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Analyzing the nonlinear system by designing an optimum digital filter named Hermitian-Wiener filter

Qiaoyu Wang[1*]   Kai Kang[1]   Jiayi Meng[2]

1. Electrical and Computer Systems Engineering Department, Monash University, Melbourne, Victoria, Australia
2. Faculty of Arts, Melbourne University, Melbourne, Victoria, Australia

ABSTRACT

The classical Wiener filter was engaged into identifying the linear structures, resulting in clear and incredible drawbacks in working with nonlinear integrated system. Currently, the Hermitian-Wiener system are suitable for unpredicted sub-system that consists of numerous and complex inputs. The system introduces a two-stage to analyze the subintervals where the output nonlinearities are noninvertible, through using the unknown orders and parameters. Finally, a practical strategy would be discussed to analyze the nonlinear parameters.

1. Introduction

The Hermitian-Wiener filter is mainly made of two different nonlinear subsystems that are connected in series. The original Wiener model is the basic structure of this advanced system so that it can build up and analyze the complex models, such as power amplifiers, ocean detection, advanced dynamics, and other meaningful applications [1].

The estimation of one unknown signal from another is one of the difficult problems in signal processing. In many applications, the desired signal is not available or observed directly and it would be noisy and distorted by unpredictable noise signals. In some simple environments it may design a classical filter with lowpass, high pass, or bandpass function[12].

However, the Hermitian-Wiener methods are hard to recognize the parameters than classical Wiener filters in practical application. More specifically, the complexity of Hermitian-Wiener filter has two different stages to process unknown signals. It means that the former has more processing steps to get desired signals [3].

In this paper, we apply the Hermitian-Wiener filter which is aimed to solve the nonlinear problems in nonlinear subsystems. Also, it is noticeable that the nonlinearities are not invertible in their own processing intervals. Thus, the purposes of this method expand the analyzing of frequency domain. In addition, the system can observe a series of constant signals that are estimated by controllers. In the first stage, estimate the input signals

Corresponding Author:
Qiaoyu Wang,
Electrical and Computer Systems Engineering Department, Monash University, Melbourne, Victoria, Australia;
Email: 1643360071@qq.com

that will transfer to the output nonlinearity and identify the parameters of the later orders. When the linear identification is determined, the subsystem frequency benefits can be available after backlash inversion.

In the next section, the primary problems will be demonstrated. Also, the main details of the advanced methods would be given in section 2. The results of linear and nonlinear would be showed in section 3.

2. Problem Statements about Nonlinearity

The basic formula can be derived as Hermitian-Wiener model with input nonlinearity by this equation.

$$y(t)=x(t)+\delta(t)=h(w)+\delta(t)$$
$$w(t)=g(t)*v(t); where\, v=f(u), g(t)=L^{-1}$$

The noise $\delta(t)$ is ergodic and it is a stationary sequence with zero-mean. Particularly, the input nonlinearity is an unknown model outside the frequency intervals [4].

On the other hand, output also has nonlinearity within frequency working subintervals. Also, this property is not invertible. To be more specifically, the orders p and other parameters would change during all subintervals. The key step is to identify the accurate prediction of the nonlinear intervals and the linear frequency domain [5].

3. Working Stage of the Hermitian-Wiener filter

3.1 For the First Experiment

I derived the Weiner-Hopff equations used for calculating the FIR Weiner filter coefficients w based on the formula.

$$Rv_2w=rv_1v_2$$

This formula is the equation in its current form useful for calculating the Weiner Filter. Also, it turns out that the RHS of the above equation is rxv_2.

$$x(n)=d(n)+v_1(n)$$
$$v_1(n)=0.7v_1(n-1)+g(n)$$
$$v_2(n)=-0.5v_2(n-1)+g(n)$$

In Matlab, we generated 500 samples of the desired signal $d(n)$ (for φ use the random phase distributed between $[-\pi\ \pi]$) and generate by filtering $g(n)$ with filter parameters $a_1= 0.7$ and $a_2= -0.5$, respectively. Also, we generated the AR processes $v_1(n)$ and $v_2(n)$ and the sequence $x(n)$ from $d(n)$ and $v_1(n)$. Then, we generate the correlation matrix Rv_2 from $v_2(n)$ use the covar.m Matlab function. Next, we generate the vector rxv_2 from $x(n)$ and $v_2(n)$ using the Matlab built-in function xcorr.m by the unbiased version of xcorr. Finally, we solved the linear equations in Matlab to calculate the coefficient vector w, for the FIR Weiner filter of orders $p = 4, 10, 12$ [6].
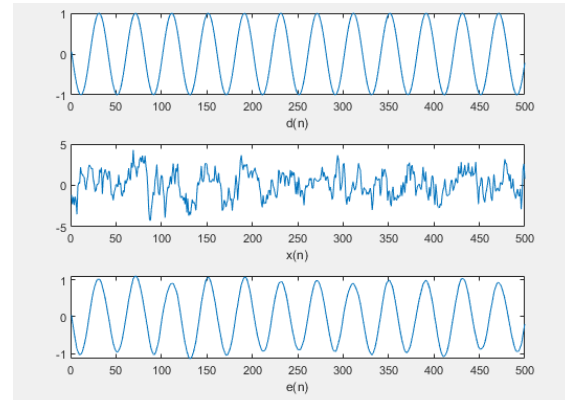

Figure 1. FIR Weiner Filter Matlab Results

3.2 For the Second Experiment

I found the autocorrelation sequence rd(k) of d(n) and then plot the power spectrum (PSD) of d(n) from rd(k). Also, I used PSD = fft (xcorr(d(n),'unbiased'), 1024).

In addition, I plot the magnitude of the frequency response of this Wiener filter. Also, comparing the frequency response with the power spectrum of d(n) and comment on the relation between the two frequency responses based on using 'freqz' to find the magnitude spectrum from filter coefficients[7].
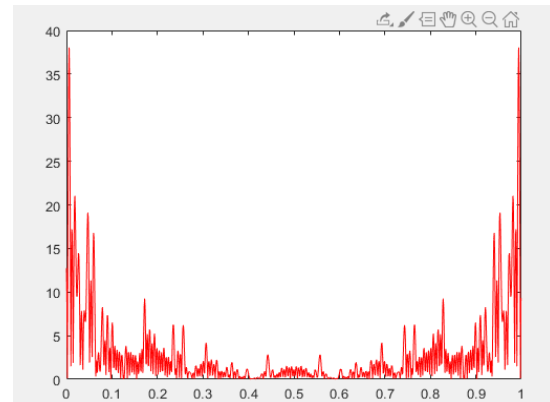

Figure 2. FIR Weiner filter Frequency responses
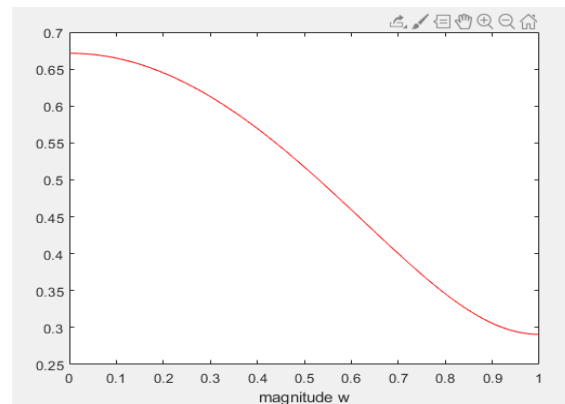

Figure 3. FIR Weiner filter Magnitude

It can be seen from the experimental results that the upline cut-off frequency and downlink cut-off frequency of the filter are about 0.2 and 0.8 respectively. When the frequency response is 0.2-0.8, the filter is in a normal filtering state with strong anti-interference ability and noise reduction ability, and the power spectrum conforms to the working state of the filter. When the frequency response is 0-0.2 and 0.8-1, the filter is in a divergent state with too much interference and noise and weak anti-interference and noise reduction ability, which conforms to the experimental results of power spectrum.

4. Analyzing Linear system

The problem of analyzing the linear subsystem is identify the specific details of subintervals. First of all, an ideal controller is designed that focus on compensating for input nonlinearity. This system is utilized to transformed to deal with the unpredictable internal signals $v(t)$ and $w(t)$.

According to this point, the nonlinearity of input and output are unpredictable, the system can just estimate this changeable property. It is simple for users to assume that the estimated points have been determined.

However, if we know the input nonlinearity is polynomial function, introduce a controller to monitor the input of the system, which would result in the inverse at the system output. And theoretically, the outcome of the system would be equivalent to a linear subsystem with transfer function, where the frequency analyzing method is a better way to identify the parameters for continues processing[8].

5. Conclusion

Wiener filter has the advantages of a wide range of adaptability. It can be applied whether stationary random process is continuous or discrete, scalar or vector. The experimental results show that the waveform is stable, the predicted value fluctuates great and the error value is large. Therefore, the disadvantage of wiener filter is that it is difficult to meet the requirement of obtaining all the observed data, and it cannot be used in the case of non-stationary random processes with noise, and it is not convenient to apply it in the case of vector. In addition, the use of a linear shift-invariant Wiener filter will not be optimum. In the future, we will use adaptive Wiener filter to get ideal waveform

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