An Online Scheme for Delayed MISO System Identification

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ABSTRACT

The issue of parametric estimation in time delay models is the main topic of this research article. Multiple-Input Single-Output (MISO) Continuous-Time (CT) systems with numerous unknown time delays characterize these models. Two different recursive parametric estimate techniques are explored in this paper, the strategic application of Sequential Nonlinear Least Squares (SNLS) to attain global convergence and the Recursive Least Squares (RLS) technique in conjunction with the Gauss-Newton algorithm with the goal of achieving local optimization. Both approaches contribute to the comprehensive understanding of the parametric estimation landscape for time delay models. In a pivotal stride towards enhancing convergence, the research proposes a hybridization of the two methods. This synergistic approach is designed to leverage the strengths of both SNLS and the RLS-Gauss-Newton combination, fostering improved overall convergence properties. To substantiate the credibility and effectiveness of the proposed methodologies, the conducted research provides comprehensive simulation results. These simulations offer concrete examples of the efficacy and practicality of the suggested techniques in real-world situations, and they make significant contributions to the field of parametric estimation for time delay models.

Keywords-continuous-time system; online identification; multiple-input single-output system; multiple unknown time delays; RLS; Gauss-Newton algorithm; Sequential Nonlinear Least Square (SNLS) algorithm; hybrid method

I. INTRODUCTION

By providing concrete examples of the effectiveness and suitability of the suggested techniques in practical settings, simulations significantly contribute to the field of parametric estimation for time delay models. The ability to precisely characterize and predict the behavior of such systems is fundamental for optimizing performance, ensuring stability, and enhancing overall efficiency. As technological advancements continue to drive innovation across various industries, the importance of accurate time delay system identification becomes increasingly pronounced. From critical applications in process control to telecommunications and beyond, the ability to capture and understand temporal delays is integral to the design, analysis, and optimization of complex systems. Several studies focus on time-delay systems and their relevance in modeling and controlling diverse systems. Relevant studies have been conducted in the fields of biology, chemistry, economics, mechanics, viscoelasticity, physics, physiology, population dynamics, and engineering sciences [1-8]. Moreover, time delays are commonly introduced by components like actuators, sensors, field networks, and wireless communications within feedback loops. These delays entail implications relevant to the overall performance and stability of systems across various disciplines. In the expansive landscape of system identification involving time delays, many techniques have been proposed [9-18]. These approaches have evolved to cater to the complexities associated with temporal dependencies, addressing the intricacies of processes where delays play a pivotal role. In essence, these techniques represent a continuum of exploration and innovation in the field of time delay system identification. This dynamic area of research continues to progress, driven by the need to enhance people's understanding of temporal dependencies and develop robust methodologies applicable across diverse domains.

Even if the aforementioned advancements take place, problems still exist, particularly with the Multiple-Input Single-Output (MISO) time delay system identification. The interaction of numerous inputs poses a unique set of challenges, necessitating the emergence of innovative approaches. In addition, the study of the considered MISO process serves as a foundation for developing robust system identification techniques. Successfully identifying the parameters of this complex system can have broad applications in fields, such as control engineering, signal processing, and dynamic modeling. In this context, the goal of the current research is to investigate the online identification of MISO CT models with multiple unknown time delays.

II. SYSTEM DESCRIPTION AND IDENTIFICATION MODEL

The envisioned MISO process with numerous time delays is delineated through the following representation:

$$x(t) = \frac{G_1(s)}{F(s)} e^{-d_1 s} u_1(t) + \ldots + \frac{G_r(s)}{F(s)} e^{-d_r s} u_r(t) \qquad (1)$$

with:

$$e^{-d_j s} u_j(t) = u_j(t - d_j) \qquad (2)$$

where $j = 1\ldots..r$ responds to the time delay.

The significance of studying the MISO process:

- Realistic Modeling: Many real-world systems exhibit MISO configurations, where multiple factors endow a single observed outcome. Understanding and accurately modeling such systems are essential attributes for the performance of effective control, analysis, and prediction.
- Challenges of Time Delays: The inclusion of unknown time delays reflects real-world scenarios where systems often exhibit temporal delays in responding to inputs. Investigating the aforesaid delays is crucial for capturing the true dynamics of the system.
- System Identification Implications: The study of the considered MISO process serves as a foundation for developing robust system identification techniques. Successfully identifying the parameters of this complex system can have broad applications in fields, like control engineering, signal processing, and dynamic modeling. E

Equation (1) could be rewritten as:

$$x(t) = \frac{G_1(s)}{F(s)} u_1(t - d_1) + \ldots + \frac{G_r(s)}{F(s)} u_r(t - d_r) \qquad (3)$$

$F(s)$ and $G_j(s)$ are parameterized as follows:

$$F(p) = 1 + f_1 s + \ldots + f_p s^p \qquad (4)$$

$$G_j(s) = g_{j0} + g_{j1} s + \ldots + g_{jq_j} s^{q_j} \qquad (5)$$

Equation (1) is summarized as:

$$\sum_{i=0}^{p} f_i s^{p-i} x(t) = \sum_{j=1}^{r} \sum_{i=1}^{q_j} g_{ji} s^{q_j - i} u_j(t - d_j) \qquad (6)$$

A low-pass filter is used in order to allow signals with a frequency lower than a certain cutoff frequency to pass through, while attenuating or blocking signals with frequencies higher than the cutoff. This frequency point determines the boundary between the frequencies that pass through the filter with minimal attenuation and those that are significantly attenuated. In this research work, the following filter is implemented to filter input/output data:

$$K(s) = \frac{1}{(\alpha s + 1)^p} \qquad (7)$$

The low-pass filter described in (7) ensures that the signals of interest are effectively transmitted or processed while suppressing unwanted high-frequency components. The first side of system (6) is now multiplied by the $K(s)$ defined in (7). The employment of the bilinear transformation permits the acquisition of a DT estimation model:

$$\begin{aligned} &\bar{y}_0(k) + \sum_{i=1}^{p} f_i \bar{y}_i(k) = \\ &= \sum_{j=1}^{r} \sum_{i=1}^{q_j} g_{ji} \bar{u}_{j_{(p-q_j+1)}}(k - \tilde{d}_j) + v(k) \end{aligned} \qquad (8)$$

such that:

$$v(k) = \sum_{i=0}^{p} f_i \bar{e}_i(k) \qquad (9)$$

$$\bar{e}_i(k) = K_i(q^{-1}) \bar{e}(k) \qquad (10)$$

and:

$$\begin{aligned} \bar{u}_{j_i}(k) &= K_i(q^{-1}) \bar{u}_j(k) \\ \bar{y}_i(k) &= K_i(q^{-1}) \bar{y}(k) \end{aligned} \qquad (11)$$

$$K_i\left(q^{-1}\right) = \frac{\left(1+q^{-1}\right)^i (T/2)^i \left(1-q^{-1}\right)^{p-i}}{\left[\alpha\left(1-q^{-1}\right) + (T/2)\left(1+q^{-1}\right)\right]^p} \qquad (12)$$

The bilinear transformation is a mathematical technique commonly deployed in the field of signal processing and control system design. It acts as a method for converting continuous-time systems or filters into discrete-time equivalents. This transformation is particularly useful when working with analog systems and aiming to implement them in a digital environment. In this research work, the primary purpose of the bilinear transformation is to map the frequency domain characteristics of a continuous-time system to a discrete-time system. This is essential when transitioning from analog to digital signal processing. The bilinear transformation is defined by:

$$s = \frac{2}{T}\left(\frac{1-q^{-1}}{1+q^{-1}}\right) \tag{13}$$

which leads to:

$$q^{-1} = \frac{2-sT}{2+sT} \tag{14}$$

The *j*-th time delay $\tilde{d}_j$ is given by:

$$\tilde{d}_j = d_j / T = l_j + \Delta_j / T \tag{15}$$

where $0 \le \Delta_j < T$ and l_j is a non-negative integer.

III. IDENTIFICATION APPROACH BY USING THE SEQUENTIAL NONLINEAR LEAST SQUARES METHOD

The identification approach employing the Sequential Nonlinear Least Squares (SNLS) method is a powerful and widely utilized technique in the field of system identification. This method is particularly valuable when dealing with complex systems characterized by nonlinearities and unknown time delays. The SNLS method provides an effective means to iteratively estimate the parameters of a dynamic system, optimizing the fit between the model and observed data.

The key components of the SNLS method are:

- Sequential Estimation: The SNLS method operates in a sequential manner, meaning that it either processes one sample of data at a time or that it processes the latter in small batches. This sequential approach allows for real-time parameter updates as new data become available, making it suitable for dynamic systems with changing characteristics.
- Nonlinear Least Squares Optimization: At the core of the SNLS method lies the optimization of parameters using the nonlinear least squares criterion. This involves minimizing the sum of the squares of the differences between the observed and the predicted values. The iterative nature of the SNLS method refines parameter estimates to converge towards an optimal solution.
- Simultaneous Parameter Estimation: SNLS is capable of simultaneously estimating multiple parameters of a system. This is especially advantageous in scenarios where parameters are interdependent or when multiple aspects of the system need to be concurrently identified.

The proposed method includes the simultaneous estimation of both time delays and the parameters defined as follows:

$$\hat{\theta} = [\hat{f}^T, \hat{g}_1^T, ..., \hat{g}_r^T] \tag{16}$$

with:

$$\hat{f} = [\hat{f}_1, ..., \hat{f}_p] \tag{17}$$

$$\hat{g}_j^T = [\hat{g}_{j1}, ..., \hat{g}_{jq_j}] \tag{18}$$

$$\hat{d}^T = [\hat{d}_1, ..., \hat{d}_r] \tag{19}$$

The generalized vector in the context of the SNLS method plays a pivotal role in the formulation and optimization process for system identification. This vector encapsulates the estimated parameters and the associated time delays within the dynamic system under consideration. The representation of the generalized vector is instrumental in expressing the mathematical model and in iteratively refining the parameter estimates to achieve convergence.

The generalized vector is:

$$\Theta = \left[\theta^T, d^T\right]^T \tag{20}$$

The sampled output is:

$$\overline{y}_0(k) = \varphi^T(k, \hat{d})\hat{\theta} + v(k) \tag{21}$$

$\varphi^T(k, \hat{d})$ is defined as:

$$\varphi^T(k, \hat{d}) = [-\varphi_{\overline{x}}^T(k), \varphi_{\overline{u}_1}^T(k-\tilde{d}_1), ..., \varphi_{\overline{u}_r}^T(k-\tilde{d}_r)] \tag{22}$$

with:

$$\varphi_{\overline{y}}^T(k) = \left[\overline{y}_1(k), ..., \overline{y}_p(k)\right] \tag{23}$$

$$\varphi_{\overline{u}_j}^T(k-\tilde{d}_j) = \left[\xi_{(p-q_j+1)\overline{u}_j}(k-\tilde{d}_j), ..., \xi_{p\overline{u}_j}(k-\tilde{d}_j)\right] \tag{24}$$

The prediction error is:

$$e(k) = \overline{y}_0(k) - \hat{y}(k) \tag{25}$$

The prediction error, represented in (25), is a critical concept in the context of system identification and predictive modeling. It represents the disparity between the predicted output of a model and the actual observed output at a sampling period *T*. The prediction error serves as a key metric in assessing the accuracy and performance of a model, providing insights into how well the model captures the underlying dynamics of the system. A prediction error of zero signifies perfect agreement between the model's predictions and the actual observations.

The generalized observation vector is:

$$\Phi(k, \hat{\Theta}) = \frac{-\partial e(k)}{\partial \hat{\Theta}} = \left[\varphi(k, \hat{d}), \frac{-\partial e(k)}{\partial \hat{d}}\right] \tag{26}$$

where $\frac{\partial e(k)}{\partial \hat{d}_j}$ and $\Phi(k,\hat{\Theta})$ are described in [13].

The following criterion is considered:

$$V(\hat{\Theta}) = \frac{1}{N-h_s}\sum_{k=h_s+1}^{N}\frac{1}{2}\left(\alpha(k)^{h_s+N-k}e^2(k)\right) \tag{27}$$

The SNLS algorithm is summarized as:

$$\Theta(k) = \Theta(k-1) + P(k)\Phi(k,\Theta)\varepsilon(k,\Theta) \tag{28}$$

During the SNLS optimization process, the generalized vector (28) is iteratively adjusted to minimize the discrepancy between the predicted and observed values in the least squares sense. The optimization aims to find the values of the generalized vector that result in the best fit between the model and the real-world data. The formulation of the generalized vector is integral to the objective function that is minimized during each iteration of the SNLS algorithm. The algorithm systematically refines the components of the vector, updating the parameter estimates and time delays to improve the accuracy of the model.

$$L(k) = \frac{P(k)\Phi(k,\Theta)}{\alpha(k) + \Phi^T(k,\Theta)P(k)\Phi(k,\Theta)} \tag{29}$$

$$P(k) = \frac{1}{\alpha(k)}\left(P(k-1) - L(k-1)\Phi^T(k,\Theta)P(k-1)\right) \tag{30}$$

The flow chart of the SNLS method is shown in Figure 1.

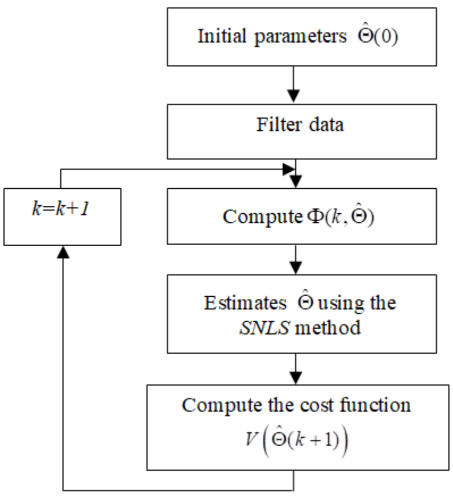

Fig. 1. Flow chart of the SNLS method.

IV. RECURSIVE LEAST-SQUARES METHOD (RLS)

RLS is a recursive estimation algorithm commonly employed for updating parameter estimates sequentially as new data become available. It is particularly well-suited for real-time applications and scenarios where the system's characteristics may evolve over time. RLS efficiently handles parameter variations by continuously adapting to changing conditions.

The following criterion is considered:

$$V(\hat{\Theta}) = \frac{1}{N-h_s}\sum_{k=h_s+1}^{N}\frac{1}{2}\left(\alpha(k)^{h_s+N-k}e^2(k)\right) \tag{31}$$

The prediction error is:

$$e(k) = \bar{y}_0(k) - \varphi^T(k,\hat{d})\hat{\theta} \tag{32}$$

The parametric model of the plant (8) is described by the following regression form:

$$\bar{y}_0(k) = \varphi^T(k,d)\theta + r(k) \tag{33}$$

where $\varphi^T(k,d)$ is the new observation vector defined as:

$$\varphi^T(k,d) = [-\varphi_{\bar{y}}^T(k), \varphi_{\bar{u}_1}^T(k-\tilde{d}_1), \ldots, \varphi_{\bar{u}_r}^T(k-\tilde{d}_r)] \tag{34}$$

and $\varphi_{\bar{y}}^T(k)$ and $\varphi_{\bar{u}_j}^T(k-\tilde{d}_j)$ are defined in (23) and (24).

The developed approach is based on the identification of the linear parameters with the RLS algorithm. Then, the time delays in the nonlinear part are estimated by the Gauss-Newton algorithm. This clearly means that:

$$\left[\theta^T, d\right]^T = \arg\min_{\theta,d} J(\theta,d). \tag{35}$$

The flow chart of the GN-RLS method is depicted in Figure 2.

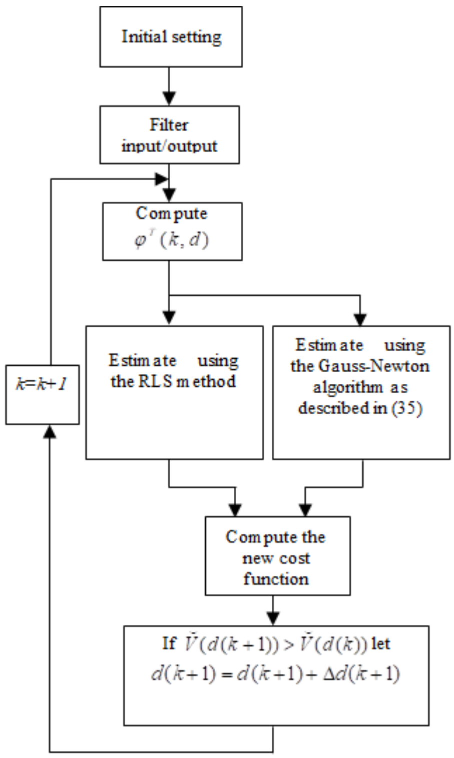

Fig. 2. Flow chart of the GN-RLS method.

V. THE PROPOSED HYBRID METHOD

The proposed hybrid method, which combines the strengths of the Gauss-Newton Recursive Least Square (GN-RLS) method with the Sequential Nonlinear Least Square (SNLS) method, represents an advanced and versatile approach to system identification. This fusion of techniques harnesses the complementary features of GN-RLS and SNLS, aiming to enhance the accuracy, efficiency, and adaptability of parameter estimation in dynamic systems. The flow chart of the hybrid method is portrayed in Figure 3.

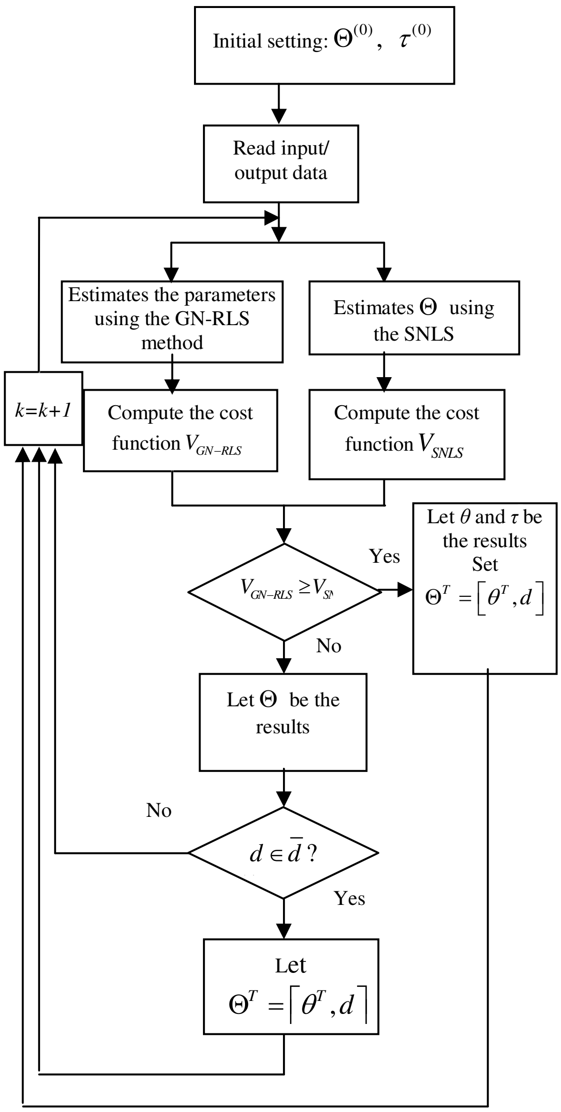

Fig. 3. Flow chart of the proposed hybrid method.

In summary, the hybrid GN-RLS-SNLS method stands as a sophisticated approach to system identification, leveraging the combined strengths of the GN-RLS and the SNLS techniques for enhanced performance and adaptability.

VI. SIMULATION RESULTS

For the GN-RLS method, the forgetting factor is given as β = 0.882, $p_0 = 10^6$, and the *GN-RLS* is the same as in the SNLS method (SNR = 5 dB). The obtained results are illustrated in Table I.

Table I provides an obvious indication that the estimated parameters acquired through the GN-RLS method closely align with the target values, suggesting a high degree of accuracy and precision in the parameter estimations and highlighting the efficacy of the GN-RLS method in capturing the underlying characteristics of the data. To fully appreciate the significance of this observation, it is essential to scrutinize the details presented in Table I. This level of clarity is valuable in scientific and research contexts, where the accuracy of parameter estimates is crucial for drawing meaningful conclusions or making informed decisions. Researchers and analysts can leverage this information to assert the robustness of the GN-RLS method in accurately reproducing the target parameters. The proximity of the estimated values to the target values in Table I may serve as a foundation for building confidence in the method's capability to model and predict the underlying dynamics of the system or phenomenon under investigation.

TABLE I. PARAMETER ESTIMATES

	True	**Initial**	**Estimates with GN-RLS**	**Estimates with the proposed hybrid method**
f_1	3	0	3.0310±0.0310	3.0094±0.0094
f_1	2	0	2.0112±0.0112	1.9819±0.0181
g_{11}	1	0	1.0747±0.0747	0.9933±0.0067
g_{12}	2	0	1.9911±0.0089	1.9585±0.0415
g_{21}	2	0	2.0330±0.0330	1.9935±0.0065
g_{22}	2	0	2.0136±0.0136	2.0140±0.0140
d_1	8.84	9	8.8690±0.029	8.8455±0.0055
d_2	1.87	2	1.8763±0.0063	1.8760±0.006

In summary, the evident accuracy of the GN-RLS method in reproducing target parameter values, as demonstrated by the data in Table I, should be emphasized. The high degree of concordance between the estimated and the target values is underscored, affirming the method's suitability for the specific analysis or modeling task at hand.

In this simulation case, the noise magnitude is adjusted to get the same SNR as in the GN-RLS and the SNLS methods. The outcomes of the numerical simulation conducted using the hybrid method presented in this study surpass the performance of both the SNLS and the GN-RLS methods, suggesting that the hybrid approach yields more satisfactory results, indicating a superior capability in capturing the intricacies of the simulated system or phenomenon. Exploring factors, like error metrics, convergence rates, or any other relevant performance indicators can provide a more thorough understanding of the excellence of the proposed hybrid method. Additionally, awareness of the simulated system traits, such as nonlinearity or complexity, can contribute to a more comprehensive interpretation of the comparative performance.

VII. CONCLUSION

In this research study, three distinct methodologies were employed for the identification of parameters in Multiple-Input Single-Output (MISO) Continuous-Time (CT) systems characterized by multiple unknown time delays, using sampled input-output data. The initial approach involves the simultaneous identification of the system, deploying the Sequential Nonlinear Least Squares (SNLS) algorithm. The second technique integrates the Recursive Least Squares (RLS) method with the Gauss-Newton (GN) algorithm. Subsequently, a hybrid method was devised by combining the SNLS and GN-RLS techniques, with the aim of enhancing overall accuracy. The SNLS algorithm, implemented for simultaneous identification, offers a sequential and iterative optimization process to refine parameter estimates. The second technique, GN-RLS, synergizes the recursive adaptability of RLS with the optimization power of the GN algorithm to achieve more robust parameter updates.

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