

Design of Adaptive Estimator for Nonlinear control system in Noisy Domain

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Abstract

In the recent research studies, adaptive control has been used to monitor a reference control system that has been selected by the researcher. The acceptable reference system can be executed with the presence of nonlinearity and undesirable switches, as they have been disabled. This research study examines the challenges in adapting the state and time-varying parameters, when noise and state disturbances are present in a nonlinear control system. Additionally, this adaptive controller points out the best or most accurate option based on recursive least squares calculations by using the sensor data. This convergence has a rate of arrival with a set time of origin that serves as an estimate for error estimation. In addition, this research work has evaluated the amount of variance in the estimate, which has been caused by external disturbances using adaptive estimators from the reference value present in the noisy domain. The findings obtained via simulation demonstrate the performance of the adaptive estimator through the difference obtained between the reference value and observed value.

Keywords: Adaptive estimator, RLS

1. Introduction

In recent years, disturbance and uncertainty commonly exist in the form of external influences, system dynamics, and/or parameters that are unknown. The three primary ways of controlling system disturbances are:

1. Robust control
2. Optimal control
3. Adaptive control

While the former approaches involve in the design and manufacturing of a product with a design that can handle any kind of variance, the latter uses additional loops to accommodate the randomness of a specified class [1]. The theory of adaptive control has been discussed for a couple of years prior, which has expanded into one of the biggest areas of research in terms of algorithms, analytical tools, and design methodologies [2].

One particularly challenging issue in the field of adaptive control is the creation of observers who use online methods to estimate the full state and the parameters of the system [3]. Several publications in this family of adaptive extended state observers improve the applicability of state observers to nonlinear disturbed systems [4].

Due to Lipschitz nonlinear systems, adaptive observer synthesis is usually required. To guarantee the state estimation error converges to zero, state estimation error convergence conditions are defined by using Linear Matrix Inequalities (LMIs). In addition, a shape that is adaptable to various uses and environments is provided, which is used to conduct both adaptive estimates and also comply with new rules [5]. The nonlinear systems found by Farza et al are said to be capable of being synthesized using an adaptive observer to quickly compute the present state

and unknown parameters in the presence of continuous stimulation [6]. This class of nonlinear systems includes nonlinear systems with parameterization that have wide and non-discriminatory specifications [7, 8].

Tyukin I et al. introduce weakly attracted sets and non-uniform convergence in forward-complete Single-Input Single-Output nonlinear systems as well as an adaptive observer for the asymptotic reconstruction of the state and parameter values in a specific class of systems [9]. Oyvind N et al. proposes that adaptive observers, which use delays, be first suggested by these researchers. Increasing the computing effort is while giving better parameter estimates and certain resilience characteristics is possible with this approach [10, 11].

To estimate the time-varying parameters of missing data systems, Ding F et al developed a recursive least-squares method [12]. In the article by Stepanyan V et al., the authors describe a kind of nonlinear system with unknown parameters that vary over time. Observers are more likely to develop a single-point estimate, while parameter mistakes are kept to a minimum [13]. The unique variable-length sliding window-based least-squares method was developed by Jiang J et al. An expensive CPU method is recursive least-squares (RLS). While this alternate method provides a possible alternative to RLS, it may not always be effective [14]. Rios H et al investigated the efficacy of two methods in the context of time-varying and fixed-time noise data [15].

2. Organization of the Research

The rest of this research article constructed as follows; Section 3 provides related research work of adaptive parameter estimation process. Section 4 discusses methodologies for adaptive parameter estimation. Section 5 discusses about obtained results for estimated model. Section 6 concludes our proposed research work with future enhancement.

3. Preliminaries

Wei et al performed an in-depth investigation on parameter identification by utilizing more recent data. The damaged wing's web application is also being investigated in the performed research work. It was also examined if the study could find and describe mutational parameters and comprehend how lateral and longitudinal components interrelate. The three primary components that go into the limited recursive least-squares method are made up of three main pieces. The Forgetting Factor must be addressed since it addresses the issue of data buildup. There is a possibility that the estimation is inaccurate owing to outdated identification methods. Reducing the amount of accumulated sampling data is feasible if only data that is relevant to the current estimate is used [16].

More ever wei et al proposed the second limit item as a unique offline experience that uses the item. To ensure that all of the limit parameters are of equal magnitude, the Weighting Matrix found at the end of the focus is utilized. Data collection, prior research, and prudent use of the Forgetting Factor in the recursive least squares parameter estimation method are the subjects of the study [16].

Control systems that use absolute and relative stability which are named the gain margin (GM) and phase margin (PM) are termed in the classical control. Adaptive control systems suffer from a lack of information about stability margins. Stability margins in the literature are either conservative, according to numerical simulations, or they are established with precise accuracy for specific specialized adaptive control systems [17]. This research lacks equipment that might be used for analytics. This dissertation aims to discover how adaptive control systems achieve stable behavior concerning a control gain matrix's parameter range. For example, while specific adaptive state feedback control systems may not be relevant in the preceding example, nonlinear adaptive

control systems that use feedback linearization or backstepping designs may be, and specific adaptive state feedback control systems may be relevant in other instances [18, 19].

Generally, researchers are studying monographs, surveys, high-profile periodicals, and bibliographies suddenly became interested in piecewise linear systems. Generally the stability function is considered to be more prominent in continuous models rather than in discrete models, which are made up of a large number of separate components. One situation in which a system that has strong asymptotic stability may fall is when one or more subsystems are quickly reconfigured [20]. In certain switching sequences, even if subsystems become chaotic, the system stays linear. This has a direct bearing on the goal.

1. Regardless of the system subsystem changes, the system will approach asymptotic (or exponential) stability.
2. Asymptotic (or exponential) stability may not be ensured if you transfer subsystems. Thus, there must be criteria to guarantee this feature.

A slower switching approach for "average dwell-time" circumstances was derived from the characterization of an asymptotic stable piecewise linear system.

4. Methodologies

4.1 Adaptive Parameter Estimation

In the indirect adaptive control law, there is an adaptive estimation procedure. by implementing a candidate Lyapunov function, a stability analysis will reveal the appropriate adaptive updates of A and B to be made as follows,

$$\dot{A}(t) = -Pex^T\sigma_A$$

$$\dot{\hat{B}}(t) = -Pex^T\sigma_B$$

4.1.1 Estimation tuning parameter:

Although, theoretically, they have matrices with positive definite elements, the controls' final set of values is not affected by the usage of positive definite matrices; instead, the difference between the actual and reference states' values is what determines the control settings [21]. There is an equation which specifies that " $P=PT>0$ " is a $n \times n$ matrix, which is found by solving the algebraic Lyapunov equation.

$$A_{RM}^T P + P A_{RM} = -Q$$

4.1.2 Stable adaptive estimating formula by lyapunov

In order to maintain asymptotic tracking of the reference trajectories as well as limited (stable) adaptive parameters, the adaptive estimator is constructed in such a way. The Lyapunov function may be used to verify this.

$$V = \frac{1}{2} e^T P_e + (\Delta A \sigma - \Delta A T) + t_r (\Delta B \sigma B - \Delta B T)$$

This means that since the closed-loop system is limited by the Lyapunov direct approach, it will be stable (bound)." When applied to the tracking error, Barbalat's Lemma then demonstrates asymptotic stability. Another benefit of the suggested technique is that it makes it possible to converge on parameters even when the closed-loop system is stimulated continuously [22, 23].

4.2 Recursive Least Squares (RLS)

The RLS method is used to a dynamic system where the state equations are organized into enhanced states. In addition to the state variables, enhanced states include parameters to be evaluated.

$$x_k = \Phi_k \theta_{k-1} + v_k, \quad k = 0, 1, \dots$$

$$y_k = H_k x_k + w_k \quad k = 0, 1, \dots$$

Where computing the current output (from sensor measurement), the residual error ($y_{k+1} - \hat{y}_{k+1}$) is calculated and multiplied by a gain that determines the direction of the update. And this update is then added to the prior estimate (which is now known as θ_k) to ultimately establish the current estimate (which is now known as θ_{k+1}). Specifically defining the parameter update enables for both online and offline applications where k is defined as the number of iterations that a given step undergoes. Updating parameters as defined as,

$$\theta_{k+1} = \theta_k + K(y_{k+1} - \hat{y}_{k+1})$$

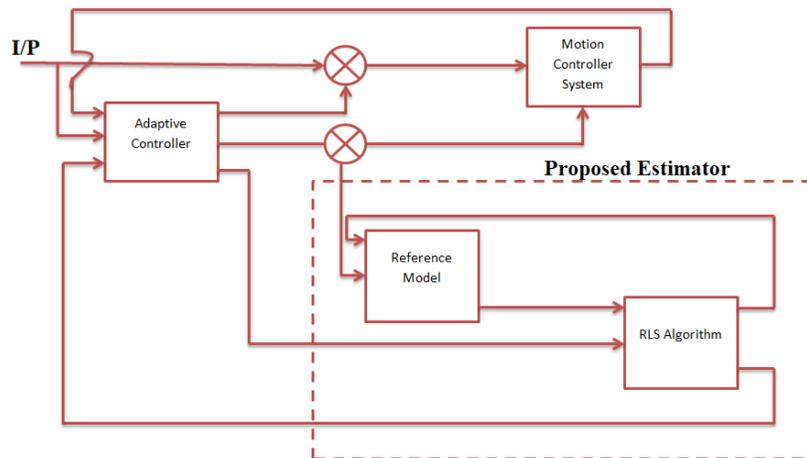


Figure 1. Proposed block diagram

Figure 1 shows the proposed block diagram for designing an estimator for motion controller system. Adaptive controller can be optimized through the input and RLS algorithm. The RLS method is summarized using the following outline: The before implementing the method, the augmented and linearized dynamics matrices must be initialized. The initialization of the enhanced states may happen when the trim settings or prior test data are found. Proposed estimator contains reference model and RLS algorithm. The varied optimized RLS algorithm is a feedback for the reference model with motion controller system which should be turned through adaptive estimator. Also, in certain applications, the covariance matrix is usually initialized to higher values, in the range of minimum percentage between reference value and obtained value. Once the algorithm calculates the forgetting factor λ , the next step is to select a constant value for it with optimal value [24, 25]. For most implementations, higher value near to 1% is acceptable values for λ . While under this condition, a smaller value for λ should be used example 0.001%, it should be noted that when the dynamics of the system are not rapidly changing, a larger value for λ is recommended. This is called optimized RLS algorithm for adaptive estimators for various parameters. To update the state transition matrix, the method first needs that the input and output of the system to be gathered.

5. Results & Discussion

The adaptive estimator is distinct from conventional methods like the Kalman filter in that it differs greatly. The simulation highlights these disparities even more, which may then help to enhance the system further. The first formulation of the adaptive estimator was intended to predict 6 parameters of roll rate and yaw rate state estimating parameter. Table 1 contains roll rate and yaw rate states' estimated parameters.

Table 1. Nomenclature

Notation	Explanation
$L_v, L_p,$ L_r	Roll rate state Estimated parameter
$N_v, N_r,$ N_p	Yaw rate state estimated parameter

The traditional filtering approach can correct 99% of the time with a higher period. But the traditional filtering method has never once failed to correctly estimate a parameter in a random field. Figure 2 a shows L_v (Vs) Time in seconds. Figure 2 b shows L_p vs. time in seconds. Due to the scale of the system, the adaptive estimator cannot make simultaneous estimates of so many parameters.

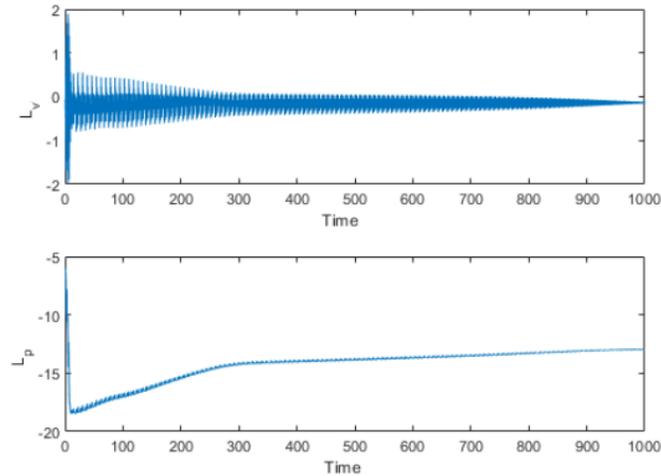


Figure 2. Adaptive Estimation of Parameters L_v and L_p without Noise

Figure 3 a & b shows the adaptive estimation of parameters L_r and N_v through without noise. Figure 3 a shows L_r (Vs) Time in seconds. Figure 3 b shows N_v vs time in seconds.

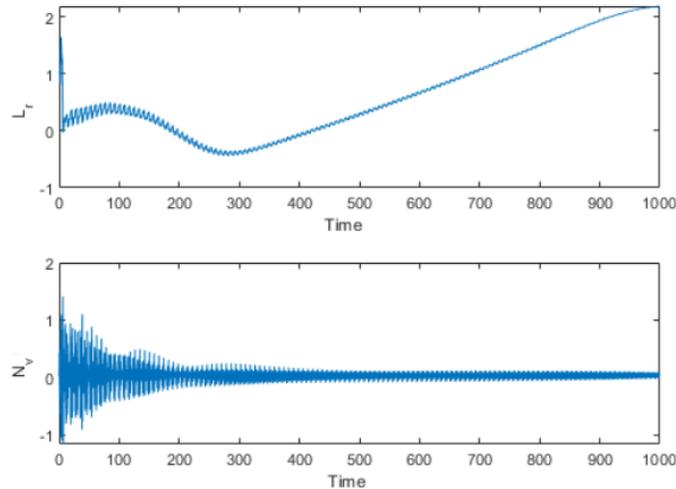


Figure 3. Adaptive Estimation of Parameters L_r and N_v without Noise

To illustrate this, initialize all parameters to their actual values. When several parameters must be set to their actual values, issues arise. In experiments using adaptive estimators, it was found that the estimation of a maximum of six parameters could be achieved. However, it is discovered that when noise is introduced to the system, there is a significant change in performance. Figure 4 shows the adaptive estimation of parameters N_p and N_r through with noise. Figure 4 a shows N_p (Vs) Time in seconds. Figure 4 b shows N_r vs. time in seconds. Our proposed system gets good to come back in adaptive stable condition for motion controller system.

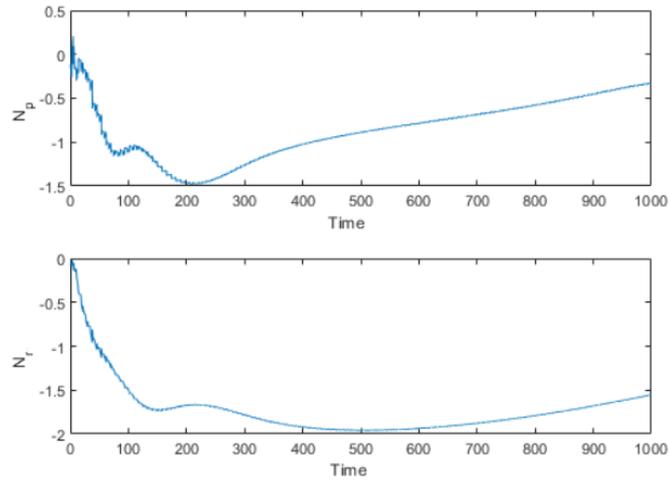


Figure 4. Adaptive Estimation of Parameters N_p and N_r with Noise

The calculated six parameters have acceptable accuracy even in the noise-free scenario. While there are issues with the current system, including sluggish convergence, it does meet most of our needs. System values may take a long time to converge and can take much longer than the filtering approach to do so. The current data compares almost inversely to the case adaptive model that means the decline in performance occurs as the number of factors increases [26, 27]. Figure 4 shows the adaptive estimation of parameters N_p and N_r with noise. In this graph, the pending curve is viewing as in the graph identify as a nonlinearity function.

A summary of the adaptive estimator results can be seen in Table 2. The proposed RLS algorithm may potentially tune to improve those estimated parameters. It was examined through the simulation and tested with noise measurement for solving the tuning challenges. Figure 5 shows the difference in estimated parameters from the reference value in terms of percentage in various parameters with the proposed algorithm.

Table 2. Adaptive estimator parameter estimated with noise

Estimated Parameter	Reference Value	Adaptive Estimator	Difference in Percentage
L_v	-0.138	-0.2134	7.54%
L_p	-13.01	-13.78	77%
L_r	2.22	2.501	28.1%
N_v	0.0512	0.066	1.48%
N_p	-0.361	-0.0811	27.99%
N_r	-1.26	-1.995	73.5%

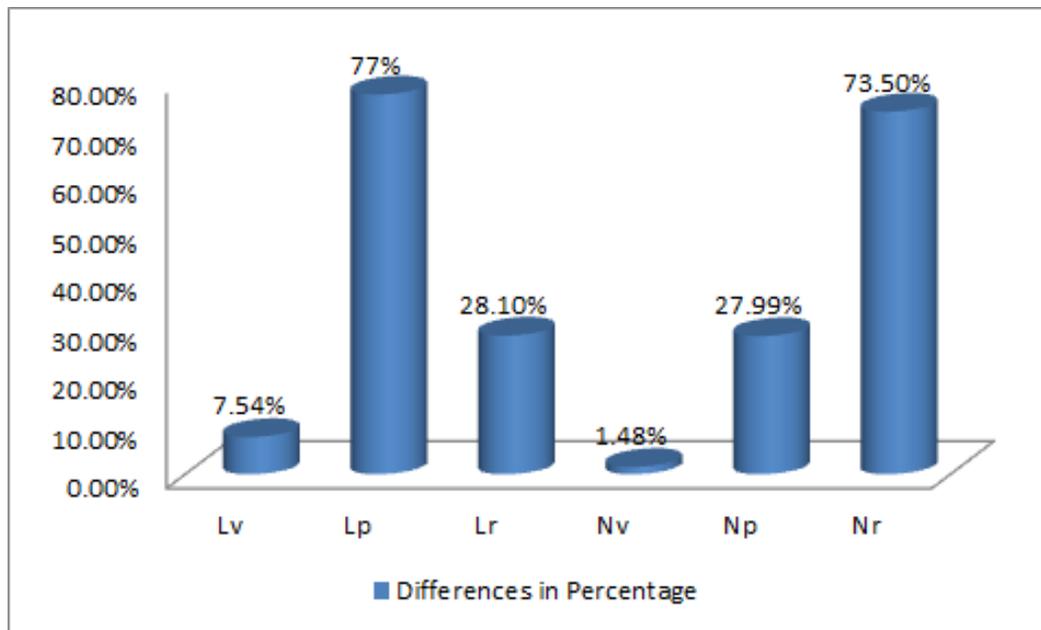


Figure 5. Differences of Adaptive Estimators in Various Parameters

6. Conclusion

Thus, the proposed algorithm has performed well in a noise environment for analyzing adaptive estimator parameters. Time-domain parameter estimation methods have been studied most extensively, which means that the majority of the research is focused on this particular area. However, the proposed research has investigated other alternatives such as adaptive estimation using the RLS approach. Specifically, online estimation of system parameters is facilitated for motion controller systems by analyzing several recursive least-squares techniques using adaptive estimator. The future research will be focused on minimizing the obtained adaptive estimator differences from the reference value. Meanwhile, RLS and traditional filtering algorithms remain difficult due to their complex computational intensity, particularly when contrasted with frequency-domain methods like the Discrete Fourier transform (DFT) [28, 29].

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