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# Review On Digital Filter Design Techniques

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***Abstract*-*Measurement Noise Elimination is considered as one of the most important problem in signal processing. Several solutions have been proposed by many researchers using different techniques. Some of them have been successfully applied on real time measurement and others their performances have been extensively tested via simulation studies. In this paper, a general review of the design techniques, related to this topic, ranging from the classical digital filter design to the modern adaptive filter design, is given. Simple simulation results are also presented to show the performances of the well-established and promising methods.***
***Key words*: *Digital Filter, Adaptive, Noise Cancellation, Simulation***

## I. INTRODUCTION

Many process measurements are corrupted by random disturbances known as noise. These disturbances arise from various sources. Some are due to short-term process inconsistencies inherent to plant operation such as flow turbulence and others are features of the instrument used for the measurement. These features include electromagnetic interference, thermal noise, contact noise, quantization errors, inconsistent laboratory analyses and so on. The information contained in the measurement may be rendered ambiguous due to the presence of noise. This will, in turn, lead to poor monitoring and control of the plant. Clearly, to improve the plant performance, noisy measurements should be processed in order to cancel noise from them.The problem of noise cancellation is usually posed as follows:

Given a measured signal d (t) constituted by two components: the signal of interest s(t) and an interfering disturbance, commonly termed noise, n(t) (i.e., s(t) is the wanted part of the signal while n(t) is the unwanted part of it ), remove or reduce to minimum, the noise n(t), to produce the best possible reconstruction of s(t).

For the case, where the signals are deterministic, and the band of frequencies of, both, the signal of interest and the noise are known a priori and do not overlap, design is made in the frequency domain and assumes that the band of frequencies of both the signal and the noise are known a priori [1,2]. Such methods of design yield the classical lowpass, highpass, passband, and stopband filters. However when the noise is a large amplitude random signal or the signal of interest is itself a random signal and we wish to separate it from other signals, the deterministic designs above would be unable to obtain a good estimate of the desired signal and the statistical filtering approach becomes more appealing. Therefore, to estimate the signal the problem should be tackled in a statistical way. Estimation of the signal from noisy measurements has been studied, by many researchers, through the development of several numerical algorithms for the design of optimal digital filters [3-5].

Wiener and Kalman started by developing optimal filter algorithms, using linear theory, for the estimation of signals from noisy measurements. These algorithms have been found to present certain restrictions [3]. Several algorithms have been developed to overcome the restrictions encountered using the Kalman and Wiener filters. Generally, the developed methods are computationally cheap when compared with Wiener and Kalman designs [3,6]. Some of them have been successfully applied to real time measurements and others their performances have been extensively tested via simulation studies.

The objective of this work is to present the popular digital filtering techniques, starting from the classical filters to the modern adaptive filtering methods. Most of the work is focused on describing the adaptive filtering technique known as Adaptive Noise Cancellation (ANC) method, used for the estimation of a signal from noisy measurements. This technique is widely used in modern industry, and can be considered as an interesting technique for the development of smart sensor [7].

## II. CLASSICAL DIGITAL FILTERS

Digital filters have many advantages over analog filters. Compared to their analog counterparts, digital filters are:

More precise and consistent in a wide range of environments with little possibility for drift.

Used to filter sensor signals precisely for closed loop control of physical systems, information detection, and pattern recognition. Implemented on a general-purpose computer or on a dedicated digital signal processing hardware chip.

Digital filters can be represented by their unit impulse response in the time domain and in the transform domain by their transfer function. The impulse response of linear time invariant systems can be either finite or infinite and this property determines the classification of the

Digital filters as either infinite impulse response (IIR) or finite impulse response (FIR) systems.

The general classical digital filter general form is represented by a linear invariant system

$$y(kT) = \sum_{i=0}^{nb} b_i x(kT - nbT) + \sum_{j=1}^{na} a_j\, y(kT - naT) \qquad (1)$$

From equation (1), if $a_j$=0, the corresponding filter is nonrecursive filter (FIR). If one, or more, coefficient, $a_j$, is or more not equals to zero, the corresponding filter is recursive filter (IIR). Nonrecursive filters are filters where the output *y(k)* is a function of the current and past inputs only. No past outputs are used to predict the current filter response. Therefore no feedback is used in the filter representation. Recursive filters are filters where the output *y(t)* is function of the past inputs and its past output values. In these types of filters, an inherent feedback exists in the filter representation that is why they are called recursive filter.

To avoid the introduction of large time delay in the system, the structure of the filter designed is chosen such that it is of low order (i.e., first, second or third)

*A. Design of Classical Digital Filters*

Design of classical digital filters is concerned with two class filters: the IIR and FIR filters. These filters include the classical type filters such as low pass, high pass, band pass, and the stop band. The IIR class employs the classic designs such as Butterworth, Chebyshev, inverse Chebyshev and Elliptic, and the FIR class employs the Parks-McClellan equiripple design algorithm [2]. Generally, the design of classical digital filters involves, the following steps:

Determine the desired response. The desired response is normally specified in the frequency domain in terms of the desired magnitude response (for example, pass band response, pass band frequency, stop band attenuation).

Select a class of filters to approximate the desired response (for example, Butterworth low pass filter with IIR filter structure or Chebyshev low pass filter with IIR filter structure).

Analyze the filter performance, via simulation, to determine whether the filter satisfies all the given criteria.

Implement the best filter using a general-purpose computer or a custom hardware ship.

Software packages are available to design classical digital filters that meet the required specifications [8].

Classical filters can be used only if the signals are deterministic, and the band of frequencies of both the signal of interest and the noise are known a priori and do not overlap (or overlap but with high signal to noise ratio).

However when the noise signal has frequencies spread over a wide spectrum or the signal of interest is itself a random signal and we wish to separate it from other signals, the deterministic designs above would be unable to obtain a good estimate of the desired signal. As a matter of fact, if the noise is white, its frequency spectrum would be a flat line which certainly covers the desired band of frequencies of the signal of interest. The design of a filter which lets the desired band of frequencies to pass, would pass with it, in general, a great deal of noise. Therefore to estimate the signal, the problem should be tackled using more advanced techniques such Wiener and Kalman filters, and the adaptive filtering techniques.

## III. WIENER AND KALMAN FILTERS

Estimation of the signal from noisy measurements has been studied, by many researchers, through the development of several numerical algorithms for the design of optimal digital filters. Wiener and Kalman started by developing optimal filter algorithms, using linear theory, for the estimation of signals from noisy measurements [3]. These algorithms are usually developed assuming that the model of the process is available, the signal is stationary, there is no correlation between signal and noise, and the noise statistics are known. Such conditions, however, are seldom encountered in process plants. Time varying characteristics, process interactions, and nonlinear behavior often restrict the applicability of these algorithms.

Several algorithms have been developed to overcome the restrictions encountered using the popular Kalman and Wiener filters. Generally, the developed methods known as ANC are computationally cheap when compared to Wiener and Kalman designs [3,7].

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The description of these techniques is given next.

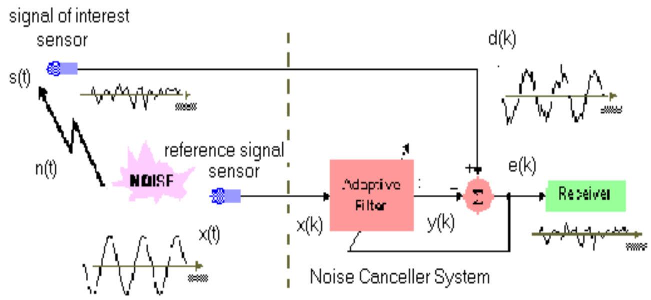


Fig. 1 Adaptive Noice Cancellation

## IV. ADAPTIVE NOISE CANCELLATION TECHNIQUES

ANC is a variation of optimal filtering of Wiener and Kalman discussed. While in the Wiener and Kalman designs only one input is required, a second input is necessary in the technique of ANC. This latter input, called reference noise should be measured in the noise field, where the measuring sensor is carefully positioned such that the reference noise would be free from the signal of interest. The reference noise is thus strongly correlated with the noise component and can be assumed to be related to it through a linear or nonlinear function [3]. The ANC makes use of the two inputs in order to predict the noise component and subtract it from the noise-corrupted signal. This approach is computationally cheap compared with the Wiener and Kalman designs and has been successfully applied to many problems including cancellation of engine noise in the transmission of speech from an aircraft, monitoring featal heart beat, and cancellation of unwanted machinery vibrations [3, 7]. In general, ANCs can be used in any other situation where a coherent noise reference is available.

### *A. Example Of Adaptive Filtering Applications*

Fig. 1 shows an example of the adaptive filtering technique application, currently used, known as noise cancellation.

A signal s (t) to be transmitted is corrupted by noise, from, for example engine vibration. By using an adaptive filter it is possible to minimise the error introduced by the noise n(t). As shown in the figure, using the reference signal x(k) which, is highly correlated with the noise and using the noisy measurement as inputs to the noise canceller, a perfect reconstruction of the signal s(t), e(t) canceller is obtained.

### *B. Concept of Adaptive Noise Cancellation Technique*

The structure of an adaptive noise canceller is illustrated in Fig. 2.

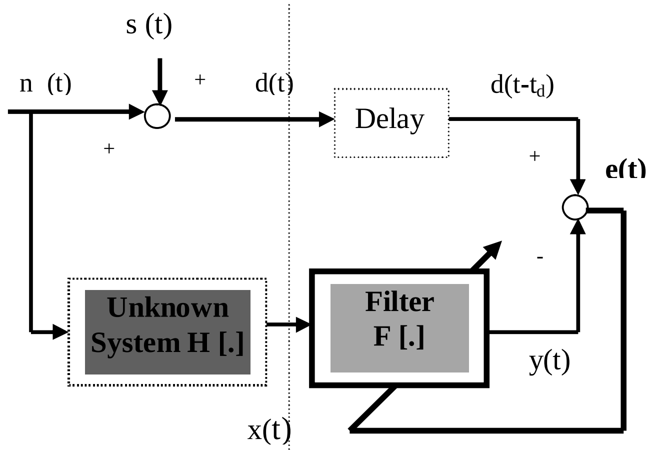


Fig. 2 Concept of the Adaptive Filter

As shown in Fig. 2, the signal of interest s (t) is corrupted by the noise n (t) to yield the measured signal d (t)=s(t)+n(t). This latter is delayed by time $t_d$ to ensure the causality of the filter F [.] and to solve the stability problem of the filter when the system H [.] is non-minimum phase. It is assumed that n (t) and s (t) are uncorrelated and that the noise *n(t)* passes through a transmission channel with an unknown transfer function H[.] to yield the reference input x(t) .The objective of the design is to estimate the parameters of the filter F[.] which operates on x(t) to produce y(t) which cancels the noise in the measurement d(t) by minimising the cost function $E[e^2(t)]$. Where E[.] represents the mean and e(t), the error signal, is obtained from the block diagram above as :

$$e(t)=d(t-t_d)-y(t) = s(t-t_d)+n(t-t_d)-y(t)$$

It can be shown that the cost function can be reformulated as:

$$\mathbf{Min}\ (E[e^2(t)])=E[s^2(t-t_d)]+\mathbf{min}(E[(n(t-t_d)-y(t))^2]) \quad (2)$$

Which shows that E $[e^2(t)]$ is minimized when $E[(n(t-t_d)-y(t))^2]$ is a minimum or when *y(t),* the output of the filter F[.], cancels the noise $n(t-t_d)$ in the primary channel. The optimal filter coefficients are obtained by differentiating the cost function E $[e^2(t)]$ with respect to the filter parameter, $\theta$, and then to obtain the minimum we set the result, which is the gradient, equal to zero, i.e.,

$$\Delta/\delta\theta^T (E\ [e^2 (t)])=0 \quad (3)$$

The solution of equation (3) gives the optimal filters parameters. Several adaptive algorithms, related to non-recursive filters, have been developed to update the filter parameters. These are based on the gradient methods and the popular least square theory. Among the gradient based adaptive algoritms are the Newton, the steepest descent and the famous Least Mean Square (LMS) algorithm. Gradient algorithms are among the class of

recursive algorithms where the previous estimated parameter vector is used together with some additive corrective term in order to predict the current parameter vector estimate.

The corrective term also depends on a positive scalar, $\mu$, called algorithm stepsize which influences to a large extent, the properties of convergence of the adaptive algorithm. In this paper, description of the famous LMS algorithm, is given.

Reference [3] gives a good detailed description of other gradient techniques.

The LMS has generated a lot of interest in industry and has become very popular because of its simplicity and ease of implementation compared to other gradient methods.

### *C. LMS For Parameter Estimation*

The noise cancellation filter has two inputs *x(t)* and *d(t),* and one output *e(t)* as shown in Fig. 2. The input *x(t),* called the *reference signal,* is measured in the noise field in such a way that it is strongly correlated with the noise field *n(t)* and free from the signal s(t).

The LMS in the ANC is used to estimate the parameter of the filter F[.]. The most commonly used filter strutures are FIR filters and IIR filters. IIR are very convenient representation for noise cancellation because they give a very good matching with the system characteristics with a significantly reduced number of terms compared with FIR. Thus they allow a considerable reduction in the amount of computations per iteration and henceforth a high potential of real time applications.

If the transmission channel between the reference signal and the noise interference is essentially propagation delays and multipath, the FIR model structure is very appropriate. For that transmission channels which contain strong resonance, an IIR model structure is to be used as it requires fewer parameters to accurately model the system.

If the filtering system model F[.] structure is assumed an FIR system in the adaptive noise canceller of Fig. 2 and given a reference signal *x(t),* and the filter model last updated parameters at time *t-1*, the linear prediction of the noise interference is given by

$$y(t) = \hat{n}(t/t-1) = \sum_{k=0}^{nb} b_k x(t-k) \quad (4)$$

The linear prediction signal error is then simply

$$e(t) = n(t) + s(t) - \hat{n}(t/t-1) \quad (5)$$

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and then the LMS update for the FIR filter coefficients is given by

$$b_k(t) = b_k(t-1) + 2\mu\ e(t)\ x(t-k) \qquad (6)$$

Where $\mu$, less than 1, is the algorithm stepsize.

The LMS algorithm was initially derived for the estimation of FIR filter parameters. Its simplicity and robustness have generated interest in developing an LMS algorithm for the estimation of IIR filter parameters. The LMS update of the IIR filter parameter estimates $b_i$ and $a_j$ at time $t$ are obtained as follows:

$$b_i(t)=b_i(t-1)+2\mu_b x(t-i)e(t) \qquad (7)$$
$$a_j(t)=a_j(t-1)+2\mu_a y(t-j)e(t) \qquad (8)$$

The predicted noise interference is computed as:

$$y(t) = \hat{n}(t/t-1) = \sum_{i=0}^{nb} b_i(t)x(t-i) + \sum_{j=1}^{na} a_j(t)\, y(t-j) \qquad (9)$$

And the signal error is computed as:

$$e(t) = d(t-t_d) - \hat{y}(t/t-1) \qquad (10)$$

To ensure convergence, the step sizes $\mu_b$ and $\mu_a$ should be carefully chosen. Generally, values much smaller than one are used for these parameters.

### *D. Other Estimation Algorithms*

The estimation of the filter parameter in the ANC system shown in Fig. 2 can also be interpreted as an identification problem. As can be noticed from Fig. 2, the optimal design of the filter F [.] will be the inverse of H [.] such that

$$y(t)= n(t-t_d)= F[x(t)] = H^{-1}[x(t)] \qquad (11)$$

Where $H^{-1}[.]$ is assumed to exist and stable. Since

$$d(t-t_d)=n(t-t_d)+s(t-t_d) \qquad (12)$$

Using equation (11) yields

$$d(t-t_d)= F[x(t)]+s(t-t_d)=H^{-1}[x(t)]+s(t-t_d) \qquad (13)$$

In system identification studies, equation (13) would be interpreted as a system $H^{-1}[.]$ with input x(t), measured output $d(t-t_d)$ and an unobservable coloured noise $s(t-t_d)$.

Estimation of the parameters of $H^{-1}[.]$ can therefore be considered as a parallel identification scheme as illustrated in Fig 3.

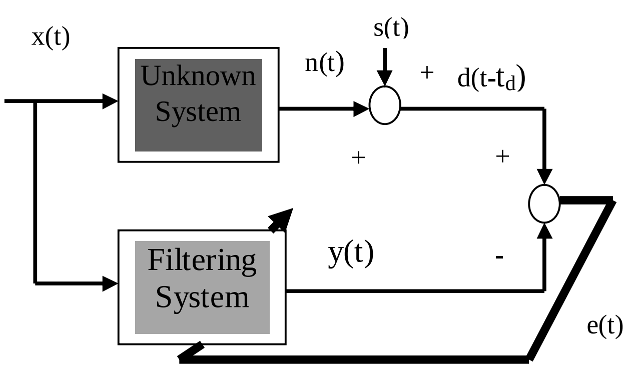


Fig. 3: ANC configured as identification System.

Volume 3 Issue X, October 2015
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This configuration is employed in process identification in many control problems and also in acoustic echo cancellation where the unknown system would be the transfer function of the teleconferencing room.

Minimising the mean of the errors squared $\frac{1}{N}\sum_{i=N}^{N} e^2(i)$ and assuming convergence would yield $F[.]=H^{-1}[.]$ and y(t) would be optimal prediction of the noise $n(t-t_d)$ and cancels the noise from the measurement.

When using the LMS algorithm, in certain cases, stability problems have been encountered for the estimation of IIR filter parameters. Owing to that, other techniques for parameter estimation had been to be found.

Using the above configuration for the ANC system, other well known estimation algorithms based on the least square theory, such as the Recursive Least Square (RLS) and the Recursive Instrumentation Variable (RIV) algorithms, are used for the estimation of the filter parameters.

Though computationally more complex, due to the considerable development in computer technology (regarding the processing time), RLS and RIV algorithms have regained a lot of interest for their application in Adaptive Filtering systems. Simulation results have shown, these algorithms lead to a superior convergence time and a more accurate convergence quality compared to the LMS algorithm. Detailed descriptions of the RLS and RIV used for ANC are given in reference [6]. ANC is a highly recommended method for signal estimation whenever a reference noise can be provided. The design of the correct adaptive digital filter is crucial for obtaining correct results. This would include the choice of the correct structure for the digital filter and the choice of the right adaptive algorithm which is stable, robust and computationaly, can comply with the signal's time constant and the chosen sampling time value. The power of the noise cancellation technique when compared to the other classical techniques, stems from the fact that the method is adaptive, computationally cheap, and can yield big noise reduction without noticeable distortion of the signal of interest.

## V. SIMULATED EXAMPLES

To illustrate the performance of the ANC techniques, results from simulated systems obtained from reference [3, 4] are presented. The good convergence behaviour of the LMS and RLS algorithms is shown in Fig. 4(a), 4(b) and 4(c). This shows the successful reconstruction of the original signal.

## VI. CONCLUSION

This paper has reviewed measurement noise cancellation techniques based on digital signal processing. These range from the classical digital filters to the modern adaptive filters. A short description of the techniques used for the design of classical digital filters and more detailed description of the adaptive filtering techniques and their applications have been given. The derivation of different configurations of the adaptive filtering technique as system identification and as an adaptive noise cancellation (ANC) is given. ANC has been shown to provide a highly efficient approach to optimal signal estimation. The performance of ANC filters depends critically on the correct filter structure. A comparative study based on the simulation of different filter structures has been investigated. This included the common finite impulse response (FIR) and the infinite impulse response (IIR) filters. FIR filters generated good performances but only at a large computational cost because the large number of terms included in filter structure to match the system characteristics. IIR filters gave incredibly good performances with a considerably smaller number of filter terms and therefore a significant reduction in the computational complexity. After selecting the filter structure, the filter parameters were estimated using different estimation algorithms such as LMS, RLS and RIV. The LMS would achieve accurate filter parameter estimates provided that the value of the step size $\mu$ is chosen small and this leads to longer convergence time. The RLS and the RIV yielded a much faster convergence time but they are computationally more complex.

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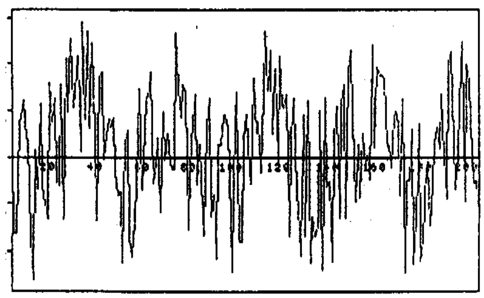
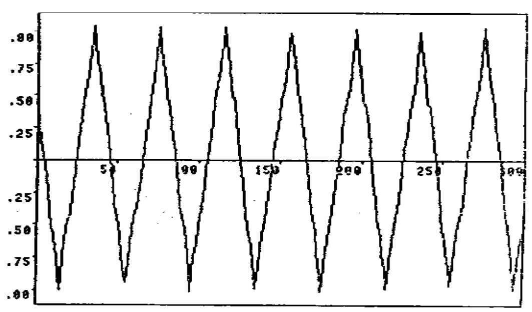


Fig. 4(a): Saw tooth measured signal, d (t)=s(t)+n(t) corrupted by noise n(t), use in the simulation of the ANC. The signal to be estimated is s (t)



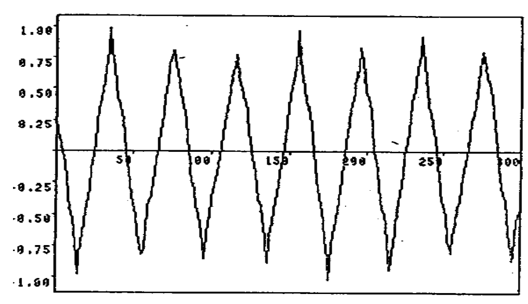
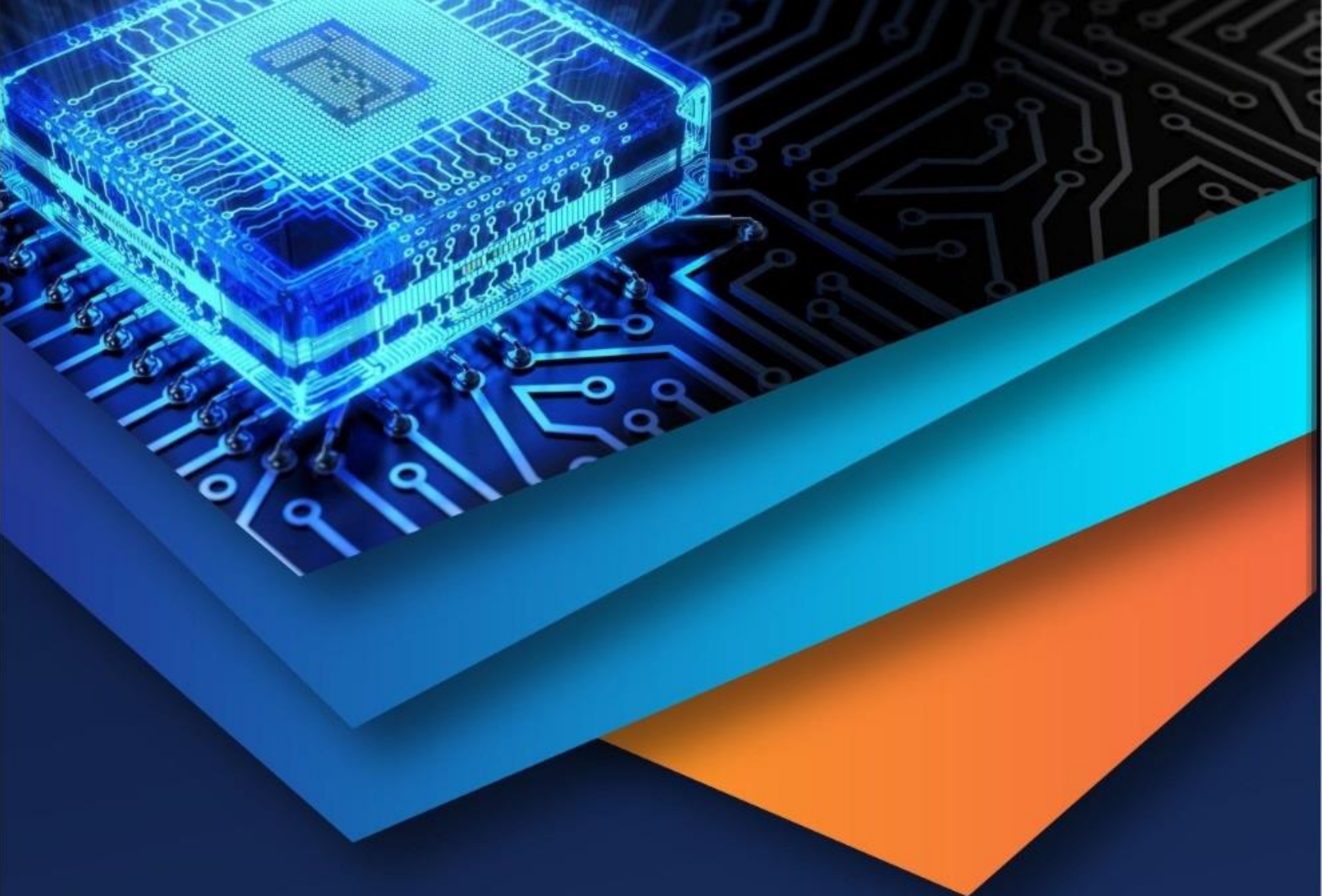


Fig. 4(b): Estimated signal, s(t), using LMS algorithm and FIR filter with $n_b$=10 and $t_d$=5.

Fig. 4(c): Estimated signal, s(t), using RLS algorithm and FIR filter with $n_b$=10 and $t_d$=5.



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