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QUALITY COMPARISON BETWEEN HYBRID REGULARIZED EXPONENTIAL FORGETTING ALGORITHM WITH ALTERNATIVE COVARIANCE MATRIX AND SELECTED STANDARD LONG-RUN ON-LINE IDENTIFICATION METHODS OF INDUSTRIAL SYSTEMS

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Abstract. This paper compares the quality of standardly used ON-LINE identification algorithms like directional forgetting and regularized exponential forgetting with the hybrid algorithm of exponential forgetting with an alternative covariance matrix. It points also to the behavior of selected algorithms in different deployment conditions and different run times. Particularly interesting is the long-run deployment, which correlates with use in industry. Based on the results obtained, decisions will be taken about the suitability of the hybrid regularized exponential forgetting algorithm with an alternative covariance matrix for selected industrial deployment scenarios.

Keywords: recursive algorithm, forgetting method, time varying parameters, long-run on-line identification, adaptive control

Mathematics Subject Classification: Primary 60A05, 08A72; Secondary 28E10

1 Introduction

The current character of real systems and their subsequent identification in practice clearly demonstrates the variability of their parameters [1,2,3]. This negative effect, in conjunction with adaptive control, prevents unlimited monitoring of the changes of parameters in time. The direct consequence of these negative effects is the impossibility of applying the standard recursive least squares method for estimating the linear regression model parameters. The reason is that simple, constant supply of new information causes, among other things, the system gain of the algorithm to converge to zero. This results in the destabilization of the numerical method for estimating the parameters, which is the "Blow up" problem [4].

The solution to this problem could be achieved by forgetting surplus information. The first techniques based on this principle include Exponential Forgetting (EF), Directional Forgetting (DF) (the basic idea was to reduce the concentration of the maximal reliability function or the „a posteriori" density function), or subsequent modifications based on different methods of

regularization or stabilization of the covariance matrix. Regularized Exponential Forgetting (REF) or Stabilized Linear Forgetting (SLF) methods are examples of the latter.

Another possible solution to the problem of destabilization can be the use of new procedures using the preservation of ,,a priori" information about the system in the form of an alternative covariance matrix (ACM). The classic REF algorithm can be expanded with ACM to create the REFACM algorithm. Another developmental step is to combine the benefits of the REF and REFACM algorithms into a single block in the form of the Hybrid Regularized Exponential Forgetting Algorithm with Alternative Covariance Matrix (HREFACM). Quality aspects of our newly developed HREFACM algorithm is the subject of this article, which focuses on assessing its quality under various operating conditions.

2 Problem formulation

Let us consider a stochastic system, in which the observations are obtained at discrete time points k = 1,2 ....,. The directly controlled input u_k and the indirectly controlled output y_k (also may be multidimensional), can be arranged in the data pairs d_k = (uk, yk). The set of all observer data about the system up to time t is determined by D_t = (d_1, d_2, ... d_t). The dependence of the new data pair (u_k, y_k) on the previous observations D_{k-1}, can be expressed by a conditional probability density function (p.d.f.) with the following structure:

$$p(y_k, u_k | D_{k-1}, \theta_k) = p(y_k | u_k, D_{k-1}, \theta_k) p(u_k | D_{k-1}) \tag{1}$$

The incomplete knowledge of the system is expressed by the vector of unknowns, which consists of time-varying parameters $\theta_k \in \theta$. Note that the input generator is described by the second part of this equation, and the first part characterizes the system.

The Bayesian approach:
If an unknown parameter, described by θ, is interpreted as a random variable, then the uncertainties θ, assuming the knowledge of the observed data D_t, is naturally expressed by the ,,a posteriori" conditional probability density function (p.d.f.) $p(\theta/D_t)$ conditionally dependent on D_t. This is generally determined by the Bayes theorem. If the input generator does not produce any new information compared to the information obtained from the observed data $p(u_k/D_{k-1}, \theta_k) = p(u_k/D_{k-1})$ k = 1,....t. The Bayes theorem is simplified [5]:

$$p(\theta | D_t) \propto p(\theta) \prod_{k=1}^{t} p(y_k | u_k, D_{k-1}, \theta) \tag{2}$$

An important special case in the first part of the equation (1) occurs when the output y_k depends on the previous data u_k, D_{k-1} over the known finite-dimensional vector function $\phi(u_k, D_{k-1}) = \phi_k$. This occurs in the following case:

$$p(\theta | D_t) \propto p(\theta) \prod_{k=1}^{t} p(y_k | u_k, D_{k-1}, \theta) \tag{3}$$

Based on the supposition that the „a priori" (p.d.f.) is normal $N\left(\hat{\theta}_0, P_0\right)$ then it can be easily deduced that the „a posteriori" (p.d.f.) $p(\theta/D_t)$ produced by Bayes rule (2) is normal $N\left(\hat{\theta}_t, P_t\right)$ with recursively modified statistics:

$$\hat{\theta}_k = \hat{\theta}_{k-1} + \frac{P_{k-1}\Phi_k}{\sigma^2 + \Phi'_k P_{k-1}\Phi_k}\hat{e}_k, P_k^{-1} = P_{k-1}^{-1} + \frac{\Phi_k \Phi'_k}{\sigma^2} \tag{4}$$

where $\hat{e}_u = y_k - \hat{\theta}'_{k-1}\Phi_k$ expresses the prediction error. Now it can be seen that recursive relations (4) are identical to the famous recursive least square algorithm.

3 Universal recursive forgetting algorithm

Most methods designed for time-varying cases can be expressed as modifications of least squares recursive (LSR), typically with a method implementation of forgetting old data, to prevent gain of the algorithm to converge to zero. Each method can be expressed as a special case of the following universal forgetting algorithm [6]:

Measured data contribution:

$$\hat{\theta}_{k|k} = \hat{\theta}_{k|k-1} + \frac{P_{k|k-1}\Phi_k}{\sigma^2 + \Phi'_k P_{k|k-1}\Phi_k}\hat{e}_k, P_{k|k}^{-1} = P_{k|k-1}^{-1} + \frac{\Phi_k \Phi'_k}{\sigma^2} \tag{5}$$

Time contribution:

$$\hat{\theta}_{k+1|k} = \hat{\theta}_{k|k}, P_{k+1|k} = F\left\{P_{k|k}\right\}\left(\geq P_{k|k}\right) \tag{6}$$

The contribution from the measured data is not affected by the parameters changed by the time. The time representation (6) represents the change of the parameter vector between two measurements. Time contribution equations can be derived analytically, if there is an explicit model of parameter changes. Such a case is extremely unsuitable, so an heuristic procedure must be used. It is usually assumed that θ is approximately constant in the time horizon N >> 0, and then an „ad hoc" method of forgetting is added, through the implementation of the forgetting operator F{·}.

The well-known method of exponential forgetting leads to this following contribution to the change of the covariance matrix:

$$P_{k+1|k} = \left(P_{k|k-1} - \frac{P_{k|k-1}\Phi_k \Phi'_k P_{k|k-1}}{1 + \Phi'_k P_{k|k-1}\Phi_k}\right)\frac{1}{\lambda} \tag{7}$$

The EF method was very widespread, achieving good results in a number of cases. However, if the data are not sufficiently informative for a long period of time (the regression vector sequence insufficiently builds up some parts of the parameter space), the corresponding

matrix P eigenvalues will grow above all boundaries [7]. One way to remove a blow-up problem is to keep $P_{k+1/k}$ eigenvalues on a pre-specified interval $[\lambda_0, \lambda_1]$ see [8]. The following time contribution is used:

$$P_{k+1|k} = \left(1 - \frac{\lambda_0}{\lambda_1}\right) P_{k|k} + \lambda_0 I \tag{8}$$

where ($P_{1/0} = \lambda_1 I$) and I is a ,,ones" matrix of this corresponding dimensions, $\lambda(\geq 0)$ and $\lambda(>0)$. Modification of the covariance matrix (8) was introduced to negate the convergence of the eigenvalues $P_{k+1/k}$ to zero. Generally, the $P_{k+1/k}$ matrix should be selected as:

$$P_{k|k} \leq P_{k|k+1} < \infty I \tag{9}$$

In this case, it is limited from the bottom and from the top. Then the exponential convergence of identification algorithms is guaranteed [8]. This can be compared with the time contribution for (EF) [9], in which old information are suppressed evenly in the parameter space. Kulhavý and Kárny [6] have designed an algorithm that forbids only part of the parameter space affected by the last data contribution. In this case, the time contribution is given as follows:

$$P_{k+1|k}^{-1} = P_{k|k}^{-1} - k_k \Phi_k \Phi_k', k_k = (1-\lambda)\left[1 + \frac{1}{\Phi_k' P_{k|k-1} \Phi_k}\right] \tag{10}$$

For $\Phi_k' P_{k,k-1} \Phi_k > 0$. In general, it can be stated that in the recursive calculation of the covariance matrix there must be avoided the tending to lose tracking on one hand, and on the other hand the uncontrollable increase of the $P_{k+1/k}$ eigenvalues.

4 REF and SLF techniques

Assuming there is no explicit model of the process parameter changes the ,,a prioral" information can be quantified by introducing an alternative p.d.f. $p^*(\theta_{k+1}/D_k)$. The problem is then the construction of the p.d.f. $p(\theta_{k+1}/D_k)$ based on two hypotheses, which are described by the ,,a posteriori" p.d.f. $p(\theta_k/D_k)$ (this is the case without any parameter changes) and the alternative p.d.f. $p^*(\theta_{k+1}/D_k)$ (this is the case where the parameters change most significantly). For simplification we use $p_0(\theta)$, $p_1(\theta)$ and $p^*(\theta)$ for the ,,a posteriori", alternative and resulting p.d.f. as follows:

Kulhavý and Kraus [6] formed the task of selecting p^*, assuming the recognition of p_0 and p_1 as a Bayes theorem decision-making problem. In the following we recall the results of their solution. After adding the probabilities λ and 1-λ to the hypothesis p_0 and p_1. Considering p_0, p_1 belonging to the class of normal divisions N that can be expressed:

$$p_{\hat{\theta},P} = \frac{1}{\sqrt{2\Pi}} |P|^{-\frac{1}{2}} \exp\left(-\frac{1}{2} \left(\theta - \hat{\theta}\right)' P^{-1} \left(\theta - \hat{\theta}\right) \right) \tag{11}$$

the parameters $\hat{\theta}$ and P determine the mean value and covariance of the p.d.f. The results are shown below (considering $\hat{\theta}_1 = \hat{\theta}_0$)

EF:

$$\hat{\theta}^* = \hat{\theta}_0, P^{*-1} = \lambda P_0^{-1} + (1-\lambda) P_1^{-1} \tag{12}$$

LF:

$$\hat{\theta}^* = \hat{\theta}_0, P^* = \lambda P_0 + (1-\lambda) P_1 \tag{13}$$

Consider a model of a system with time-variable parameters θ_k (3).

Adding a standard LSM algorithm (5) with exponential or linear looping (12), (13) allows the changes of parameters to be monitored. The alternative mean value is set equal to a-posteriori $\hat{\theta}_{k+1|k}^{alt} = \hat{\theta}_{k|k}$ and the alternative covariance matrix is set equal to a-priori covariance $P_{k+1|k}^{alt} = P_{1,0} = Q$.

Using this selection we are able to apply a general recursive forgetting algorithm with the following form of the forgetting operator:

$$F\left\{P_{k|k}, Q\right\} = \left[\lambda P_{k|k}^{-1} + (1-\lambda) Q^{-1}\right]^{-1} \tag{14}$$

which creates a harmonious mean value for REF and:

$$F\left\{P_{k|k}, Q\right\} = \lambda P_{k|k} + (1-\lambda) Q \tag{15}$$

creating an algorithmic mean value for SLF. In both cases, the a-priori covariance matrix Q is not forgotten and is repeatedly taken into account in each step of the recursive identification of k.

5 Notes on Numerical Processing

The data contribution in the generalized recursive forgetting algorithm is given (5). Using a well- known lemma on inversion of matrix, considering the covariance matrix in L-D factorizations the form may be produced:

$$L'_{k|k} D_{k|k} L_{k|k} = L'_{k|k-1} D_{k|k-1} L_{k|k-1} - \frac{L'_{k|k-1} D_{k|k-1} L_{k|k-1} \Phi_k \Phi'_k L'_{k|k-1} D_{k|k-1} L_{k|k-1}}{\sigma^2 + \Phi'_k L'_{k|k-1} D_{k|k-1} L_{k|k-1} \Phi_k} \tag{16}$$

Instead of adjusting the covariance matrix as a whole, its expression can be modified in the factorized form to ensure its positive definition. The second element of the forgetting

algorithm is its time post. The application of the regulation of the covariance matrix by an alternative matrix causes an increase in calculation requirements. In both cases (12), (13) a weighted sum of two fully ranked matrices P_0^{-1}, P_1^{-1} or P_0, P_1. This problem was solved by using a dyadic reduction, which is the core tool used for solving this type of tasks.

The dyadic reduction can be used to solve the weighted summation of two full matrices in factorized form. The equation (13) represents the time contribution to the change of the covariance matrix:

$$P = \lambda \sum_{i=1}^{\dim_{L_0}} L'_{0,i} D_{o,i} L_{o,i} + (1-\lambda) \sum_{i=1}^{\dim_{L_{01}}} L'_{1,i} D_{1,i} L_{1,i}, \dim_{L_0} = \dim_{L_1} \quad (17)$$

$L_{0,i}$ ($L_{1,i}$) are line vectors applied as the i-th line of the lower triangle of the triangular matrix L_0(L_1). The important factor is that the diagonal elements of both triangular matrices equal one, considering the dyadic reduction algorithm assumes that the element $f_0 = 1$ is rightly placed in the reducing line f. A closer look at algorithm performing a weighted sum of two covariance matrices can be found in the factorized expression [6].

6 Augmenting REF with ACM

The involved REF augmentation considers addition and keeping the initial information in the Alternative Covariance Matrix (ACM) form as shown in [8]. The augmentation is based on the modified Dyadic reduction algorithm. The main difference is that instead of adding a-priori covariance matrix Q, ACM is computed at each step. ACM stabilizes the evolution of matrix P(0) after the recursive update. This operation is necessary for the REF algorithms to be augmented by the stabilization component in the ACM form. The aforementioned stabilization component prevents the destabilization of the original algorithms in long running applications when slow time changes are to be expected in the observed parameters in relation to the sampling period. The modified REF algorithm augmented with ACM is to be called REFACM.

A hybrid algorithm combines the advantages of both previously presented algorithms. The application of the REF algorithm is used in short time simulations, while the advantages of the REFACM algorithm is utilized in long time simulations, emulating the long-run operation of time variant dynamic systems. For this purpose, we created a new block module in Matlab Simulink. When the quality of REFACM is dominating over REF, as shown in Fig. 1., the block module switches from the REF algorithm to the REFACM. The REF algorithm runs at the beginning and after the result samples of PE and IS are better than REF in several successive steps in a row the algorithm is switched to REFACM. The resulting hybrid algorithm has been named HREFACM. The choice between the REFACM and REF algorithm is based on the mixing ratio of integral sum of prediction error (PE) and the integral sum of the Euclidian norm of parameters (outputs) error (IS).

7 Simulational algorithm verification methodology

Model number one and model number two have a different approach to input excitation (input signal generator A and B). The models were created for the purpose of verification of the properties of the algorithms. All the algorithms were subjects of the same test with identical length using the two featured models. The test compared the quality of the algorithms by the observation of time variant parameters of a dynamic DF.

All the results were evaluated and analyzed using a table where algorithm quality was shown numerically through parameters IS and PE.

Description of models no. 1 and no. 2
Model number one is a second order model considering external disturbance v(t):

$$y_k = \sum_{i=1}^{2} a_i y_{k-i} + \sum_{i=0}^{2} b_i u_{k-i} + \sum_{i=0}^{2} d_i v_{k-i} + e_k, e_k \approx N\left(0,\sigma^2\right) \tag{18}$$

The values of constant parameters equal: a2 = -0.9, b0 = 0.5, b1 = -0.25, b2 = 0.1, d1 = 0.8, d2 = 0.2, $\sigma = 0.1$.

In the first half of the simulation the time variant parameter was set to a(1) = 0.98. This value was constant in the first half of the n simulation steps. Afterwards, at the time t = n / 2 the parameter value was changed to a(1) = − 0.98. The outside disturbance was simulated as a square signal periodically changing its value from +1 to −1 every hundred simulation steps. The main difficulty of the identification was the rarely occurring disturbances, which contained minimal information about the parameter d(i).

For the needs of the simulation, two input signal generators were assumed:

- Input signal generator A: discrete white noise generator
- Input signal generator B: the input signal has been generated using the following equation: $u_k^* = 0.8u_{k-1}^* + 0.2u_k$, where u*k is normally distributed white noise and u*k-1 is the previous input value. For model no. 2. only one change has been realized in comparison to model no. 1. This was carried out by altering the time variant parameter a(1,k) = 0.98 cos(2π k/250). In this case, two different input generators were considered as well:
    - Input signal generator A: discrete white noise generator
    - Input signal generator B: the input signal has been generated similarly to model no 1., where u(k) has been only chosen from the interval u(k) ~ (0.5, 1).

All the algorithms were subject to the same test of the identical length, using the featured model. All the results were graphically evaluated and analyzed in a table in which the algorithm quality was shown numerically through IS and PE. The model for verification was chosen from [6].

8 Verification – MATLAB Simulink

A universal user interface was created along with a set of S-Function libraries used for the verification of the simulation. The interface allows the user to select input data, simulated model and the observed algorithm. Output of the discussed simulations is a graphic representation of the observed parameters along with a data file containing the results for the analysis. Integral sum (IS) of the Euclidian norm of parameter error and prediction error PE has been shown, which is the amount exceeded by the interval $\pm 3\sigma 2$. The simulation experiments will be marked by the character pair XY, where X is the number of the utilized model (no. 1 or no. 2) and Y represents the generator utilized (A, respective B).

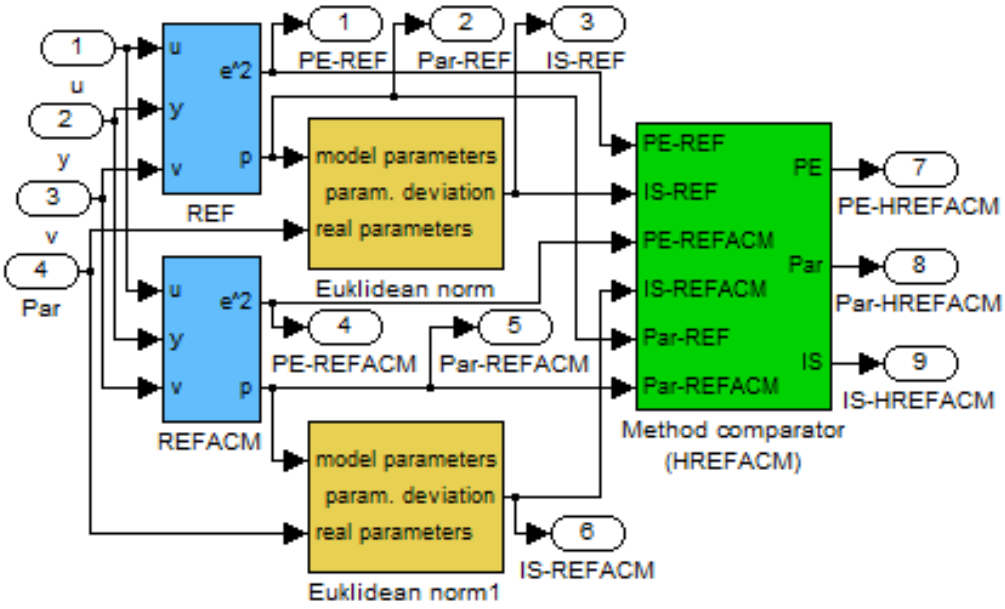

Fig. 1. HREFACM setup for benchmarks with algorithm in Matlab Simulink environment.

9 Evaluation of simulation results

The result section contains all the results in the form of a table. Tables (1) to (5) include detailed description and evaluation of the algorithm behavior during different simulations of duration n = 1 200, 6 000, 12 000, 60 000 and 120 000. The result confirms HREFACM algorithm quality in comparison to REF or REFACM. The results in Table (2); clearly state that at the simulation length n = 12 000 steps the properties of long lasting runs are already appearing., which in the case 1A achieved better results than REF. The data introduced in Table (5) confirm the HREFACM algorithm quality. The PF algorithm achieves excellent results also. It is clear, that using ACM as if a constraint has been enforced on parameter trending, which also implies the improvement of IS parameters in comparison to the results achieved by REF. The convergence of the REF covariance matrix is faster and finite in contrast to HREFACM, where the convergence is slower and the addition of excited ACM cannot be finite. The obtained simulation results and HREFACM algorithm behavior at 6 000 and 120 000 simulation steps show that as the running length increases the quality improves, in contrast to REF. The comparison is shown in Figure 1. The weighting factor λ used for the calculation of the quality of HREFACM algorithms equals λ=0.8.

1 200 steps		1A	1B	2A	2B
SF	IS	409,7	390,7	689,6	805,7
	PE	151	70	326	143
REF	IS	68,5	72,1	168,7	258,2
	PE	16	11	38	26
REFACM	IS	103,9	101,1	339,6	474,1
	PE	29	36	110	65
HREFACM	IS	68,5	72,1	168,7	258,2
	PE	16	11	38	26

Tab.1. IS and PE values of the observed algorithms during 1 200 simulation steps.

6 000 steps		1A	1B	2A	2B
SF	IS	356,6	957,3	3499,4	4016,0
	PE	130	131	1723	717
REF	IS	118,3	120,3	740,9	1336,7
	PE	18	12	174	103
REFACM	IS	127,4	177,8	963,8	1985,1
	PE	27	34	239	166
HREFACM	IS	127,1	176,4	961,7	1971,4
	PE	26	31	228	151

Tab.2. IS and PE values of the observed algorithms during 6 000 simulation steps.

12 000 steps		1A	1B	2A	2B
SF	IS	645,7	1604,6	6701,0	7474,5
	PE	253	214	3892	1488
REF	IS	168,9	253,9	1457,2	2525,3
	PE	11	12	303	124
REFACM	IS	162,9	296,3	1844,9	4507,3
	PE	19	24	523	317
HREFACM	IS	159,4	284,7	1784,9	4321,2
	PE	19	28	634	421

Tab.3. IS and PE values of the observed algorithms during 12 000 simulation steps.

60 000 steps		1A	1B	2A	2B
SF	IS	3734,8	8923,5	34241,6	33456,4
	PE	217	198	2002	745
REF	IS	512,5	2814,3	4403,2	2747,6
	PE	17	12	402	241
REFACM	IS	410,2	1241,2	3608,3	12607,4
	PE	21	31	654	439
HREFACM	IS	159,4	284,7	1364,7	4321,2
	PE	19	28	634	421

Tab.4. IS and PE values of the observed algorithms during 60 000 simulation steps.

120 000 steps		1A	1B	2A	2B
SF	IS	7234,8	17823,5	68601,8	76824,3
	PE	423	398	3892	1488
REF	IS	1035,4	3419,5	8976,2	33848,8
	PE	17	12	402	241
REFACM	IS	880,8	2914,3	1844,9	4507,3
	PE	51	29	654	439
HREFACM	IS	842,2	2914,3	1784,9	4321,2
	PE	46	26	634	421

Tab.5. IS and PE values of the observed algorithms during 120 000 simulation steps.

Conclusion

Based on our verified simulations using our universally developed test environment in MATLAB, we have come to the following conclusions. For short runtimes of the identification algorithm, classical methods like SF and REF are sufficient. The advantages of the tested HREFACM algorithm will only occur with long-term algorithms over 60,000 steps. Beyond that number of steps it is then advantageous to use it, because its hybrid properties are well adapted to the initial rise phase where it behaves as an REF algorithm. After that, in the long-term use it will again show its qualities when operating in the mode as the REFACM algorithm. Thus, the proposed hybrid algorithm combines the benefits of both algorithms and in the end is versatile and therefore suitable for industrial deployment.

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