Developing Fuzzy Inference System For Assessing Quality Of Distorted Images

Indrajit De and Jaya Sil

Abstract— **Non existence of full proof method of feature extraction of images and lack of well defined relationship between image features and its visual quality, make quality assessment of distorted/decompressed image without reference to the original image extremely difficult task. Under such circumstances, human reasoning based on subjective information play vital role in assessing quality of image. The paper aims at assessing the quality of distorted/decompressed images without any reference to the original image by designing a fuzzy inference system.**

Five benchmark images- Lena, Mandril, Woman with Hat, Woman_Blond_Hair and Baby are decompressed using LBG (Linde, Beuzo, Gray) procedure with varying codebook sizes and divided into different connected regions. In our problem domain the input of the fuzzy inference system is comprised of four crisp measured data expressed using linguistic variables: *area*, *extent*, *eccentricity* and *convex area* obtained from the connected regions while output is made up of linguistic variable *quality* of images and measured using peak signal to noise ratio (PSNR) of the decompressed images with respect to the original images. The linguistic variables are represented by fuzzy sets whose degree of membership values obtained using Gaussian distribution functions with varied mean and standard deviation. In consultation with human observers various fuzzy *if-then* rules are constructed where the regional parameters and quality of the images are mapped as antecedents and consequents of the rules, respectively. Finally, by applying Mamdani inference rule, the quality of a new distorted/decompressed image is predicted. Different test images after decompression and inducting distortion by *Gaussian* and *white noises* are applied to the system for quality prediction without reference to the original image. Thus, we develop a robust fuzzy inference system producing output comparable with the two reported no reference techniques. Results are validated with the objective measure of image quality. Results are validated with the objective measure of image quality and compared with the existing no-reference techniques.

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***Index Terms*—Fuzzy systems, Gaussian noise, Image compression, Image region analysis**

I. INTRODUCTION

DIGITAL images are subject to loss of information, variety of distortions during compression and transmission through the channel and therefore, visual quality deteriorates at the receiving end. It is therefore, important to maintain the quality of the image in order to utilize the image for various applications. Quality prediction of an image by modeling physiological and psycho visual features of the human visual system or by signal fidelity criteria have been already reported though each of these approaches has several shortcomings. Since human beings are the ultimate consumers of almost all the image content, the most reliable means of measuring the image quality is subjective evaluation based on the opinion of the human observers [3]. However, subjective testing is not automatic and expensive too. On the other hand, most objective image quality assessment methods [2] either require access to the original image as reference [2] or only can evaluate images, degraded with predefined distortions and therefore, lacking generalization approach. Other than the traditional methods, one recent work [3] is reported, which does not require full access to the reference image but only needs partial information, in the form of a set of extracted features. This approach is superior compare to the exiting objective methods by paying extra cost of transmitting additional information along with the compressed image to the other end. Additional information may be embedded in the image as hidden message and the distorted image is decoded at the receiving end to provide an objective measure of the quality. This method requires higher processing time compare to the methods discussed earlier and quality improvement depends on the extracted features and therefore, may be partial.

Two prominent works have been reported relating to no-reference image quality evaluation, (i) Wang, Bovic and Shiekh's no-reference JPEG image quality index and (ii) H.Shiekh's quality metric based on natural scene statistics (NSS) model applied on JPEG2000 compressed images. In Wang et al's work the image is scanned first horizontally and then vertically for computing the blurring and blocking features of compressed images. Quality of the image is computed by combining these features, and hence the method is computationally inefficient. Moreover, the process has taken only JPEG compressed images for experiment and finally local spatial regional texture variations of the image are not considered in their work. The work of H. Sheikh et. al. assesses the quality of images afflicted with ringing and blurring distortion resulting from JPEG2000 compression. Their work uses natural scene statistics models to provide a ‘reference’ against which the distorted images can be assessed. Their model works only on JPEG compressed images and does not consider any spatial texture variation of the image due to which local statistics of the image may vary.

To address the shortcomings of the existing methods, in the paper, we propose a fuzzy system where (i) the decompressed images obtained by LBG (Linde, Beuzo, Gray) procedure is divided into different regions and several regional parameters of these regions are computed, (ii) *area*, *extent* , *eccentricity and convexarea* of these regions and *quality* of the images are linguistic variables, which take values represented by fuzzy sets. The degree of membership values of fuzzy sets are obtained using Guassian distribution functions with varied mean and standard deviation, (iii) in consultation with human observers various fuzzy if-then rules are constructed where the parameters and quality of five benchmark gray level images-Lena, Mandril, Woman with Hat, Woman_Blond_Hair and Baby are mapped as antecedents and consequents respectively and (iv) finally, by applying Mamdani inference rule [1], the quality of a new distorted/decompressed image is predicted without any reference to the original image. Results are validated with the objective measure of image quality and compared with the existing no-reference image techniques.
The paper is divided into five sections. Section II describes the procedures required to frame the background for developing such an autonomous system. Extraction of different statistical parameters and generation of fuzzy rules using those parameters for image quality measurement is presented in section III. Results are demonstrated in section IV while conclusions are summarized in section V.

II. BACKGROUND

A. FuzzySystem

Fuzzification has the effect of transforming crisp measured data into suitable linguistic values. Fuzzy *If-Then* rules express the input-output relationship of a system using linguistic variables with proper semantics available from domain experts. The inference engine is the kernel of the fuzzy system and has the ability to simulate human decision making by performing approximate reasoning. There are mainly two prominent types of fuzzy inference systems (FIS) in practice, Mamdani-Assilian type and Takagi-Sugeno-Kang type. The primary goal of FIS is building fuzzy linguistic control rules by analyzing the actions of experienced human operators represented as fuzzy sets. So to get a crisp output from the fuzzy variable of consequent a defuzzification process [1] is required.

B The Model

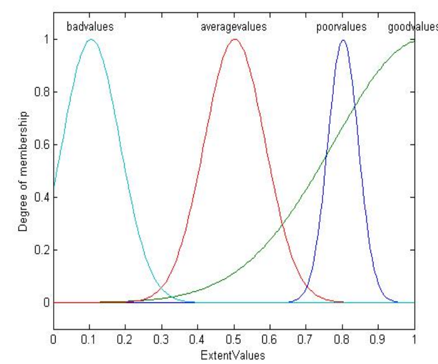
The Mamdani-Assilian type FIS has been designed in the work consisting of five components:

(a) *Input-Output space*: In our problem domain the input space is comprised of three crisp measured data expressed using linguistic variables: *area*, *extent* and *eccentricity* obtained from connected regions of decompressed images. Similarly, the output space is made up of linguistic variable *quality* of images and measured using peak signal to noise ratio (PSNR) of the decompressed image with respect to the original image.

(b) *Fuzzification*: The crisp measured data are transformed to suitable values using fuzzy sets. For instance, measured *area* values are classified using three fuzzy sets- *Good values*, *Average values* and *Bad values*, with the help of the following functional relation:

Good values (0<= *area*<=4)
f(*area*)= Average values (5<=*area*<=7)
Bad values (8<=*area*<=10)

But in fuzzy set an *area* value= 7 is classified as 0.2% *Average value* and 0.8% *Bad value*.



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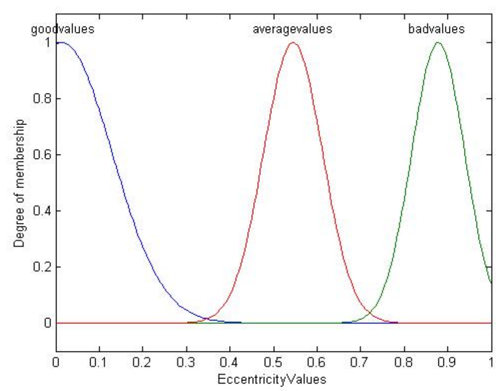

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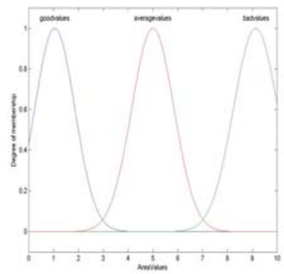

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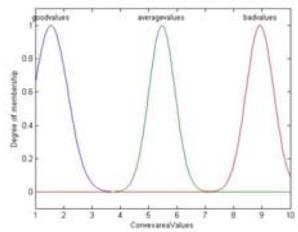

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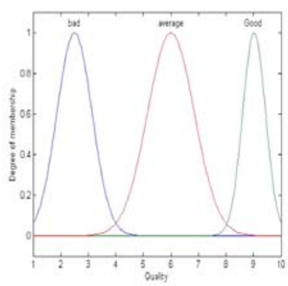


(e)

Fig. 2 : (a) Membership function plot for Extent parameter, (b) Membership function plot for Eccenricity parameter, (c) Membership function plot for Area parameter, (d) Membership function plot for Convex area parameter and (e) Membership function plot for Quality parameter

(c) *A Rule-base:* The general form of the rules in multi-input-single-output (MISO) system is:
If '*AreaValues*' are 'Good values (0 pixel per region to 3 pixel per region)' and '*ExtentValues*' are 'Good values (0.5 to 1)' and '*EccentricityValues*' are 'Good values (0 to 0.5)' and 'ConvexareaValues' are 'Good values (1 to 3 pixels per region)' then '*quality*' is 'good (7 to 10)'(Fig. 1).

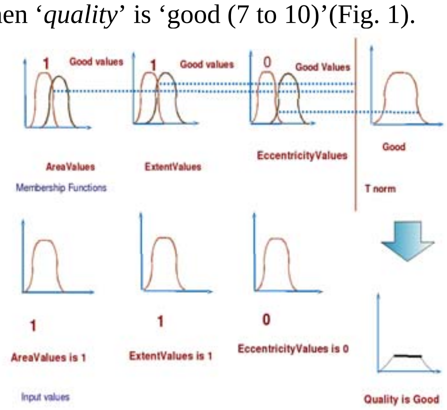


Fig. 1. An example of the Rule-base of the proposed method.

Different fuzzy variables are represented by certain types of membership functions, shown in Fig. 2.

(d) *An Inference engine*: The max-min compositional operator and min operation of fuzzy implication rule (Mamdani inference rule) is used for computational simplicity and efficiency.

(e) *A Defuzzifier:* The centroid method [1] is used for defuzzification of fuzzy variables.

C. Reasons for Selection of parameters:

Area is the number of pixels in a particular region. This number is inversely proportional to granularity of the image. For good quality images resolution is more giving rise to more number of regions, so number of pixels per region becomes less(in the extreme nearing one per region) for total number of pixels remaining constant. For bad quality images the reverse happens. An example is given in the Fig. 3 where quality of an image has been taken as the objective quality measure peak signal to noise ratio (PSNR) of the images with respect to respective original images. From the figure it is certain that the relation between PSNR and number of regions is generally linear.

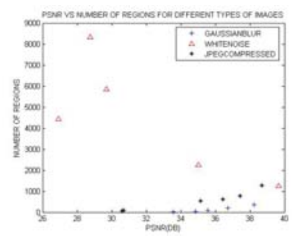


Fig 3. PSNR vs Number of regions.

Extent is the proportion of the pixels in the rectangle, surrounding the concerned region. Selection of extent follows same law as above. The *eccentricity* of the ellipse has the same second-moments as the region concerned. For good quality images having large number of regions the ellipse concerned almost encompasses one pixel only per region resembling a circle, so the eccentricity tends to zero for them. Other values nearer to one occur for average to bad quality images. Convexarea is the number of pixels present in the conveximage of the region, where conveximage is the binary image of the convex hull of the region. The variation of this number also follows the same principle as that of Area parameter.

III. PROCEDURE

The five standard gray level benchmark images- Lena, Mandril, Woman with Hat, Woman_Blond_Hair and Baby are used to train the FIS for generalizing the fuzzy rules already formed discussed in the previous section. The images are converted to gray level images and then to JPEG images so that our method can be compared with other existing methods [3], [4] work only on JPEG images. Each of the images is compressed and decompressed using LBG algorithm [6] and for each image, codebooks are produced having different sizes like 32, 128, 256, 512 and 1024

TABLE I
RANGE OF DIFFERENT FUZZY VARIABLES

Values of Area	Values of Extent	Values of Eccentricity	Values of Convex area	Values of Quality (Output)
Good values(1 to 3 pixels per region)	Good values(0. 4 to 1.0)	Good values (0 to 0.3)	Good values (1 to 3 pixels per region)	Good quality (0.7 to 1)
Averag e values(4 to 6 pixels per region)	Average values(0. 4 to 0.6)	Average values(0.4 to 0.6)	Averag e values (4 to 7 pixels per region)	Average quality (0.4 to 0.6)
Bad values(7 to 10 pixels per region)	Bad values(0 to 0.3)	Bad values(0.7 to 1.0)	Bad values (8 pixels to 10 pixels per region)	Bad quality (0 to 0.3)
Bad values(7 to 10 pixels per region)	Poor values(0. 7 to 0.9)	Bad values(0.7 to 1.0)	Bad values (8 pixels to 10 pixels per region	Bad quality (0 to 0.3)

codebook vectors. For each such decompressed image the value of the scalar regional parameters (*area*, *extent*, *eccentricity and convex area*) are obtained and used as training inputs to the FIS while the output is the *quality* of the respective images.

After training standard test '*face*' images have been taken from the live database of H.R.Sheikh-release-2 [5]. The images were already created with several types of distortions, out of which three categories have been taken for testing: Gaussian blur, JPEG compressed and white noise incorporated images. The same way inputs and output of test images are extracted and applied to the FIS for assessing quality of the respective images.

A Range of different Fuzzy Variables

In general, the regional parameter values depending on maximum frequencies are used to select different range (good, bad, average and poor) of values of fuzzy variables (Table 1). These values are obtained from the respective frequency distributions of decompressed images with varied codebook size. For instance, 32 and 128 size codebook images, 256 and 512 size codebook images and 1024 size codebook images are used for *bad*, *poor*,*average* and *good* membership values of the inputs respectively. Similarly, linguistic variable *quality* of the image takes fuzzy values like *good*, *average* and *bad* decided by human experts based on the subjective judgment and having membership values ranging from 1 to 10 (Table 1).

IV. RESULTS

A. Results obtained from the FIS described in different tables. The results are described in different tables. In Table 2 different attribute values of the decompressed training images are listed which were compressed using LBG algorithms. In Table 3 different test image attributes with varied distortion types are listed and in Table 4 the values of image quality for the test images obtained from different quality measurement methods are compared.

TABLE 2
THE
ATTRIBUTES OF TRAINING IMAGES FOR DIFFERENT PROCESSING PARAMETERS

Image name	Image Attributes		Attribute values		
			MIN	MAX	AVERAGE
LENA, MANDRIL, BABY, WOMAN_BLOND_HAIR, WOMAN_WITH_HAT	Image Size	Column Size	480 pixels	800 pixels	640 pixels
		Row Size	512 pixels	720 pixels	616 pixels
	Codebook Size		32	1024	528
	Compression Rate(In Bits Per Pixel)		0.078125	0.15625	0.1171875
	Compression Ratio		51.2 : 1	102.4 : 1	

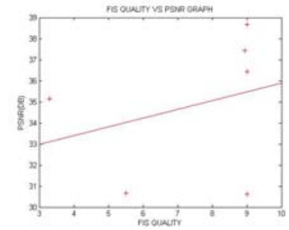
TABLE 3
THE ATTRIBUTES OF DIFFERENT TEST IMAGES WITH VARIED DISTORTION (GAUSSIAN BLUR, WHITE NOISE, JPEG COMPRESSION) AND THEIR RESPECTIVE ATTRIBUTE VALUES.

Image name	H. Shiekh, Bovic, Kormack Process	Wang, Shiekh Process	Quality (Proposed process)/Linguistic variable
GAUSSIAN BLUR			
Img132	78.5510	6.6272	5.54(AVERAGE)
Img162	79.7664	9.0866	9.01(GOOD)
Img36	74.0736	8.0136	3.3(BAD)
JPEG COMPRESSED			
Img138	79.5797	-6.1314	3.3(BAD)
Img154	79.6471	-4.5741	5.52(AVERAGE)
Img168	79.9117	9.6770	9.01(GOOD)
WHITE NOISE INCORPORATED			
Img119	80.0207	8.6895	9.01(GOOD)
Img162	79.7664	9.0866	9.01(GOOD)
Img60	80.0208	6.3326	9.00(GOOD)

B Validation of Results

From the result it is evident that the proposed method gave in general almost same inferences about quality of the images concerned as that of Wang, Bovic, Shiekh, whereas Shiekh, Bovic, Kormack process gave hayware results regarding the concerned images. Sometimes Wang's process also gave wrong result for certain images but for those cases also the proposed method yielded coherent results with respect to subjective quality judgement of images.

Fig 4, 5 and 6 give the correlations between PSNR and different no reference image quality metrics including the proposed quality metric for different distortion types.

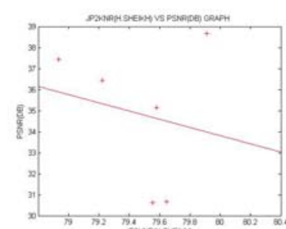


(a)

Fig 4. Different quality values vs PSNR for JPEG compressed images

TABLE 4.
COMPARISON OF NO-REFERENCE IMAGE QUALITY METRICS

Image Name (same as in LIVE database)	Type of Distortion	Attribute Image Size	Attribute Values 512×512		
img132, img162, img36, img42, img61, img82	Gaussian blur incorporated image	Standard deviation	Min 0	Max 3.54	Avg 1.77
img128, img1, img107, img154, img168, img190, img26, img89	jpeg compressed image	Bit rate	Min 0	Max 1.47	Avg 0.735
img11, img119, img162, img28, img3, img60	White noise incorporated image	Standard deviation of white noise	Min 0	Max 1	Avg 0.5



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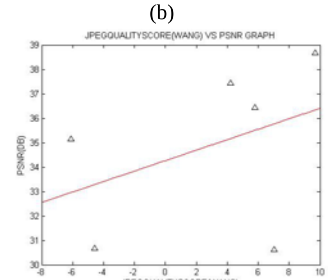
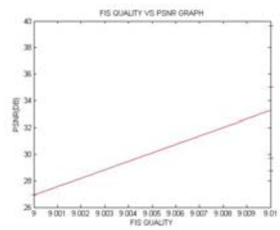


(c)

Fig 4. Different quality values vs PSNR for JPEG compressed images

TABLE 5
PEARSON PRODUCT MOMENT CORRELATION COEFFICIENT FOR VARIED DISTORTION TYPES

Distortion type	PSNR vs Proposed quality values	PSNR vs Wang, Shiekh quality values	PSNR vs Shiekh, Bovic, Kormack quality values
Gaussian blur	0.71124	0.9146	0.0513
JPEG compression	0.2977	0.4027	- 0.1948
White noise	0.9299	0.6090	- 0.9071



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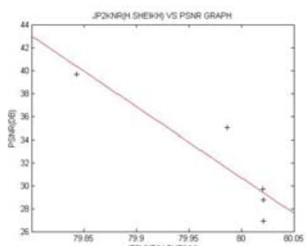

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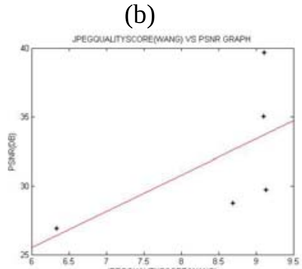
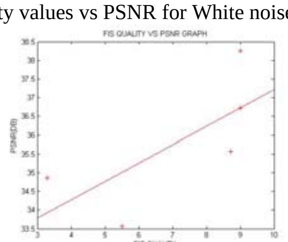
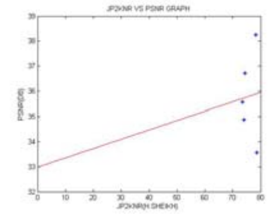


(c)

Fig 5. Different quality values vs PSNR for White noise incorporated images



(a)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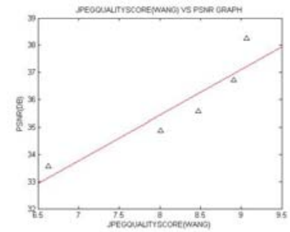

(c)

Fig 6. Different quality values vs PSNR for Gaussian blur having images.

V. CONCLUSIONS

Pearson product moment correlation is a powerful measure to compute linearity between two variables. So to measure the performance of the proposed method with the other two methods in comparison with a well known objective image quality measure like PSNR the Pearson product moment correlation coefficient has been calculated and given in Table5.

It can be concluded from the above graphs (Fig. 3, 4 and 5) and Table 5 that the proposed process outperformed H.Sheikh, Bovic, Kormack's procedure and almost at per with Wang, Bovic, H.Shiekh's process for different noise incorporated face image types with computationally simpler process.

The proposed process utilized FIS built with decompressed training images, where loss of information was present. Even then the process gave compatible and in some cases better results compared with the other two processes. Also in the proposed process spatial texture variation was taken care of in the form regional segmentation of images and extracting scalar regional parameters which was absent in both the above mentioned processes.

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