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# Noise Cancellation in Monte Carlo Simulation

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## Abstract:

For processing signals and in control application filters are essential, linear optimums discrete time filters such as wiener filter and Kalman filter are on orthogonal principle. For non stationary cases of having a presence of noise, adaptive wiener filter has to be applied using Monte Carlo Simulation 250 samples were used for 50 runs. Coefficients of linear filter are used to estimate the additive white noise. Error is calculated and RMS value of each error is added to the sample for desired signal. FIR wiener filters of order 6, 12, 24 were chosen for adaptive operators .Simulation results were quite encourage in the sense that noise was suppressed to maximum extends. Adaptive methods noisy higher number of samples and more than 100 runs are linear to yield better results.

**Keywords:** Noise Cancellation, Monte Carlo Simulation, Wiener Filter, Optimal Filter, Wiener-Hopf Equations, Wide-Sense Stationary Random Processes, Discrete Wiener Filter, Discrete Kalman Filter

## 1. Introduction

The idea of utilizing a filter to remove a preferred signal as of noisy information measurements, change signals, hold back noise, take apart two signals which might be assorted in single size, and so on. Most advantageous filters[1] are exploiting for gain a superlative guesstimate of aspiration signal from noisy measurements. A particular normal filters like low pass, high pass and band pass filters[2]. The most effective filters studied in this paper are linear optimum DTF[3], which include DWF[4] and DKF[5]. Theory arose because of the in adequacy of the Wiener-Kolmogorov theory for coping with certain applications in which non stationary of the signal and/or noise was intrinsic to the problem[6,7]. Predicament of devise a filter that would bring into being the optimum estimate of a signal from a noisy measurements or observations. The discrete appearance of the WF problem, represented in Figure 1. It is to design a filter to recover a signal d (n) from noisy studies,

$$m(l) = c(l) + d(l) \tag{1}$$

assuming that both c(l) and d(l) are WSSRP.

## 2. Mathematical Formulation

### 2.1 Wiener-Hopf Equations

FIRWF that produces the MMSE[8] of a prearranged process c(l), by pass through a set of study transmitted process m(k). It is assumed that m(l) and c(l) are jointly WSS with known autocorrelations, $r_x(k)$ and $r_d(k)$, and known cross-correlation $r_{dx}(k)$.

$$W(z) = \sum_{k=0}^{p-1} w(l) z^{-l} \tag{2}$$

With m (k) the input to the filter, the output, which we denote by $\hat{c}(l)$ ,

$$\hat{c}(l) = \sum_{i=0}^{p-1} w(x) m(l-x) \tag{3}$$

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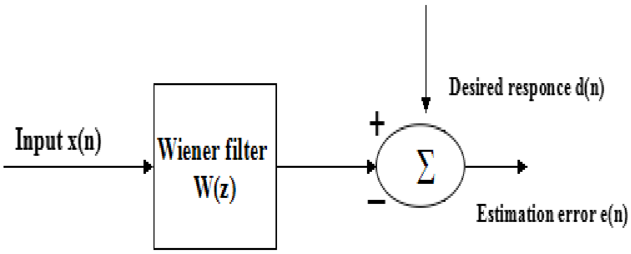



**Figure 1.** Representing operation of Wiener filtering.

With

$$\emptyset(n) = d(n) - \sum_{l=0}^{p-1} w(x)m(l-x) \tag{4}$$

Here error e represented as $\emptyset$

it follows that

$$\frac{\partial \emptyset^*(n)}{\partial \emptyset^*(k)} = -m^*(n-k) \tag{5}$$

And Eq. (4) becomes

$$E\{\emptyset(l)m^*(l-h)\} = 0; k = 0,1 \ldots Q-1 \tag{6}$$

By applying the projection theorem. Substituting Equation. (5) into Equation. (6)

$$E\{c(l)m^*(n-k)\} = \sum_{l=0}^{p-1} w(x)\ E\{\emptyset(l)m^*(l-h)\} = 0; k = 0,1 \ldots Q-1 \tag{7}$$

$$\sum_{l=0}^{p-1} w(l)r_x(k-l) = r_d(k)\ \ k = 0,1,\ldots..p-1 \tag{8}$$

which is the matrix form of the WHE.

$$R_x w = r_{dx} \tag{9}$$

Where $R_x$ is a p×p Hermitian Toeplitz matrix[9]

$$\xi = E\left\{|e(n)|^2\right\} = E\left\{e(n)\left[d(n) - \sum_{l=0}^{p-1} w(l)x(n-l)\right]^*\right\}$$

$$= E\{e(n)d^*(n)\} - \sum_{l=0}^{p-1} w^*(l)E\{e(n)x^*(n-l)\} \tag{10}$$

$$\xi_{\min} = r_d(0) - \sum_{l=0}^{p-1} w(l)r_{dx}^*(l) \tag{11}$$

Using vector notation,

$$\xi_{\min} = r_d(0) - r_{dx}^H w \tag{12}$$

Alternatively, since

$$w = R_x^{-1} r_{dx}$$

$$\xi_{\min} = r_d(0) - r_{dx}^H R_x^{-1} r_{dx} \tag{13}$$

## 2.2 Noise Cancellation

One of the applications of WF is the problem assign to as noise[10] termination. The aspiration of a noise canceller is to guesstimate a signal c(l) beginning a noise altered inspection

$$m(l) = c(l) + d_1(l) \tag{14}$$

That is recorded by a primary sensor as shown in Figure 2. With a noise canceller, the autocorrelation of the noise is obtained from a less important sensor that is laid within the noise field[7].

$$\hat{c}(l) = m(k) - \hat{d}_1(k) \tag{15}$$

The (WHE) for the noise termination system may be derived as follows.

$$R_{v2}\, w = r_{v1v2} \tag{16}$$

For the cross-correlation between $d_1(k)$ and $d_2(k)$ we have

$$r_{v_1v_2}(k) = E\{v_1(l)v_2 * (l-k)\} = E\{[m(l) - d(l)]v_2 * (l-k)\} = E\{m(l)v_2 * (l-k)\} - E\{d(m)v_2 * (l-k)\} \tag{17}$$

Therefore, the WHE are

$$R_{v_2}w = r_{mv_2} \tag{18}$$

# 3. Implementation of Noise Cancellation

Let the desired signal be c(l)=sin(n0.05π) and the noise sequences be $v_1$ (k) and $v_2$ (k) as shown in Figure 2.

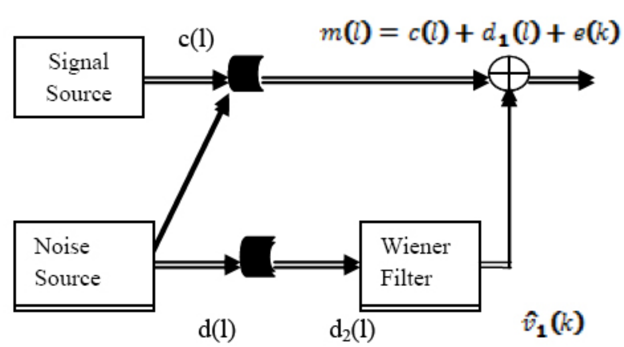



**Figure 2.** Wiener noise cancellations using a secondary sensor to measure the additive noise $v_1$ (k).

$$v_1\,(w) = 0.8v_1\,(c\text{-}1) + h\,(l) \tag{19}$$

$$v_2\,(w) = -\,0.6v_1\,(c\text{-}1) + h\,(l) \tag{20}$$

The autocorrelation of $v_2(k)$ is estimated using the sample autocorrelation as shown in Eq.(22).

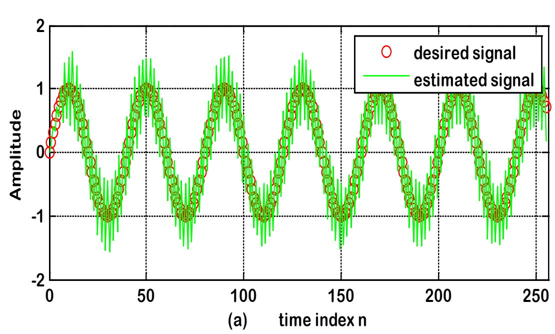
$$\hat{r}_{v_2}(n) = \frac{1}{N}\sum_{k=0}^{N-1} v_2\,(l)v_2(l-n) \tag{21}$$

Similarly, for $\hat{r}_{mv_2}$ the sample cross correlation as shown Eq. (23).

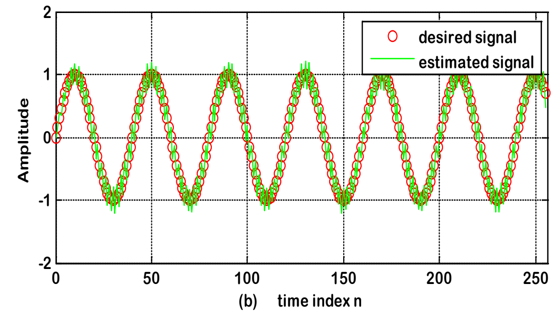
$$\hat{r}_{mv_2}(\mathbf{n}) = \frac{1}{\mathbf{N}}\sum_{\mathbf{n}=0}^{\mathbf{N}-1} \mathbf{m(l)}\,v_2\,(\mathbf{l}-\mathbf{n}) \tag{22}$$

## 4. Monte Carlo Simulation and Results

For the purpose of presentation of the results in simulation, 256 samples are considered. Monte Carlo simulation[11,12] is carried out with 50 numbers of runs. 256 samples of desired signal c (l) is generated. For 50 runs, 256 samples of noise signal g(n) , noise in the primary sensor $v_1$(l), reference signal used by secondary sensor $v_2$(l) and the corrupted signal $m(l) = c(l) + d_1(l)$ are generated. For 50 runs, the biased autocorrelation matrix of $v_2$ (l) i.e., $R_{v2}$ and the biased cross correlation among m (l) and $v_2$ (l) i.e., $r_{xv2}$ are estimated. The coefficients of the WF w (k) are found by using the Equation (19). The estimate $\hat{v}_1(l)$ of additive white noise $v_1$ (l) is generated by filtering $v_2$(n) using Wiener filter. Finally, the approximation of desired signal d (l) is computed by subtracting $\hat{v}_1(l)$ from primary signal m (k).50 estimates of desired signal are produced. For each of the 50 runs, error is calculated by subtracting the estimate of desired signal from d (l). The Root Mean Square (RMS) value of error at each sample is calculated. The RMS value of error[13,14]



**(a)**



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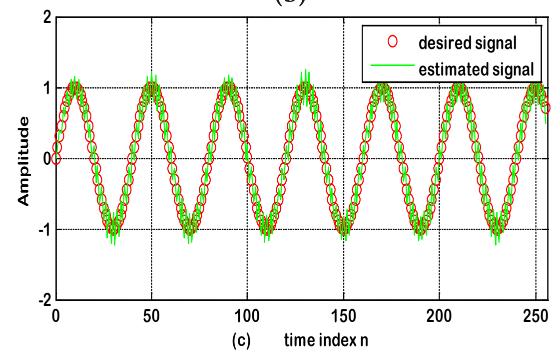

**(c)**

**Figure 3.** Noise Cancellation. **(a)** Output of 6th order Wiener noise canceller, **(b)** Output of 12th order Wiener noise canceller, **(c)** Output of 24th order Wiener noise canceller

at each sample is added to each sample of desired signal and plotted. FIR Wiener filters of orders 6, 12 and 24 were found by solving Equation (21). The results are publicized in Figures 3.

## 5. Conclusion

The Wiener filter is insufficient for dealing through situations in which non stationary of the signal noise is essential to the problem. In such circumstances, adaptive Wiener filter is required and it is in realization. Results of adaptive techniques of linear are quite matching to our expectation. For higher number of samples are greater seen, SNR is likely to improve the method proposed in this paper is an efficient method of filtering with comparatively less complication.

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