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Preliminary results for ARIMA adaptation algorithms with time-varying matrix adaptation gain

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Abstract

This note introduces two ARIMA type adaptation/learning algorithms that use a time -varying matrix adaptation gain. Simulations illustrate the performance of one of the algorithms.

1 Algorithm I

The algorithm of Eq. (16) from [1] is replaced by:

$$\hat{\theta}(t+1) = H_{PAA}(q^{-1})[F(t)\phi(t)\epsilon(t+1)] = \hat{\theta}(t) + H_{DAG}(q^{-1})[F(t)\phi(t)\epsilon(t+1)] \quad (1)$$

The explicit form of the adaptation algorithm becomes:

$$\begin{aligned} \hat{\theta}(t+1) = & d_1\hat{\theta}(t) + d_2\hat{\theta}(t-1) + \dots \\ & + F(t)\phi(t)\epsilon(t+1) + c_1F(t-1)\phi(t-1)\epsilon(t) + c_2F(t-2)\phi(t-2)\epsilon(t-1) + \dots \end{aligned} \quad (2)$$

The expression of the matrix adaptation gain is given by:

$$F(t+1) = \frac{1}{\lambda_1(t)} \left[F(t) - \frac{F(t)\phi(t)\phi^T(t)F(t)}{\frac{\lambda_1(t)}{\lambda_2(t)} + \phi^T(t)F(t)\phi(t)} \right] \quad (3)$$

where $\lambda_1(t)$ and $\lambda_2(t)$ allow to obtain various profiles for the adaptation gain $F(t)$ (see [2]). $\phi(t)$ is given by Eq. (3) from [1] and $\epsilon(t+1)$ is given by:

$$\epsilon(t+1) = \frac{\epsilon^\circ(t+1)}{1 + \phi^T(t)F(t)\phi(t)} \quad (4)$$

where $\epsilon^\circ(t+1)$ is given by:

$$\epsilon^\circ(t+1) = y(t+1) - \hat{\theta}_0^T(t)\phi(t) \quad (5)$$

and $\hat{\theta}_0(t)$ is given by:

$$\begin{aligned} \hat{\theta}_0(t) = & d_1\hat{\theta}_0(t) + d_2\hat{\theta}_0(t-1) + \dots \\ & + c_1F(t-1)\phi(t-1)\epsilon(t) + c_2F(t-2)\phi(t-2)\epsilon(t-1) + \dots \end{aligned} \quad (6)$$

2 Simulation results

The system considered in [1] for simulation is used also for the case of time-varying matrix adaptation gain. A pseudo random binary sequence (PRBS) is used as excitation signal. The least squares algorithm is used for updating the adaptation gain $F(t)$ ($\lambda_1(t) = \lambda_1 = 1, \lambda_2(t) = \lambda_2 = 1$). The initial parameter estimates are set to 0 (initial squared parameter distance = 4). Figure 1 shows the results of the simulation (zoom) for the classical recursive least square algorithm ($H_{DAG}^{ii} = 1$, i.e. $c_1 = c_2 = d'_1 = 0$) and the ARIMA2 algorithm ($c_1 = 0.5, c_2 = 0.05, d'_1 = 0.5$) using recursive least squares algorithm for updating the matrix adaptation gain $F(t)$. The case without measurement noise and the case when a white noise is added on the output signal (signal/noise ratio (standard deviation) = 33 dB) have been considered. In both situations the ARIMA2 algorithm provides better adaptation transients.

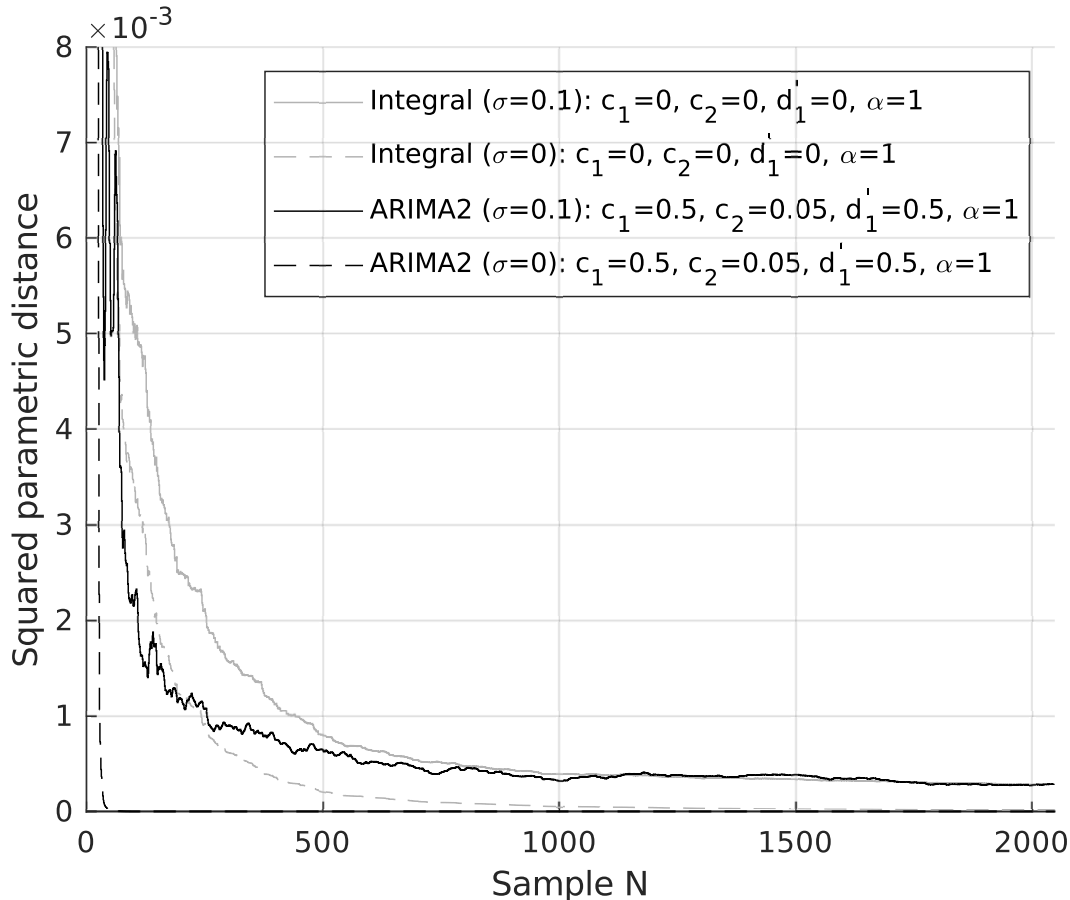


Figure 1: Evolution of the squared parametric distance (zoom) using ARIMA2 algorithm with least squares adaptation gain and the standard least squares algorithm ($c_1 = c_2 = d'_1 = 0$)

3 Algorithm II

The algorithm given in Eq. (7) is replaced by:

$$\hat{\theta}(t+1) = \hat{\theta}(t) + F(t)H_{DAG}(q^{-1})[\phi(t)\epsilon(t+1)] \quad (7)$$

i.e. the dynamic adaptation gain acts only on the gradient (or its approximation). The explicit form of the adaptation algorithm becomes:

$$\hat{\theta}(t+1) = d_1\hat{\theta}(t) + d_2\hat{\theta}(t-1) + \dots + F(t)[\phi(t)\epsilon(t+1) + c_1\phi(t-1)\epsilon(t) + c_2\phi(t-2)\epsilon(t-1) + \dots] \quad (8)$$

where $F(t)$ and $\epsilon(t+1)$ are given respectively by Eqs. (3) and (4). ϵ° is given by Eq. (5) where $\hat{\theta}_0(t)$ is given now by:

$$\hat{\theta}_0(t) = d_1\hat{\theta}(t) + d_2\hat{\theta}(t-1) + \dots + F(t)[c_1\phi(t-1)\epsilon(t) + c_2\phi(t-2)\epsilon(t-1) + \dots] \quad (9)$$

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