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Comparative analysis of Direct and Indirect Model Reference Adaptive Control by Extended Kalman Filter

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Abstract

Considerations about the increasing complexity of technological systems have stimulated the interest in hybrid systems that can successfully manage switching behaviour or approach nonlinearity. Hybrid systems are made up of two parts: a constant dynamics component and a switching mechanism. This article investigates the effectiveness of direct and indirect model adaptive control approaches for any common tool for hybrid modelling and approximation nonlinear systems. A reference model may be linear or partially refined, specifies the desired loop system behavior that the adaptive controllers are capable of achieving in the face of unknown system dynamics regardless of the system dynamics. Individual control gains are obtained for each subsystem and it is also carefully tuned to the altered behavior of each system. Through the application of dynamic gain adjustment, singularities in the principle of certainty equivalence are avoided indirectly. The state of the reference model is asymptotically monitored for both techniques by assuming that a shared Lyapunov feature is available for the switched reference model.

Keywords: MRAC, parameter estimation

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1. Introduction

Model reference adaptive control (MRAC) is an adaptive control system that intends to provide an optimal set of reference trajectories for the natural system. An adaptive controller generates the control inputs required by the natural system, while taking the required dynamics into account [1]. State-space representation depicts state vector x (which represents the state of the natural system) and state vector x_{RM} (which represents the state of the reference model). The reference models and the system definitions are as follows:

$$\dot{x} = Ax + Bu_s$$

$$\dot{x}_{RM} = A_{RM}x_{RM} + B_{RM}u_r$$

The reference model is designed by using a reference input u_r, which is the result of a user-generated calculation. One additional thing to consider is that the natural system's input u_s is different from the one used to control the system; it is based on the adaptive control rule [2]. The system and input matrices of the reference model are matrices A_{RM} and B_{RM} respectively, whereas the system and input matrices of the reference model are matrices A_{RM} and B_{RM}.

1.1 Adaptive hybrid control

It should be made clear in the next phase that the hybrid systems may include unknown or changing parameters by setting up the conditions for adaptive hybrid control. It uses the model adaptive control to monitor the system, whose selected reference system is model reference control. Therefore, by choosing a suitable reference system, the undesired switches and non-linearity will be removed from the hybrid open loop systems. Existing techniques for general switched systems and partially refined systems may be separated into MRAC [3]. A theoretical and practical framework for designing control systems are critical to a system's operation is

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necessary, such as flight control systems to monitor the required distance. Adaptive controls are attractive for systems that are very reliant on delivering precise performance. Recently, a great deal of work has been done in the field of adaptive control for delivering aircraft flying systems due to failures and uncertainty [4].

1.2 Indirect Model Reference Adaptive Control (MRAC)

In the indirect approach, model adjustments to control the gains are much weaker. Hybrid systems are more often used to handle difficult non-linearities. Hybrid systems use continuous dynamics by integrating with a switching mechanism [5]. In mixed logical, dynamical, linear, and partly refined systems, various classifications exist, such as blended logical, dynamic, linear, and partially refined. The state input area and different linear subsystems control system dynamics are each polytopeized in partially refined systems. Other types of linear switched systems include partially refined systems and non-exogenous state-dependent signals. More recent examples of systems using partially refined systems may be found in power converters, biosystems, pneumatic systems, and maritime control systems [6-8]. Since their universal approximatability extends to nonlinear systems and it is widely known that partially refined systems may be found in all industrial areas. The movement of a dynamic system and the design of such system may complicate the system stabilization, control ideas, and observer designs, which have been developed by hybrid system research that has extended on the notion of the linear system [9, 10].

1.3 Motivation of MRAC

Combined direct and indirect adaptive schemes developed and applied for the control of an auto catalyzed chemical reaction in which is a typical second-order nonlinear dynamic system often encountered in biomass processes [12, 13]. The system dynamics is defined as follows,

$$\dot{x}_1 = a x_1 x_2 - b x_2$$

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$$\dot{x}_2 = -\theta x_1 x_2 - b x_2 + u$$

Positive constant related to the stoichiometry and 'b' is a positive constant related to the dilution rate of the process. The parameter u is a positive constant related to the specific reaction rate and is assumed to be unknown and changing. It is assumed that parameters a and b are known and are set to a = 4 and b = 2 for the simulation study [11, 14].

2. Organization of the Research

The remaining part of this research paper is organized as follows: Section 3 summarizes the existing research works on MRAC. Section 4 covers the parameter estimation methods developed for direct and indirect model reference adaptive systems. Section 5 compares the outcomes of parameter estimation techniques for MRAC. Section 6 summarizes the research findings and discusses about the next research directions.

3. Preliminaries

Recent NASA study shows that, the estimation of online in-system, real-time parameter is now possible with the development of computer capability. Dynamic control with real time parameter estimates was the second critical breakthrough and these breakthroughs methods are combined for delivering significant progress in aircraft dynamics [15, 16]. Nguyen solved several issues connected to the implementation of adaptive control techniques (2018). In the face of unexpected dynamic and disturbance variations, this research demonstrates the significance of adaptability [17]. According to the manufacturer, the system must be able to appropriately adapt to the actuator rate and position restrictions. Please bear in mind that, a formal certification process has not yet been established for adaptive control aircraft controllers. Since there is no accepted fidelity criterion, the fidelity of adaptive control systems may vary. The task of fulfilling the

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necessary requirements guarantees the maintenance of appropriate margins obtained by the separate adaptive control systems [18].

The concept of lesser squares employs previous techniques, which have explored computational techniques for the calculation of the estimator and its corresponding features. The approach for determining parameter values are by combining data from several sources, including input and output data. Any of these options has a significant benefit due to the unique nature of the solution. The computational techniques of the algorithm have demonstrated that they decrease data accumulation time while at the same time increasing the correctness of the results. In improving the parameter estimate, the problem of restricting data collection was important.

Much of the older parameter estimates research goes back to the 1970s and is drawn from NASA investigations. A major focus of the period was the estimating of parameters and in conjunction with adaptive control systems which was proven beneficial. There were significant benefits of a reconfigurable control paradigm including the flexibility to adapt controls and quick flight tests. With regard to the goal, however, the job presented considerable obstacles because of the need to execute it in real time.

The factors examined in this study are extremely different yet they have certain similarities. Many other studies have found a methodology often utilized to offer important insight into the most effective and efficient ways of parameter identification using a least squares approach. While the benefit of an extended Kalman filter and the least square approach may be, these techniques must be applied to the time domain so that it is effective. One example of this is the fact that RLS prohibits noise structure modelling in the system, while EKF may need a calculation quantity. As a result, the hardware requirements for the DFT are reduced, and are frequently used in frequency domain technology [19].

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4. Methodologies

Since the tracking error dynamics and the identification error model are parameterized, the parameter error vector is also found to be the same. A priori, the updated dynamics will always be implemented in this manner. In reality, it is the direct result of the system dynamics determined by the system structure. Direct adaptive control methods may lead to parameterization of the error dynamics. The proposed research work attempts to compare additional criteria that are required and sufficient for getting the same parameterization for direct and indirect adaptive schemes, so that the suggested approach may be further expanded to cover a wider range of nonlinear systems [20].

4.1 Parameter Estimation Methods

In fact, many parameter estimate approaches are available in the literature, each with its own strengths and weaknesses. Two well-known time domain parameter estimate methods are shown here: the RLS and the EKF. This estimation is based on the implementation of these techniques, which were described here. Also, this research work discusses about the significance of persistent stimulation while describing the parameter estimation. For example, a simple aircraft model can be constructed through Indirect MRAC and later it is applied to it.

4.2 Extended Kalman Filter (EKF)

The recursive least square (RLS) and the EKF are almost identical in many ways. An additional structure called gain structure is used in both the algorithms. In this structure, the gain has the function of setting the direction in which the parameters are updated. The EKF states that, the enhanced state vector must be specified prior to implementation. xa is defined as an augmented state vector whose elements are:

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$$x_a^T(t) = [x^T(t), \theta^T]$$

In the state variable equation, the vector x represents the state variables of the system and the vector θ represents the parameters that need to be estimated. The EKF method has two parts that are repeatedly iterated over a large number of iterations. In the prediction phase, the EKF uses the nonlinear dynamics equations to propagate the enhanced state vector. The prediction stage follows, in which the EKF implements a correction step that updates the prediction based on present system measurements [21]. A diagram describing the prediction and correction processes is shown below. The prediction of states (prediction of state vs. state covariance) is defined as,

$$\hat{x}_a\left(\frac{k}{k-1}\right) = \hat{x}_a\left(k - \frac{1}{k} - 1\right) + \int_{t_{k-1}}^{t_k} f_a[x_a(\tau), u(k-1)]d\tau$$

$$\hat{P}\left(\frac{k}{k} - 1\right) = \emptyset(k, k-1)\hat{P}\left(k - \frac{1}{k} - 1\right)\emptyset^T(k, k-1) + Q(k-1)$$

Figure 1 shows block diagram for flow of updating state estimate with correction.

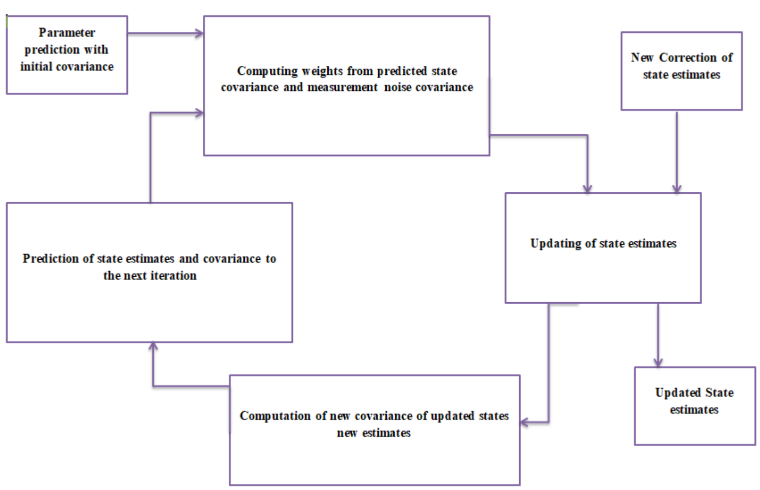

Figure 1. Updating state estimate with correction

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4.3 EKF Correction

Step 1:

The corrected optimal estimate (measurement update):

$$\hat{x}_a(k/k) = \hat{x}_a(k/k-1) + K(k)\{y(k) - h_a[\hat{x}_a(k/k-1)]\}$$

Step 2:

where the Kalman gain is defined as:

$$K(k) = \hat{P}\left(\frac{k}{k-1}\right) C^T(k) \left[C(k)\hat{P}\left(\frac{k}{k-1}\right) C^T(k) + R(k)\right]^{-1}$$

Step 3:

The covariance matrix is then updated as follows:

$$\hat{P}(k/k) = [I - K(k)C(k)]\hat{P}\left(\frac{k}{k-1}\right)$$

The process noise covariance Q= $\{v\ vT\}$ and the measurement noise covariance R=$\{w\ wT\}$ should be well-tuned to achieve the desired performance of the EFK. White and Gaussian processes are used to simulate process and measurement noise, which are said to be uncorrelated (independent) and regularly distributed (normal). The EKF would be iterated over the length of data already collected in the case of an offline application. Online applications continue to use the EKF for parameters estimation, however. While this may occur even if the estimated parameters converge to their actual values, it is notable that this is often true with regard to parameter estimation over time [22].

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5. Results & Discussion

In Table 1, the differences in the estimation results from the two methods are presented for each estimated parameter. Due to this, the percentage difference was calculated for the first six parameters, rather than all 10. Additionally, this method had the greatest mistake percentages of any scenario with noise, while at the same time having the lowest error percentages when the noise is not present. Figure 2 shows the obtained estimation graph for EKF and indirect MRAC.

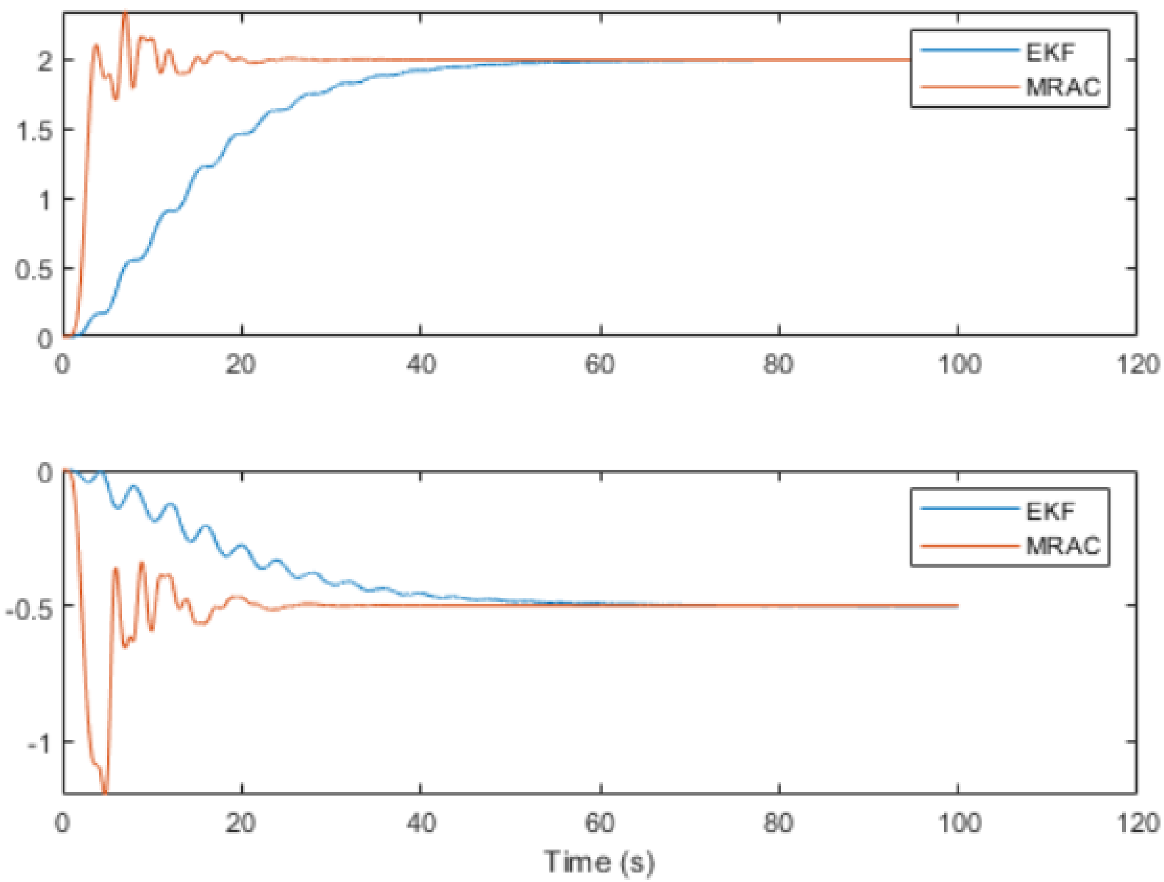

Figure 2. Model Estimation between EKF and Indirect MRAC

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Table 1. Percent Difference Estimation Comparison of the EKF, Adaptive Update and the Indirect MRAC-EKF

Model Estimator		**Without Noise**		**With Noise**	
Parameter	**Benchmark Value**	**EKF**	**Indirect MRAC-EKF**	**EKF**	**Indirect MRAC-EKF**
L_v	-0.1377	1.96%	9.04%	0.99%	9%
L_p	-12.5	0.001%	0.69%	0%	8%
L_r	2.142	4.7%	16.78%	1.95%	11%
N_v	0.0422	1.98%	10.89%	19.5%	1%
N_p	-0.3597	3.969%	19.87%	18.67%	7.67%
N_r	-1.2125	2.975%	3.99%	23%	1.95%

The Root Middle Square Error (RMS) was computed for each state under the MRAC and MRAC-EKF headings in Table 2. There was a limited ability of the indirect MRAC to estimate all 10 parameters by enabling the indirect MRAC to estimate only six parameters. This comparison study shows which MRAC works best in our specific scenario. The Indirect MRAC-EKF is often better than the Indirect MRAC.

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Table 2. RMSE State Tracking Performance of the Indirect MRAC and Indirect MRAC-EKF

Model Estimator	**Without Noise**		**With Noise**	
Updated State	**Indirect MRAC**	**Indirect MRAC-EKF**	**Indirect MRAC**	**Indirect MRAC-EKF**
v	0.367	1.289	4.012	1.478
p	0.111	0.041	0.499	0.123
r	0.001	0.028	0.078	0.129
θ	0.029	0.071	0.437	0.221

6. Conclusion

The proposed comparative study finds the other options, such as the Kalman filter estimate and extended Kalman filter estimate for direct and indirect MRAC, which are not frequently examined. This research work has successfully enhanced the Kalman filter estimate technique for any adaptive approach and classic estimation methods in a situation, where models relate to indirect model control. An extensive research study has been conducted to estimate methods and their application inside an adaptive control framework. In addition, the impact of applying the RLS and EKF to estimate parameters on adaptive control was not extensively studied. This paper only provides the foundation for future study and, of course, many more investigations are still possible.

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