

## Fuzzy Perceptual Watermarking For Ownership Verification in DCT Domain

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### Abstract:

An adaptive watermarking method based on the human visual system model and the fuzzy inference system in DCT domain is proposed. Fuzzy logic is used for data fusion and builds a HVS model for spatial masking in DCT domain. Modeling spatial masking is a complicated task and there is no single theoretical formulation to precisely compute the perceptual value for a corresponding wavelet coefficient. Fuzzy logic is used for data fusion and operates on the HVS model for spatial masking in DCT domain. The fuzzy input variables (brightness, luminosity, texture, active pixels, num of objects) are computed for each wavelet coefficient in the image. The output of the fuzzy system is a single value which gives a perceptual value for each corresponding DCT coefficient. The fuzzy based watermarks are robust to attacks and at the same time achieve a high level of imperceptibility.

### Keywords:

watermarking, fuzzy logic, digital images, HVS characteristics, DCT Domain.

### 1.Introduction:

Digital image watermarking techniques are used to establish authenticity, ownership and copyright protection of the digital content. It is primarily classier as robust and fragile. Robust watermarking of the host image deals with the enhanced possibility of recovery of the embedded content even after executing image processing attacks over the signed image. The embedding of digital content within low frequency coefficients of the image in transform domain leads to robust watermarking .On the other hand, the watermarking is found to be fragile if embedding is done in high frequency coefficients.

With the increase in the availability of digital data, there is a pressing need to manage and protect the illegal duplication of data. Image Watermarking is the technique of hiding an invisible signal in the image for authentication. The watermark inserted in the image should be irremovable and unalterable, and the change it introduces to the image should be imperceptible. A robust watermarking scheme should embed a watermark into the most perceptually significant regions of the host image. However, to be undetectable to the human visual system (HVS), a watermark must be located in the most perceptually insignificant regions of the host image.

The two requirements are in direct conflict with each other. Thus, there is a need for an algorithm to insert high energy watermarks which are imperceptible at the same time. This paper addresses that need by constructing fuzzy perceptual masks. Therefore, at present, the focus of research on image watermarking is limited to three main issues. These are visual/perceptible quality of signed and attacked images, robustness and watermark embedding capacity. Among these, the former two are more significant as these are often found to be mutually exclusive. Therefore, this problem is now converged to minimize the trade off between the two.

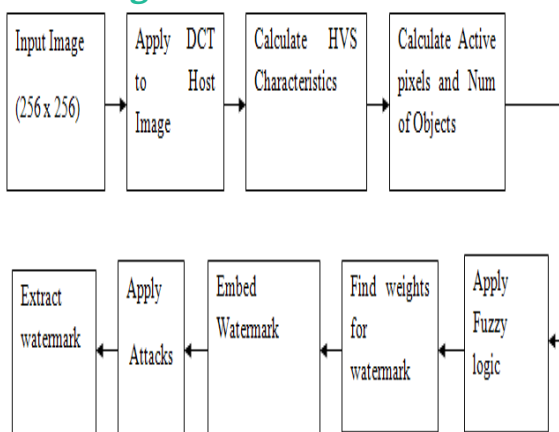
### II. Related work:

Watermarking can be grouped into two categories: spatial domain methods and frequency domain methods. The discrete cosine transform (DCT) represents an image as a sum of sinusoids of varying magnitudes and frequencies. The dct2 function computes the two-dimensional discrete cosine transform (DCT) of an image. The DCT has the property that, for a typical image, most of the visually significant information about the image is concentrated in just a few coefficients of the DCT.

For this reason, the DCT is often used in image compression applications. There is a current trend towards approaches that make use of information about the human visual system (HVS) [2], to produce a more robust watermark. Such techniques use explicit information about the HVS to exploit the limited dynamic range of the human eye. Fuzzy rules have been developed in the spatial domain to embed the watermark using gray scale distribution and texture as fuzzy inputs. Fuzzy inference filter has been used to choose entropy of wavelet coefficients to embed watermarks. Watermarking scheme based upon human visual mask in the DCT domain and fuzzy logic technique have been the main focus in the past related work.

Barni et al. [7] propose a method to evaluate the optimum weighting factor for each DWT coefficient according to psycho visual considerations. In [7], weighting factor is composed by the product of two terms: the first is the local mean square value of the DWT coefficients in detail sub bands at the first decomposition level which represent the distance from the edges, while the second is the local variance of the low-pass sub band which gives a measure of texture activity in the neighborhood of the pixel. To fuse the information, Barni et al. decided to multiply the two terms, since the eye is less sensitive to changes in textured areas, but more sensitive near edges where as Lewis and Knowles [8] proposed to simply add the two contributions. This paper implements a simple model of HVS spatial masking using fuzzy logic in the wavelet domain. The algorithm constructs a fuzzy perceptual mask which fuses texture and luminance content of all the image sub bands. The mask is computed for each wavelet coefficient.

**III. Block Diagram:**



**Fig1. Block Diagram**

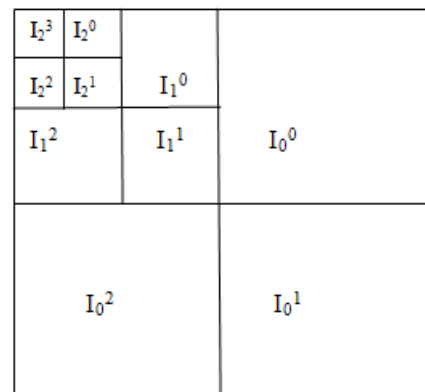
**IV. Proposed Method:**

The watermark insertion and detection algorithms are detailed in the following sub-sections.

**V. Watermark Insertion:**

The algorithm for embedding the watermark in a host image is as follows:

Step 1: Decompose the original grayscale image 256x256 using DWT up to four levels using Debauchies6 filtering kernel. Call  $I_l^\theta$  the sub band at resolution level  $l=0,1,2,3$  and with orientation  $\theta \in \{0,1, 2,\}$  (see Fig. 1).



**Fig: 2 Decomposition of an Image in 3 resolution levels**

Step 2: The fuzzy inputs corresponding for each wavelet coefficient are computed using the modified psycho visual model given by Barni et al. This model exploits the limitation of the human eye using three major components required for spatial masking i.e. brightness, edge and texture sensitivity, active pixels, num of objects.

**a. Brightness sensitivity:**

This term  $L$  takes into account the local brightness based on the gray level values of the low pass version of the image (Equation 1 and 2).

$$L(l, i, j) = \frac{1}{256} I_3^3 \left( 1 + \frac{i}{2^{3-l}}, 1 + \frac{j}{2^{3-l}} \right)$$

$$L(l, i, j) = \begin{cases} 1 - L(l, i, j), & \text{if } L(l, i, j) < 0.5 \\ L(l, i, j), & \text{otherwise} \end{cases}$$

..... (2)

b. Texture parameter: This term E is composed of local variance of the sub band. This contribution is computed in a small 2\*2 neighborhood corresponding to the location of the wavelet coefficient.

$$E_2(l, i, j) = \left[ \sum_{x=0}^1 \sum_{y=0}^1 \text{var} \left\{ I_3 \left( 1+y + \frac{i}{2^{3-i}}, 1+x + \frac{j}{2^{3-j}} \right) \right\} \right]^{0.2}$$

..... (3)

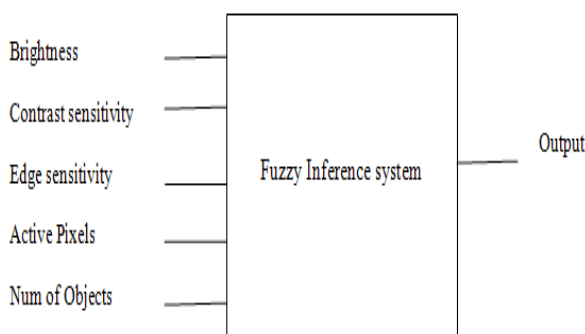
c. Edge sensitivity: The innermost term E in the equation corresponds to the local mean square value of the DWT coefficients in all detail sub bands. Again these contributions are computed in a small neighborhood corresponding to the location of the coefficient.

$$E_l(l, i, j) = \left[ \sum_{k=0}^{3-i} \frac{1}{16} \sum_{\theta=0}^2 \sum_{x=0}^1 \sum_{y=0}^1 \left[ I_{k+\theta} \left( y + \frac{i}{2^k}, x + \frac{j}{2^k} \right) \right]^2 \right]^{0.2}$$

..... (4)

d. Active Pixels: For the Host Image of size (256 256), consider the [8 8] blocks. Apply DCT to each block and consider the pixels whose intensity levels are less than avg intensity levels which are calculated using `statxtrc()` function. e. Num of Objects: `bwconncomp(BW)` returns the connected components CC found in BW binary image. Num of objects is one of the fields of the connected components.

Step 3: The above computed values are fed as fuzzy inputs to a fuzzy inference system (FIS).

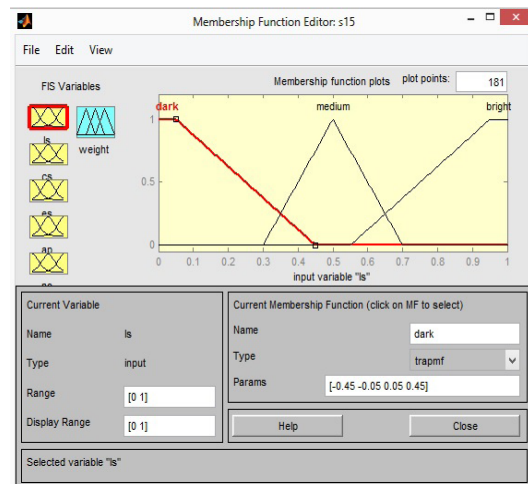


**Fig :3 Block Diagram For Fuzzy inference Systems**

Fuzzy input and output variables are plotted below.

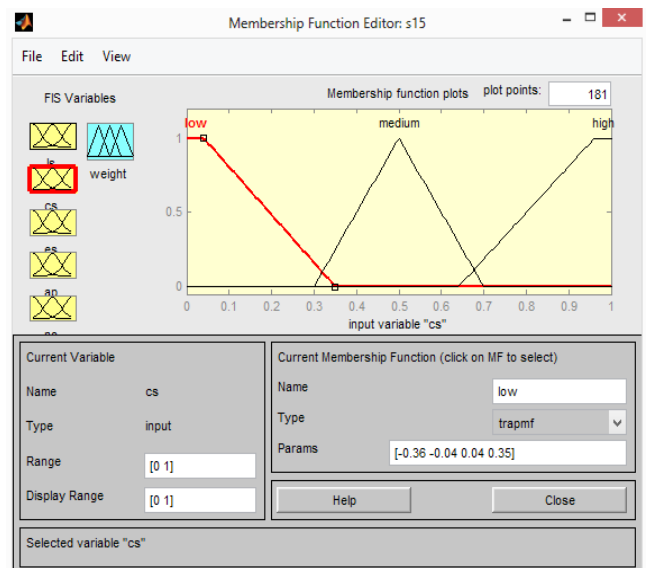
**Fuzzy Input Variables:**

1. Brightness sensitivity of the eye The brightness can be categorized as dark, medium or bright. The figure below plots the fuzzy input variable with less, moderate and high brightness values.



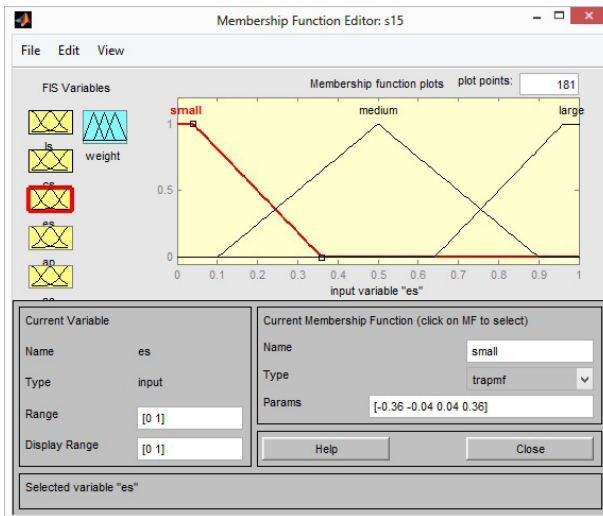
**Fig:4 Fuzzy Values For Luminous Sensitivity**

2. Texture sensitivity of the eye The eye's response to texture is classified into 3 categories low, medium, and high. Plots below illustrate smooth, medium and rough texture values for this fuzzy input variable.



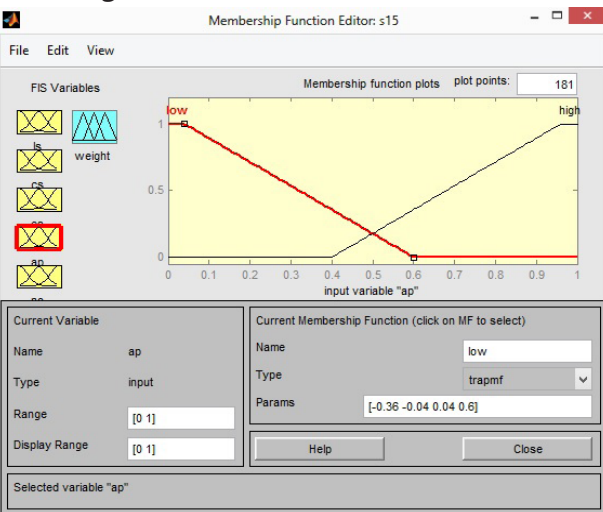
**Fig:5 Fuzzy Values For Contrast sensitivity**

3. Edge distance or edge sensitivity The edge distance can be small, medium, or large as shown in the plots below.



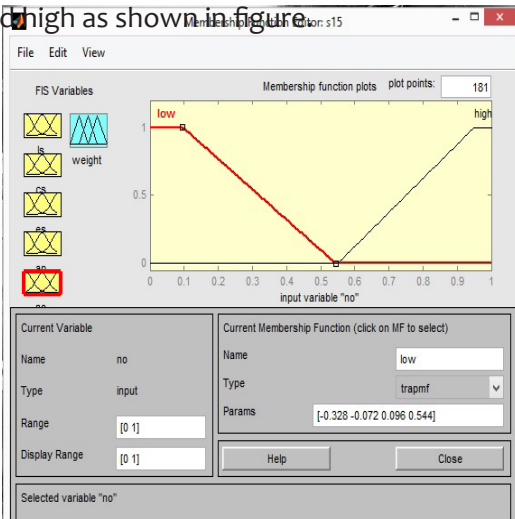
**Fig 6: Fuzzy Values for Edge sensitivity**

4. Active pixels Active pixels can be low or high as shown in figure.



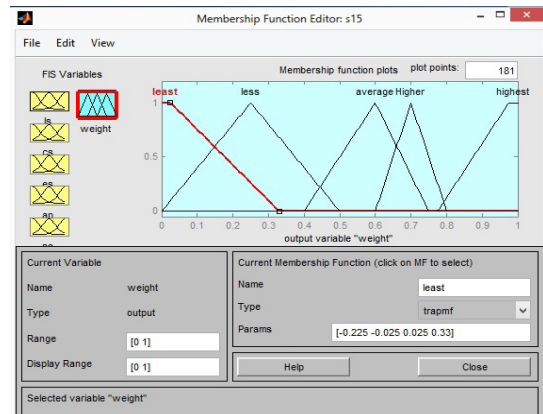
**Fig 7: Fuzzy Values for Active pixels**

5. Number Of Objects Num of Objects can be classified low and high as shown in figure.



**Fig : 8 Fuzzy Values For Num Of Weights**

Fuzzy Output Variables W=Weighting Factor Output of the FIS is a weighting factor that can take the following values - least, less, average, higher, and highest. Plots for the values are shown in Fig.



**Fig :9 Fuzzy Values For Weights**

### Fuzzy Rules

The fuzzy rules are derived are based on the following facts:

- a. The eye is less sensitive to noise in those areas of the image where brightness is high or low.
- b. The eye is less sensitive to noise in highly textured areas but, amongst these, more sensitive near the edges.
- c. The eye is less sensitive in the regions with high brightness and changes in very dark regions.

A Total of 27 rules are developed and are listed below.

- 1.If luminous sensitivity is dark AND Contrast sensitivity is low AND edge sensitivity is small then Weight is least.
- 2.If luminous sensitivity is dark AND Contrast sensitivity is medium AND edge sensitivity is small then Weight is least.
- 3.If luminous sensitivity is dark AND Contrast sensitivity is high AND edge sensitivity is small then Weight is least.

4.If luminous sensitivity is medium AND Contrast sensitivity is low AND edge sensitivity is small then Weight is least.

5.If luminous sensitivity is medium AND Contrast sensitivity is medium AND edge sensitivity is small then Weight is least.

6.If luminous sensitivity is medium AND Contrast sensitivity is high AND edge sensitivity is small then Weight is least.

7.If luminous sensitivity is bright AND Contrast sensitivity is low AND edge sensitivity is small then Weight is least.

8.If luminous sensitivity is bright AND Contrast sensitivity is medium AND edge sensitivity is small then Weight is least.

9.If luminous sensitivity is bright AND Contrast sensitivity is high AND edge sensitivity is small then Weight is least.

10.If luminous sensitivity is dark AND Contrast sensitivity is low AND edge sensitivity is medium AND Active pixels is low AND no of objects is high then Weight is less.

11.If luminous sensitivity is dark AND Contrast sensitivity is high AND edge sensitivity is medium AND Active pixels is low AND no of objects is high then Weight is higher.

12.If luminous sensitivity is dark AND Contrast sensitivity is medium AND edge sensitivity is medium AND Active pixels is low AND no of objects is high then Weight is higher.

13.If luminous sensitivity is medium AND Contrast sensitivity is low AND edge sensitivity is medium AND Active pixels is low AND no of objects is high then Weight is less.

14.If luminous sensitivity is medium AND Contrast sensitivity is high AND edge sensitivity is medium AND Active pixels is high AND no of objects is low then Weight is Average.

15.If luminous sensitivity is medium AND Contrast sensitivity is medium AND edge sensitivity is medium AND Active pixels is high AND no of objects is low then Weight is Average.

16.If luminous sensitivity is bright AND Contrast sensitivity is low AND edge sensitivity is medium AND Active pixels is high AND no of objects is low then Weight is less.

17.If luminous sensitivity is bright AND Contrast sensitivity is high AND edge sensitivity is medium AND Active pixels is high AND no of objects is low then Weight is Average.

18.If luminous sensitivity is bright AND Contrast sensitivity is medium AND edge sensitivity is medium AND Active pixels is low AND no of objects is high then Weight is higher.

19.If luminous sensitivity is dark AND Contrast sensitivity is low AND edge sensitivity is large AND Active pixels is high AND no of objects is low then Weight is less.

20.If luminous sensitivity is dark AND Contrast sensitivity is medium AND edge sensitivity is large AND Active pixels is low AND no of objects is high then Weight is higher.

21.If luminous sensitivity is dark AND Contrast sensitivity is high AND edge sensitivity is large AND Active pixels is low AND no of objects is high then Weight is highest.

22.If luminous sensitivity is medium AND Contrast sensitivity is low AND edge sensitivity is medium AND Active pixels is high AND no of objects is low then Weight is less.

23.If luminous sensitivity is medium AND Contrast sensitivity is medium AND edge sensitivity is medium AND Active pixels is high AND no of objects is low then Weight is average.

24.If luminous sensitivity is medium AND Contrast sensitivity is high AND edge sensitivity is medium AND Active pixels is low AND no of objects is high then Weight is higher.

25.If luminous sensitivity is bright AND Contrast sensitivity is low AND edge sensitivity is medium AND Active pixels is high AND no of objects is low then Weight is higher.

26.If luminous sensitivity is bright AND Contrast sensitivity is low AND edge sensitivity is medium AND Active pixels is high AND no of objects is low then Weight is higher.

27.If luminous sensitivity is bright AND Contrast sensitivity is medium AND edge sensitivity is medium AND Active pixels is low AND no of objects is high then Weight is highest.

Step 4: The above procedure of computing the weighting factor is computed for the all the coefficients in I band where level  $l=0,1,2,3$  and with orientation  $\epsilon\{0,1,2\}$ .

$$W_l^\theta(i, j) = I_l^\theta(i, j) + \alpha w^\theta(i, j)$$

.....(5)

Where  $\alpha=0.0001$

$w(i, j)$  = weighting factor computed by FIS  $l$  = sub band at resolution level  $0,1,2,3$  and  $\epsilon\{0,1,2\}$ . represents orientation.

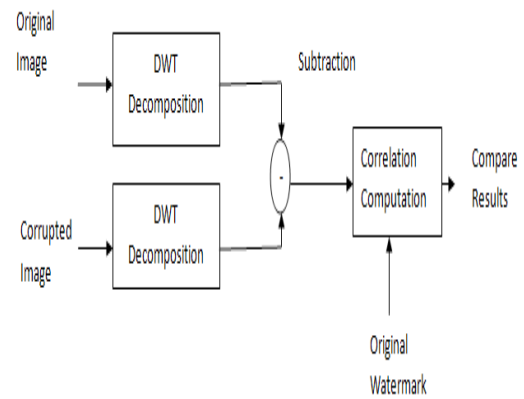
### VI. Watermark Detection:

A non blind method is used to extract the watermark. Algorithm for extracting the watermark is as follows:  
Step 1: Compute the Daubechies-6 DWT of the image that has to be tested for attacks against the original image.

Step 2: Subtract the coefficients of the two images to obtain the watermark.

Step 3: Correlate the original watermark ( $W$ ) with the recovered watermark ( $W'$ ) to determine the authenticity.

The watermark extraction performance is evaluated by correlating coefficients of the extracted watermark  $W'$  and the original watermark  $W$ .



**Fig 10: Correlation Of Extracted Watermark**

### VII. Results:



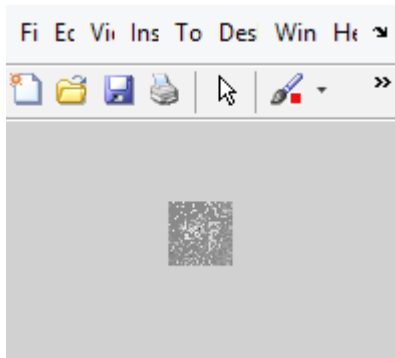
**Fig 11: Input Image**



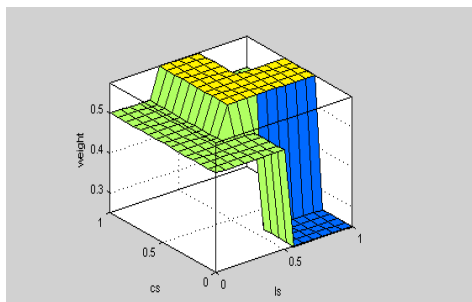
**Fig 12: DCT Transformed Image**



**Fig: 13 Watermarked Image**



**Fig: 14 Watermark**



**Fig: 15 Surface Plot**

PSNR and MSE Values between input image and the watermarked image are

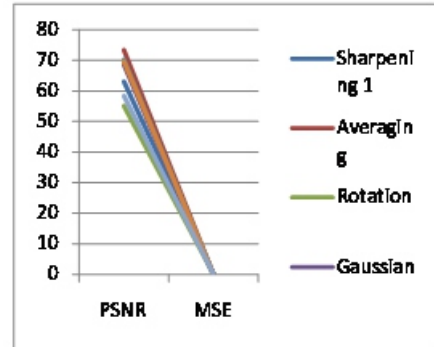
PSNR: 110.7699

MSE: 5.4462e-07

Attacks	Sharpening	Averaging	Rotation	Salt and pepper noise	Gaussian	Motion Blur	Vertical flip
PSNR	62.9836	73.2897	55.0276	70.2416	68.5080	69.5816	58.2612
MSE	0.0327	0.0030	0.2043	0.0062	0.0092	0.0072	0.0970

Tab:1 Comparison table for PSNR and MSE For Different Attacks

**Tab:1 Comparison table for PSNR and MSE For Different Attacks:**



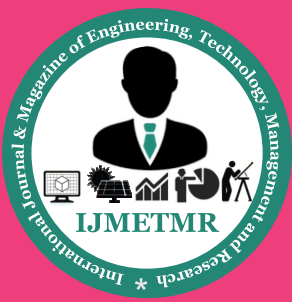
**Fig: 16 Plot For PSNR and MSE For Different Attacks**

## VIII. Conclusion:

This paper has proposed using fuzzy logic to model HVS spatial masking in DCT and wavelet domain. Fuzzy perceptual masks have been developed which allow high density and high energy watermarks. The fuzzy based watermarks are robust to attacks and at the same time achieve a high level of imperceptibility. Wavelet maxima with zero tree structures can be further added as input fuzzy variables and exploited to build a more sophisticated model. This work can be further extended to fragile watermarks and blind watermarking.

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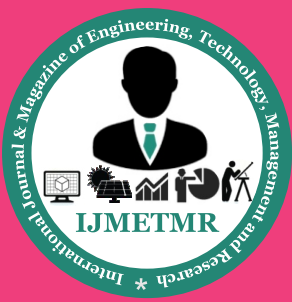
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