Identification by Recursive Least Squares with RMO
Applied to a Robotic Manipulator

Darielson A. Souza, Josias G. Batista, Laurinda L. N dos Reis, José R. O Júnior, José N. N Júnior
Department of Electrical Engineering, Federal University of Ceará.
Fortaleza, CE, Brazil
darielson@dee.ufc.br

Killldary A. Santana
Department of Electrical Engineering, Federal University of Ceará.
Sobral, CE, Brazil

Antônio B. S. Júnior
Department of Industry, Federal Institute of Ceará.
Maracanaú, CE, Brazil

Rui A. M. Araújo
Institute of Systems and Robotics (ISR-UC), and Department of Electrical and Computer Engineering (DEEC-UC).
University of Coimbra, Polo II, PT-3030-290 Coimbra, Portugal

Abstract—The present work presents a hybrid identification of recursive least squares with a metaheuristic called radial movement optimization (RMO) applied to the joints of a cylindrical robotic manipulator. The main contribution of the research is to consider the covariance matrix with RMO. At the end a comparative analysis will be made with some classic methods. The results of the identifications were tested with the RMSE. A covariance matrix has also been generated from manipulator identifications.

Keywords—Systems identification; Mechanical system; Optimization; Robotic arm

I. INTRODUCTION

Robotics has great importance in the vast majority of current applications, but control techniques have been constantly tested [1]. The main advantages of manipulator robots in the industries are: speed, torque and precision, these characteristics are essential for a good performance in the accomplishment of tasks [2].

For this, this work has the contribution of presenting a hybrid system using the recursive least squares method with a radial motion optimization algorithm (RMO) [3], [4] to tune the P matrix of the recursive least squares method.

The proposed method will be compared with other identification, such as classical recursive least square and a Kalman filter. The methods are compared and evaluated by root mean square error (RMSE).

II. SYSTEM DESCRIPTION

The cylindrical manipulator has 3 degrees of freedom, the first degree is the base that has rotational movements, the second degree is linear that is the trunk that makes the movements in the vertical, the third degree is what makes the movements in the horizontal, and by the fourth and fifth grade is the claw that is also called the end-effect. [5]. Figure 1 shows the cylindrical manipulator without the end-effect. Figure 1 shows a demonstration of the actual manipulator used in the work, the same has the joints with three-phase induction motors. The manipulator that will be used has three degrees of freedom, but only the data acquisition of the third board was prepared. The mechanical and electrical behavior was collected to make the identification. Specifying the collection, the current and velocity were captured during the activation of the 1st joint. The goal is to create a model that satisfies the mechanical behavior of the model.

III. SYSTEMS IDENTIFICATION

The data to be identified are real data collected: current in the input and speed in the output. Where the position of the label (input and output) will be scrambled, to avoid overfitting. After the data set will be divided into 80% for training and 20% for tests.

A. Recursive Least Squares (RLS)

The recursive least squares algorithm (RLS) has a great advantage over the others due to its speed with its way of working in batch. One of the disadvantages is to consider is to consider the covariance matrix P during the identification process [6]. Figure 2 presents how the identification is made,
ie always the algorithm result is compared to the actual facings collected from the plant in parallel.

![System Model](image)

Figure 2. Recursive least squares identification.

B. Hybrid Identification

As we have seen before the search of the matrix \( P \) in the least squares recursive can be a problem when it is initiated in the wrong way. The RMO metaheuristic will be used to solve this problem, thus doing a search that tries to minimize an objective function that is the RMSE, as shown in Eq. (1).

\[
\sqrt{\sum_{t=1}^{T}(\hat{y}(t) - y(t))^2}
\]

(1)

where: \( y(t) \): observation, \( \hat{y}(t) \): estimate, \( T \): the amount of iterations.

Radial movement optimization is a novel global optimization technique used to solve the complex optimization problems. The technique for global optimization of multivariable complex system, called radial movement optimization (RMO) is developed by [3].

After adjusting the \( P \) matrix with the RMO in the RLS, \( P \) was obtained from the equation below Eq. (2).

\[
\begin{bmatrix}
7.533 & 0 & 0 & 0 \\
0 & 14.0801 & 0 & 0 \\
0 & 0 & 18.8185 & 0 \\
0 & 0 & 0 & 38.9121
\end{bmatrix}
\]

(2)

The transfer function generated after searching the covariance matrix for a better result is in Eq. (3).

\[
\frac{2.546+3.917z^{-1}}{1-0.4187z^{-1}-0.5657z^{-2}}
\]

(3)

C. Kalman Filter

The Kalman Filter is a set of mathematical equations that constitutes an efficient recursive estimation process, since the quadratic error is minimized. By observing the variable called "observation variable", and another variable not observable, called "state variable" can be estimated efficiently. Past states, current state and even predicted future states can be estimated [6].

IV. RESULTS

In this section the results of the identifications will be presented using RLS with RMO, Classical RLS and Kalman Filter. The comparative analysis will be done with the RMSE. The Figures below present the test identifications, that is to say with the already trained algorithms. This shows the error for better viewing.

The TABLE I presents the results of the identifications taking into account the validations using the RMSE as evaluation parameter.

**TABLE I. COMPARISON OF RESULTS WITH RMSE**

<table>
<thead>
<tr>
<th>Methods</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>RLS</td>
<td>0.0814</td>
</tr>
<tr>
<td>Kalman Filter</td>
<td>0.0763</td>
</tr>
<tr>
<td>RLS+RMO</td>
<td>0.0759</td>
</tr>
</tbody>
</table>

According to the TABLE I, the RLS+RMO yielded a better estimate with RMSE of 0.0759. Thus it was able to overcome the Kalman filter and the classic Recursive least square.

V. CONCLUSIONS

A hybrid method of identification of systems was presented trying to solve a problem of weighting, so with the solution solved the objectives were: The RLS method was lighter, had superior results to other methods and objected to a faster convergence.

As a proposal of future work is intended to make an adaptive control project with the model generated to have a better accepted validation. Thus each change of the operation point will be generated a new identification, consequently a control project.

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REFERENCES


