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Adaptive Inverse Control

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Abstract

A plant can track an input command signal if it is driven by a controller whose transfer function approximates the inverse of its transfer function. A stable inverse can be obtained even if the plant is nonminimum-phase. No direct feedback is used, except that the plant output is monitored and utilized to adapt the parameters of the controller. A model-reference inverse control system can learn to approximate a desired reference-model dynamics.

Control of internal plant disturbance is accomplished with an optimal adaptive disturbance canceller. It does not affect plant dynamics, but feeds back plant disturbance in a way that minimizes disturbance power at the plant output.

Similar principles can be utilized to control nonlinear systems. Neural networks are used to build a model of the plant and to construct its "inverse"

1 Introduction

This paper presents techniques for solving adaptive control problems by means of adaptive filtering.

Many problems in adaptive control can be divided into two parts: (a) control of plant dynamics, and (b) control of plant disturbance. Very often, a single system is utilized to achieve both of these control objectives. Our approach however treats each problem separately. Control of plant dynamics can be achieved by preceding the plant with an adaptive controller whose transfer function is the inverse of that of the plant. Control of plant disturbance can be achieved by an adaptive feedback process that minimizes plant output disturbance without altering plant dynamics.

The principle of control of plant dynamics can be extended to deal with nonlinear plants. In that case, tapped delay lines and neural networks are used in place of linear adaptive filters.

2 Adaptive Inverse Control for Linear Plants

2.1 Direct plant identification

Adaptive plant modeling or identification is an important function. Fig. 1 illustrates how this can be done with an adaptive FIR filter. The plant input signal is the input to the adaptive filter. The plant output signal is the *desired response*, the target signal for the filter output. The adaptive algorithm, LMS [1] or RLS [2], minimizes mean square error, causing the model $\hat{P}$ to be a best least squares match to the plant P for the given input signal and for the given set of parameters (weights) allocated to $\hat{P}$.

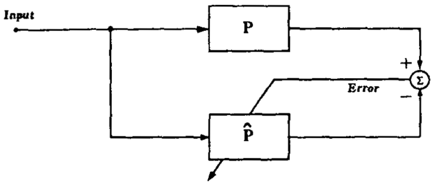

Figure 1: Direct plant identification.

2.2 Inverse plant identification

Another important function is inverse plant identification. This technique is illustrated in Fig. 2. The plant input is as before. The plant output is the input to the adaptive filter. The desired

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response for the adaptive filter is the plant input in this case. Minimizing mean square error causes the adaptive filter $\widehat{P^{-1}}$ to be a best least squares inverse to the plant P for the given input spectrum and for the given set of weights of the adaptive filter. The adaptive algorithm attempts to make the cascade of plant and adaptive inverse behave like a unit gain. This process is often called deconvolution.

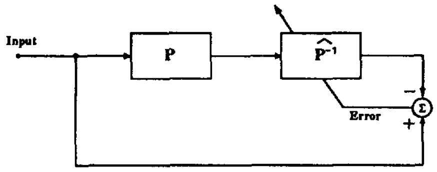

Figure 2: Inverse identification.

For sake of argument, the plant is assumed to have poles and zeros. An inverse, if it also had poles and zeros, would need to have zeros where the plant had poles and poles where the plant had zeros. Making an inverse would be no problem except for the case of a nonminimum-phase plant. It would seem that such an inverse would need to have unstable poles, and this would be true if the inverse were causal. If the inverse could be noncausal as well as causal however, then a two-sided stable inverse would exist for all linear time-invariant plants in accord with the theory of two-sided Laplace transforms.

A causal FIR filter can approximate a delayed version of the two-sided plant inverse, and an adaptive FIR filter can self-adjust to this function. The method is illustrated in Fig. 3. The time span of the adaptive filter (the number of weights multiplied by the sampling period) can be made adequately long so that the mean square error of the optimized inverse would be a small fraction of the plant input power. To achieve this objective with a nonminimum-phase plant, the delay Δ needs to be chosen appropriately. The choice is generally not critical however.

The inverse filter is used as a controller in the present scheme, so that Δ becomes the response delay of the controlled plant. Making Δ small is generally desirable, but the quality of control depends upon the accuracy of the inversion process which sometimes requires Δ to be of the order of half the length of the adaptive filter, or less.

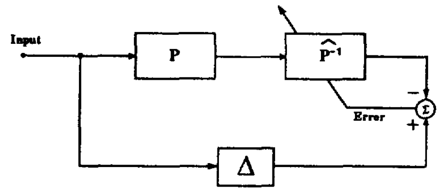

Figure 3: Delayed inverse identification for a nonminimum-phase plant.

A simulation experiment has been done to illustrate the effectiveness of the inversion process. Fig. 4 shows the impulse response of a nonminimum-phase plant having a small transport delay. Fig. 5 shows the impulse reponse of the best least squares inverse with a delay of $\Delta = 50$ sample periods. Fig. 6 is a convolution of the plant and its inverse impulse response. The result is essentially a unit impulse at a delay of 50.

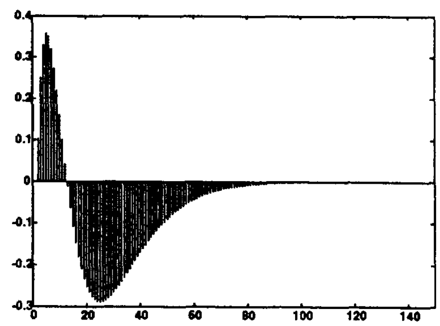

Figure 4: Impulse response of nonminimum-phase plant.

A model-reference inversion process is shown in Fig. 7. A reference model is used in place of the delay of Fig. 3. Minimizing mean square error with the system of Fig. 7 causes the cascade of the plant and its "model-reference inverse" to approximate closely the response of a model M. Much is known about the design of model reference systems [3]. The model is chosen to give a desirable response to the overall system. Some delay may need to be incorporated into the model in order to achieve low error.

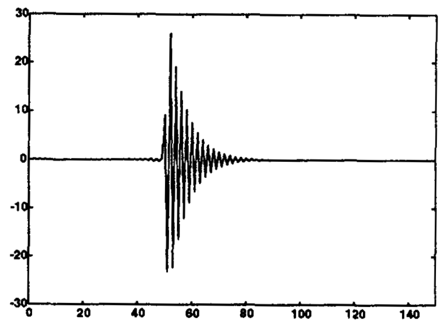

Figure 5: Impulse response of delayed inverse.

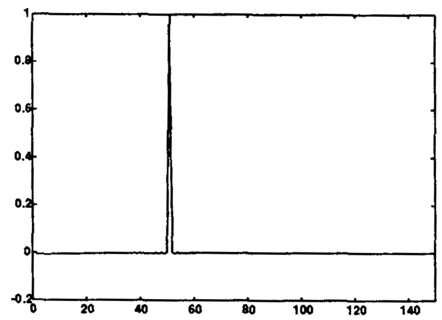

Figure 6: Convolution of plant with delayed inverse.

2.3 Adaptive Control of Plant Dynamics

Now having the plant inverse, it can be used as a controller to provide a driving function for the plant. This simple idea is illustrated in Fig. 8 for minimum-phase plants. Fig. 9 shows the corresponding scheme for nonminimum-phase systems. Many simulation examples have been performed, with consistently good results, as long as the plant is stable or is first stabilized by feedback. Extensive analysis will be presented in the forthcoming book by Widrow and Walach [4].

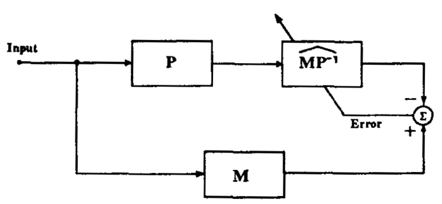

Figure 7: Model-reference plant inverse.

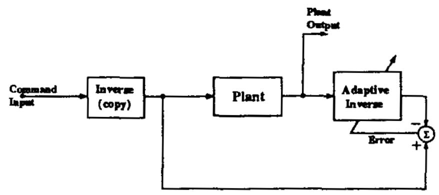

Figure 8: Inverse control scheme for minimum-phase plants.

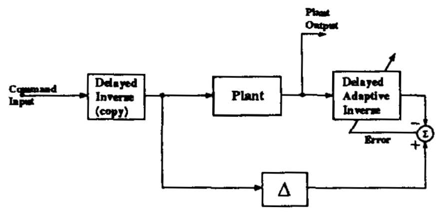

Figure 9: Inverse control scheme for nonminimum-phase plants.

2.4 Adaptive Plant-Disturbance cancelling

The systems of Fig. 8 and Fig. 9 only control and compensate for plant dynamics. The disturbance appears at the plant output unabated. The only way that the plant output disturbance can be reduced is to obtain this disturbance from the plant output and process it, then feed it back into the plant input. The system shown in Fig. 10 does this.

In Fig. 10, an exact copy of $\hat{P}$ is fed the same input signal as the plant P. The output of this $\hat{P}$ copy is subtracted from the plant output. Assuming that $\hat{P}$ has a dynamic response essentially identical to that of the plant P, the difference in the outputs is a close estimate of the plant disturbance. This disturbance is filtered by Q and then subtracted from the plant input. The filter Q is generated by an off-line process that delivers new values of Q almost instantaneously with new values of $\hat{P}$, which adapts continually to keep up with changes in the plant P.

The filter Q is essentially the best inverse

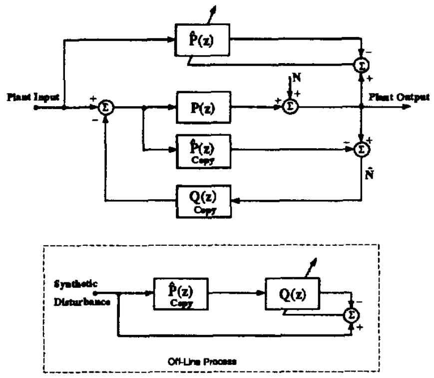

Figure 10: Disturbance cancelling system.

(without delay) of P. The *synthetic disturbance* used to train Q should have a spectral character like that of the plant disturbance. It is shown in the Widrow and Walach book [4] that the disturbance cancelling system of Fig. 10 adapts and converges to minimize the plant disturbance at the plant output. As such, it is an optimal linear least squares system. There is no way to further reduce the plant disturbance.

The system of Fig. 10 appears to be a feedback system. However, if $\hat{P}$ is dynamically the same as P, the transfer function around the loop is zero. The transfer function from the *Plant Input* point to the *Plant Output* point is the same as that of the plant alone. Thus, the disturbance canceller does not affect the plant dynamics.

Almost perfect disturbance cancellation is possible with a minimum-phase plant. With a nonminimum-phase plant, even optimal cancelling will not cancel all the disturbance. Fig. 11 and Fig. 12 show results of a plant disturbance cancellation experiment. Although the plant in this case was nonminimum-phase, the results are quite good.

3 Nonlinear Inverse Control

The principles of inverse control can be extended to deal with nonlinear systems. Nonlinear systems behave quite differently from their linear counterparts. For example, whereas a linear system possesses a unique inverse, nonlinear systems have only local inverses, valid only in a bounded region of the signal space. In addition, left and

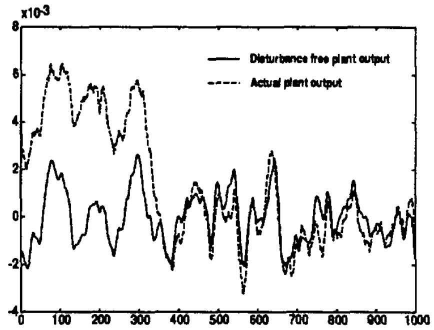

Figure 11: Output of undisturbed plant and output of disturbed plant, with and without disturbance canceller (canceller turned on at $k = 300$).

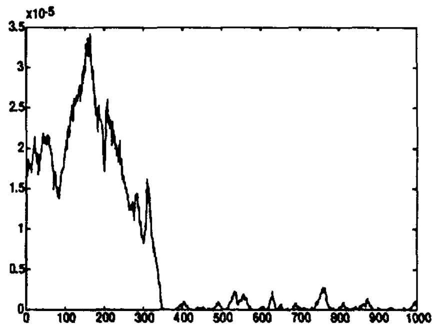

Figure 12: Instantaneous power of plant output disturbance (canceller turned on at $k = 300$).

right inverses are in general different, as in the case of multi-input multi-output linear systems. As linear adaptive filters are used to control linear plants, the "inverse" controller for nonlinear plants involves a type of recurrent neural network. The ability of multilayered neural networks to approximate nonlinear mappings over compact regions as detailed in [5] makes them useful in identifying direct and inverse models.

The inverse control of nonlinear plants involves a two-stage process where a model of the plant is first constructed (identification) and second the plant model is inverted.

The system is modelled through the use of a feedforward multilayered neural network fitted with tapped delay lines at its input and output and a feedback loop. With an appropriate number of hidden neurons, such a neural network can represent a system of the form

$$y_k = f(y_{k-1}, y_{k-2}, \cdots, y_{k-n}, u_{k-1}, \cdots, u_{k-p})$$

over a bounded region of input space. The choice of the integers n and p is part of the modelling design and follows from requirements of model accuracy. The identification scheme is founded on a standard technique, which is the nonlinear equivalent of the equation-error formulation described in [6], and is called a *series-parallel* model in [7]. The choice of this formulation allows the use of the standard backpropagation algorithm for training the neural network.

The second step is the design of the controller. Once the neural network has been trained to perform plant identification, the controller, also implemented as a neural network, is trained to behave like the inverse of the system. The algorithm used for training the controller is a variant of the recurrent backpropagation algorithm [8]. As previously mentioned and unlike linear systems, nonlinear systems do not commute with their inverses. This restriction demands that the controller be trained upstream from the plant model and that the error signal be backpropagated through the plant model as shown in Fig. 13.

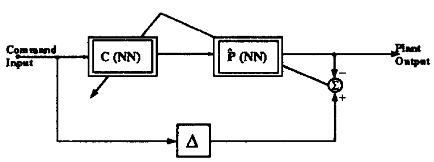

Figure 13: Inverse control for nonlinear systems.

3.1 Example

Let's consider the nonlinear plant suggested in [7] and defined by the equation:

$$y_k = \frac{y_{k-1}}{1 + y_{k-1}^2} + u_{k-1}^3$$

The input signal is confined in the interval $[-1, 1]$. Fig. 14 shows the training configuration for the plant model. It had two inputs, the external input u and the output from the real plant, and one output. It had one hidden layer with 10 units. The result of the plant identification is displayed in Fig. 15. Specifically, the outputs of the plant and plant model are compared when the same test signal is fed to their inputs. Here the test signal is chosen as a sinusoid with increasing amplitude.

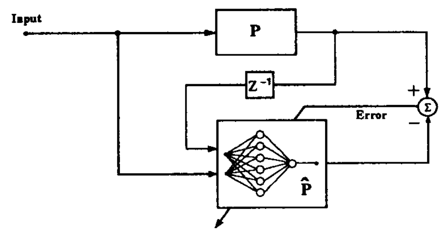

Figure 14: Configuration for plant identification.

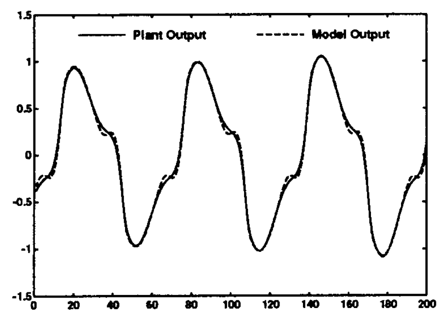

Figure 15: Result of nonlinear plant identification.

Training of the inverse controller C is illustrated in Fig. 16. The neural network controller had a two-tap tapped delay line as input, a hidden layer with 10 units and one output which is fed to the plant model. The error is backpropagated through the plant model using online recurrent backpropagation. The time plots of Fig. 17 show the command input fed to the trained inverse controller versus the plant output. Although there are errors, the agreement between the two signals is very good. The important thing to note is that the controller is trained to be an inverse to the plant model and not the plant itself. Consequently, good performance of the controller is contingent on building an accurate model for the plant.

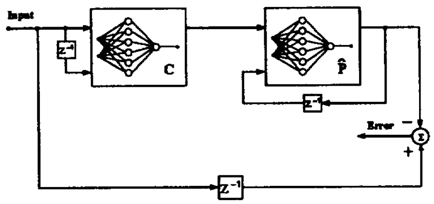

Figure 16: Configuration for training of inverse controller.

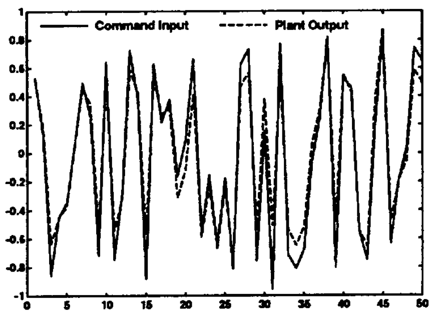

Figure 17: Performance of inverse controller.

4 conclusion

Methods for adaptive control of plant dynamics and for control of plant disturbance for unknown linear plants have been described. In addition extension of control of plant dynamics to nonlinear plants using neural networks have been presented. For their proper application, the plant must be stable. An unstable plant could first be stabilized with feedback, then adaptively controlled. Details will be found in the Widrow and Walach book, which is in press.

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