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A Fuzzy & K-L Based Reduced Reference ImageQuality

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Abstract: *Reduced-reference (RR) image quality measures aim to predict the visual quality of distorted images with only partial information about the reference images. In this paper, in first stage uses present thresholding technique between probability distribution of local entropy of reference and their corresponding images using relative entropy (also known as the Kullback-Leiber discrimination distance function) as a criterion of thresholding of probability distribution of local entropy between references and distorted of their reference image. After then we create a model FIS (Fuzzy Inference System) and then use as input KLD and get quality score of distortedimage.*
Key words: *Local entropy, probability distribution of local entropy, KLD, Fuzzy InferenceSystem.*

I. Introduction

Image quality is a characteristic of an image that measures the perceived image degradation (typically, compared to an ideal or perfect image). Imaging systems may introduce some amounts of distortion or artifacts in the signal, so the quality assessment is an importantproblem.

In practical applications, images undergo different types of processing including acquisition, transmission or compression, which often generate some annoying distortions. The most annoying impairments are blocking, ringing, and blur artifacts. Blocking manifests as artificial horizontal and vertical discontinuities in some block-based compression methods. Blur is also a common artifact which affects the details of the image due to several phenomena such as defocusing or filtering. Ringing is another annoying degradation which is essentially due to quantization, and is generally defined as noise around edge points or in contrastedtransitions.

To quantify the visual impact of these annoying degradations, a number of subjective and objective measures have been proposed [1]. Subjective evaluation is regarded as the most reliable approach for assessing image quality. Unfortunately, subjective methods are complex, time consuming and impractical for real-time applications. Understanding and applying the knowledge of human visual perception is recognized as the most promising approach for developing objective methods consistent with human judgment. Three categories of image quality assessment are commonly used: Full- Reference (FR), No Reference (NR) and Reduced Reference (RR) methods. Full Reference methods need both the original image and its degraded version. Most of the existing Image Quality Metrics (IQM), such as PSNR, SSIM [2], SNRWAV [3], VIF [4] and so on, belong to this family. However, in real applications the original image is not always available. Hence, NR methods are most appropriate as they require only the degraded image. During the last decade, a number of NR metrics have been proposed [5]-[8]. However, NR-IQMs are limited by the type of the degradation contained in the image. Indeed, NR-IQMs are developed for particular artifacts, hence limiting their use to certain applicationsonly.

Reduced Reference approaches present a good compromise between FR and NR approaches. Only some features, such as edges or some visual descriptors, are extracted from the original and thedegradedimages. From the structural information conveyed by these descriptors, a metric is then derived and used as an IQM. There are relatively few successful RR-IQMs that have been discussed in the literature, including the popular RRIQA[9]-[10].

The general RRIQA framework described in Fig. 1 leaves flexibilities on the selection of RR features. This is indeed the major challenge in the design of RRIQA algorithms, where the appropriate RR features are desirableto:

(1) Provide an efficient summary of the referenceimage;
(2) Be sensitive to a variety of imagedistortions;
(3) Be relevant to the visual perception of imagequality.

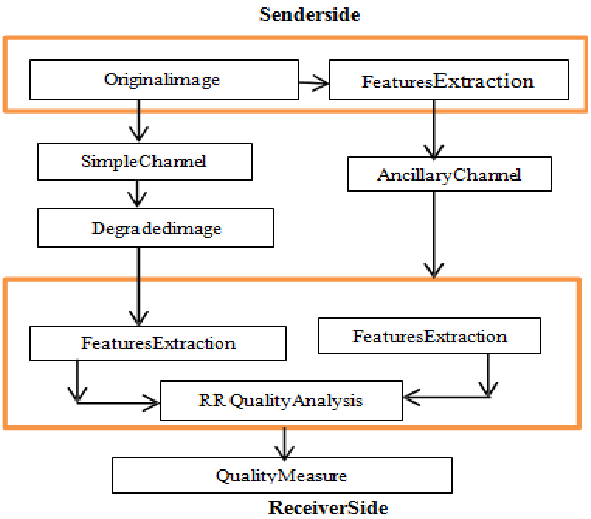


Figure1

Another important aspect that has to be kept in mind in the selection of RR features is to maintain a good balance between the data rate of RR features and the accuracy of image quality prediction .With a high data rate, one can include a large amount ofinformation about the reference image, leading to more accurate estimation of image quality degradations, but it also becomes a heavy burden to transmit theRRfeaturestothereceiver.Ontheotherhand,alowerdataratemakes it easier to transmit the RR information, but more difficult for accurate quality estimation. In practical implementation and deployment, the maximal allowed RR data rate is often given and must be observed .Overall, the merits of an RRIQA system should not be gauged only by the quality prediction accuracy, but by a tradeoff between the accuracy and the RR datarate.

The primary goal of our paper is to perform Reduced-Reference Image Quality Assessment using local entropy and Fuzzy Inference System We have developed RRIQA based on Local entropy and relative entropy. In first stage we have used present thresholding technique between probability distribution of local entropy between reference and their corresponding distorted images then find relative entropy (also known as the Kullback-Leiber discrimination distance function) as a criterion of thresholding of probability distribution of local entropy between references and distorted of their reference image. After then create a model FIS (Fuzzy Inference System) and then use as input KLD and get quality score of distortedimage.

II. Review of Existing Technologies

Reduced Reference IQA. Reduced-reference (RR) IQA methods provide a solution for cases in which the reference image is not fully accessible. Methods of this type generally operate by extracting a minimal set of parameters from the reference image, parameters which are later used with the distorted image to estimate quality. Extensive research has been done in the area of image quality assessment. Various methods are used to obtain the quality of the received image at the receiver side as that of the original image at the senderside.

In [10], Rehman and Wang present an RR IQA method of SSIM. Instead of directly constructing an RR algorithm to predict subjective quality, this method extracts statistical features from a multiscale, multi-orientation divisive normalization transform. The authors construct a distortion measure by following the philosophy analogous to that in the construction of SSIM. Based on the linear relationship between RR SSIM and FR SSIM given a fixed distortion type, a regression by discretization method is used to estimatequality.

In [11], Wang and Simoncelli presented an RR IQA method which operates based on a wavelet-domain statistical model of images. Quality is estimated based on the Kullback-Leibler divergence between the marginal probability distribution of wavelet coefficients of the reference and distortedimages.

In [12], Li and Wang presented an RR algorithm based on a divisive normalization image representation. By using a Gaussian-scale mixture-based statistical model of wavelet coefficients, a divisive normalization transform (DNT) is applied to the images. Quality is estimated by comparing a set of RR statistical features extracted from DNT-domain representations of the reference and distortedimages.

In [13], Ma et al. presented an RR algorithm based on DCT coefficient statistics. First, the DCT coefficients of image blocks are grouped into several representative sub-bands.Next, a generalized Gaussian distribution is employed to model the distribution of coefficients within each sub-band. Quality is then estimated based on the distance between distributions of the reference and distortedimages.

In [14], Soundarararajan and Bovik presented a framework for RR IQA based on information-theoretic measures of differences between the reference and distorted images by using the entropies of wavelet coefficients. This algorithm differs from other approaches in terms of the amount of data needed for the entropy-difference calculations and in terms of the scalability in the amount of information that is needed from the referenceimage.

In [15], a performance evaluation study of ten image quality assessment algorithms conveys that there is very much difference between machine and human evaluation of image quality. Among theten algorithms that , DCTune (A technique for visual optimization of DCT quantization matrices for individual images) performs statistically worse than peak signal to noise ratio (PSNR), and just noticeable difference (JND),structural similarity(SSIM), information fidelity criterion (IFC), and Visual Information Fidelity (VIF) perform much better than the rest of the algorithms. They found, VIF as best in the considered 10 algorithm set. This work helped us in understanding different algorithms in the area of signal processing to perform image quality assessment. Among different objective metrics, as it is desirable to have perceptually relevant objective metrics, we used Similarity Index (SSIM) to validate ourresults.

III. Procedure

A. Image data set and itsexplanation

Our algorithm is trained on our own database. This database contains 21 high resolution 8 bits/pixels gray scale images as reference or original and corresponding 373 salt & pepper images. The mean opinion scores (MOS) of the image is provided to describe the subjective quality of the degradedimages.

The database has been divided into two sets to simplify the process of testing and training. Among the two sets, one set is used for training which contains 19 original images and their corresponding 314 distorted images. Another set (Group1) is used for testing which contains 6 original images and 36 corresponding distortedimages.

Our algorithm is also validated on Tampere Image Database 2008 (TID2008) [19]. TID2008 contains 17 types of distortions across 1700 distorted images .we take five original images and their corresponding 22 distorted (salt &pepper) images (Group2).

B. RRIQM SystemStructure

1. We extract the local entropy as a features and find the probability distribution for original images and there correspondingimages.
2. The probability distributions have been used to find theKLD.
3. Threshold Analysis and to find KLD between every interclass images with their corresponding distortedimages
4. Creation of Fuzzy Inference System based onKLD.

B.1. LocalEntropy

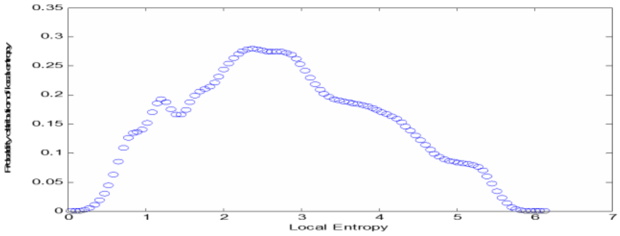
We find out the local entropy of each image where each output pixel contains the entropy value of the 9-by-9 neighborhood around the corresponding pixel in the input image. For pixels on the borders of the image, local entropy uses symmetric padding. In symmetric padding, the values of padding pixels are a mirror reflection of the border pixels in theimage.

We find out the probability distribution of local entropy for the images using the equation 1. Asfollows

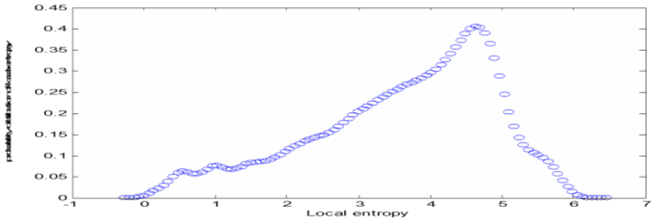
$$p(x_i) = n(x_i)/N \qquad (1)$$

In the above equation p(xi) is the probability of each pixel entropy and n(xi) is the no of occurrence of each pixel entropy and N is the total no ofpixel.

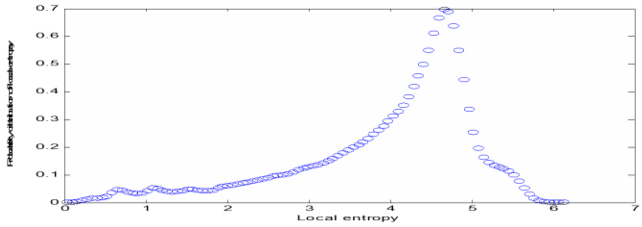
(a) (b) (c) (d)



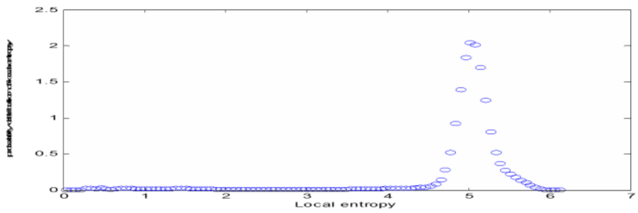
(a1)



(b1)



(c1)



(d1)

Figure2

Local entropy and Probability distribution of local entropy graph of “Child” images with salt & pepper type of distortions, with different noisedensity0.01, 0.08&0.9forimageb,c&drespectively.Where “a” is Reference image and (b), (c) and (d) are distorted images their corresponding a1, b1, c1 & d1aregraphs. We can see and analyses from figure 1, the images and graphs pair ((a, a1), (b, b1), (c, c1), (d, d1)) when noise density is increase of the images the peak of the graph beincreased.

B.2. RelativeEntropy(Kullback-LeiblerDistance)

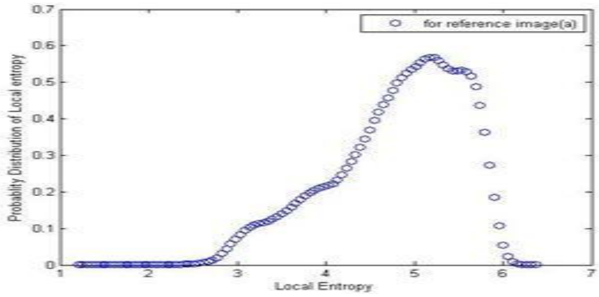
Let p(x) and q(x) denote the probability distribution functions of the local entropy of Reference and distorted images, respectively. Let x = {x1, x2, x3, ,..................xn} be a set of N randomly and independently local entropy. Kullback-Leibler distance (KLD) between p(x) andq(x):

$$l(p|x) - l(q|x) \to d(p\|a) = \int p(x) \log \left({}^{p(x)}\!/_{q(x)} \right) dx \qquad (2)$$

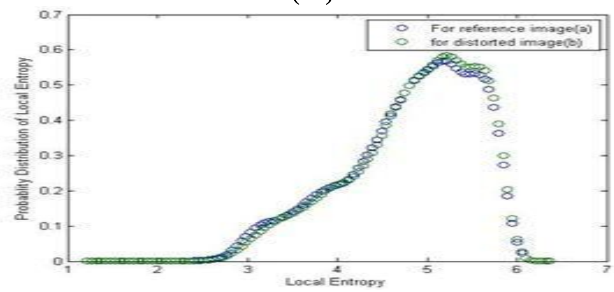
In this paper, we use KLD to quantify the difference of local entropy distributions between a distorted image and a perfect quality reference image. We then examine how this quantity correlates with perceptual image quality for a wide range of distortiontypes.

Assume that p(x) and q(x) are associated with the reference and distorted images, respectively. To estimate the KLD between them using equation 3.2, We can analysis from the set of KLD values if KLD is low that means p(x) and q(x) are close then error is small else error is high. The overall distortion between the distorted and reference images is defined as KLD between p(x) and q(x) and set the threshold value for every class (good, average and bad) of image for finding the quality score through FIS (Fuzzy InferenceSystem).

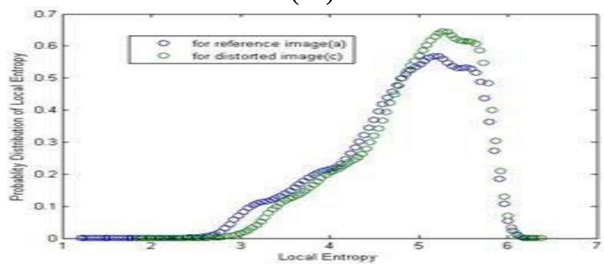
(a) (b) (c)



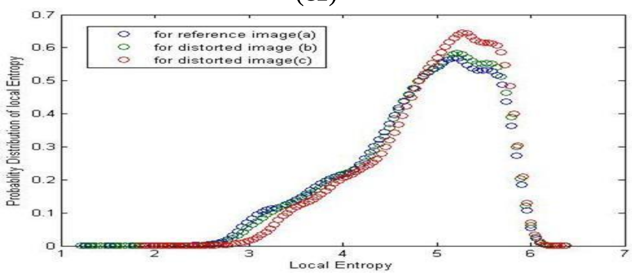
(a1)



(b1)



(c1)



(d1)

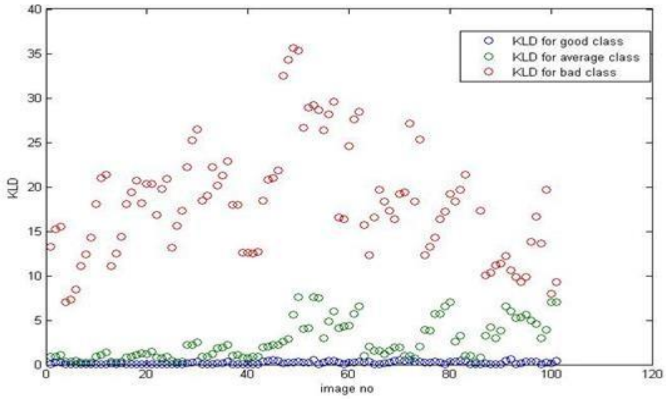
Figure 3

Comparison of peak of graph between reference image and distorted images (b),(c) of "Women" with noise density 0.008 and .05 of salt & pepper, (a1) graph for original image(a),(b1) graph for (a) and (b) images, (c1) graph for (a) and (c) images, (d) graph for (a),(b) and (c) images

We can see and analyses from figure 2, in the graphs (d) when noise density is increased the peak of the graph be increased. After then find KLD between reference images and their corresponding distorted images.

B.3. ThresholdAnalysis

For thresholding analysis of KLD values, the distorted images are partitioned in to three interclasses (good, average and bad) analyses from figure 3.4 based on. Peak distance between reference and their corresponding distorted graph (KLD). If KLD is small then distorted image is good class of image, KLD is medium then distorted image belong to average class of image else distorted image belongs to bad class of image. Figure 3 shows the KLD value for different class of distortedimages.



KLDvaluefordifferentdistortedclassimages (good,average,bad)
Figure 4

B.4. Fuzzy InferenceSystem(FIS)

Mamdani FIS is the most used in the developing fuzzy models. Mamdani architecture used in this thesis for estimation of the Quality of an image is illustrated in Figure 4 with one input (kld), one output variables(quality) and three fuzzy rules. The rule base for Mamdani model can be writtenas

The rule base for Mamdani model can be written as FuzzyRule:

If (x is $A_i = M_{1,i}$) {premise}

Then $f_i = M_{o,j}$ {consequent}

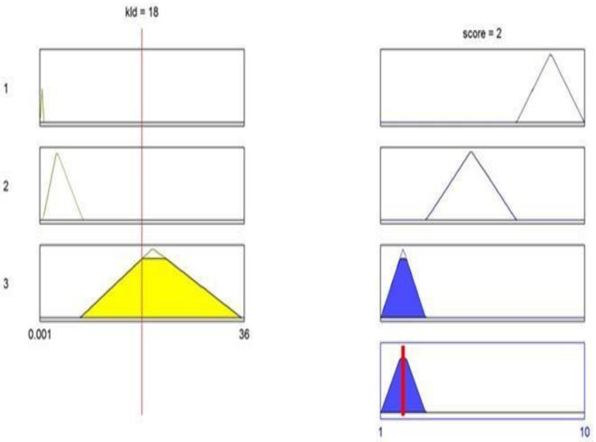
Where x represents the input (KLD),linguistic label of input(High, average and bad) and M_{1i}, f_i and ith MF of input (x), the output of the jthrule,andthejthoutputMF.BothinputandoutputMFhavetheirown parameters depending upon the shape of the MF and are called premise, and consequent parameters respectively.

In this thesis, the following trimf MFs for the inputs(kld) and output (S_score) variable are used

$$m(x) = \begin{cases} 0, & z < a \\ \dfrac{z-a}{b-a}, & a \le z < b \end{cases}$$

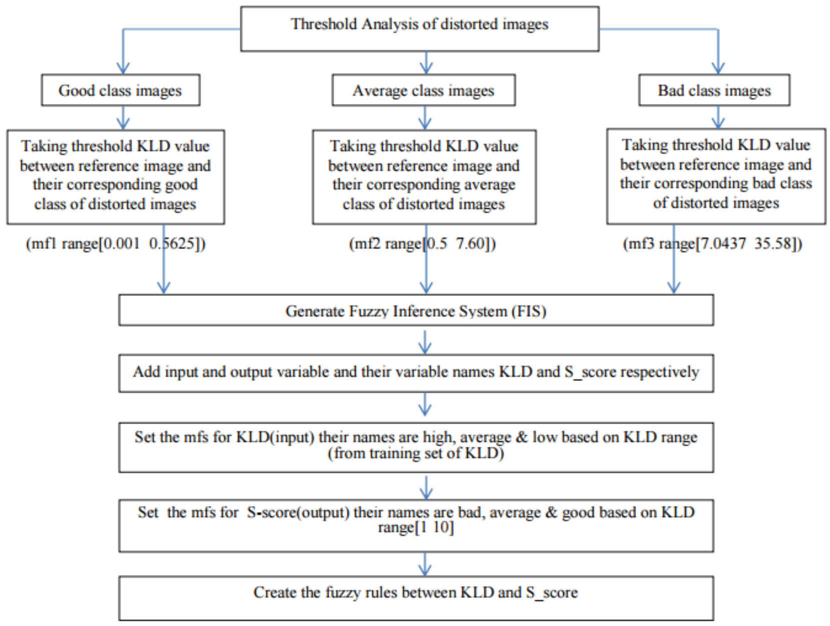
$$\begin{cases} 1 - \dfrac{(z-b)}{c-b}, & b \le z < c \\ 0, & c \le z \end{cases}$$

For the input variable KLD we defined three membership functions (high, medium and low) .For first membership function(mf1)name is high membership function the value of [a b c] is [.001 .1430 .5625] from training set of good class images. Where a and b are minimum and maximum value of KLD of good class respectively. The value of c is calculated by mean of KLD value of good class.similarly for medium memberships(mf2) the value of [a b c] is [.5 2.98 7.6043] and low membership function(mf3) the value [a b c] is [7.0437 19.9 35.5823].For the output variable S score we defined three membership functions (good ,average and bad) .for the good membership function(mf1) the parameters value of [a b c] are [1 2 3]. Similarly for average memberships(mf2) function the parameters of [a b c] are [3 5 7] and similarly for bad memberships(mf3) function the parameter value of [a b c] are [7 8.510]. Finally evaluate the FIS using KLD as input and get the quality score as output. Rule viewer in figure 4 show quality scores for a particular inputKLD.



RuleView
Figure 5

C. Training Methodology FrameWork



Training Methodology
Figure 6

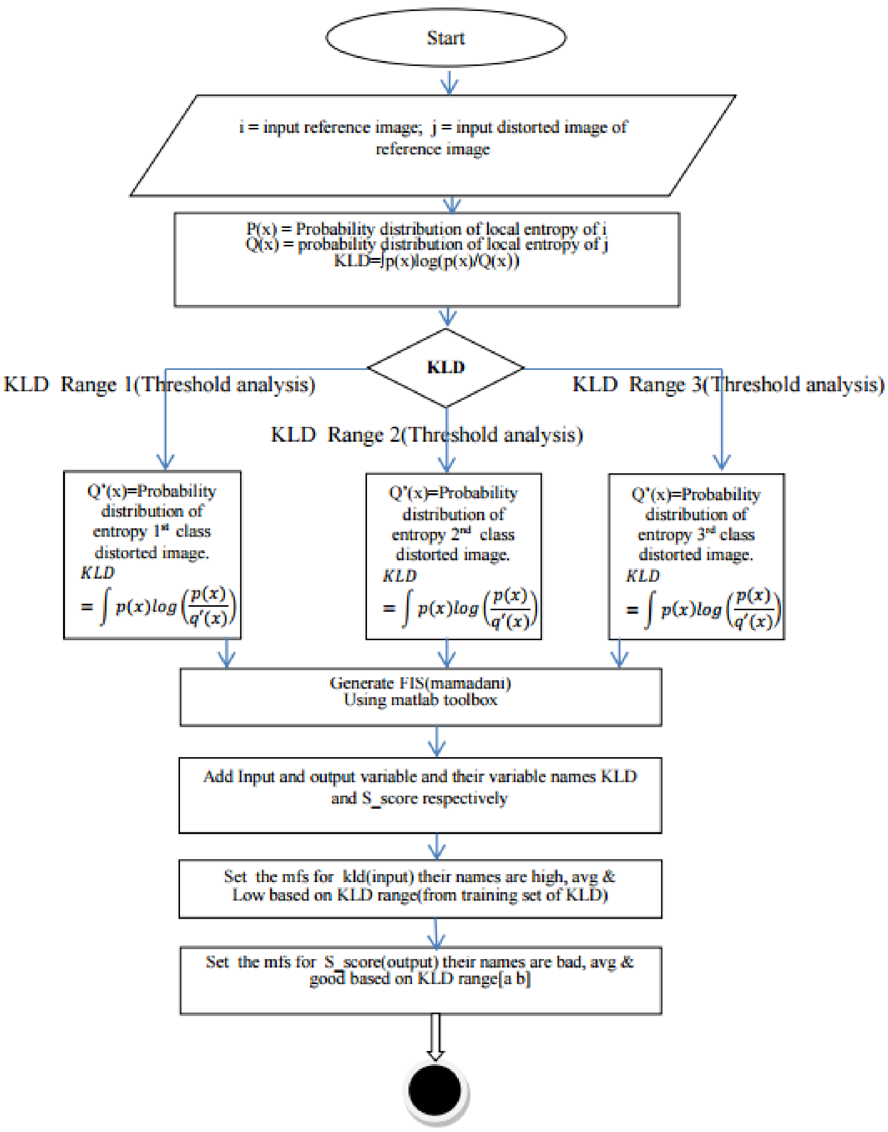
D. Proposed Algorithm

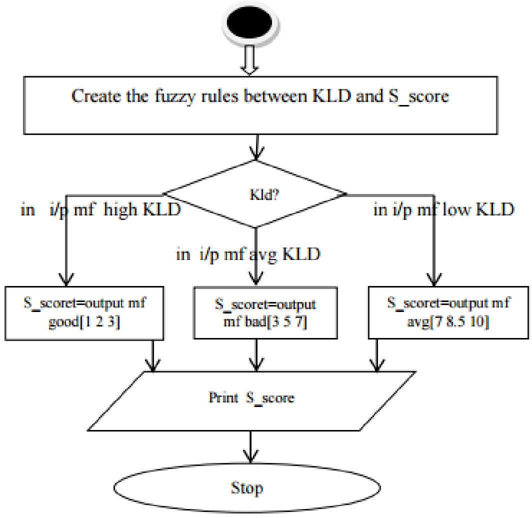
Begin
Step1:- i = Read the reference image and j=Read the distorted image corresponding to referenceimage.
Step2:- p(x) = probability distribution of local entropy of i and q(x)=probability distributionoflocalentropy of j.
Step3:- Find the distance between p(x) and q(x), using KLD (Kull-backleiblerdistance).
Step4:- if KLD<0
KLD =-1*KLD
End if
Step5:- if KLD in range 1 then
KLD infirstclass
Elseif
KLD in secondclass
Else
KLD in thirdclass
Endif
Step6:- Generate the Fuzzy InferenceSystem

(a) Define the name ofFIS.
(b) Addtheinputandoutputvariable
Inputvariable=KLD, range=[0.00135.58]
Outputvariable=score,range=[110]
(c) Set the membership function and their type(trimf)for input KLD
Membershipfunction1=Low,range=[0.001 0.143 0.5625]
Membershipfunction2=medium,range=[0.5 2.98 7.6]
Membershipfunction3=high,range=[7.04 19.9 35.58]
(d) Setthemembershipfunctionandtheirtype(trimf)foroutputscore
Membershipfunction1=good,range=[78.510]
Membershipfunction2=average,range=[357]
Membershipfunction3=bad,range=[123]
(e) SettherulesbetweenInput/outputmembershipfunction
R1:ifKLDishighthenscoreisbad
R2: if KLD is medium then score is average
R3: if KLD is low then score isgood

Step7:- Printscore

E. Flowchartfortheproposedmethod





Flow-chart
Figure 7

IV. Testing Methodology And Results Analysis

To evaluate the performance of the new proposed image quality index, we used the popular Tampere Image Database (TID 2008) [16]. This database uses 25 reference images and contains 17 types of degradations with 100 images per distortion (with their associated MOS). Here, we focus only on some common distortions, namely salt & pepper.

We take five original images and their corresponding 20 distorted (salt &pepper) images (Group 2) from Tampere Image Database (TID 2008) and 6 original images and 36 corresponding distorted images Figure 7 (Group 1) for testing the proposed algorithm and trained on our owndatabase.

Figure 8a. Group1 Testing Reference Image

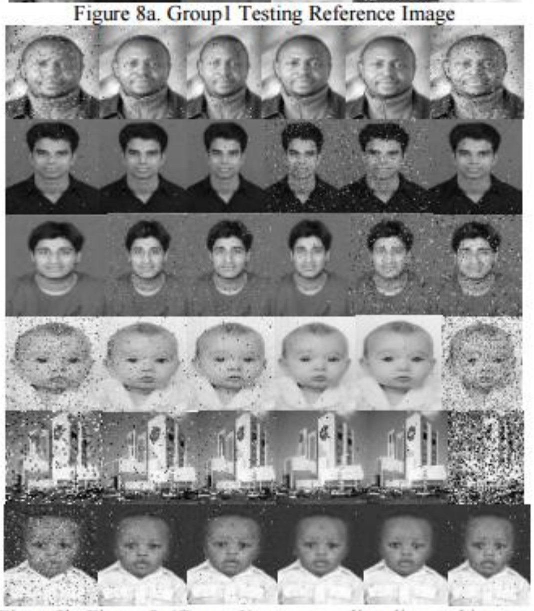


Figure8b. Figure 8a(Group 1) corresponding distorted images

Figure 9a. Group2 Testing Images

Figure 9b. Figure 9a (Group 2) corresponding distorted images

4a. Evaluation of TestResults

We evaluate our obtained result using Pearson's correlation coefficient and the Spearman rank-order correlation coefficient (SROCC).

Table 1.TID 2008 database (group2) and own database (group1):
Pearsoncorrelationsforconsidereddistortion,Salt&pepper

Objective quality to own objectivequality	**Pearson Correlation**	**Pearson Correlation**
	Group 1images (Own database)	Group 2images (TID2008database)
SSIM andS_score	0.8328	0.8097
MSSIM andS_score	0.7331	0.8615
VIF andS_score	0.8092	0.6804
PSNR andS_score	0.8282	0.7412

Table 2.TID 2008 database (group2) and own database (group2):
Spearman rank-order correlation coefficient (SROCC) for considered distortion, Salt & pepper

Objective quality to own objectivequality	**Spearman Correlation**	**Spearman Correlation**
	Group 1 images (Own database)	Group 2images (TID2008database)
SSIM andS_score	0.8649	0.8097
MSSIM andS_score	0.9260	0.8600
VIF andS_score	0.9540	0.9402
PSNR andS_score	0.9466	0.9472

V. Conclusion

We studied the problem of reduced reference image quality assessment by measuring the changes in local entropies between the reference and distorted images. A new thresholding method based on the relative entropy concept (KLD) is presented in this thesis. The idea is to find a threshold value of KLD which partitioned the three interclass (good, average and bad) of distorted of their corresponding reference image. KLD between probability distribution of local entropy is differing with change in noise density of images. We used Type-1 FIS(Fuzzy Inference System) to measure the Quality of a distortedimage.

VI. Future work

In future work we can implement to extract other features of distorted and their corresponding reference images to minimise the overlapping KLD range in Type-1 Fuzzy Inference System(FIS) and also try to develop the type-2 FIS because type2 give the good score than type-1 FIS. A fuzzy logic system (FLS) described using at least one type-2 fuzzy set is called a type-2 FLS. Type-1 FLSs are unable to directly handle rule uncertainties Type-1 FLSs are unable to directly handle rule uncertainties because they use type-1 fuzzy sets that are certain (viz, fully described by single numeric values). On the other hand, type-2 FIS's are useful in circumstances where it is difficult to determine an exact numeric membership function, and there are measurementuncertainties.

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