Adaptive Inverse Control with IMC Structure Implementation on Robotic Arm Manipulator

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Abstract

In this paper, an adaptive inverse control with internal model control (IMC) structure is proposed and implemented on a robotic arm manipulator system. The plant is stabilized using a simple lead-lag controller and the inverse of the plant is estimated using normalized least mean square (nLMS) algorithm. Radial base transfer function is used as an input mask to the adaptive algorithm. A delayed version of the reference signal is compared with the plant output to produce the error for the adaptive algorithm. The error signal is masked by a hyperbolic tangent sigmoid transfer function and the learning rate is adjusted automatically. A rate limiter is used in the model identification part to eliminate oscillatory plant output behavior. Comparison between adaptive inverse control and IMC structure is implemented and results are shown to demonstrate the effectiveness of the proposed method.

1. Introduction

Adaptive control is used when the plant characteristics are time variable or nonstationary. Adaptive control strategy was suggested in 1950 but due to the implementation issues raised from the complexity of the algorithm research work in this area was not progressed. Further researches in the 1960s, lead to its establishment [1]. In adaptive control, it is necessary to design online the parameters controller to cope with variations in the plant characteristics. An identification process could be used to estimate the plant characteristics over time, and these characteristics could be used to parameterize the controller and vary the parameters to directly minimize the mean square error. The difficulty with this approach is that, regardless of how the controller is parameterized, the mean square error versus parameter values would be a function not having a unique minimum and one that could easily become infinite if the controller parameters were pushed beyond the brink of stability. In the 1970’s an alternative look at the subject of adaptive control was introduced known as adaptive inverse control [2]. In simple format, it involves an open-loop control with the controller transfer function as an inverse of the plant. It is a novel approach to the design of control systems and regulators. Some of the latest work in this area was presented in 2004, by introducing an adaptive inverse control based on Parandtle-Ishlinskii hysteresis operator for piezoelectric actuator system to compensate hysteresis nonlinearity [3] and [4]. Experiments were performed on a micropositioning system driven by piezoelectric actuator. In the same year, a model reference adaptive inverse control system (MRIAC) based on fuzzy neural networks that has an adaptive disturbance canceller and feedback compensation to counteract the MRIAC’s direct current zero-frequency drift was presented in [5]. Aiming at the main steam temperature control system, a strategy of adaptive inverse control based on paralleled self-learning neural networks was proposed in [6]. Adaptive inverse control implementation in the Internal Model Control (IMC) structure gained popularity as the controller of the IMC structure performs the inverse functionality. The IMC structure has been successfully used for open-loop stable plants. It is composed of the explicit model of the plant and a stable feed-forward controller which is usually the inverse model of the plant. The scheme is depicted in Figure 1.

Figure 1. Basic IMC Structure.
Construction of the inverse model directly by the transcription of the parameters of the estimated forward model in the IMC structure is presented in [7]. A multivariable adaptive decoupling IMC was develop in [8].

In this paper, we present an adaptive inverse control (AIC) with IMC structure. An implementation in the robotic arm manipulator system is presented. The plant in this case is unstable and the IMC as well as the AIC structure can be implemented after stabilizing the plant [1], [9]. A simple lead-lag controller is used to stabilize the plant. Normalized least mean square (nLMS) algorithm is used to estimate the parameters of the plant. Radial base transfer function is used as an input mask to the adaptive algorithm. A delayed version of the plant input is compared with the difference between the estimated model and the plant output to produce the error signal. The hyperbolic tangent sigmoid transfer function is applied to the error signal before it is used by the forward model estimation algorithm. The nLMS learning rate is automatically adjusted to be inversely proportional to the absolute value of the error signal. The inverse model is produced in the same way as the forward model with the input coming from the reference signal and the error is compared between a delayed version of the reference signal and the estimated forward model output.

2. AIC with IMC structure Design

The control objective is to develop position tracking control strategy for a single link robotic arm manipulator system using AIC with IMC structure. It is necessary to stabilize the DC motor angular position based on the input voltage before proceeding with the development of the AIC and IMC structure (Figure 2). Assuming that the plant has a transfer function \( P(s) \), a simple lead-lag controller \( LL(s) \) is used to stabilize the angular position as given below

\[
LL(s) = \frac{b_1 s + b_0}{s + a_0}
\]  

(1)

The next step is to implement the proposed AIC with IMC structure (Figure 3).

Consider the continuous-time unstable plant transfer function \( P(s) \) that is stabilized by the Lead-Lag controller \( LL(s) \). Let \( h_d(s) \) denote the zero-order hold. The discrete-time version of the plant and the Lead-Lag controller will be \( P(z) \) and \( LL(z) \). \( u(k) \) is the control input to the plant and \( y(k) \) is the plant output. The control objective is to synthesize \( u(k) \) such that \( y(k) \) tracks some bounded piecewise continuous desired trajectory \( r(k) \).

2.1. Adaptive identification of the forward model

As shown in Figure 3, the forward model \( M(z) \) of the IMC structure is adaptively identified using the nLMS algorithm. Let \( \hat{y}(k) \) be output of the identified model. Let \( \hat{y}(k) \) track \( u(k-L_2) \), an \( L_2 \)-sample delayed \( u(k) \). Then

\[
\hat{y}(k) = \varphi_{mdl}^T(k)\hat{\theta}_{mdl}(k-1)
\]  

(2)

Where the regression variables \( \varphi_{mdl}(k) \) holds a masked version of the control input signal using neural networks radial basis transfer function given by

\[
\varphi_{mdl}(k) = [u_{rly}(k),u_{rly}(k-1),\ldots,u_{rly}(k-p)]
\]  

(3)

where the neural networks radial basis transfer function is defined as

\[
u_{rly}(k) = e^{-\beta |u(k-L_2)|^2}
\]  

(4)

The parameter estimation law to identify the forward model based on nLMS is given by

\[
\hat{\theta}_{mdl}(k) = \hat{\theta}_{mdl}(k-1) + \frac{\gamma_{mdl}(k)\varphi_{mdl}(k)}{\alpha + \varphi_{mdl}^T(k)\varphi_{mdl}(k)}\varepsilon_{reg}(k)
\]  

(5)

where \( \alpha > 0 \) is a small positive constant and the residual error is masked by a hyperbolic tangent sigmoid neural network transfer function

\[
\varepsilon_{reg}(k) = \frac{2}{1+e^{-2\beta_{mdl}(k)}} - 1
\]  

(6)

where \( \beta_{mdl}(k) \) is the residual error and given by

|Figure 3. AIC with IMC structure. |
\[ \beta_{mld}(k) = u(k - L2) - y(k) - \hat{y}(k) \quad (7) \]

\[ \gamma_{mld}(k) \] is a proposed automatic adjustment of the nLMS learning rate and is inversely proportional to the residual error and given by

\[ \gamma_{mld}(k) = \frac{\|\beta_{mld}(k)\|}{\|\beta_{mld}(k)\|^2 + b} \quad (8) \]

where \( f \leq \gamma_{mld}(k) \geq g \), \( f < g \) and \( 0 < f, g \leq 2 \) remains as the learning rate bound and \( b \) is the specified normalization bias parameter.

2.2. Adaptive Inverse Design

The inverse model \( Q(z) \) shown in Figure 3 uses the nLMS algorithm to adaptively satisfy the IMC structure. The control input \( u(k) \) that is required such that \( y(k) \) tracks the reference signal \( r(k) \) and is given by

\[ u(k) = u_{inv}(k) - y(k) + \hat{y}(k) \quad (9) \]

where \( u_{inv}(k) \) is the output of the inverse model and is given by

\[ u_{inv}(k) = \varphi_{inv}^T(k) \hat{\theta}_{inv}(k - 1) \quad (10) \]

In a similar way to the forward model identification method, the regression variables \( \varphi_{inv}(k) \) contains a masked version of the reference signal using neural networks radial base transfer function given by

\[ \varphi_{inv}(k) = [r_{rbf}(k), r_{rbf}(k - 1), \ldots, r_{rbf}(k - p)] \quad (11) \]

where \( r_{rbf}(k) = e^{-[r(k)]^2} \quad (12) \)

The nLMS algorithm for the parameter estimation law define it by

\[ \hat{\theta}_{inv}(k) = \hat{\theta}_{inv}(k - 1) + \frac{\gamma_{inv}(k) \varphi_{inv}(k)}{\alpha + \varphi_{inv}^T(k) \varphi_{inv}(k)} \varphi_{inv}(k) \quad (13) \]

where the neural network hyperbolic tangent sigmoid transfer function is masking the residual error \( \varphi_{inv}(k) \) and is given by

\[ \varphi_{inv}(k) = \frac{2}{1 + e^{-2\beta_{inv}(k)}} - 1 \quad (14) \]

where \( \beta_{inv}(k) \) is the residual error between a delayed version of the reference signal and the forward model estimated output and is given by

\[ \beta_{inv}(k) = r(k - L1) - \hat{y}(k) \quad (15) \]

where \( \gamma_{inv}(k) \) is the same proposed automatic learning rate adjustment for the nLMS algorithm in (8) with the residual error of \( \beta_{inv}(k) \) and is given by

\[ \gamma_{inv}(k) = \frac{\|\beta_{inv}(k)\|}{\|\beta_{inv}(k)\|^2 + b} \quad (16) \]

3. AIC Design

In this section we discuss the design of adaptive inverse control system that uses the similar introduced algorithm to synthesize \( u(k) \) such that \( y(k) \) tracks some bounded piecewise continuous desired trajectory \( r(k) \) as given in [2]. We will assume using the same lead-lag controller design in (1) to stabilize the plant before anything. Figure 4 shows a block diagram of the proposed structure.

Figure 4. Adaptive Inverse Control.

The adaptive inverse controller \( Q(z) \) produce the system control input \( u(k) \) that is required such that \( y(k) \) tracks the reference input signal \( r(k) \) and is given by

\[ u(k) = \varphi^T(k) \hat{\theta}(k - 1) \quad (17) \]

where the regression variables of \( \varphi(k) \) are given by

\[ \varphi(k) = [r_f(k), r_f(k - 1), \ldots, r_f(k - p)] \quad (18) \]

where \( r_f(k) \) is the output of the neural network radial base transfer function layer of a given net reference input signals \( r(k) \) and is given by

\[ r_f(k) = e^{-[r(k)]^2} \quad (19) \]

The parameter estimation law uses nLMS algorithm and is given by

\[ \hat{\theta}(k) = \hat{\theta}(k - 1) + \frac{\gamma(k) \varphi(k)}{\alpha + \varphi^T(k) \varphi(k)} \varphi(k) \quad (20) \]

A neural networks hyperbolic tangent sigmoid transfer function \( \varphi(k) \) produce and output from the residual error of a delayed version of the reference input and the plant output given by

\[ \varphi(k) = \frac{2}{1 + e^{-2\beta(k)}} - 1 \quad (21) \]

The residual error \( \beta(k) \) in this case is given by
\[ \beta(k) = r(k - L) - y(k) \]  
(22)

Also, the automatic learning rate adjustment given in (8) is implemented here and it is given by

\[ \gamma(k) = \frac{|\beta(k)|}{\|\beta(k)\|^2 + b} \]  
(23)

4. Experimental Results

An implementation on a robotic arm manipulator (single link) system is discussed here. The lead-lag controller design to stabilize the system reveals the parameter selection given in (1) for \( b_1=50, b_0=50, a_1=1 \) and \( a_0=200 \). Due to the nature of the system, the reference signal has a rate limiter to smoothen the adaptive tracking behavior of the system with a rising slew rate equal 1 and a falling slew rate equal -1. For the same purpose, another rate limiter is introduced in the adaptive algorithm. In this section, the two cases of AIC with IMC structure and AIC will be shown.

4.1. AIC with IMC Structure

The sample time used is 5 milliseconds and the implementation was done with delay \( L1= 5 \) milliseconds and \( L2= 500 \) milliseconds. Also, the bounds of (8) for the automatic learning rate adjustment of the forward model are \( f=0.001 \) and \( g=0.5 \), while the selection for the inverse model are \( f=0.01 \) and \( g=0.1 \).

Figure 5 shows that the output (position) of the plant converges quickly to the desired reference input signal.

Figure 6 shows the error between the estimated output of the forward model and the plant output for the AIC with IMC structure.

Figure 7 shows the control input \( u(t) \).

Figure 8 shows the desired output tracking reference input for the AIC with IMC structure with reduced \( L2 \).
Now, we will show the effect of varying some parameters to the overall system performance. First, it was found that reducing the time delay ($L_2$) will negatively impact the performance of the overall system. Reducing the time delay to $L_2 = 50$ milliseconds results in the tracking between the desired plant output and the reference input is shown in Figure 8. The error and the control input are shown in Figure 9 and 10.

Next, we will show the impact on changing/eliminating the rate limiter imposed at the forward model adaptive identification algorithm. Figure 11 shows the tracking behavior becoming oscillatory and the same impact is observed in the error and control input of Figure 12 and 13. The impact of removing the presented automatic adjustment of the learning rate is shown here. Figure 14 shows the difficulty of the tracking process. The error as well as the plant input are shown in Figure 15 and 16 respectively.

4.2. AIC

The structure shown in Figure 4 is implemented in the same system and the results shows that the automatic adjustment of the learning rate has its benefit more when used in AIC with IMC structure. Figure 17 shows the tracking behavior and Figure 18 shows the control input.
4.3. AIC

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5. Conclusion

In this paper we discussed the adaptive inverse control with IMC structure and its implementation on robotic arm manipulator. Stabilizing the plant was done using a simple lead-lag controller. The forward model and inverse model were adaptively corrected using the nLMS algorithm. Radial base transfer function was used to produce a layer to the adaptive algorithm from a net input. The residual error is masked by a hyperbolic tangent sigmoid transfer function. An automatic adjustment of the learning rate was introduced. Experimental results were shown with presentation of
the impact of changing some parameters to the overall performance of the system.

Figure 17. Desired output tracking reference input for the AIC system.

Figure 16. Control input for the AIC structure.

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References


