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Identification of Continuous-Time Systems with Time Delays by Global Optimization Algorithms and Ant Colony Optimization

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1. Introduction

There are systems which have inherent time delay. If the time delay used for controller design does not coincide with the real process time delay, than a close-loop system can be unstable, or may cause efficiency lost (Bjorklund & Ljung, 2003; Boukas, 2003; Li & Wan, 2002). The identification of linear systems with unknown time delay is important and should be treated as first task during system analysis and control design. This problem can become more complicated for the multi-input single-output (MISO) system, where the solution space is multi-modal.
The most of conventional system identification techniques, such as those based on the non-linear estimations method, for example separable nonlinear least squares (SEPNLS) method, are in essence gradient-guided local search methods. They require a smooth search space or a differentiable performance index. The conventional approaches in the multi-modal optimisation can easily fail in obtaining the global optimum and may be stopped at a local optimum (Chen & Hung, 2001; Harada et al., 2003). One of the possible solution of this problem is use of a SEPNLS methods with global optimisation elements (Chen & Wang, 2004), for example Global SEPNLS (GSEPNLS), known from the literature (Previdi & Lovera, 2004).
New possibility in identification of systems with multi modal solution space is opened by application of the computational intelligence methods (Papliński, 2004; Path & Savkin, 2002; Shaltaf, 2004; Yang et al., 1997). Ant Colony Optimization (ACO) is one among them. Ants are known as a social insects. They exhibit adaptive and flexible collective behavior to achieve various tasks. The macro-scale complex behavior emerges as a result of cooperation in micro-scale.
This paper considers the problem of parameter estimation for continuous-time systems with unknown time delays from sampled input-output data. The iterative separable nonlinear least-squares (SEPNLS) method and global separable nonlinear least-squares (GSNLS) method (Westwick & Kearney, 2001) are presented. We have extended this method by using the ACO. The ACO proposed in the paper is looking for the time delays. Another parameters of linear system are obtained during evaluation of leaving pheromone, by using the SEPNLS method.

2. Problem description

The dynamic of continuous-time MISO system with unknown time delays can be described as:

$$\sum_{i=0}^{n} a_i p^{n-i} x(t) = \sum_{j=1}^{r} \sum_{k=1}^{m_j} b_{jk} p^{m_j - k} u_j(t-\tau_j) \tag{1}$$

where

$a_0 = 1$; $b_{j1} \neq 0$;

p - differential operator;

$u_j(t)$ - j-th input;

τ_j - time delay of *j-th* input;

x - non-disturbed output of system;

We assume the parameters n and m_j are known.

The measurement output is disturbed by stochastic noise:

$$y(t) = x(t) + v(t) \tag{2}$$

The zero order hold is used

$$u_j(t) = \tilde{u}_j(k) \quad \text{for} \quad (k-1)T \le t < kT\,, \tag{3}$$

where T – sampling period.

The problem studied here is as follows: how to estimate the time delays and the system parameters from sampled data representation of the inputs and the noisy output.

3. SEPNLS estimation method

The low-pass pre filter Q(p) is used in order to obtain direct signal derivatives (Iemura et al., 2004):

$$Q(p) = \frac{1}{(\alpha p + 1)^n} \tag{4}$$

where α is the parameter of the Q(p).

Using the pre-filter Q(p) and bilinear transformation in the system (1) we can obtain an approximated discrete-time estimation model of the original system:

$$\xi_{0\bar{y}}(k) = \sum_{i=1}^{n} a_i \xi_{i\bar{y}}(k) = \sum_{j=1}^{r} \sum_{l=1}^{m_j} b_{jl} \xi_{(n-m_j+1)\bar{u}_j}\left(k - \bar{\tau}_j\right) + r(k) \tag{5}$$

where

$$r(k) = \sum_{i=0}^{n} a_i \xi_{i\bar{v}}(k)\,, \tag{6}$$

$$\tilde{\tau}_j = \frac{\tau_j}{T} = \rho + \frac{\Delta}{T}, \qquad 0 \le \Delta < T \tag{7}$$

and

$$\xi_{i\gamma_i}(k) = \frac{\left(\frac{T}{2}\right)^i \left(1+z^{-1}\right)^i \left(1-z^{-1}\right)^{n-i}}{\left(\alpha\left(1-z^{-1}\right)+\frac{T}{2}\left(1+z^{-1}\right)\right)^n} \frac{1+z^{-1}}{2} \gamma_j(k), \qquad \gamma = [y, \quad u, \quad v] \tag{8}$$

The model (5) can be written in the vector form:

$$\xi_{0\bar{y}}(k) = \varphi^T(k,\tau)\theta + r(k) \tag{9}$$

where

$$\begin{aligned}\varphi^T(k,\tau) = [&-\xi_{1\tilde{y}}(k),\ldots,-\xi_{n\tilde{y}}(k),\xi_{(n-m_j+1)\tilde{u}_1}(k-\tilde{\tau}_1),\ldots,\\ &\xi_{n\tilde{u}_1}(k-\tilde{\tau}_1),\ldots,\xi_{(n-m_j+1)\tilde{u}_r}(k-\tilde{\tau}_r),\ldots,\xi_{n\tilde{u}_r}(k-\tilde{\tau}_r)]\end{aligned} \tag{10}$$

$$\theta^T = \left[a_1,\ldots,a_n,b_{11},\ldots,b_{1m_j},\ldots,b_{r1},\ldots,b_{rm_j}\right] \tag{11}$$

The parameters of the model can be estimated as the minimizing arguments of the LS criterion

$$V_N(\theta,\tau) = \frac{1}{N-k_s}\sum_{k=k_s+1}^{N}\frac{1}{2}\varepsilon^2(k,\theta,\tau) \tag{12}$$

$$\varepsilon(k,\theta,\tau) = \xi_{0\bar{y}}(k) - \varphi^T(K,\tau)\theta \tag{13}$$

The vectors of the time delays τ and linear parameters θ are estimated in a separable manner. The linear parameters, when the time delays are known, can be obtained from linear LS method:

$$\hat{\theta}_N(\tau) = R^{-1}(N,\tau)f(N,\tau) \tag{14}$$

where

$$R(N,\tau) = \frac{1}{N-k_s}\sum_{k=k_s+1}^{N}\varphi(k,\tau)\varphi^T(k,\tau) \tag{15}$$

$$f(N,\tau) = \frac{1}{N-k_s}\sum_{k=k_s+1}^{N}\varphi(k,\tau)\xi_{0\bar{y}}(k) \tag{16}$$

The time delays τ can be estimated as the minimizing arguments of the criterion

$$\hat{\tau} = \arg\min_{\tau} \breve{V}_N(\tau) \tag{17}$$

where

$$\breve{V}_N(\tau) = \frac{1}{N-k_s} \sum_{k=k_s+1}^{N} \frac{1}{2} \breve{\varepsilon}^2(k,\tau) \tag{18}$$

and

$$\breve{\varepsilon}(k,\tau) = \xi_{0\bar{y}}(k) - \varphi^T(k,\tau) R^{-1}(N,\tau) f(N,\tau) \tag{19}$$

The all time delays occurring in the system can be computed by the iterative algorithm

$$\hat{\tau}_j^{l+1} = \hat{\tau}_j^l + \Delta\hat{\tau}_j^{l+1} \tag{20}$$

where

$$\Delta\hat{\tau}_j^{l+1} = -\mu \left[\breve{R}_j\left(\hat{\tau}_j^l\right) \right]^{-1} \breve{V}_j^{'}\left(\hat{\tau}_j^l\right) \tag{21}$$

The parameter μ determines the step size of the algorithm. The Hessian of the LS criterion $\breve{R}_j(\tau)$, which permits to use information about the local curvature of the error-surface (Westwick & Kearney, 2001), may be calculated as

$$\breve{R}_j(\tau) = \frac{1}{N-k_s} \sum_{k=k_s+1}^{N} \psi_j^2(k,\tau), \tag{22}$$

and the gradient of LS criterion $\breve{V}_j^{'}(\tau)$ can be obtained from:

$$\breve{V}_j^{'}(\tau) = -\frac{1}{N-k_s} \sum_{k=k_s+1}^{N} \psi_j(k,\tau) \breve{\varepsilon}(k,\tau) \tag{23}$$

The derivatives $\psi_j(k,\tau)$ are defined as

$$\begin{aligned}\psi_j(k,\tau) = \frac{\partial \breve{\varepsilon}(k,\tau)}{\partial \tau_j} = \frac{\partial \varphi^T(k,\tau)}{\partial \tau_j} R^{-1}(N,\tau) f(N,\tau) \\ + \varphi^T(k,\tau) \frac{\partial R^{-1}(N,\tau)}{\partial \tau_j} f(N,\tau) \\ + \varphi^T(k,\tau) R^{-1}(N,\tau) \frac{\partial f(N,\tau)}{\partial \tau_j}\end{aligned} \tag{24}$$

After suitable differentiations:

$$\begin{aligned}
&\varphi_{\tau_j}(k,\tau)=\frac{\partial\varphi^T(k,\tau)}{\partial\tau_j}=\left[0_{1xm},0_{1xm},\dots,0_{1xm},\right.\\
&-\xi_{(n-m)\bar{u}}(k-\tilde{\tau}),-\xi_{(n-m+1)\bar{u}}(k-\tilde{\tau}),\dots,\\
&\left.-\xi_{(n-1)\bar{u}}(k-\tilde{\tau}),0_{1xm},\dots,0_{1xm}\right]
\end{aligned} \tag{25}$$

$$\begin{aligned}
&R_{\tau_j}(N,\tau)=\frac{\partial R^{-1}(N,\tau)}{\partial\tau_j}\\
&R_{\tau_j}(N,\tau)=\frac{1}{N-k_s}\sum_{k=k_s+1}^{N}\varphi_{\tau_j}(k,\tau)\varphi^T(k,\tau)
\end{aligned} \tag{26}$$

$$\begin{aligned}
&f_{\tau_j}(N,\tau)=\frac{\partial f(N,\tau)}{\partial\tau_j}\\
&f_{\tau_j}(N,\tau)=\frac{1}{N-k_s}\sum_{k=k_s+1}^{N}\varphi_{\tau_j}(k,\tau)\xi_{0\bar{y}}(k)
\end{aligned} \tag{27}$$

finally we can get

$$\begin{aligned}
&\psi_j(k,\tau)=\varphi_{\tau_j}^T(k,\tau)R^{-1}(N,\tau)f(N,\tau)\\
&-\varphi^T(k,\tau)R^{-1}(N,\tau)\left[R_{\tau_j}(N,\tau)+R_{\tau_j}^T(N,\tau)\right]R^{-1}(N,\tau)f(N,\tau)\\
&+\varphi^T(k,\tau)R^{-1}(N,\tau)f_{\tau_j}(N,\tau)
\end{aligned} \tag{28}$$

I. The SEPNLS algorithm

1. Let l = 0. Set the initial estimate of the time delays $\hat{\tau}_j^{(l)}=\hat{\tau}_j^{(0)}$.
2. Compute Hessian $R(N,\tau)$ and gradient $f(N,\tau)$ of the linear LS criterion, for the assumed time delays $\hat{\tau}_j^{(l)}$ - expressions (15) – (16)
3. Compute Hessian $\breve{R}_j(\tau)$ and gradient $\breve{V}_j^{'}(\tau)$ of LS criterion by harness equations (22) – (28)
4. Compute new value of the time delays $\hat{\tau}_j^{l+1}$ by using the equation (20) and (21)
5. Check if the new time delays belong to permissible area. If not, let decrease the increment of time delays $\Delta\hat{\tau}_j^{l+1}=\upsilon\Delta\hat{\tau}_j^{l+1}$, where υ is a random variable, and go back to step 4.
6. Check if the new value of LS criterion $\breve{V}_N\left(\hat{\tau}_N^{(l)}\right)$ is smaller than the anterior $\breve{V}_N\left(\hat{\tau}_N^{(l+1)}\right)\le\breve{V}_N\left(\hat{\tau}_N^{(l)}\right)$. If not, decrease the increment of the time delays

$$\Delta\hat{\tau}_j^{l+1}=\upsilon\Delta\hat{\tau}_j^{l+1}\,, \tag{29}$$

where υ is a random variable, and go back to step 4.

7. If the stopping condition is satisfied, go to the next step 7, else let l = l + 1 and go back to step 2.
8. Compute the linear parameter vector from linear LS criterion (14), and terminate algorithm.

4. The global SEPNLS estimation method (GSNLS)

The SEPNLS method can converges to the local optimum. It is possible to apply stochastic approximation (Bhart & Borkar, 1999) with convolution smoothing to the SEPNLS method in order to reach the global optimum (Iemura et al., 2004). The estimate of the time delay in GSNLS can be obtain as

$$\hat{\tau}_j^{(l+1)} = \hat{\tau}_j^{(l)} - \mu^{(l)}\left(\left(\breve{R}_j\left(\hat{\tau}_j^{(l)}\right)\right)^{-1}\breve{V}_j'\left(\hat{\tau}_j^{(l)}\right) + \beta^{(l)}\eta\right) \tag{30}$$

where $\eta \in R^r$ is a random vector used to perturb τ. The values of η are generated by Gaussian, uniform, or Cauchy distribution probability density function. The values of μ and β control its variance.

The value of β has to be chosen large at the start of the iterations and decreased to zero when the global minimum is reached (Yang et al., 2005). It can be obtain for

$$\beta^{(l)} = \beta_0 \breve{V}_N\left(\hat{\tau}_N^{(l)}\right) \tag{31}$$

where the LS criterion $\breve{V}_N\left(\hat{\tau}_N^{(l)}\right)$ is given by equation (18). The value of $\breve{V}_N\left(\hat{\tau}_N^{(l)}\right)$ decreases during the sequence of iterations, which cases that disturbances of τ decrease too.

5. Ant colony optimization (ACO)

Recently, researchers in various fields have showed interest in the behaviour of social creatures to solve various tasks. The ants exhibit collective behaviour to perform task as foraging, building a nests. These tasks can not be carried out by one individual. The macro-scale complex behaviour emerges as a result of cooperation in micro-scale. This appears with out any central or hierarchical control. A way of communicating between individuals in colony is chemical substances called pheromones (Agosta, 1992; Bonabeau et al., 1999). Ants looking for food lay the way back to their nest with a specific type of pheromone. Other ants can follow the pheromone trail and find the way to the aliments. Pheromones remain in the some way superimpose and intensify, concurrently the pheromones evaporate in time and their intensity decreases. A specific map of pheromones is created on the search space. This map is not unalterable and can bring into line with ambient. Each ant looks for food independently of the others and moves from nest to source of food. There are a lot of ways in which ants can go. Ants choose a way for theirs leverage three sources of information

- the own experience
- the local information
- the pheromone trail.

The own experience permits to recognize place when it already was and avoid looping of the way. For the artificial ant it permits to allocate particular value to appropriate seeking parameters.
The local information determines permissible way. Ants can recognize and sidestep hindrances. In the artificial ant colony it is responsible for the search space constraint.
The pheromone trail permits to come back to the nest and find the source of food found earlier by another individuals from colony. Ants prefer this way in which intensity of pheromones is the biggest.
The intensity of the pheromone is given by the equation:

$$\tau_i(t+1) = \tau_i(t) * \rho + \frac{n}{m} \frac{J_i}{\sum_{k=1}^{n} J_i} \tag{32}$$

where:
$\tau_i(t)$ - the intensity of the pheromone at the time t
ρ - a coefficient such that $(i-\rho)$ represents the evaporation rate of the pheromone between time t and t+1.
n - an amount of ant in the nest;
m - an amount of rows in the matrix of pheromone;
The value of ρ must be set to a value less than 1 to avoid unlimited accumulation of the pheromone. The investigation where obtained for $\rho = 0,95$.
The quality function J is divided by the sum of all quality functions in order to uniform it to one. The quotient the number of ants to the number of rows in the matrix of pheromone conforms the lied intensity of pheromone to the existing pheromone.
The amount of pheromone traces was limited to specified number by removing the worst traces.
The investigations was made with the amount of pheromone trace equal double of amount of ants in the colony:

$$m = 2 * n \tag{33}$$

Every ants live in one iteration and they died after updating the pheromone trace. The new ants are created in another iteration. The time delays of the model (2) are interpreted as a decision tie inside a way of ants. It is a place where an ant has to decide about next direction of motion. The direction is randomly chosen with the probability distribution specified by the pheromone traces. The half of population of ants has disturbed direction:

$$c_{ij} = \zeta_{ijn}\beta + \zeta_{ijs}(1-\beta) \tag{34}$$

where:
i – the number of ants
j – the number of parameter – tie
ζ_{ijn} – the random number with normal distribution, inside the solution space
ζ_{ijs} – the random number with distribution defined by pheromone trace
β – a randomly coefficient of ratio of averaging.

The ants are looking only for the time delays of a model. The residual parameters of the model are obtained from SEPNLS during calculation the quality function J. It can be do because these parameters are linear and SEPNLS works efficiently with them.

6. Simulation example

The algorithm presented in the previous sections has been tested on the MISO example. We consider the following system (Papliński, 2007):

$$\ddot{y}(t)+a_1\dot{y}(t)+a_2y(t)=b_{11}u_1(t-\tau_1)+b_{21}u_2(t-\tau_2) \tag{35}$$

where

$a_1=3.0$; $a_2=4.0$; $b_{11}=2.0$; $b_{21}=2.0$

$\tau_1=9.15$; $\tau_2=2.57$;

The inputs and output signals are converted by zero-order-hold operation with sampling period $T=0.05$. The pre-filter $Q(p)$ with $\alpha=0.4$ is used. As a input signals are used independent sequence of uniform distribution between 0 and 1. The signal to measurement noise ratio SNR is 5%. A data set of 1000 samples was generated for the identification process. The algorithms are implemented for 250 iterations. The initial values of time delays $\tau^{(0)}$ are randomly chosen between 0 and 25.

All algorithms, presented in the paper were running 200 times. The GSNLS was used with variance coefficient $\mu=10^6$.

The solution space of time delays is multimodal and the global optimum is not reached in every time. Therefore the percentages of identified time delays, with error les than 10%, can be treated as a main quality function and they are presented in Fig. 1

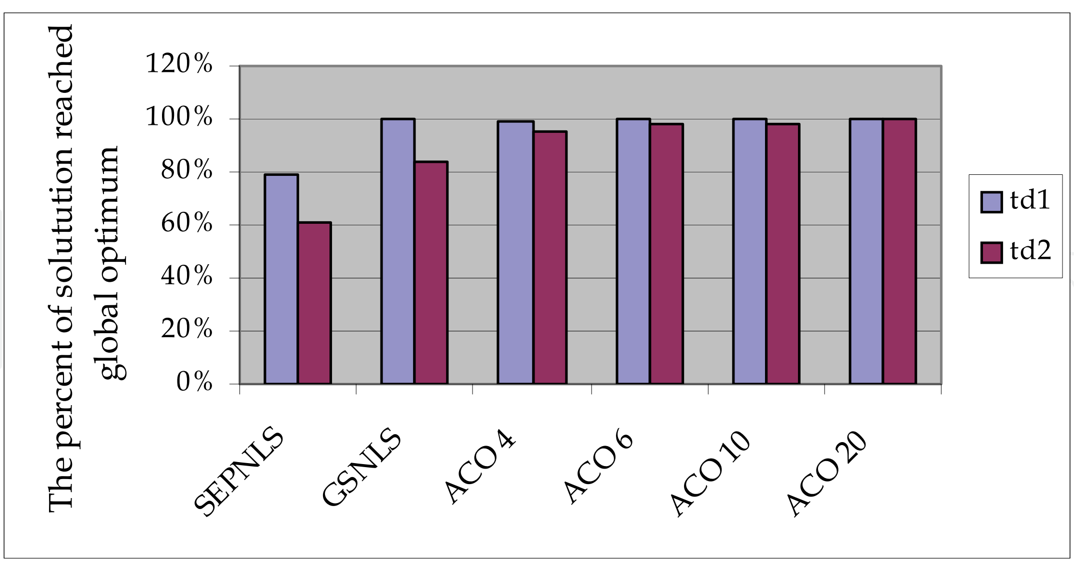

Fig. 1. The percent of identified time delays τ_1 , τ_2 which are reached global optimum for SEPNLS, GSNLS and ACO with 4, 6, 10 and 20 ants in the colony

For the SEPNLS the global optimum are reached only at 60% of trials. These results strongly depend on the initial values, because algorithm can not miss the attraction area of the local minimum. The GSNLS works better, but still more than 16% of solution is bed. The AM gave the best solution. The results depend on the number of ants in computational colony. Bigger number of individuals make better accuracy. But even small colony wit 4 ants gave better results than SEPNLS and GSNLS.

The Table 1 presents the mean value of identified time delay and references standard deviation. The ACO algorithm gave much better results than SEPNLS and GSNLS. The augmentation of amount of ants in ACO only little improves obtained results. It confirms the conclusion obtained from Fig. 1. If we look only for solution laying in the global optimum, all algorithms give similar accuracy. This is presented in the Table 2.

	The amount of ants	t_1 of the plant	td1 (identified)	t_2 of the plant	td2 (identified)
SEPNLS	-	9,13	9,88 ± 5,02	2,57	7,17 ± 8,04
GSNLS	-	9,13	9,27 ± 0,04	2,57	5,22 ± 6,64
ACO	4	9,13	9,26 ± 0,18	2,57	2,66 ± 0,18
ACO	6	9,13	9,24 ± 0,07	2,57	2,66 ± 0,13
ACO	10	9,13	9,26 ± 0,05	2,57	2,67 ± 0,11
ACO	20	9,13	9,25 ± 0,04	2,57	2,68 ± 0,08

Table 1. The mean value of identified time delay and references standard deviation

	The amount of ants	t_1 of the plant	td1 (identified)	t_2 of the plant	td2 (identified)
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GSNLS	-	9,13	9,27 ± 0,04	2,57	5,22 ± 6,64
ACO	4	9,13	9,26 ± 0,18	2,57	2,66 ± 0,18
ACO	6	9,13	9,24 ± 0,07	2,57	2,66 ± 0,13
ACO	10	9,13	9,26 ± 0,05	2,57	2,67 ± 0,11
ACO	20	9,13	9,25 ± 0,04	2,57	2,68 ± 0,08

Table 2. The mean value of identified time delay and standard deviation of it for the solution laying in the global optimum

The time of computation is one of the parameters indicating the performance of iterative algorithms. These times are presented in the Fig. 2. For the ACO algorithms the time of computation depends linearly on the amount of ants. For the colony with 12 ants and less, this time is not bigger than for SEPNLS and GSNLS. For these two last, the time is comparable. The standard deviation of the time of computation is shown in the Fig. 2. The ACO with a few ants has the smallest deviation of time of computation. For the SEPNLS and GSNLS the number of repetition in every iteration is variable and depends on indirect solutions.

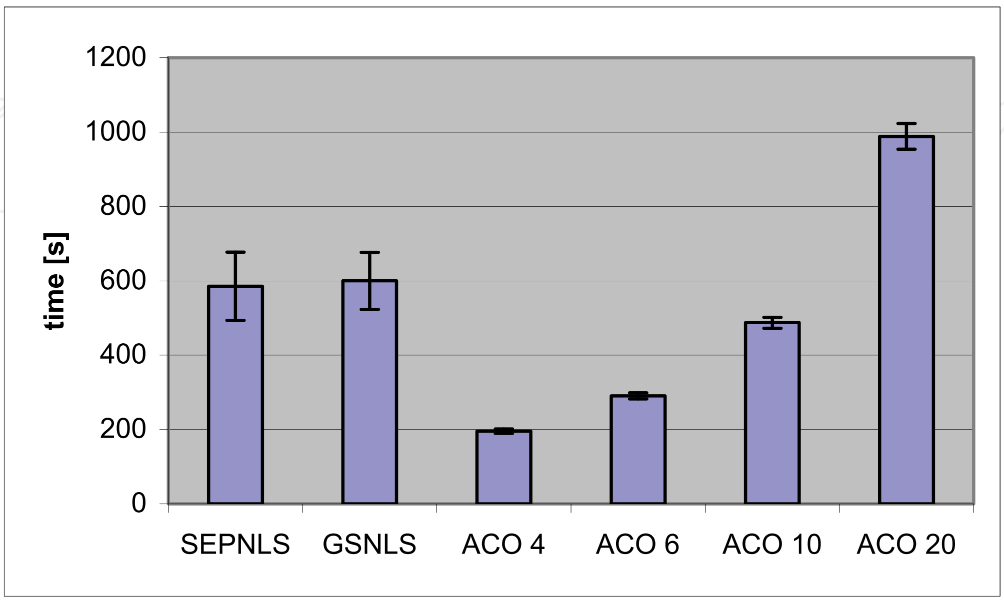

Fig. 2. The time of computation with standard deviation

7. Conclusion

In this paper a separable nonlinear least squares method is developed for identification of systems with time delays. The SEPNLS is vulnerable to local minima in the error surface. The solution depends on the initial values used for identification. The efficiency of this algorithm is poor.

The GSNLS applies the stochastic approximation to the SEPNLS method. It permits to leave the attraction area of a local minimum and reach the global optimum. The efficiency of this algorithm is good.

The ACO has the best performance even for small amount of ants. The algorithm with four ants is fast and quite good. We obtain solution tree times faster and better than from SEPNLS and GSNLS The augmentation of amount of ants permits to improve slightly accuracy of identification of time delay, but the time of identification is increasing linearly too.

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