Research on Photoelectric Detection and Identification System Based on Three-Stage Multiple Innovation Recursive Least Squares Algorithm

JING Min

School of Mechanical Engineering
Shaanxi University of Technology
Shaanxi, China

Abstract — In this paper, the author researches on photoelectric detection and identification system based on a three-stage multiple innovation recursive least squares algorithm. A TSMIRLS algorithm is derived utilizing some of the recent research improvements in the field of RLS identification. Through a simulation example, it is shown that the proposed algorithm improves accuracy in terms of the parameter estimation, in comparison with the existing identification techniques. Although the proposed TSMIRLS provides increased accuracy, it involves a heavier computational burden, especially when it is used in the multi-innovation form. In order to fit for less computational time, an alternative to TSMIRLS algorithm, that is a TSMISG algorithm, is also presented. Depending upon the accuracy and computational time requirements, a selection can be made between the two algorithms.

Keywords - photoelectric detection; identification system; three-stage multiple innovation recursive least squares algorithm.

I. INTRODUCTION

Since the age of industrial revolution, control systems have become an integral part of it. From the manual control to automatic control, controlling mechanisms have made great progress. The advent of computer based technology has lifted control systems to a new level. The integration of computer with traditional control systems has provided improved performance and reliability.

Model predictive control (MPC) is the most widely applied advanced control technique in the process industries. MPC uses the plant model to predict its behavior over a certain time horizon. At each time interval, a cost function is minimized to optimize the future behavior of the plant by calculating a sequence of optimal future inputs. Only the first value from the sequence is applied and rests are ignored. The process of optimal sequence calculation is repeated at each sampling instant. MPC has shown improved results when it is applied on MIMO systems, and has become an important tool for controlling systems with constraints. Originally, MPC was developed to focus on some performance demands in the petroleum industry, but its application areas are now increasing each year, and these techniques can now be found in a variety of industries like automotive, mining, chemical and food processing [1,2].

Over the last few decades, theoretical development in the field of MPC has leaped forward as compared with its practical implementations. There is some gap between the theoretical and practical progresses of MPC. The work in [3] is widely considered to be the pioneering work in regard to linking MPC theory to its practical implementation.

Two survey papers [1, 2] about the industrial MPC development give important details on the progress of industrial MPC technology. Some theoretical details of the MPC algorithms are discussed in [3].

II. THE THREE STAGE MULTI-INNOVATION RECURSIVE LEAST SQUARES ALGORITHM

In general, the accuracy of RLS parameter estimation can be improved by using the multi-innovation scheme. We firstly describe the three stage RLS algorithm, and then use the multi-innovation scheme for improvement.

Define the following three intermediate variables:

\[ y_1(t) = y(t) - \phi_1^T(t) \hat{\theta}_1 - \phi_1^T(t) \tilde{\theta}_1 \]  
\[ y_2(t) = y(t) - \phi_2^T(t) \hat{\theta}_2 - \phi_2^T(t) \tilde{\theta}_2 \]  
\[ y_3(t) = y(t) - \phi_3^T(t) \hat{\theta}_3 - \phi_3^T(t) \tilde{\theta}_3 \]

From (1)-(3), the system can be decomposed into the following three subsystems:

\[ y_1(t) = \phi_1^T(t) \hat{\theta}_1 + v(t) \]  
\[ y_2(t) = \phi_2^T(t) \hat{\theta}_2 + v(t) \]  
\[ y_3(t) = \phi_3^T(t) \hat{\theta}_3 + v(t) \]  

DOI 10.5013/IJSSST.a.16.1A.13 13.1 ISSN: 1473-804x online, 1473-8031 print
In order to improve the accuracy of the above three stage RLS algorithm, we use MIRLS. MIRLS uses \( p \) innovations at each iteration, where \( p \) is the innovation length. Although MIRLS increases the computational burden and requires storing more data, it provides higher accuracy in parameter estimation which may be preferred for MPC. Then we can have the following equation (7)-(8).

\[
U_{k}^{2} = 4KT \int_{f_{1}}^{f} R(f) df
\]

\[
U_{k}^{2} = 4KT \Delta f
\]

Adaptive techniques are widely used in the industries. These schemes are applied to the systems which are affected by unmeasured disturbances. In almost all the adaptive techniques, the main focus is the estimation of disturbances. Generally, the disturbance is estimated adaptively, so that its time varying characteristics can be properly captured, and their effect is included in the MPC formulations. The ARIMA model is commonly used in many adaptive MPC schemes. This structure assumes that the integrated white noise is the source of the disturbance. The following equation (9)-(10) is shown as:

\[
I_{k}^{2} = U_{k}^{2} / R^{2} = 4KT \Delta f / R
\]

\[
U_{y} = \sqrt{4KT \Delta f}
\]

This scheme requires two optimization problems to be solved at every time instant. This is a big issue when dealing with the MIMO systems. Its alternative is the velocity form approach where the steady state targets are zero. However, the response to unmeasured disturbances is sluggish by the velocity form approach. It has been shown that, in regard to the MPC performance, the regulator scheme discussed above gives better results than the velocity form approach which is shown as equation (11):

\[
D_{k}(x, y) = f_{k}(x, y) - b_{k}(x, y)
\]

From equation (11), it can be seen that the main purpose of the regulator is to drive the system states and inputs to their steady state targets. The second optimization problem to be solved is in the target calculator block. The steady state targets for state and input are computed by solving the following optimization problem:

\[
R_{k}(x, y) = \begin{cases} 
0, & D_{k}(x, y) < T \\
1, & D_{k}(x, y) \geq T 
\end{cases}
\]

There are two optimization problems to be solved in this scheme. There is a target calculator block, whose purpose is to calculate the steady state targets. The main purpose of the regulator block is to guide the system towards these steady state targets in the presence of constraints. The variables \( u_{sp} \) and \( y_{sp} \) are set-points for the input and output, respectively. The model has disturbance states which cannot be controlled by the inputs of the plant; the regulator block shifts the targets to compensate the disturbance effects. The optimization problem that is solved in MPC regulator is described as \( X^{T} \) which can be represented by the K Gauss equation seen in (13)-(14).

\[
P(X_{t}) = \sum w_{i, t} \times \eta(X_{t}, \mu_{i}, \tau_{i}, \sum i_{t, t}) (13)
\]

\[
\eta(X_{t}, \mu_{i}, \tau_{i}, \sum i_{t, t}) = \frac{1}{(2\pi)^{\frac{p}{2}} |\sum i_{t, t}|^{\frac{1}{2}}} (14)
\]

One of the widely used methods for achieving the offset-free control is by augmenting the system with a disturbance model. The disturbance value is estimated from the difference between the actual and predicted outputs. One of the widely used disturbance models in MPC is the constant output disturbance model. The combination of plant and disturbance models, in the case of the constant output disturbance, is defined as

\[
y(t) = y(t) - \phi(t)\theta (15)
\]

If we have unbiased prediction of the steady state, and the optimization problem has a feasible solution, then we can guarantee offset-free control in MPC. The unbiased predictions of steady state are achieved with the introduction of an integral action in the state observer. We can conclude in equation (16)-(18):

\[
w_{i, t} = (1 - \alpha) \times w_{i, t - 1} + \alpha (16)
\]

\[
\mu_{i, t} = (1 - \rho) \times \mu_{i, t - 1} + \rho \times X_{t} (17)
\]

\[
\sigma_{i, t}^{2} = (1 - \rho) \times \sigma_{i, t - 1}^{2} + \rho \times (X_{t} - \mu_{i, t})^{2} (18)
\]

### III. Experiment Results and Discussion

In this section, two examples are presented to show the effectiveness of the proposed three stage identification algorithm. Firstly, a SISO EBJ model is estimated using the TSMISG algorithm. Secondly, an aero-thermic plant is simulated in the presence of additive disturbance to compare TSMIRLS and TSMISG algorithms. The accuracy and computational demands of both algorithms are illustrated. For comparison, the estimation errors for BJ, DVBJ and EBJ models against time are shown in Fig. 1. It can be observed from Fig. 1 that the parameters estimation using EBJ model shows more accurate results. Fig.3 shows that, by using the TSMISG algorithm with EBJ model, it is able to estimate the non-stationary disturbance. Because of having an additional term for representing the non-stationary disturbance in its structure, EBJ model provides better system representation when the system is subjected to non-stationary disturbance.

To improve the accuracy in estimation of EBJ model parameters, the multi-innovation scheme is used in the derivation of TSMISG algorithm. We select three different values (i.e., \( p = 1, 3, 5 \)) to compare the results for the multi-innovation scheme. The parameter estimates with different innovation lengths are shown, and their errors are shown in Fig. 2. It can be observed from Fig. 2 by increasing the length of the innovation vector, accuracy are also improved.
v(t) is white noise signal with zero mean and finite variance. Only the non-stationary disturbance is added to the output. For achieving persistent excitation, inputs $u_1$ and $u_2$ are selected as white noise with zero mean.

Fig. 4 shows the two test signals for each input and the corresponding output. Both three stage algorithms are used to estimates the parameters of model described in equation (7). Fig. 5 shows estimation errors by TSMIRLS and TSMISG algorithms with $p=1$ and $p=5$, respectively. It can be observed that TSMIRLS is more accurate in terms of parameter estimation.

In this paper, the author researches on photoelectric detection and identification system based on a three-stage multiple innovation recursive least squares algorithm. A
TSMIRLS algorithm is derived utilizing some of the recent research improvements in the field of RLS identification. Through a simulation example, it is shown that the proposed algorithm improves accuracy in terms of the parameter estimation, in comparison with the existing identification techniques.

It is the job of controller to achieve the desired targets without violating constraints. In most of the MPC techniques, a second optimization problem, known as the steady-state optimization, is also solved at each sampling instant. The steady state targets are calculated at each sampling instant by solving a separate optimization problem. This is required because the targets can vary with time due to the presence of disturbances. In most of the MPC algorithms, both optimization problems are expressed in terms of a quadratic program (QP), and their solutions can be obtained using some standard approaches.

ACKNOWLEDGEMENTS
The work is supported by Shaanxi Provincial Education Department Key Laboratory Projects (Program No.12JS036).

REFERENCES