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DE-Noising of ECG Signal Using Hybrid Adaptive Filters

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Abstract: Electroencephalograph (EEG), which is the measure of the brain activity, the shape of this signal tells much about the condition of the heart of the patient. Naturally the EEG signal gets distorted by different artifacts which must be removed otherwise it will convey an incorrect information regarding the patient's heart condition. Several simple and efficient LMS and Normalized LMS adaptive filters, which are computationally superior having multiplier free weight update loops are used for cancellation of noise in EEG signals. Implementing Hybrid algorithm on ANC provides better performance than adaptive technique used to enhance the EEG signal. In this work, fidelity parameters like signal to noise ratio (SNR), MSE and LSE have to be computed.

Keywords: Adaptive filters, Electroencephalograph, Hybrid Algorithm

I. INTRODUCTION

Rapid Advances in the VLSI technology and digital communications or digital signal processing has brought more attention to the adaptive least squares (LS) methods. Many digital signal processing applications requires linear filters and adaptive techniques in signal processing and analysis. The reference and error channels of active noise control (ANC) systems may be saturated in real-world applications if the noise level exceeds the dynamic range of the electronic devices. This nonlinear saturation degrades the performance of ANC systems that use linear adaptive filters with the filtered-least-mean-square (FLMS) algorithm. Adaptive filters have been included in the syllabus of undergraduate digital signal processing (DSP) courses. The LMS algorithm has been extensively used in many applications as a consequence of its simplicity and robustness. The LMS based adaptive filters used in all sparse systems for noise Cancellation. Adaptive algorithms are applicable to system identification and modeling, noise and interference cancelling, equalization, signal detection and prediction. LMS Algorithm is widely used in a variety of applications, ranging from speech enhancement and biomedical signal processing to active control of sound and vibration. Adaptive Filters are widely used in numerous industrial applications Acoustics, communications, automatic control and seismology. Information processing in variable and noisy environments is usually accomplished by means of adaptive filters. Adaptive filters are successfully using in FT Analysis and in Fractional Fourier Transform. Adaptive filtering involves the change of filter parameters (coefficients) over time. It adapts to the change in signal characteristics in order to minimize the error. In adaptive filters, the weight vectors are updated by an adaptive algorithm to minimize the cost function. The algorithms used by us for noise reduction in ECG in this thesis are least mean square (LMS), Normalized least mean square (NLMS), sign data least mean square (SDLMS), sign error least mean square (SELMS) and sign-sign least mean square (SSLMS) algorithms.

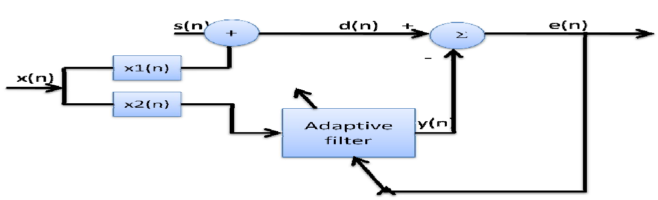

Fig1:Block diagram of adaptive LMS filter

II. EEG PROCESSING

The Electroencephalographic (EEG) is a graphical representation of neuron functionality and is an important tool used for diagnosis of brain abnormalities. In clinical environment during acquisition, the EEG signal encounters with various types of artifacts. The predominant artifacts present in the EEG includes: baseline wander (BW), power-line interference (PLI), muscle artifacts (MA) and

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motion artifacts (EM). These artifacts strongly affects the ST segment, degrades the signal quality, frequency resolution, produces large amplitude signals in EEG and masks tiny features that are important for clinical monitoring and diagnosis. Cancelation of these artifacts in EEG signals is an important task for better diagnosis. The extraction of high-resolution EEG signals from recordings which are contaminated with background noise is an important issue to investigate. The goal of EEG signal enhancement is to separate the valid signal components from the undesired artifacts, so as to present an EEG that facilitates easy and accurate interpretation. Many approaches have been reported in the literature to address EEG enhancement using both adaptive and non-adaptive techniques.

III. HYBRID ALGORITHM

The proposed hybrid adaptive algorithm is constructed form the Fixed LMS and Normalized LMS algorithms by combining with a hybrid factor. This hybrid factor is a tunable parameter varies from 0 to 1 to get the optimized values of hybrid LMS algorithm. The detail discuss about the three algorithms was given below

A. *Fixed LMS Algorithm*

The mathematical morphology (MM) provides an efficient frame work for analyzing the Fixed LMS adaptive filters. MM provides the weight update equation for FIXED LMS adaptive filter used in speech processing

The weight update equation of Fixed LMS Algorithm is

$$y(n) = w_0(n) + w_1(n)u(n-1) + \ldots + w_{M-1}(n)u(n-M+1) \text{----------------(3.1)}$$

$$= \sum_{K=0}^{M-1} w_K(n)u(n-k) = w(n)^T u(n), n = 0,1,2,3,\ldots\ldots\ldots\infty \text{--------------(3.2)}$$

Error between the filter output y(t) and desired signal d(t) :

$$e(n) = d(n) - y(n) = d(n) - w(n)^T u(n) \text{--------------------------------(3.3)}$$

Change the filter parameters according to

$$w(n+1) = w(n) + \mu u(n)e(n) \text{------------------------------------ (3.4)}$$

B. *Normalized Lms Algorithm*

The weight update equation of Normalized LMS Algorithm is discussed below

Modify at time n the parameter vector from $w(n) to w(n+1)$ fulfilling the constraint $w^T(n+1)u(n) = d(n)$ ----------------------- (3.5)- with the "least modification" of $w(n)$ i.e. with the least Euclidian norm of the difference

$$w(n+1) - w(n) = \delta w(n+1) \text{--------------------------------- (3.6)}$$

Thus it minimize

$$\|\delta w(n+1)\|^2 = \sum_{K=o}^{M-1} (w_K(n+1) - w_K(n))^2 \text{---------------------- (3.7)}$$

Under the constant $w^T(n+1)u(n) = d(n)$ --------------- (3.8)

The solution can be obtained by Lagrange multipliers method:

$$j(w(n+1),\lambda) = \|\delta w(n+1)\|^2 + \lambda\{d(n) - w^T(n+1)u(n)\} \text{---------------------- (3.9)}$$

$$j(w(n+1),\lambda) = (w_K(n+1) - w_K(n))^2 + \lambda\left(d(n) - \sum_{i=0}^{M-1} w_i(n+1)u(n-i)\right) \text{-----------------(3.10)}$$

To obtain the minimum of , $j(w(n+1),\lambda)$ check the zeros of criterion partial derivatives:

$$\frac{\partial j(w(n+1),\lambda)}{\partial w_j(n+1)} = 0$$

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$$\frac{\partial}{\partial w_j(n+1)}\left[\sum_{k=0}^{M-1}\left(w_K(n+1)-w_k(n)\right)^2+\lambda\left(d(n)-\sum w_i(n+1)\mu(n-i)\right)\right]=0 \quad \text{----------} \; (3.11)$$

$$2\left(w_j(n+1)-w_j(n)-\lambda u(n-j)\right)=0 \quad \text{-------} \; (3.12)$$

$$w_j(n+1)=w_j(n)+\frac{1}{2}\lambda u(n-j) \quad \text{----------------------------------} \; (3.13)$$

where λ will result from

$$d(n)=\sum_{i=0}^{M-1} w_i(n+1)u(n-i) \quad \text{------------------------------------} \; (3.14)$$

$$d(n)=\sum_{i=0}^{M-1}\left(w_i(n)+\frac{1}{2}\lambda u(n-i)\right)u(n-i) \quad \text{---------------------------} \; (3.15)$$

$$d(n)=\sum_{i=0}^{M-1} w_i(n)u(n-i)+\frac{1}{2}\lambda\left(u(n-i)\right)^2 \quad \text{---------------------------} \; (3.16)$$

$$\lambda=\frac{2\left(d(n)-\sum_{i=0}^{M-1} w_i(n)u(n-i)\right)}{\sum_{i=0}^{M-1}\left(u(n-i)\right)^2} \quad \text{------------------------------------} \; (3.17)$$

$$\lambda=\frac{2e(n)}{\sum_{i=0}^{M-1}\left(u(n-i)\right)^2} \quad \text{--} \; (3.18)$$

Thus, the minimum of the criterion $j(w(n+1),\lambda)$ will be obtained using the adaptation equation.

$$w_j(n+1)=w_j(n)+\frac{2e(n)}{\sum_{i=0}^{M-1}\left(u(n-i)\right)^2}u(n-j) \quad \text{-----------------------------} \; (3.19)$$

In order to add an extra freedom degree to the adaptation strategy, one constant, μ, controlling the step size will be introduced:

$$w_j(n+1)=w_j(n)+\mu\frac{1}{\sum_{i=0}^{M-1}\left\|u(n-i)\right\|^2}e(n)u(n-j) \quad \text{--------------------} \; (3.20)$$

$$=w_j(n)+\frac{\mu}{\left\|u(n)\right\|^2}e(n)u(n-j) \quad \text{---------------------------------------} \; (3.21)$$

To overcome the possible numerical difficulties when $\left\|u(n)\right\|$ is very close to zero, a constant *a* >0 is used:

$$w_j(n+1)=w_j(n)+\frac{\mu}{\left\|u(n)\right\|^2}e(n)u(n-j) \quad \text{--------------------------------} \; (3.22)$$

This is the updating equation used in the Normalized LMS algorithm.

C. Hybrid LMS Algorithm

The Hybrid LMS algorithm is formed by combining the Fixed LMS algorithm and Normalized LMS algorithm with parameter ‘k’**,** where k is varied from 0 to 1. The weight updated equation for Hybrid LMS algorithm is

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$\mathbf{w_k}$(n+1)=k*(Normalized LMS algorithm)+(1-k)*(Fixed LMS algorithm)— (3.23)

when k=0 the above hybrid LMS algorithm behaves like a Fixed LMS and when k=1 it behaves like a Normalized LMS algorithm, so by varying 'k' between 0 to 1 we will get readings between the below said algorithms.

IV. DESIGN OF HYBRID ADAPTIVE LMS ALGORITHM

A. Fixed LMS algorithm

The Figure:1shows the block diagram of Adaptive filter with Fixed LMS Algorithm. Which processes the noised ECG signal through it. Where the adjustable weights are typically determined by the LMS Algorithm, the weight update equation is

w(n+1)=w(n)+μ*e(n)*v1(n)

y(n)=w(n)+e(n)*v1(n)

B. Steps to design adaptive Filter with Fixed LMS

1) Create or record actual speech signal.
2) Create or record a noise signal.
3) Correlate noise by passing through a Fixed LMS adaptive filter.
4) Merge Noise signal with actual ECG signal.Calculate error e(n)
5) Update weight equation w(n)
6) Repeat step 6 and calculate adaptive output y(n) until error is minimized.
7) Calculate the fidelity parameters

C. Normalized LMS algorithm

The adjustable weights are typically determined by the LMS Algorithm, the weight update equation is

$$w_j(n+1) = w_j(n) + \frac{\bar{\mu}}{\|\underline{x}(n)\|^2} e(n)x(n-j) - -(1)$$

D. Steps to design adaptive Filter with Normalized &variable step size LMS Algorithms

1) Create or record actual speech signal.
2) Create or record a noise signal.
3) Correlate noise by passing through a Normalized LMS adaptive filter.
4) Merge Noise signal with actual ECG signal.
5) Calculate error e(n)
6) Update weight equation w(n)
7) Repeat step 6 and calculate adaptive output y(n) until error is minimized.
8) Calculate the fidelity parameters

E. Hybrid LMS algorithm

The Figure:1 shows the block diagram of Adaptive filter with Hybrid LMS Algorithm. The Hybrid LMS algorithm is formed by combining the Fixed LMS algorithm and Normalized LMS algorithm with parameter 'k'**,** where k is varied from 0 to 1

The weight updated equation for Hybrid LMS algorithm is

w_k(n+1)=k*(Fixed LMS algorithm)+(1-k)*(Normalized LMS algorithm)

when k=0 the above hybrid LMS algorithm behaves like a Normalized LMS and when k=1 it behaves like a Fixed LMS algorithm, so by varying 'k' between 0 to 1 we will get readings between the below said algorithms.

V. SIMULATION AND RESULTS

Table-1:Performance contrast of Fixed and Normalized LMS algorithms

s.no	Type of noise	Type of algorithm	SNR	MSE	LSE
1		Fixed LMS	19.6094	0.0205	0.6712

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2	Base line	Normalised LMS	20.5523	0.0406	1.2253
3	Power Line	Fixed LMS	13.8506	0.1966	0.9829
4		Normalised LMS	15.7478	0.2226	1.0131

Table-2:Performance contrast of Hybrid LMS algorithms

S.NO	Type of noise	Hybrid Factor	SNR	MSE	LSE	Remarks
1	Base Line	0	19.6094	0.0205	0.6712	Fixed LMS
2		0.4	19.9866	0.0285	0.8928	
3		0.8	20.3637	0.0366	1.1145	
4		1.0	20.5523	0.0406	1.2253	Normalized LMS
1	Power Line	0	13.8506	0.1966	0.9829	Fixed LMS
2		0.4	14.6095	0.2070	0.9950	
3		0.8	15.3684	0.2174	1.0071	
4		1.0	15.7478	0.2226	1.0131	Normalized LMS

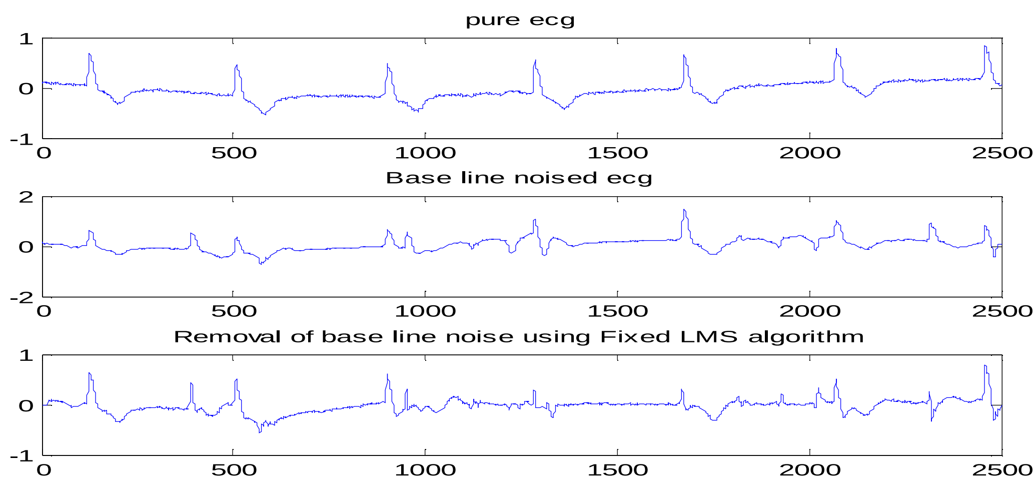

Fig3: Removal of base line noise by using Fixed LMS algorithm

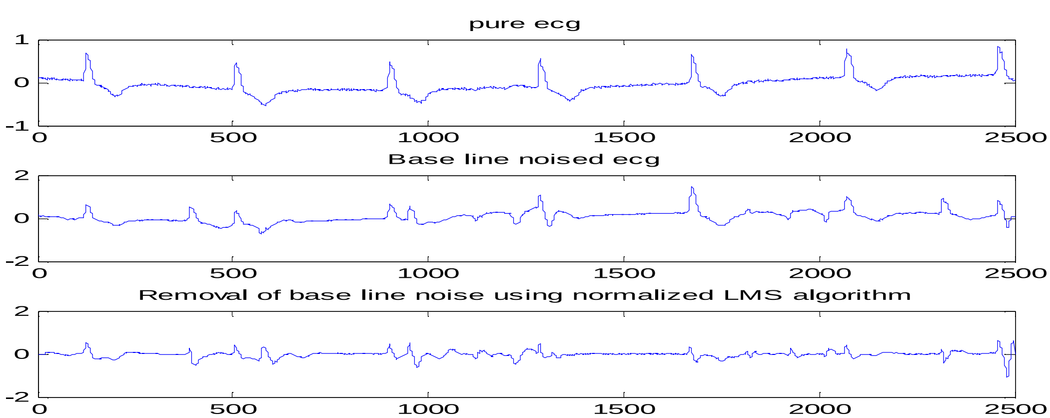

Fig4: Removal of base line noise by using Normalized LMS algorithm

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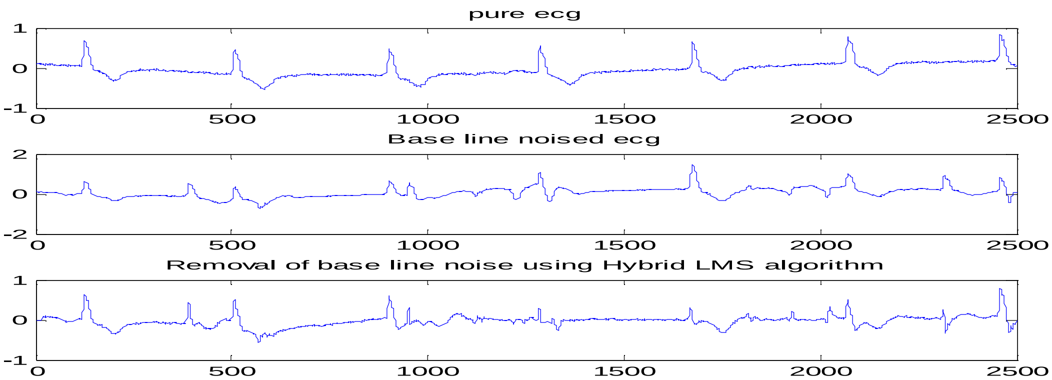

Fig5: Removal of base line noise by using Hybrid LMS algorithm

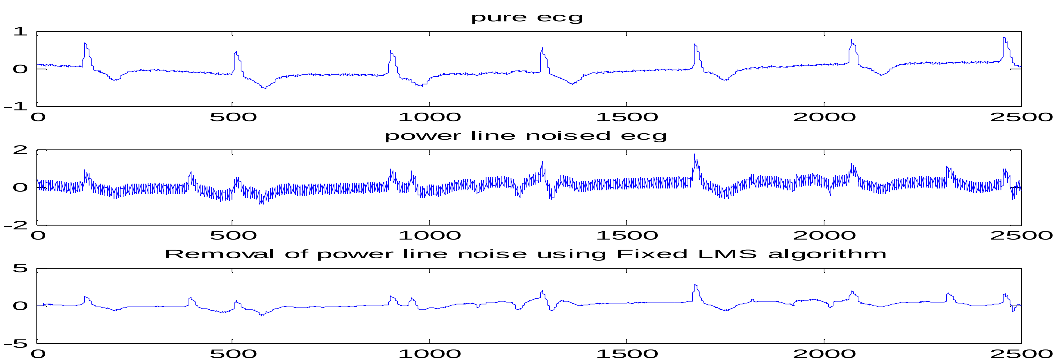

Fig6: Removal of power line noise by using Fixed LMS algorithm

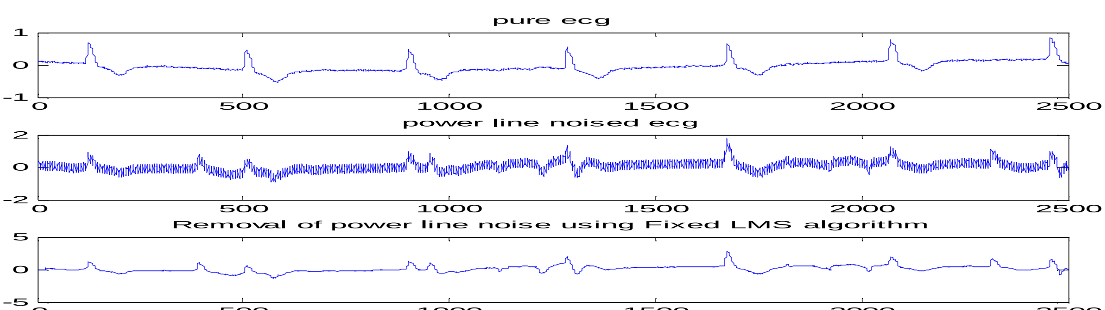

Fig7: Removal of power line noise by using NLMS algorithm

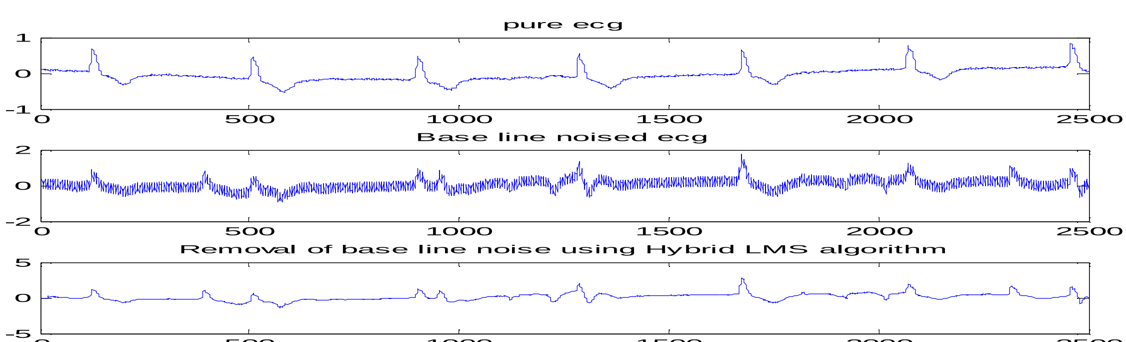

Fig8: Removal of power line noise by using Hybrid LMS algorithm

VI. CONCULUSION

In this paper the artifacts of EEG signal using LMS, NLMS and hybrid LMS algorithms are proposed and tested on real signals with different artifacts obtained from MIT-BIH database. Among the two algorithms the NLMS performs better than the LMS. The proposed tunable hybrid LMS algorithm gives optimized values for both algorithms which are presented in

Table-1 and Table-2 Respectively. From the simulation results it is clear that these two adaptive algorithms combined with Hybrid factor removes non-stationary noise effectively which are shown in terms of responses from Fig:1 to Fig:7 for both base line and Power Line Noises .Hence the proposed Hybrid algorithm is suitable for wireless biotelemetry EEG systems.

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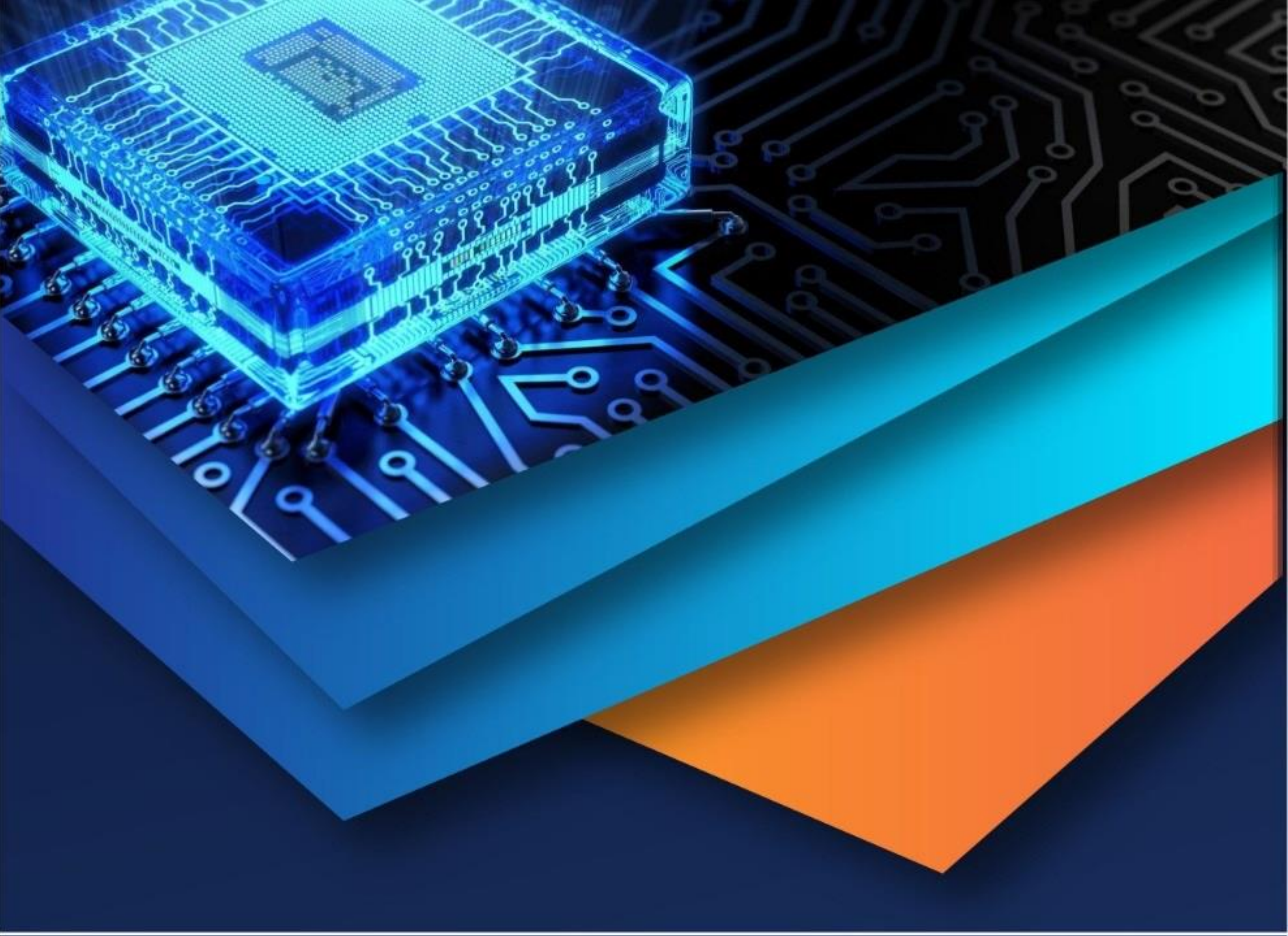

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