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A Modified Image Fusion Approach Using Guided Filter

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Abstract—A modified image fusion method using guided filter is proposed to combine images to give final fused image which contain the information common in input images as well as present in either of them. The proposed method adopts simple two scale image decomposition. Focusing on spatial context of images, guided image filter is used to preserve edge information which is uncommon in other methods. The results drawn show the effectiveness of the proposed method. In this paper, on the basis of results, the proposed method is compared with other two methods.
Keywords— Image fusion, Image decomposition, Guided filter, Edge preserving, Quality assessment.

I. INTRODUCTION

Among the various image processing techniques, the image fusion has a profound significance. Image fusion is nothing but to commingle two or more images from the source in order to put together the information from them. The information may imply here which is present in either of them and in both of them excluding noise. Images under consideration might be multifocus images, multimodal images, multisensor images, multispectral images. Image fusion based on multiscale decompositions and transformation like wavelet based image fusion [2] is proved to be successful. But to exploit consistency of pixels, proposed image fusion using guided filter is featured. This makes use of spatial context to differentiate flat and edge areas, which is used in preserving feature edges. This also includes simple two scale decomposition for which any desired method can be selected. Also the input parameters of guided filter can be adjusted to achieve desired results of image fusion.

The paper is organized as follows section 2 gives related work. A brief description of guided filter in section 3, an overview of fusion approach using guided filter in section 4, quality assessment measures in section 5, and simulation performance in section 6 and section 7 concludes the paper.

II. RELATED WORK

As the image fusion has shown its importance in variety of applications like medical imaging, remote sensing, navigation, etc. a tremendous work has been proposed. Considering the domain of image processing, the image fusion can be classified as spatial image fusion and transform based image fusion. The transform based image fusion have been proposed such as discrete wavelet transform based image fusion, discrete cosine transform based image fusion, stationary wavelet based transform fusion, etc. The transform based image fusion techniques are famous methods but show the complexity of processing like lacking translation invariance, insufficient edge preservation. While spatial image fusion techniques shows the ease of operation but fail to use spatial properties. The spatial image fusion techniques have been proposed like averaging fusion, maximum selection based image fusion, principal component analysis (PCA) based image fusion, intensity hue saturation (IHS) based image fusion, etc. The image fusion using generalised random walks, Markov random fields are able to use the spatial content to the full potential using global optimising approach. But these methods required more looping actions. Also global optimising approach fails to control smoothing of weights. So the guided filter based image fusion adds up the features as follows:

Instead of decomposing image into multiple components, the image is separated into two components only by simple processing like average filter.

The guided filter is local linear approach of filtering which makes full use of spatial context. Also, varying the value of the parameters desired fusion results can be achieved.

III. GUIDED FILTER

Assuming, G and P be the guidance image and input image respectively. Also, the output of the filter can be denoted by O.For each pixel i, the guided filter final output is local linear transform of the guidance image for window ω_k which is centred at pixel k.

$$O_i = a_k G_i + b_k, \quad \forall_i \in \omega_k \qquad (1)$$

where, the coefficients a_k and b_k are considered to be constant in window ω_k.

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The cost function in window ω_k is given to find coefficients a_k and b_k as follows:

$$E(a_k, b_k) = \sum_{i\in\omega_k}\left((a_k G_i + b_k - P_i)^2 + \varepsilon a_k{}^2\right) \quad (2)$$

where, ε controls the value of a_k which is also known as the blur degree.

The solution of the cost function considering it as linear regression model can be given by,

$$a_k = \frac{\frac{1}{|\omega|}\sum_{i\in\omega_k} G_i P_i - \mu_k \bar{P}_k}{\sigma_k^2 + \varepsilon} \quad (3)$$

$$b_k = \bar{P}_k - a_k \mu_k \quad (4)$$

where, μ_k and σ_k^2 are the mean and variance of G in ω_k,

$|\omega|$ gives the number of pixels in ω_k ,

$\bar{P}_k = \frac{1}{|\omega|}\sum_{i\in\omega_k} P_i$, is the mean of P in ω_k.

Considering, all possible windows for the image, the output is given as

$$O_i = \frac{1}{|\omega|}\sum_{k|i\in\omega_k}(a_k G_i + b_k) \quad (5)$$

The average of the values for O_i is considered as its value might be different for different windows overlapping i.

Assuming, $\sum_{k|i\in\omega_k} a_k = \sum_{k\in\omega_i} a_k$ the symmetry of the window, rewrite above equation as

$$O_i = \bar{a}_i G_i + \bar{b}_i \quad (6)$$

where, $\bar{a}_i$ and $\bar{b}_i$ are the average of coefficients for all possible windows overlapping i.

The edge detection significantly depends on ε. If the edge is present in I which represent the structure of the guidance image, the edge is transferred to the output image. For the flat region of the guidance image the output image will be average of input in ω_k. The structure of G i.e. for the edges present in the G, the output also shows edge. Above explanation regarding gray scale or single channel can be extended to colour image by applying the filter separately to each channel.

IV. A MODIFIED FUSION APPROACH USING GUIDED FILTER

The overall fusion approach can be represented in the three major parts as follows:

A. Image Decomposition

A simple average filtering is used to part the input images into the base layer and the detail layer. The base layer which is direct output of the average filter is subtracted from the respective input image to get the detail layer of that image as shown in figure The major intensity variations can be observed in the blurred base layer while the detail layer gives the structure of the image. So, the base layer is given as

$$B_n = I_n * Z \quad (7)$$

where, I_n is the nth input image, Z is the average filter.

The detail layer can be given as

$$D_n = I_n - B_n \quad (8)$$

The average filter size should be carefully controlled to maintain image quality of the final fused image.

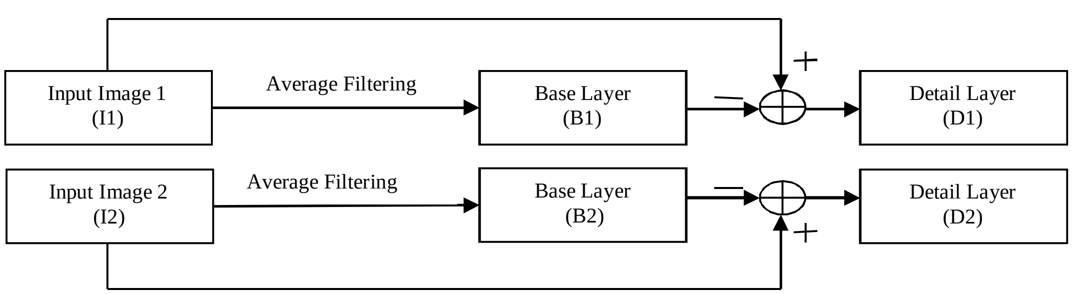

Fig.1 Two scale image decomposition

B. Guided Weight Maps

The saliency map Sn is obtained by applying the Gaussian filter on the absolute high pass image of nth image (Refer fig.2). The saliency maps are compared with each other to get weight maps in the following way:

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$$P_n^k = \begin{cases} 1 & \text{if } S_n^k = \max(S_1^k, S_2^k, \dots, S_N^k) \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

where N is number of input images,

S_n^k is the saliency value of the pixel k in the nth image.

Then the weight maps are guided by the input image in guided filter processing. The parameters are set to get suitable guided weight maps for base and detail layers of respective input image.

C. Image Reconstruction

The guided weight maps (W_n^B and W_n^D) are used for weighted summation with respective image base layer and detail layer. The result $\overline{B}$ and $\overline{D}$ i.e. fused base layer and fused detail layer are added together to get final fused image. (Refer fig.3)

$$\overline{B} = \sum_{n=1}^{N} W_n^B B_n \quad (10)$$

$$\overline{D} = \sum_{n=1}^{N} W_n^D D_n \quad (11)$$

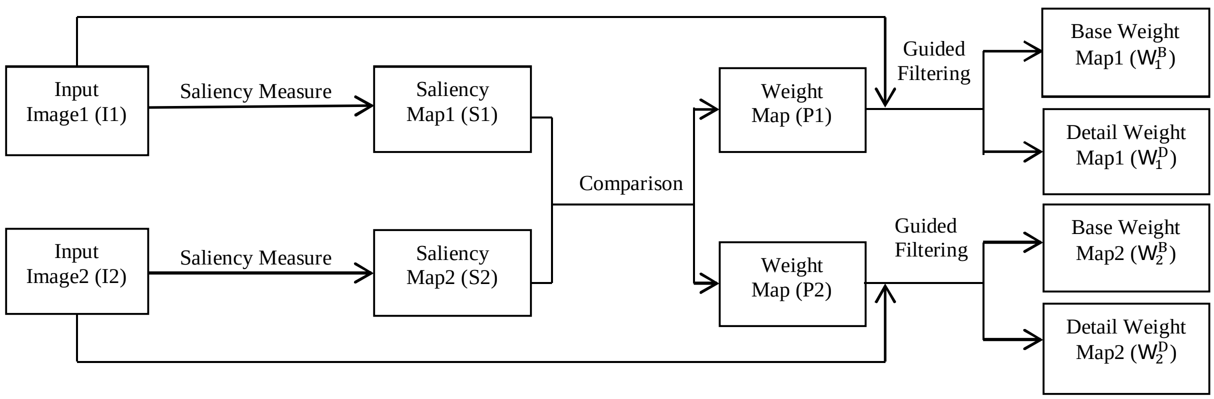

Fig.2 Guided weight maps

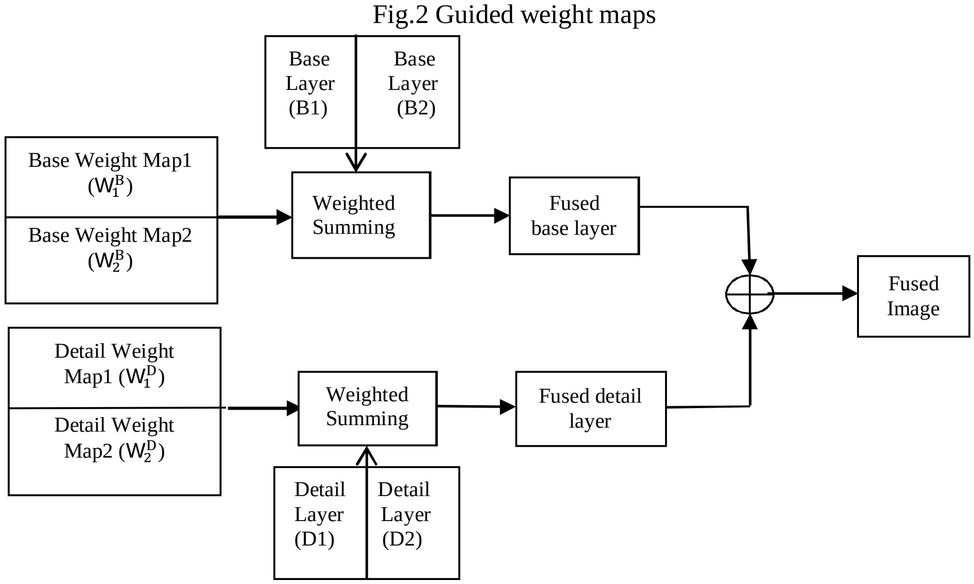

Fig.3 Image reconstruction

V. QUALITY ASSESSMENT MEASURES

Consider, A and B be the input images and F be the final fused image. The quality assessment measures used are explained in brief as follows:

A. Peak Signal To Noise Ratio (PSNR)

It gives the easy measure of peak error taking into account mean squared error (MSE) between the input and the final fused image, in decibels.

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$$\mathrm{PSNR(dB)} = 10\log\frac{N^2}{MSE} \qquad (12)$$

where, N is the maximum fluctuation in the data type. For example, N=255 for an 8 bit unsigned integer data type.

B. Normalized Mutual Information Metric (Q_{MI})

According to the classic definition of mutual information, the results tend to bias towards the input image with higher value of entropy. M. Hossny suggested modification as normalised version [9] which gives more relevant results. This metric gives estimate of information which is transferred from input image to final fused image.

The normalised mutual information can be given as

$$Q_{MI} = 2\left[\frac{MI(A,F)}{H(A)+H(F)} + \frac{MI(B,F)}{H(B)+H(F)}\right] \qquad (13)$$

where $H(A)$, $H(B)$ and $H(F)$ are the marginal entropy of A, B and F respectively and $MI(A,F)$ is the mutual information between input image A and the fused image F.

$$MI(A,F) = H(A) + H(F) - H(A,F) \qquad (14)$$

where $H(A,F)$ is the joint entropy between A and F and $MI(B,F)$ is calculated similarly as $MI(A,F)$.

C. Structural Similarity Metric (Q_Y)

This metric gives the estimation of structural inormation transferred from input image to fused image which uses structural similarity SSIM [8].

$$Q_Y = \begin{cases} \lambda_w \, SSIM(A_w,F_w) + (1-\lambda_w)SSIM(B_w,F_w), & \text{if } SSIM(A_w,B_w|w) \geq 0.75 \\ \max\{SSIM(A_w,F_w), SSIM(B_w,F_w)\}, & \text{if } SSIM(A_w,B_w|w) < 0.75 \end{cases} \qquad (15)$$

where, w is the window size.

The weight λ_w is given as:

$$\lambda_w = \frac{v(A_w)}{v(A_w)+v(B_w)} \qquad (16)$$

where, $v(A_w)$ and $v(B_w)$ are the variance of input images A and B respectively.

D. Universal Image Quality Metric (Q_C)

This metric gives universal approach to measure the information transfer from input image to fused image irrespective of viewing conditions. It uses universal image quality index (UIQI) [4].

$$Q_c = \mu_w . UIQI(A_w,F_w) + (1-\mu_w)UIQI(B_w,F_w) \qquad (17)$$

where, w is the window size.

The factor μ_w can given as

$$\mu_w = \begin{cases} 0, & \text{if } \frac{\sigma_{AF}}{\sigma_{AF}+\sigma_{BF}} < 0 \\ \frac{\sigma_{AF}}{\sigma_{AF}+\sigma_{BF}}, & \text{if } 0 \leq \frac{\sigma_{AF}}{\sigma_{AF}+\sigma_{BF}} < 1 \\ 1, & \text{if } \frac{\sigma_{AF}}{\sigma_{AF}+\sigma_{BF}} > 1 \end{cases} \qquad (18)$$

where, σ_{AF} and σ_{BF} are the covariance between A, B and F.

E. Edge Information Metric (Q_E)

This metric gives the measure of the edge information [7] transfer from input images to fused image.

$$Q_E = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M} Q^{AF}(i,j)w^A(i,j) + Q^{BF}(i,j)w^B(i,j)}{\sum_{i=1}^{N}\sum_{j=1}^{M}(w^A(i,j)+w^B(i,j))} \qquad (19)$$

where, N and M gives the width and height in terms of the number the pixels of the images respectively.

$$Q^{AF}(i,j) = Q_g^{AF}(i,j)Q_\alpha^{AF}(i,j) \qquad (20)$$

where, $Q_g^{AF}(i,j)$ and $Q_\alpha^{AF}(i,j)$ are the edge strength and orientation preservation values at pixel location (i, j) respectively. $Q^{AF}(i,j)$ and $Q^{BF}(i,j)$ are weighted by $w^A(i,j)$ and $w^B(i,j)$ respectively. $Q^{BF}(i,j)$ is calculated similarly as $Q^{AF}(i,j)$.

For all the metrics mentioned above, higher value means better performance of the image fusion.

VI. SIMULATION PERFORMANCE

The performance evaluation of the proposed system in Matlab environment is represented using the dataset of four pairs of

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multifocus images as follows:

The guided filter parameters are set as:

For base layer: Window size (w): 7, Regularization parameter (ε): 0.3

For detail layer: Window size (w): 3, Regularization parameter (ε): 0.3

Also, the proposed guided approach results are compared with other two methods:

Discrete cosine transform based image fusion method

Discrete wavelet transform based image fusion method

A. For Multifocus Colour Input Image Pairs

(a) (b) (c) (d) (e)

Fig. 4 Performance comparison for Calendar input images

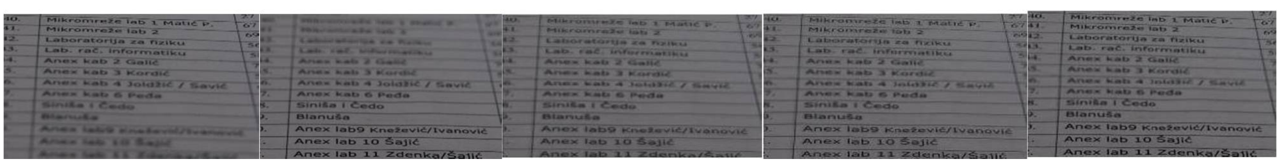
(a) Calendar Input Image 1. (b) Calendar Input Image 2. (c) DCT Method Output. (d) DWT Method Output. (e) Proposed Method Output.

(a) (b) (c) (d) (e)

Fig. 5Performance comparison for Garden input images

(a) Garden Input Image 1. (b) Garden Input Image 2. (c) DCT Method Output. (d) DWT Method Output. (e) Proposed Method Output.

B. For Multifocus Gray Scale Input Image Pairs



(a) (b) (c) (d) (e)

Fig. 6Performance comparison for Index input images

(a) Index Input Image 1. (b) Index Input Image 2. (c) DCT Method Output. (d) DWT Method Output. (e) Proposed Method Output.

(a) (b) (c) (d) (e)

Fig. 6Performance comparison for Clock input images

(a) Clock Input Image 1. (b) Clock Input Image 2. (c) DCT Method Output. (d) DWT Method Output. (e) Proposed Method Output.

(b)

TABLE I. PERFORMANCE ASSESSMENT OVERVIEW FOR CALENDER INPUT IMAGES

Quality Metric	DCT Method	DWT Method	Proposed Method
PSNR(dB)	15.28	15.68	21.50
Q_{MI}	0.91	0.88	0.92
Q_Y	0.94	0.94	0.95
Q_C	0.80	0.88	0.89
Q_E	0.76	0.79	0.80

TABLE II. PERFORMANCE ASSESSMENT OVERVIEW FOR GARDEN INPUT IMAGES

Quality Metric	DCT Method	DWT Method	Proposed Method
PSNR(dB)	24.18	19.09	25.09
Q_{MI}	0.66	0.63	0.67
Q_Y	0.86	0.90	0.91
Q_C	0.71	0.63	0.72
Q_E	0.52	0.57	0.59

TABLE III. PERFORMANCE ASSESSMENT OVERVIEW FOR INDEX INPUT IMAGES

Quality Metric	DCT Method	DWT Method	Proposed Method
PSNR(dB)	24.83	19.42	24.90
Q_{MI}	0.54	0.46	0.65
Q_Y	0.96	0.97	0.97
Q_C	0.96	0.49	0.96
Q_E	0.83	0.74	0.84

TABLE 4. PERFORMANCE ASSESSMENT OVERVIEW FOR CLOCK INPUT IMAGES

Quality Metric	DCT Method	DWT Method	Proposed Method
PSNR(dB)	22.06	20.83	22.08
Q_{MI}	0.97	0.94	0.98
Q_Y	0.87	0.92	0.99
Q_C	0.85	0.92	0.99
Q_E	0.75	0.77	0.79

Thus, the better results are observed with the proposed modified image fusion method using guided filter.

VII. CONCLUSION

The proposed method uses the multifocus image dataset in Matlab software. The result analysis shows how effectual the proposed method of image fusion is. The initial decomposition step employs a simple average filtering with proper trade-off of blurring. To use spatial consistency between pixels, guided filter is used to construct final weight maps. The parameters of the guided filter are to be set to get desired results.

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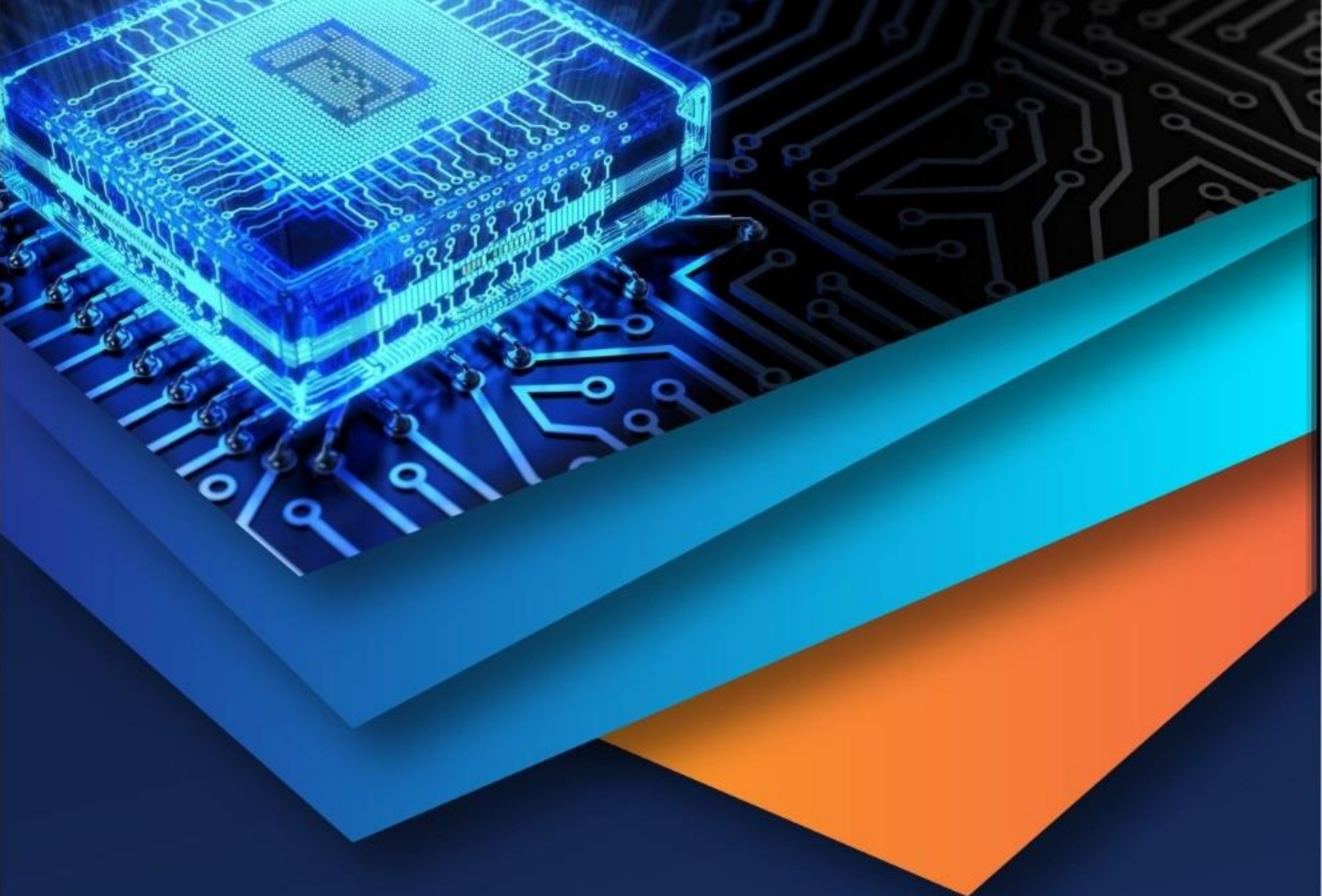

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