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A Novel Enhanced Image Denoising Algorithm Combining DWT and Curvelet Techniques with Image Fusion

Nishant Nigam[1], Simran Kalera[2], Saurabh Rajani[3]
[1,2,3] *VIT University, Vellore, Tamil Nadu, 632014 Under the guidance of Prof. Boominathan P.*

Abstract : Image denoising is a well-studied subject and used in a variety of applications from surveillance, satellite imagery to forensic sciences. This algorithm is aimed to achieve further knowledge and information to the subject. Also, our proposed algorithm could help in research of other denoising techniques to get a near-perfect visually pleasing image. The aim is to design a new algorithm for denoising images affected with Gaussian noise, using wavelet transform and image fusion techniques. We also try to achieve a good quality visually pleasing image and comparatively high PSNR performance metric with respect to existing denoised images.
Keywords: DWT, Image processing, Noises, Filters, Proposed Algorithm

I. INTRODUCTION

In our proposed method we are going to denoise the noisy image using discrete wavelet transform and Curvelet transform and fuse the two denoised images using Dual Tree – Complex wavelet transform.
The DWT denoised image and curvelet denoised image are taken and decomposed to using Dual Tree Complex Wavelet transform. DT-CWT uses complex wavelet to obtain the wavelet coefficients. The coefficients are grouped into two bands namely low pass band which is the actual down sampled image after multilevel decomposition and the other group involves coefficients which are obtained by directional selection of wavelet with input image called the orientation band. Simple average is performed for the two bands of coefficients. Then, inverse DT-CWT is taken for the averaged coefficients.

II. CURVELET TRANSFORM

Cande`s What's more Donoho suggested those curvelet change those perfect for which is with representable An bend Likewise superposition of works for Different lengths Furthermore widths complying with the scaling law width ~ length2. Curvelets contrast starting with wavelet Furthermore related systems, What's more it takes those type for essential elements, which show a helter skelter directional affectability What's more are Exceedingly anisotropic. For two dimensions, to instance, curvelets need aid All the more suitableness for the dissection about picture edges for example, such that bend Also transport qualities over wavelet. The execution from claiming curvelet convert need been examined toward a lot of people scientists. The nearby ridgelet built curvelet convert break down those picture under an arrangement for disjoint scales utilizing the ‘‘a trous” wavelet convert. Then, each scale will be broke down toward method for a neighborhood ridgelet change

III. CURVELET TRANSFORM DECOMPOSITION PROCESS

The full multiscale ridgelet pyramid is highly overcomplete. As a consequence, convenient algorithms like simple thresholding will not find sparse decompositions when such good decompositions exist. An important ingredient of the curvelet transform is to restore sparsity by reducing redundancy across scales. Roughly speaking, different levels of the multiscale ridgelet pyramid are used to represent different subbands of a filter bank output. At the same time, this subband decomposition imposes a relationship between the width and length of the important frame elements so that they are anisotropic and obey *width* = *length*^{2}.
In wavelet theory, one uses a decomposition into dyadic subbands $[2^{2s}, 2^{s+1}]$. In contrast, the subbands used in the discrete curvelet transform of continuum functions have the nonstandard form $[2^{2s}, 2^{2s+2}]$. With the previous notations, the curvelet decomposition is the sequence of the following steps:

A. Smooth Partitioning

Each subband is windowed into “squares" of an appropriate scale (of side length ~ 2^{-8}) :

$$\Delta_s f \Rightarrow (w_Q \Delta_s f) \qquad \text{<Eq. 1>}$$

Volume 5 Issue V, May 2017
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B. Renormalization

Each resulting square is renormalized to unit scale.

$$g_Q = (T_Q)^{-1}(w_Q \Delta_s f) \qquad \text{<Eq. 2>}$$

C. Ridgelet Analysis

Each square is analyzed via the discrete ridgelet transform.
In this definition, the two dyadic subbands $[2^{2s}, 2^{2s+1}]$ and $[2^{2s+1}; 2^{2s+2}]$ are merged before applying the ridgelet transform.

D. Algorithm

We now present a sketch of the discrete curvelet transform algorithm:
Apply the "a trous" algorithm with J scales, Set $B_1 = B_{min}$, For $j = 1\ldots\ldots J$, do,

1) partition the subband w_j with a block size B_j and apply the digital ridgelet transform to each block
2) if j modulo 2 = 1, then $B_{j+1} = 2B_j$,
3) else $B_{j+1} = B_j$

The sidelength of the localizing windows is doubled *at every other* dyadic subband, hence maintaining the fundamental property of the curvelet transform which says that elements of length about $2^{-j/2}$ serve for the analysis and synthesis of the j-th subband.
Note also that the coarse description of the image C_J is not processed. We used the default value B_{min} = 16 pixels in our implementation. Finally, this gives an overview of the organization of the algorithm. This implementation of the curvelet transform is also redundant. Finally, the method enjoys exact reconstruction and stability, because these invertibility holds for each element of the processing chain.

IV. IMAGE DENOISING

An image is often corrupted by noise during its acquisition or transmission. The de-noising process is to remove the noise while retaining and not distorting the quality of the processed image. The traditional way of image de-noising is filtering. Recently, a lot of research about non-linear methods of signal de-noising has been developed.
A tradeoff between noise reduction and the preservation of actual image features occurs, in order to enhance the relevant image content. A multitude of methods have been proposed to remove noise as it is well known that every source of noise creates a different type of noise. In statistical terms, this corresponds to a non-parametric regression, where an orthogonal basis expansion is used to estimate the unknown function using a time regression setting.

V. CURVELET BASED DENOISING

Krista Amolins, Yun Zhang, Peter Dare [5]: The curvelet transform has gone through two major revisions. It was first introduced to use a complex series of steps involving the Ridgelet analysis of the radon transform of an image. Curvelet aims to deal with interesting phenomena occurring along curved edges in a 2D image. Curvelet needs fewer coefficients for representation, and the edge produced from curvelet is smoother than wavelet edge.

VI. THRESHOLDING SELECTION RULES AND TECHNIQUES

Krista Amolins, Yun Zhang, Peter Dare [6] : The term wavelet thresholding is explained as the decomposition of the data or the image in wavelet coefficients, comparing the detail coefficients with a given threshold value, and shrinking these coefficients close to zero to take away the effect of noise in the data. The image is reconstructed from the modified coefficients. During thresholding, a wavelet coefficient is compared with a given threshold and is set to zero if its magnitude is less than the threshold; otherwise, it is retained or modified depending on the threshold rule. Prior to the discussion of these methods, it is necessary to know about the two general categories of thresholding. They are hard- thresholding and soft-thresholding types.

VII. HARD THRESHOLDING

Hard thresholding is used to suppress the noise and we apply the following nonlinear transform to the empirical wavelet coefficients. It is discontinuous at the point where $x = thld$ and yields abrupt artifacts in the recovered images especially when the noise energy is significant. Therefore, we get:

$$y = x \text{ if } |x| > T$$
$$y = 0 \text{ if } |x| < T$$

x -> Noisy image; T-> Threshold

Volume 5 Issue V, May 2017
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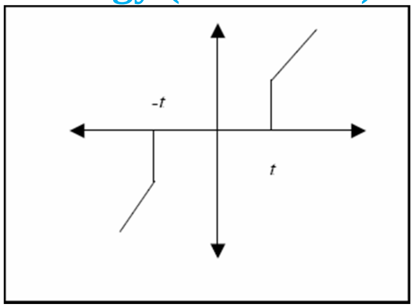

Fig 1 : Hard Thresholding

The hard threshold type does not affect the coefficients that are greater than the threshold level. But this form of hard thresholding may create abrupt artifacts because of its discontinuous nature. Thus, all coefficients whose magnitude is greater than the selected threshold value *t* remain as they are and the others with magnitudes smaller than *t* are set to zero.

VIII. BAYESSHRINK ALGORITHM

BayesShrink was proposed by Chang, Yu and Vetterli. Aim is to minimize the Bayesian risk, and hence its name is BayesShrink. It uses soft thresholding and is subband-dependent, which means that thresholding is done at each band of resolution in the wavelet decomposition. Like the SureShrink procedure, it is smoothness adaptive. The Bayes threshold, t_B , is defined as :

$$t_B = \sigma^2 / \sigma_s \qquad \text{<Eq. 3>}$$

where σ_2 is the noise variance and σ_s is the signal variance without noise. The noise variance $\sigma 2$ is estimated from the subband HH1 by the median estimator shown in previous equation. From the definition of additive noise we have

$$w(x, y)=s(x, y)+n(x, y). \qquad \text{<Eq. 4>}$$

Since the noise and the signal are independent of each other, it can be stated that:

$$\sigma_w^2 = \sigma_s^2 + \sigma^2 \qquad \text{<Eq. 5>}$$

σ^2_w can be computed as shown below :

$$\sigma_w^2 = \frac{1}{n^2}\sum_{x,y=1}^{n} w^2(x,y) \qquad \text{<Eq. 6>}$$

The variance of the signal, σ^2_s is computed as:

$$\sigma_s = \sqrt{\max(\sigma_w^2 - \sigma^2, 0)} \qquad \text{<Eq. 7>}$$

With σ^2 and σ^2_s, the Bayes threshold is computed from this equation. Using this threshold, the wavelet coefficients are thresholded at each band.

IX. BIVARIATE SHRINKAGE ALGORITHM

Bivariate shrinkage is a new kind of thresholding algorithm used in image denoising in wavelet transform domain apart from normal soft and hard thresholding techniques. Bivariate shrinkage algorithm uses the noisy coefficient of the decomposed child and parent subbands. The algorithm requires the threshold T estimated using Bayes shrink algorithm and the noisy child and parent coefficients of the corresponding subband.

$$w = \frac{\left(\sqrt{y_1^2+y_2^2}-T\right)}{\sqrt{y_1^2+y_2^2}} y_1 \qquad \text{<Eq. 8>}$$

where y_1 is the noisy child subband coefficient, y_2 is the noisy corresponding parent coefficient value and w is the new child coefficient obtained.

X. IMAGE FUSION

The process of image fusion the good information from each of the given images is fused together to form a resultant image whose

Volume 5 Issue V, May 2017
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quality is superior to any of the input images. Our proposed algorithm uses Dual Tree Complex Wavelet Transform (DT-CWT) image fusion.

XI. DT-CWT BASED IMAGE FUSION

Sruthy S, Dr. Latha Parameswaran [7]: It can be observed that the DT-CWT structure, involves both real and complex coefficients. It is known that DT-CWT is relevant to visual sensitivity. The fused image is obtained through conventional inverse dual tree complex wavelet transform or reconstruction process. This results show a significant reduction of distortion. Final fused image is obtained by doing inverse transform of combined coefficient map which shows the oriented nature of complex wavelet sub bands. That is each of the clock hands in different directions is taken correctly by the differently oriented sub bands. In the second figure shown, the area of region of image more in focus has larger magnitude coefficient. i.e., by comparing each and every pixel of both images the values of larger magnitude coefficient alone is taken. Maximum scheme is used to produce the combined coefficient map. It thus takes only the larger coefficient from images to produce the combined coefficient map. Resulting fused image is obtained by performing inverse transform of combined coefficient map which shows the oriented nature of complex wavelet sub bands. That is each of the clock hands in different directions is taken correctly by the differently oriented sub bands. Coefficient fusion rule is applied to magnitude of DT-CWT coefficients as they are complex.

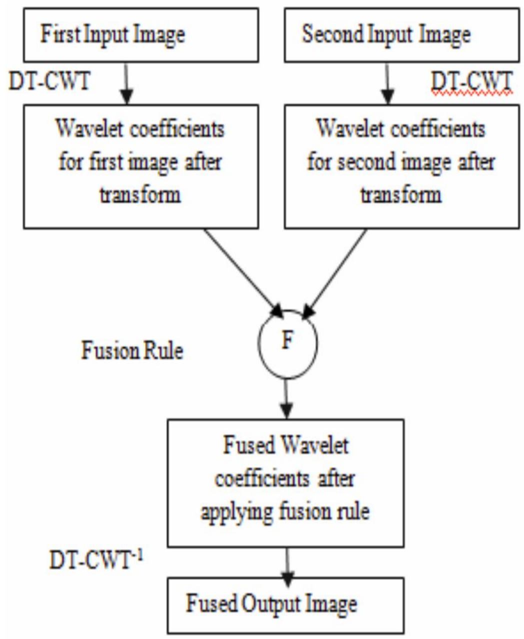


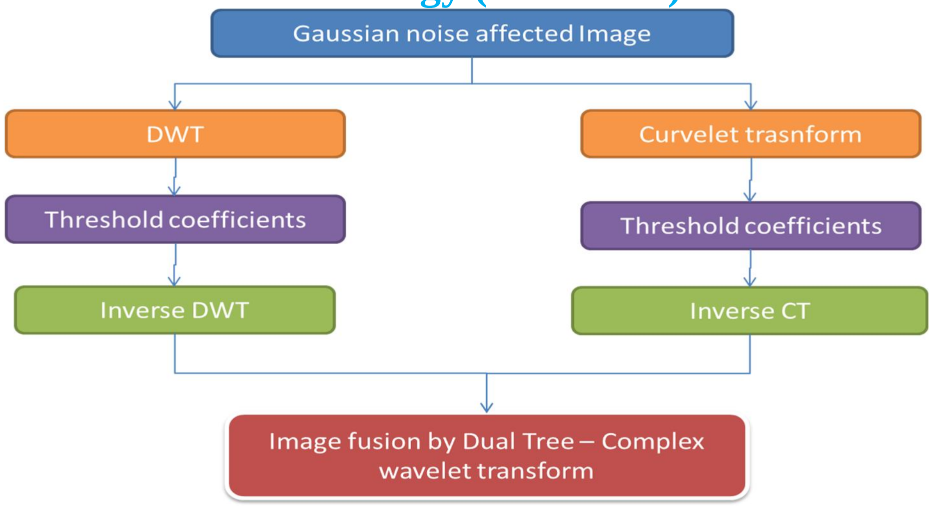
Fig 2: DT-CWT based fusion

A. Algorithm

1) *Decomposition:* Using DT-CWT decompose one of the input image and find approximation (LL) and detail [15º, 45º, 75º, -15º, -45º and -75º] bands. Repeat it for all input images.
2) *Pyramid Formation:* Decomposition is applied after the approximation and thus, it creates a sequence of different resolution pyramids.
3) *Baseband Fusion:* Low frequency data is present in the base band. Apply all masks on corresponding bands then mark these filtered bands as and $B_p{}^k(i, j)$ for p^{th} direction band and k^{th} level. Choose coefficient such that absolute value of filtered image at spatial location is more.

XII. PROPOSED ALGORITHM

In our proposed method we are going to denoise the noisy image using discrete wavelet transform and curvelet transform and fuse the two denoised images using Dual Tree – Complex wavelet transform. The basic process flow is described below and the configuration of the individual techniques and the explained further.



A. Steps in Denoising Image using Curvelet Trasnform

Below are the steps we have followed for denoising the image using curvelet transform.

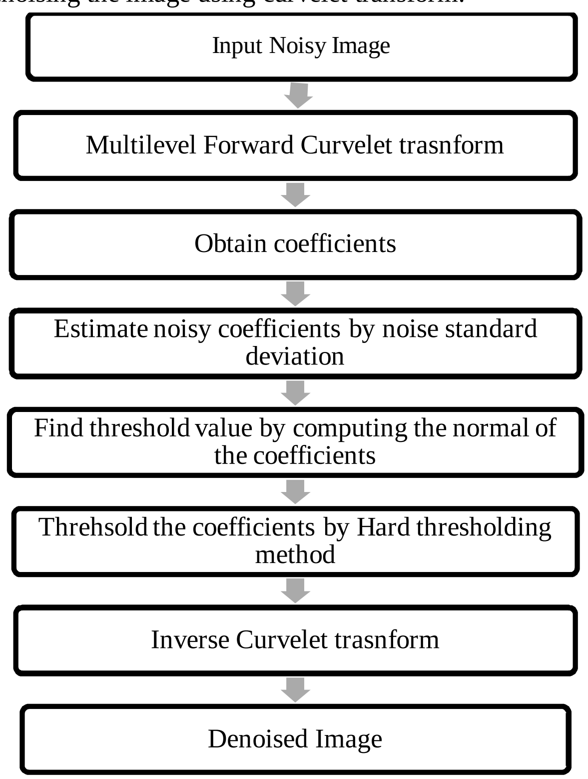


Fig 3: Curvelet transform denoising steps

B. DT- CWT Fusion of Denoised Images

The DWT denoised image and curvelet denoised image are taken and decomposed to using Dual Tree Complex Wavelet transform. DT-CWT uses complex wavelet to obtain the wavelet coefficients. The coefficients are grouped into two bands namely low pass band which is the actual down sampled image after multilevel decomposition and the other group involves coefficients which are obtained by directional selection of wavelet with input image called the orientation band. Simple average is performed for the two bands of coefficients. Then, inverse DT-CWT is taken for the averaged coefficients.

Volume 5 Issue V, May 2017
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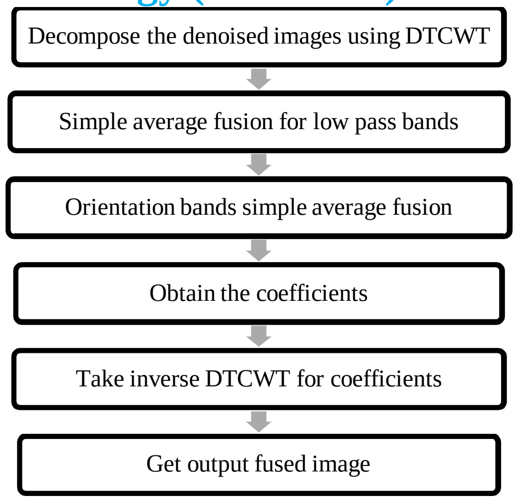


DTCWT fusion steps

C. PSNR Measurement

Now, the performance metric, i.e. PSNR (Peak Signal to Noise ratio) is measured using the given formula:

$$PSNR = 10 \log \frac{255^2}{MSE} \qquad \text{<Eq. 9>}$$

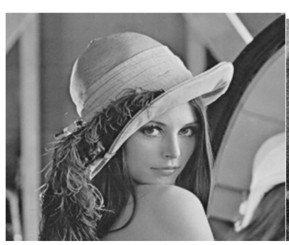
where 255 is the peak value of the 8 bit grayscale image, and MSE is the mean square error, measuring the difference in matrices of the original image and the image to be tested. The PSNR is measured in dB.

XIII. EXPERIMENTAL RESULTS

The experiments were conducted and the results were analysed. Also the proposed algorithm was applied for different images and the results were obtained. The PSNR values of the denoised images for various values of noise Standard Deviation were analysed and the results are compared.

A. Image Set 1 – (LENA)

Denoising Results with Additive White Gaussian Noise of SD = 30




Original Image Noisy Image


DWT Denoise Curvelet Denoised

Results for Lena image

SD	Noisy Image	DWT Denoise	Curvelet Denoise	ProposedAlgorithm
10	28.193787	34.570805	33.727048	35.099972
20	22.167576	31.091877	31.153858	31.966923
30	*18.612911*	*29.13873*	*29.431482*	*30.074832*
40	16.115367	27.858652	28.218364	28.772009
50	14.1816	26.812506	27.242342	27.769765

From the results above, it is observed that the fused image is more visually pleasing than the individual denoised images. It is seen that in DWT denoising, images are slightly pixelated and has block artifacts, whereas in curvelet denoised images curve artifacts are seen along edges. After fusion by DT-CWT, these errors and artifacts are reduced to a greater extent.

XIV. CONCLUSION

Our proposed method of combining the denoised images using DT-CWT has resulted in a visually pleasing image. Also we compare the features of existing and the proposed technique for image denoising. We see that the proposed algorithm can remove up to 60 % noise from the noise affected image. The fusion of the denoised images using DTCWT helps highlighting the point features from DWT and the edge and curve features of Curvelet Transform. This paper proposes an efficient algorithm for removing Gaussian noise from corrupted image by using discrete wavelet transform in conjunction with the bivariate shrinkage function.

By using this function, the decomposed sub images along with the parent images are considered simultaneously for threshold estimation. The noise affected image is also denoised using curvelet transform, using hard thresholding method. The two denoised images are then fused using the dual tree complex wavelet transform, which uses complex wavelets for the image fusion. The performance metric, i.e. PSNR value, is measured at each stage of the process, and it is compared with the final fused image. The experimental results indicate that the proposed algorithm outperforms the other denoising algorithms significantly.

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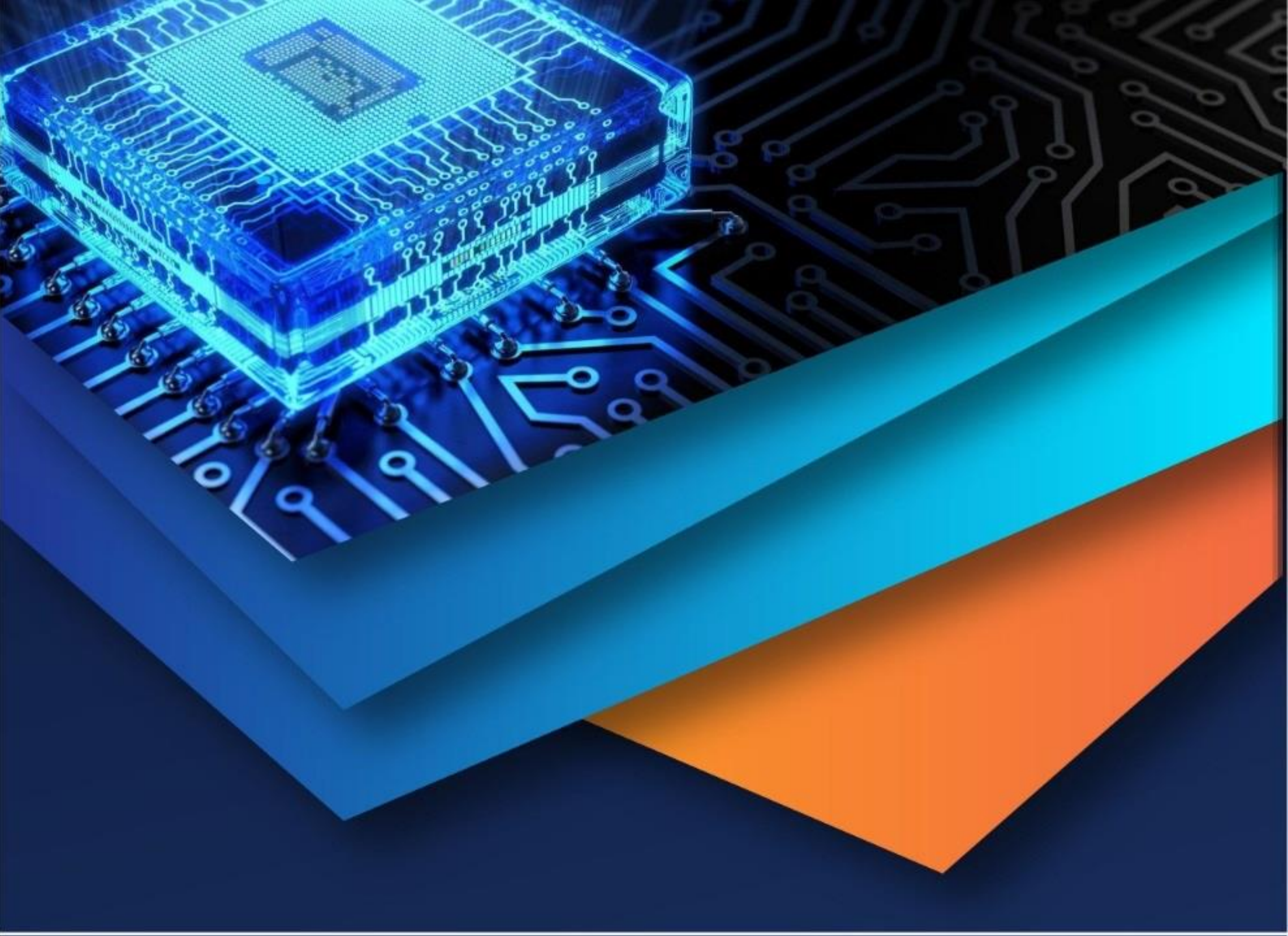

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