

then let $t_1 = t_0^1$ and

$$\delta = \min_{K_i \in \mathbb{K}} V(K_i(t_1), d_{t_1}, t_1); \quad (7)$$

Else we know a controller switch takes place at t_0^1 and after the switch $V(\hat{K}(t_0^1), d_{t_0^1}, t_0^1) = 0$. Let t_0^2 be the second instant that (5) holds. If at $t = t_0^2$ we have (6), then let $t_1 = t_0^2$ and define δ with (7); Else we know a controller switch takes place at t_0^2 and after the switch $V(\hat{K}(t_0^2), d_{t_0^2}, t_0^2) = 0$. Repeating the above precess, we can prove that there exist $t_1, \delta > 0$ such that for all $K_i \in \mathbb{K}$ we have $V(K_i, d_{t_1}, t_1) \geq \delta$ and before t_1 there are at most $(N-1)$ controller switches.
Then, similar to Lemma 1 of Hespanha et al. (2003), we can prove

$$f \leq 2N + \frac{N}{\log(1+h)} \log(\frac{V_{true}(K_{RSP})}{\delta}),$$
$$V(K_f, d_t, t) \leq (1+h) V_{true}(K_{RSP}), \quad \forall t \geq 0.$$

So, the controller switching stops finally and the final controller's cost function is bounded. Then with the cost-detectability of $(V, \mathbb{K})$, the proof is finished.□

4. SIMULATIONS AND DISCUSSIONS

4.1 Simulations

In this part, we illustrate the performance of the two modifications with numerical simulations. We present simulations of HSA, of THSA with a small and a large threshold M, and of SIHSA.
Simulation 1: HSA with a small ϵ. Consider Example 1 in Section II. Using HSA, we set $\epsilon = 0.1$, $\gamma = 0.01$ in (1), and the initial controller $\hat{K}(0) = K_2$ which is destabilizing. Let $dt = 0.01$. Simulations are carried out with MATLAB 6.5 and the result in Fig.2 shows the DAL phenomenon.

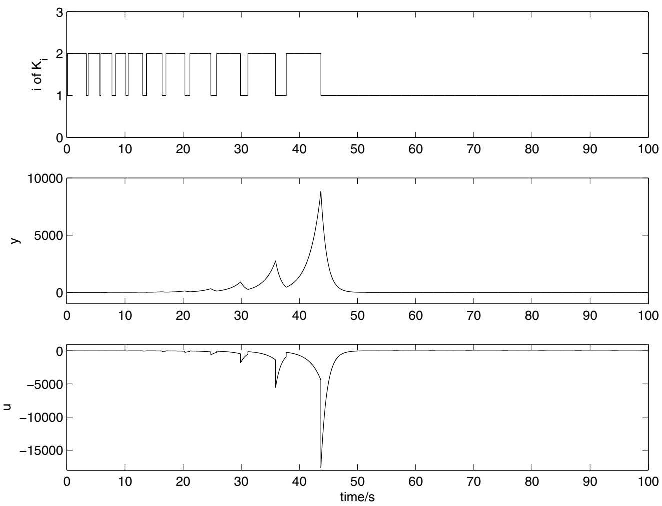

Fig. 2. Results of Simulation 1. From the top to the bottom are the index i of controller K_i, y and u.

Simulation 2: THSA with s small threshold. Consider Example 1 with the use of THSA. All parameters are the same with those in Simulation 1 and we set the threshold $M = 4$. Let $dt = 0.01$. Simulations are carried out with MATLAB 6.5 and the results are shown in Fig.3. The DAL phenomenon is significantly attenuated.

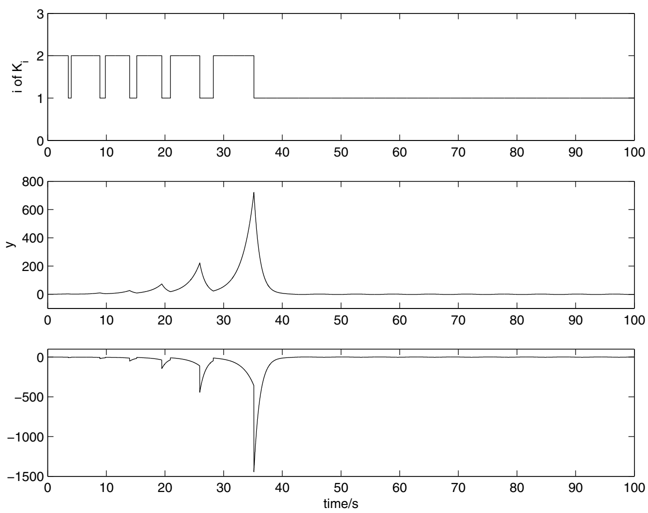

Fig. 3. Results of Simulation 2. From the top to the bottom are the index i of controller K_i, y and u.

Simulation 3: THSA with larger thresholds. Consider Example 1 and we use again THSA. All parameters are the same with those in Simulation 2 except for threshold M where we use three different values, i.e. $M = 6, 30, 150$. Let $dt = 0.01$. Simulations are carried out with MATLAB 6.5 and the results are shown in Fig.4. With these threshold values which are greater than in Simulation 2, the controller is only switched once before the plant is stabilized. As the threshold gets larger, the overshoot increases due to the longer time the destabilizing controller is in the closed-loop.

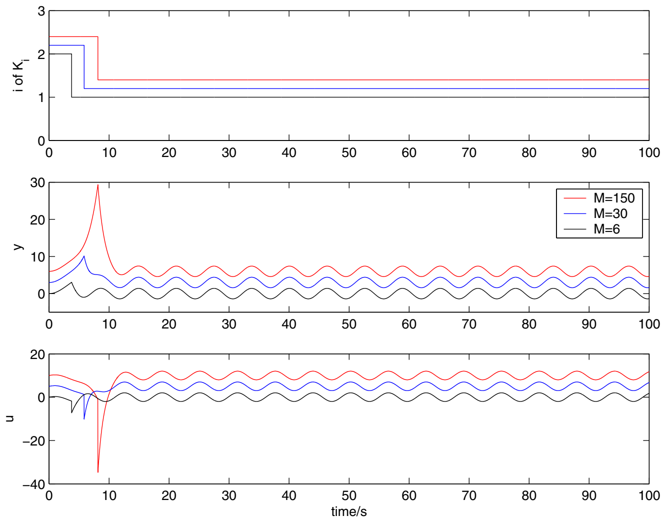

Fig. 4. Results of Simulation 3. From the top to the bottom are the index i of controller K_i, y and u. Red, $M = 150$; Blue, $M = 30$; Black, $M = 6$. To make it clear, the blue and red line i of K_i is moved upper a little.

Simulation 4: SIHSA. Consider Example 1 with SIHSA. All parameters are the same with those in Simulation 1. Let $h = 0.2$ and $dt = 0.01$. Simulations are carried out with MATLAB 6.5 and the results are shown in Fig.5.

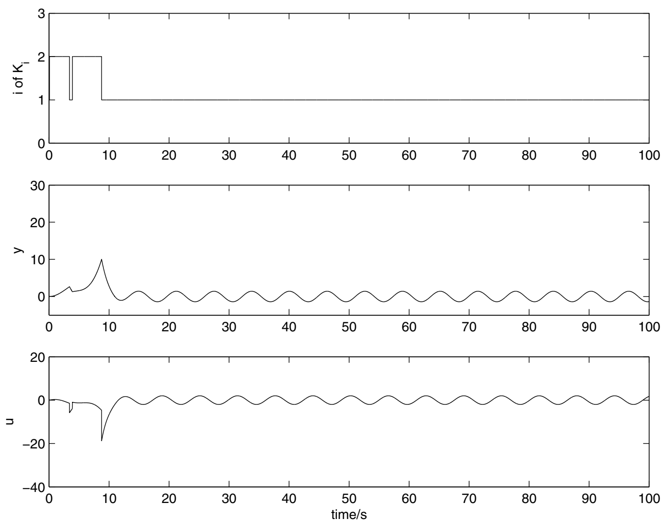

Fig. 5. Results of Simulation 4. From the top to the bottom are the index i of controller K_i, y and u.

4.2 Comparisons and discussions

As described briefly in Section I, the basic motivation of this paper is DAL phenomenon. In the preceding simulations, we observe significant DAL phenomenon in Simulation 1, moderate in Simulation 2, and less in Simulation 3 and 4. Comapred with Simulation 1 and 2, Simulation 3 and 4 have much lower overshoots of u and y and considerably reduced total number of controller switches. The relation between the overshoots and the number of controller switches can be interpreted as follows. Once a destabilizing controller is switched online, it will be kept in the closed-loop until its cost function is sufficiently big to be interfalsified by another candidate controller. That is, the control signal u and output y will increase significantly. The more frequent the destabilizing controllers are switched online, the greater the signal u and y are, and the worse the transient performance is.

It is interesting that Simulation 3 has the greatest value of the cost function of the active controller. The cost function value curves of the Simulations 1 and Simulation 3 with $M = 6$ are depicted in Fig.6. In Simulation 3, immediately before K_2 is switched offline, the active controller has a cost function value greater than 6, while the cost function value of the active controller in Simulation 1 is always less than 6. In Simulation 3, even when $M = 150$, the transient performance is still much better than in Simulation 1 and 2, while just before K_2 is switched offline we have $V(K_2, d_t, t) > 150$.

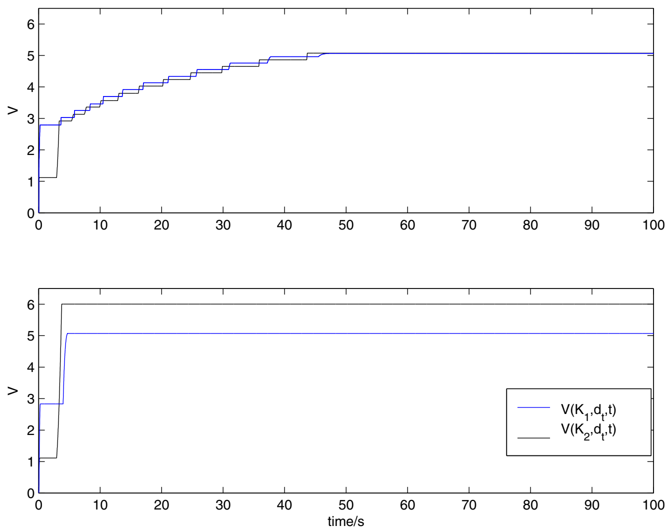

Fig. 6. Comparison between the cost function of Simulation 1 and Simulation 3 with $M = 6$. Upper: Simulation 1; Lower: Simulation 3 with $M = 6$. Blue, $V(K_1, d_t, t)$; Black, $V(K_2, d_t, t)$.

Traditionally, we tend to use HSA with a small ϵ in UAC based on the following reason. A small ϵ gives a small upper bound of the final active controller's cost function and at each time, the active controller's cost function is not much greater than the upper bound. From this reason, we believe we can find the best controller with a guaranteed transient performance. But the simulations in the preceding subsection show that the relation between the cost function of candidate controllers and the transient performance is not as straightforward as we previously believed. A small ϵ may not be the best approach because it will increase the total numbers of controller switches and leads to bad transient performance. By contrast, reducing the total number of controller switches is a more direct and promising approach to improve the transient performance. Both THSA and SIHSA can significantly decrease the total number of controller switches. If we can estimate the upper bound of $V_{true}(K_{RSP})$ with some knowledge, we can use THSA and expect at most $(N-1)$ controller switches to happen. Otherwise, SIHSA seems a better choice because its total number of controller switching is logarithmic.

From the viewpoint of controller switching, DAL phenomenon is not a problem of UAC or HSA, but a result of a too small ϵ. If a larger ϵ is used, the total number of controller switching will decrease, DAL phenomenon will be attenuated, and the transient performance will be improved. The following example illustrates that a larger ϵ can attenuate DAL phenomenon.

Simulation 5: HSA with a larger ϵ. Consider again Simulation 1. Using HSA, all parameters are the same with those in Simulation 1 except for ϵ where we set $\epsilon = 1$. Simulations are carried out with MATLAB 6.5 and the results are shown in Fig.7. The DAL phenomenon is significantly reduced.

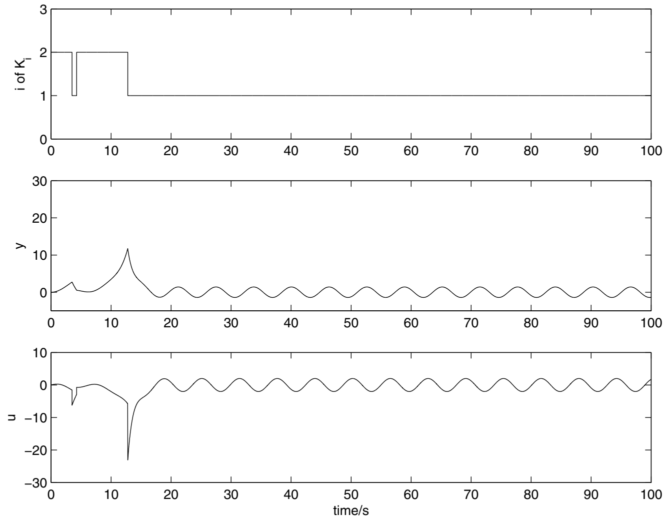

Fig. 7. Results of Simulation 5. From the top to the bottom are the index i of controller K_i, y and u.

5. CONCLUSIONS

In this paper, two modifications of HSA are used in UAC. Similar to HSA, the two modifications can also guarantee the closed-loop stability if the problem is feasible and has a cost-detectable cost function. Compared to HSA, both of the two algorithms decrease the total number of controller switches. Theoretical analysis and simulations show that the total number of controller switches directly affects the transient performance of UAC. Reducing the number of controller switches can significantly improve the transient performance. Moreover, DAL phenomenon is a result of a too small ϵ and can be attenuated with a suitable ϵ.

REFERENCES

Anderson, B.D.O. and Dehghani, A. (2008). Challenges of adaptive control—past, permanent and future. *Annual Reviews in Control*, 32(2), 123–135.

Baldi, S., Battistelli, G., Mosca, E., and Tesi, P. (2010). Multi-model unfalsified adaptive switching supervisory control. *Automatica*, 46(2), 249–259.

Baldi, S., Battistelli, G., Mosca, E., and Tesi, P. (2012). Multi-model unfalsified switching control of uncertain multivariable systems. *Int. J. Adaptive Control and Signal Processing*, 26(8), 705–722.

Battistelli, G., Hespanha, J., Mosca, E., and Tesi, P. (2013). Model-free adaptive switching control of time-varying plants. *IEEE Transactions on Automatic Control*, 58(5), 1208 – 1220.

Battistelli, G., Mosca, E., Safonov, M.G., and Tesi, P. (2010). Stability of unfalsified adaptive switching control in noisy environments. *IEEE Trans. on Automatic Control*, 55(10), 2424–2429.

Chang, M.W. and Safonov, M.G. (2008). Unfalsified adaptive control: The benefit of bandpass filters. In *Proceedings of AIAA Guidance, Navigation and Control Conference and Exhibit*, 2646–2658. Honolulu, Hawaii, USA.

Dehghani, A., Anderson, B.D.O., and Lanzon, A. (2007). Unfalsified adaptive control: A new controller implementation and some remarks. In *Proceedings of the European Control Conference*, 709–716. Kos, Grace.

Dehghani, A., Lecchini-Visintini, A., Lanzon, A., and Anderson, B.O. (2009). Validating controllers for internal stability utilizing closed-loop data. *IEEE Transactions on Automatic Control*, 54(11), 2719–2725.

Engell, S., Tometzki, T., and Wonghong, T. (2007). A new approach to adaptive unfalsified control. In *Proceedings of the European Control Conference*, 1328–1333. Kos, Greece.

Hespanha, J.P., Liberzon, D., and Morse, A. (2003). Hysteresis-based switching algorithms for supervisory control of uncertain systems. *Automatica*, 39(2), 263 – 272.

Jin, H., Chang, M.W., and Safonov, M.G. (2014). Unfalsifying pole locations using a fading memory cost function. *Asian Journal of Control.* doi:10.1002/asjc.807.

Jin, H. and Safonov, M.G. (2012). Unfalsified adaptive control: Controller switching algorithms for nonmonotone cost functions. *Int. J. Adaptive Control and Signal Processing*, 26(8), 692C704.

Manuelli, C., Cheong, S.G., Mosca, E., and Safonov, M.G. (2007). Stability of unfalsified adaptive control with non SCLI controllers and related performance under different prior knowledge. In *Proceedings of the European Control Conference*, 702–708. Kos, Greece.

Morse, A.S., Mayne, D.Q., and Goodwin, G.C. (1992). Applications of hysteresis switching in parameter adaptive control. *IEEE Transactions on Automatic Control*, 37(9), 1343–1354.

Safonov, M.G. (2012). Origins of robust control: Early history and future speculations. *Annual Reviews in Control*, 36(2), 173–181.

Stefanovic, M. and Safonov, M.G. (2008). Safe adaptive switching control: Stability and convergence. *IEEE Transactions on Automatic Control*, 53(9), 2012–2021.

Wang, R., Paul, A., Stefanovic, M., and Safonov, M.G. (2007). Cost detectability and stability of adaptive control systems. *International Journal of Robust and Nonlinear Control*, 17(5-6), 549–561.

Weller, S.R. and Goodwin, G.C. (1994). Hysteresis switching adaptive control of linear multivariable systems. *IEEE Transactions on Automatic Control*, 39(7), 1360–1375.

Wonghong, T. and Engell, S. (2012). Automatic controller tuning via unfalsified control. *Journal of Process Control*, 22(10), 2008–2025.