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Comparisons and Implementation of different Segmentation algorithm based on entropy and energy

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Abstract:* In image segmentation features like edges, boundaries etc are extracted to characterize images. This emphasizes the necessity of image segmentation, which divides an image into parts that have strong correlations with objects to reflect the actual information collected from the real world. Image segmentation is the most practical approach among virtually all automated image recognition systems. Feature extraction and recognition have numerous applications on telecommunication, weather forecasting, environment exploration and medical diagnosis. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. In this paper, there is an algorithm for extracting edges, boundaries from a given image is designed. For this canny edge detector and Otsu's method is used. Canny edge detector and otsu method is extracted from image through image segmentation using different techniques.

Keywords: ***edge detection, image segmentation, ostu method, canny edge detector.***

1. INTRODUCTION

1.1 Introduction to IMAGE Segmentation

Image segmentation refers to partition an image into different regions that are homogenous with respect to one or several image features. The process of segmenting an image is easy to define but difficult to develop.

1.1.1 The Role of Segmentation in Digital Image Processing

Digital images occur very frequently in the world today. All images on the Internet are in digital form; most images seen in magazines and newspapers have been in digital form at some point before publication; and many films have been converted to a digital format for premastering. Digital Images are processed simply to improve the quality of the image, or they may be processed to extract useful information, such as the position, size or orientation of an object. Image analysis is an area of image processing that deals with techniques for extracting information from an image. In the simplest form,

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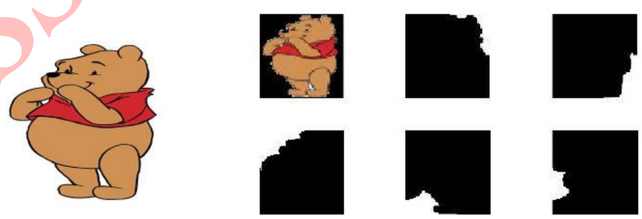
this task could be reading an address on a letter or finding defective parts on an assembly line. More complex image analysis systems measure quantitative information and use it to make a sophisticated decision such as trying to find images with a specified object in an image database. The various tasks involved in image analysis can be broken down into conventional (low level) techniques and knowledge-based (high level) techniques. Image segmentation falls into the low level category and is usually the first task of any image analysis process.For example, if the segmentation algorithm did not partition the image correctly the recognition and interpretation algorithm would not recognize the object correctly [1].Over-segmenting an image will divide an object into different regions. Under segmenting the image will group various objects into one region. The segmentation step determines the eventual success or failure of the image analysis process. For this reason, considerable care is taken to improve the probability of a successful segmentation.

1.1.2 The Image Segmentation:-

Image segmentation is an important accepts of the human visual perception. Segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels).Human use their visual scene to effortlessly partition their surrounding environment into different object to help recognize their objects, guide their movements, and for almost every other task in their lives. It is a complex process that includes many interacting components that are involved with the analysis of color, shape, motion and texture of objects. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The result of image segmentation is a set of regions that collectively covers the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristics or computed property, such as colour, intensity, or texture. Adjacent regions are significantly different with respect to certain characteristics. Segmentation algorithms generally are based on one of 2 basis properties of intensity values. Discontinuity: to partition an image based on abrupt change in intensity (such as edges).Similarity: to partition an image into region that is similar according to a set of predefined criteria [2].



(a) (b)

Fig1.1.

(a) is the original "Wini poor bear" image, and the six sub-images in (b) show the segmentation results, where the nonblack region in each sub-image means each segment. The complete eagle shape is contained in the sub-image at the first row and the first column.

1.2 Edge Detection

1.2.1 Edge

An edge is seen at a place where an image has a strong intensity contrast. Edges could also be represented by a difference in color without any difference in intensity. Of

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course there are exceptions where a strong intensity contrast does not embody an edge. Therefore a zero crossing detector is also thought of as a feature detector rather than a specific edge detector.

1.2.2 Edge detection

Edge detection is a very important area in the field of Computer Vision. Edges define the boundaries between regions in an image, which helps with segmentation and object recognition. They can show where shadows fall in an image or any other distinct change in the intensity of an image. Edge detection is a fundamental of low-level image processing and good edges are necessary for higher level processing. The problem is that in general edge detectors behave very poorly. While their behavior may fall within tolerances in specific situations in general edge detectors have difficulty adapting to different situations. The quality of edge detection is highly dependent on lighting conditions, the presence of objects of similar intensity, density of edges in the scene and the noise. While each of these problems can be handled by adjusting certain values in the edge detector and changing the threshold value for what is considered an edge no good method has been determined for automatically setting these values, so they must be manually changed by an operator each time the detector is run with a different set of data. Since different edge detectors work better under different conditions, it would be ideal to have an algorithm that makes use of multiple edge detectors, applying each one when the scene conditions are most ideal for its method of detection [3]. In order to create this system, you must first know which edge detectors perform better under which conditions. That is the goal of our project. We tested four edge detectors that use different methods for detecting edges and compared their results under a variety of situations to determine which detector was preferable under different set of conditions. This data could then be used to create multi edge-detector system, which analyzes the scene and runs the edge detector best suited for the current set of data.

1.3 Edge Detection Techniques

There are many ways to perform edge detection. However, the majority of different methods may be grouped into two categories:

1.3.1 Gradient Techniques

The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image.

1.3.2 Laplacian Techniques

The Laplacian method searches for zero crossings in the second derivative of the image to find edges. An edge has the one-dimensional shape of a ramp and calculating the derivative of the image can highlight its location.

Suppose we have the following signal, with an edge shown by the jump in intensity below

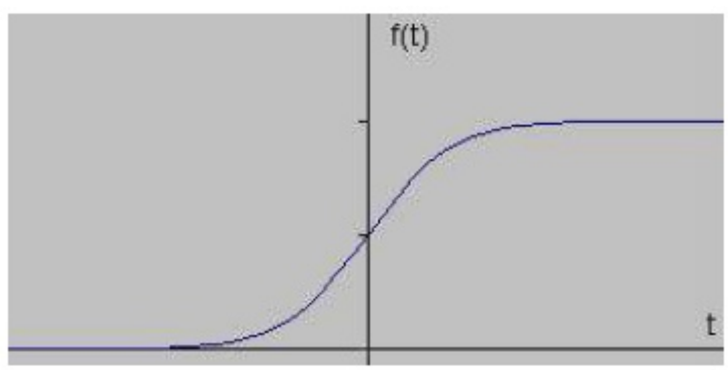

Fig 1.2(a) –Ramp signal in 1-D

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If we take the gradient of this signal (which, in one dimension, is just the first derivative with respect to t) we get the following:

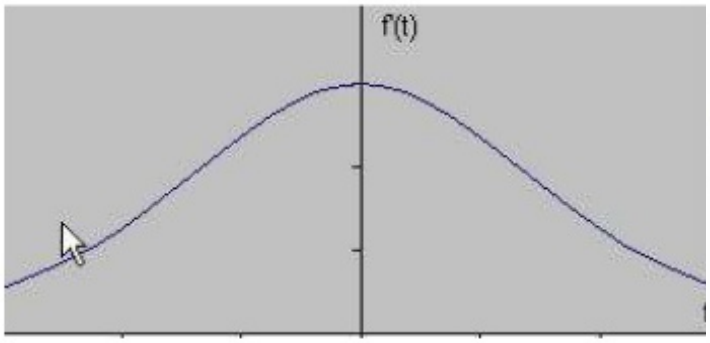

Fig 1.2(b)-First derivative of ramp signal

If we take the gradient of this signal (which, in one dimension, is just the first derivative with respect to t) we get the following:Clearly, the derivative shows a maximum located at the center of the edge in the original signal.

This method of locating an edge is characteristic of the "gradient filter" family of edge detection filters and includes the Sobel method. A pixel location is declared an edge location if the value of the gradient exceeds some threshold. Edges will have higher pixel intensity clearly; the derivative shows a maximum located at the center of the edge in the original signal. This method of locating an edge is characteristic of the "gradient filter" family of edge detection filters and includes the Sobel method [4]. A pixel location is declared an edge location if the value of the gradient exceeds some threshold. As mentioned before, edges will have higher pixel intensity values than those surrounding it. So once a threshold is set, you can compare the gradient value to the threshold value and detect an edge whenever the threshold is exceeded. Furthermore, when the first derivative is at a maximum, the second derivative is zero. As a result, another alternative to finding the location of an edge is to locate the zeros in the second derivative. This method is known as the Laplacian and the second derivative of the signal.

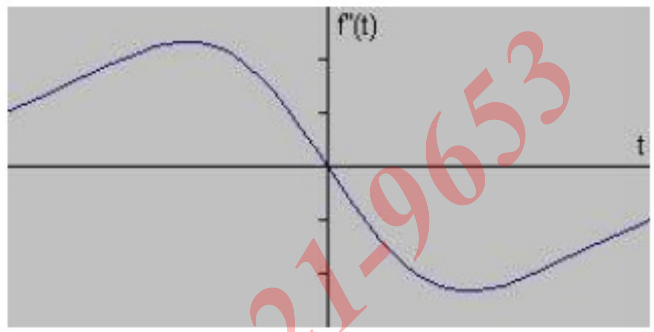

Fig.1.2.C Second derivative of ramp signal

1.3.3 Sobel operator Techniques

The Sobel operator is used in image processing, particularly within edge detection algorithms. Technically it is a discrete differentiation operator, computing an approximation of the gradient of the image intensity function. At each point in the image, the result of the Sobel operator is either the corresponding gradient vector or the norm of this vector. The Sobel operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical direction and is therefore relatively inexpensive in terms of computations. On the other hand, the gradient approximation which it produces is relatively crude, in particular for high frequency variations in the image.

In simple terms, the operator calculates the gradient of the image intensity at each point, giving the direction of the largest possible increase from light to dark and the rate of change in that direction. The result therefore shows how "abruptly" or "smoothly" the image changes at that point and therefore how likely it is that that part of the image represents an edge, as well

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as how that edge is likely to be oriented. In practice, the magnitude (likelihood of an edge) calculation is more reliable and easier to interpret than the direction calculation. Mathematically, the gradient of a two each image point a 2D vector with the components given by the derivatives in the horizontal and vertical directions. At each image point, the gradient vector points in the direction of l possible intensity increase, and the length of the gradient vector corresponds to the rate of change in that direction. This implies that the result of the Sobel operator at an image point which is in a region of constant image intensity is a zero vector and at a points on an edge is a vecor which points across the edge, from darker to brighter values [4].

The Sobel Edge Detector uses a simple magnitude. For those you of mathematically inclined, applying can be represented as: $N(x,y)=\sum_{k=-1}^{1}\sum_{j=-1}^{1} K(j,k)\,p(x-j,y-k)$ -------(1)

So the Sobel Edge Detector uses two convolution kernels, one to detect changes in vertical contrast (hx) and another to detect horizontal contrast (hy).

−1	−2	−1
0	0	0
1	2	1

−1	0	1
−2	0	2
−1	0	1

Sobel

Fig 1.3. Sobel masks used for detecting edges

The amazing thing is that this data can now be represented as a vector (gradient vector).The two gradients computed using hx and hy can be regarded as the x and y components of the vector. Therefore we have gradient magnitude and direction.

$$g=\begin{bmatrix} gx \\ gy \end{bmatrix} \quad \ldots\ldots\ldots (2)$$

$$g=\sqrt{(g_x{}^2+g_y{}^2)} \quad \ldots\ldots\ldots (3)$$

$$\theta=\tan^{-1}\left(\frac{g_y}{g_x}\right) \quad \ldots\ldots\ldots.. (4)$$

Where g is the gradient vector, g is the gradient magnitude and θ is the gradient direction.

1.3.4 Robert's Cross Operator Techniques

The Roberts Cross operator performs a simple, quick to compute, 2-D spatial gradient measurement on an image. Pixel values at each point in the output represent the estimated absolute magnitude of the spatial gradient of the input image at that point. The operator consists of a pair of 2×2 convolution kernels as shown in Figure. One kernel is simply the other rotated by 90°.

−1	0
0	1

0	−1
1	0

Fig.1.4.Robert mask used for detecting edges

These kernels are designed to respond maximally to edges running at 45° to the pixel grid, one kernel for each of the two perpendicular orientations. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (call these Gx and Gy).These can then be 224 combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient.

The gradient magnitude is given by:-

$$|G|=\sqrt{(G_x{}^2+G_y{}^2)} \quad \ldots\ldots\ldots\ldots\ldots (6)$$

An approximate magnitude is computed using

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$$|G| = |G_x| + |G_y| \qquad \text{……………..} (7)$$

Which is much faster to compute?

The angle of orientation of the edge giving rise to the spatial gradient (relative to the pixel grid orientation) is given by:

$$\theta = arc\tan\left(\frac{G_y}{G_x}\right) - \frac{3\pi}{4} \qquad \text{…………….} (8)$$

1.3.5 Prewitt operator Techniques

Prewitt operator is similar to the Sobel operator and is used for detecting vertical and horizontal edges in images.

−1	−1	−1
0	0	0
1	1	1

−1	0	1
−1	0	1
−1	0	1

Fig 1.5 Prewitt mask used for detecting edges

1.3.6 Laplacian of Gaussian Techniques

The Laplacian is a 2-D isotropic measure of the 2nd spatial derivative of an image. The Laplacian of an image highlights regions of rapid intensity change and is therefore often used for edge detection. The Laplacian is often applied to an image that has first been smoothed with something approximately a Gaussian smoothening filter in order to reduce its sensitivity to noise [5]. The operator normally takes a single gray level image as input and produces another gray level image as output.

The Laplacian L(x,y) of an image with pixel intensity value is given by:

$$L(x,y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \qquad \text{…………….}(9)$$

Since the input image is represented as a set of discrete pixels, we have to find a discrete convolution kernel that can approximate the second derivatives in the definition of the Laplacian.

Three commonly used small kernels

0	−1	0
−1	4	−1
0	−1	0

−1	−1	−1
−1	8	−1
−1	−1	−1

0	0	−1	0	0
0	−1	−2	−1	0
−1	−2	16	−2	−1
0	−1	−2	−1	0
0	0	−1	0	0

Fig 1.6 Laplacian mask used for detecting edges

Because these kernels are approximating a second derivative measurement on the image they are very sensitive to noise. To counter this, the image is often Gaussian Smoothed before applying the Laplacian filter. This post processing step reduces the high frequency noise components prior to the differential step. Since the convolution operation is associative we can convolve the Gaussian smoothing filter with the Laplacian filter first of all, and then convolve this hybrid filter with the image to achieve the required result. Doing things this way has two advantages. Since both the Gaussian and the Laplacian kernels are usually much smaller than the image, this method usually requires far fewer arithmetic operations. The LoG (`Laplacian of Gaussian') kernel can be recalculated in advance so only one convolution needs to be performed at run-time on

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the image. The 2-D LoG function centered on zero and with Gaussian standard deviation σ has the form

$$\log(x,y) = -\frac{1}{\pi\sigma^4}\left[1-\frac{(x^2+y^2)}{2\sigma^2}\right] e^{-\frac{(x^2+y^2)}{2\sigma^2}} \quad \ldots\ldots\ldots\ldots\ldots (10)$$

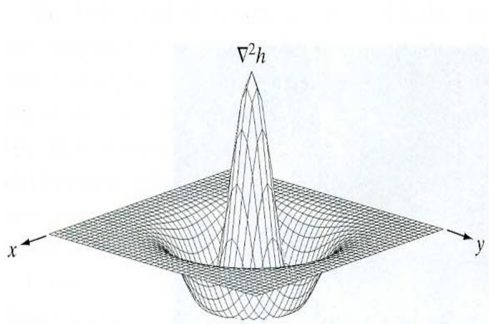

Fig1.7.Laplacian of Gaussian

Note that as the Gaussian is made increasingly narrow, the LoG kernel becomes the same as the simple Laplacian kernels shown in Figure. This is because smoothing with a very narrow Gaussian (σ <.5 pixels) on a discrete grid has no effect. Hence on a discrete grid, the simple Laplacian can be seen as a limiting case of the LOG for narrow Gaussians.

1.3.7 Canny edge detector Techniques

Canny's approach based on three objectives:

1) Low error rate:-All edges should be found and there should be no spurious responses. i.e. the edges detected must be as close as possible to the true edges.

2) Edge points should be well localized:-The edges located must be as close as possible to the true edges. i.e the distance between a point marked as an edge by the detector and the center of the true edge should be minimum

3) Single edge point response:-The detector should return only one point for each true edge point. i.e the number of local maxima around the true edge should be minimum. This means that the detector should not identify multiple edge pixels where only a single edge point exists.

The canny edge detector first smoothes the image to eliminate gradient to highlight regions with high spatial derivatives. The algorithm then tracks along these regions and suppresses any pixel that is not at the maximum (non maximum suppression). The gradient array is now further reduced by hysteresis. Hysteresis is used to track along the remaining pixels that have not been suppressed. Hysteresis uses two thresholds and if the magnitude is below the first threshold, it is set to zero (made a non edge). If the magnitude is above the high threshold, it is made an edge [5]. And if the magnitude is between the 2 thresholds, then it is set to zero unless there is a path from this pixel to a pixel with a gradient above second threshold.

Fig.1.8. a) Original Image b) Smoothed image c) Non maxima suppressed image d) Strong edges e) Weak edge f) Final image

2. OSTU METHOD THRESHOLDING

Thresholding is one of the most powerful and important tools for image segmentation. The segmented image obtained from

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thresholding has the advantages of smaller storage space, fast processing speed and ease in manipulation compared with gray level image which usually contains 256 levels. The thresholding techniques, which can be divided into bi-level and multilevel category [4]. In bi-level thresholding a threshold is determined to segment the image into two brightness regions which correspond to background and object..Otsu et.al formulates the threshold selection problem as a discriminate analysis where the gray level histogram of image is divided into two groups and the threshold is determined when the variance between the two groups are the maximum. Even in the case of uni modal histogram images, that is, the histogram of a gray level image does not have two obvious peaks, Otsu‘s method can still provide satisfactory result. In multilevel thresholding more than one threshold will be determined to segment the image into certain brightness regions which correspond to one background and several objects. The selection of a threshold will affect both the accuracy and the efficiency of the subsequent analysis of the segmented image. The principal assumption behind the approach is that the object and the background can be distinguished by comparing their gray level values with a suitably selected threshold value. If background lighting is arranged so as to be fairly uniform, and the object is rather flat that can be silhouetted against a contrasting background, segmentation can be achieved simply by thresholding the image at a particular intensity level. The simplicity and speed of the thresholding algorithm make it one of the most widely used algorithms in automated systems ranging from medical applications to industrial manufacturing

This method is subject to the following major difficulties:

1. The valley may be so broad that it is difficult to locate a significant minimum.

2. There may be a number of minima because of the type of detail in the image, and selecting the most significant one will be difficult.

3. Noise within the valley may inhibit location of the optimum position.

4. There may be no clearly visible valley in the distribution because noise may be excessive or because the background lighting may vary appreciably over the image.

5. Either of the major peaks in the histogram (usually that dye to the background) may be much larger than the older, and this will then bias the position of the minimum.

6. The histogram may be inherently multimodal, making it difficult to determine which the relevant thresholding level is.

3. PROCEDURE FOLLOWED

This method is a nonparametric and unsupervised method of automatic threshold selection for image segmentation. An optimal threshold is calculated by the discriminant criterion, namely, so as to maximize the between-class variance or to minimize the within-class variance. The method is very simple, utilizing only the zeroth and first order cumulative moments of the gray level histogram

Step1-

Let the pixels of a given image represented in L gray levels [1; 2; :::; L]. The number of pixels at level i is denoted by ni and the total number of pixels by $N = n1+n2+:::+nL$. For simplification, the gray-level histogram is normalized and regarded as a probability distribution.

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Compute the normalized histogram of the input image. Denote the components of the histogram by p_i,i=0, 1, 2…….L-1

Step 2-Compue the cumulative sums, $P_1(k)$ and $P_2(k)$,for k=0,1…L-1

$$P_1(k) = \sum_{i=0}^{k} p_i$$

$$P_2(k) = \sum_{i=k+1}^{L-1} p_i = 1 - P_1(k)$$

Step 3-Compute the cumulative means m(k) for k=0,1,2L-1

$$m(k) = \sum_{i=0}^{k} ipi$$

Step 4-Compute the global intensity mean, m_G

$$m_G = \sum_{i=0}^{L-1} ipi$$

Step 5-Compute the between class variance, $\sigma_B^2(k)$,for k=0,1,2…L-1 using

$$\sigma_B^2(k) = \left[\frac{m_G P_1(k) - m(k)}{P_1(k)[1 - P_1(k)]}\right]^2$$

Step 6-Obtain the Otsu threshold,k^* as the value of k for which $\sigma_B^2(k)$ is maximum. If the maximum is not unique, obtain$k^*$by averaging the values of k corresponding to the various maxima detected.

Step 7-Obtain the separability measure,γ^*, at k=k^*

$$\gamma(k) = \left(\frac{\sigma_G^2(k)}{\sigma_G^2}\right)$$

4. Result

Edge detection	Energy	Entropy
Sobel	.9239	.2405
Prewitt	.9245	.2390
Robert	.9529	.1639
LOG	.8958	.3078
Canny edge detector	.8214	.4663
Hysteresis thresholding	.3533	3.8658

Table I Comparison of Edge detection Technique

Otsu method	Window size	K	Energy	Entropy
Mean filter	7	.09	.7863	.5340
Mean filter	11	.010	.8867	.3285
Mean filter	7	.10	.9824	.0732
Median filter	7	.018	.8445	.4195

Table II Comparison of Otsu method with Window size

The result shows different segmentation techniques are used to smoothen an image taking segments of an image. Otsu method is used to segment an image. Median has lower energy and therefore is used to smooth the blurred image. Median filter replaces the value of a pixel by the median of the intensity levels in the neighborhood of that pixel. Median filter are effective in the presence of bipolar and unipolar noise. It shows good result for image corrupted by noise. Mean filter provides the output of corrupted images.

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5. CONCLUSION

The objective is to do the comparison of various edge detection techniques and analyze the performance of the various techniques in different conditions. There are many ways to perform edge detection. The objective function was designed to achieve the following optimization constraints maximize the signal to noise ratio to give good detection. This favors the marking of true positives. Achieve good localization to accurately mark edges. Minimize the number of responses to a single edge. This favors' the identification of true negatives, that is, non-edges are not marked The image segmentation allow the user to divides an image into parts that have strong correlations with objects to reflect the actual information collected from the real world. Image segmentation are most practical approaches among virtually all automated image recognition systems. Image segmentation is to distinguish objects from images. It classifies each image pixel to a segment according to the similarity in a sense of a specific metric distance. To avoid over-segmentation, foreground and background marker controlled algorithms are applied with useful outcomes. To evaluate the roles of both segmentation approaches, quantitative metrics are proposed rather than qualitative measures from intuition. Both histograms and to the object size can be overcome. It is very helpful for the subsequent processing and improves the success ratio The image segmentation. Probability distributions are calculated to serve as the base functions to assess digital images. Using the otsu method, the problem of its sensitivity

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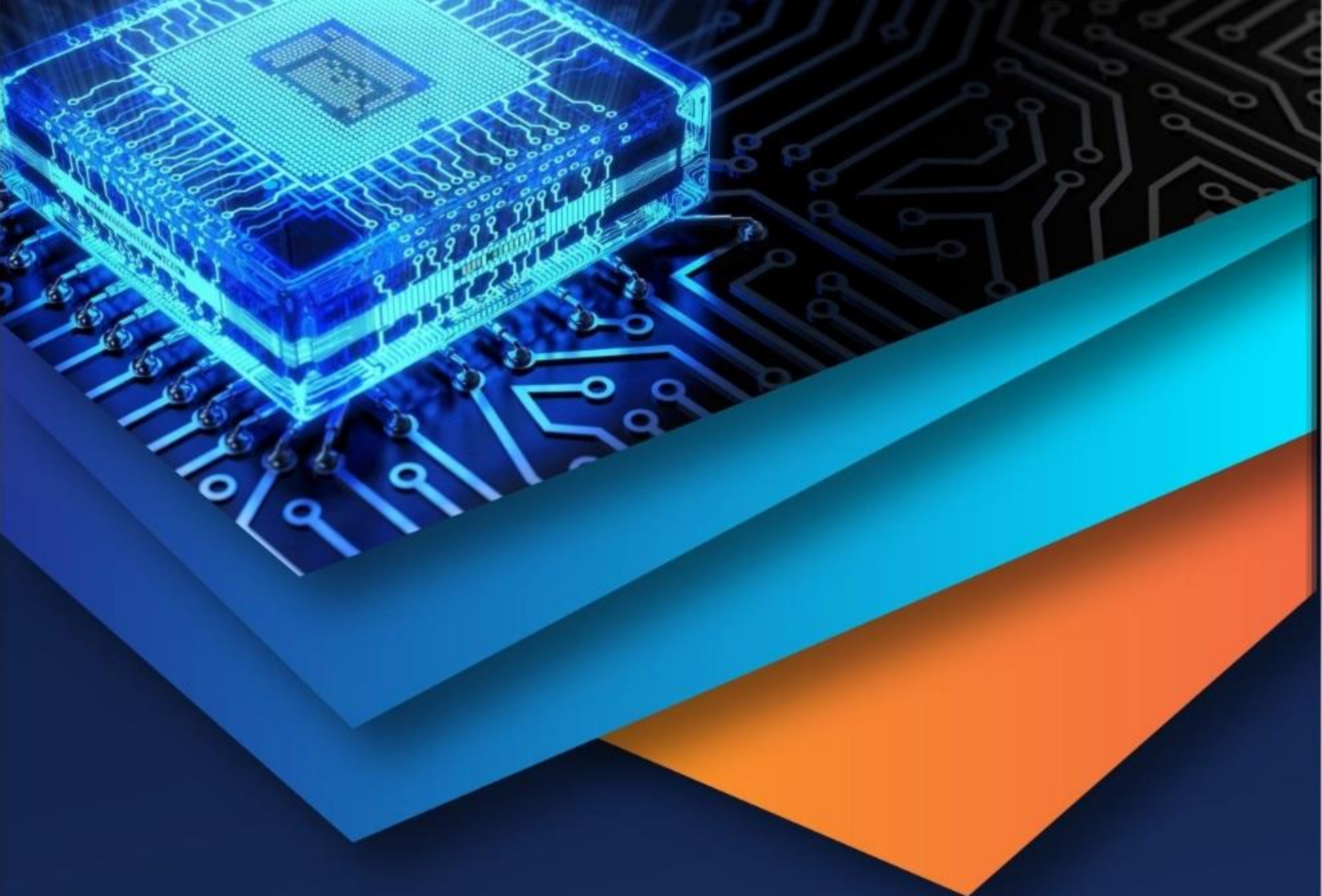

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