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Assessment of Image Quality Technics: A Comparative Study

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ABSTRACT— Now days images are used in many other fields. **Image processing** is a method to convert an image into digital form and perform some operations on it, and get an enhanced image or to extract some useful information from image. Quality of an image plays fundamental role to take important decision and therefore, its assessment is essential prior to application. The objective approaches of image quality assessment play an important role for the development of compression standards and various multimedia applications. The Gray Level Co-occurrence Matrix method represents a highly efficient technique of extracting second order statistical texture features and to extract the textural features of an image. GLCM method is proposed to extract the textural features of an image. SSIM method has nice performance in optical image quality assessment. SSIM combines the image gray intensity with textural features to measure the image structural information. These methods are used to predict the visual quality by comparing a distorted image against a reference image. In this paper we are study the different approaches of image quality assessment.

Keywords— Image Quality Assessment, Textural Feature, Grey Level Co-occurrence Matrix , Structural Similarity Index Measure, Fuzzy Set.

INTRODUCTION

The quality of the image is reduced due to the distortions and which type of distortions occurred during the transmission, storing or sharing of images between the devices. Quality measuring is needed for many applications, for example if the designer of a medical device want to decide from which device get the better results so he want to measure the quality of the images from those devices. The blur image can be easily identified by the human eye but it is difficult for the computer. To achieve the quality assessment of any image we used different texture feature of image. The Gray Level Co-occurrence Matrix is adopted to extract the textural features of image [2].There are various method to quantify the visibility of differences between a distorted image and a reference image. Here introduce different complementary framework for quality assessment based on the degradation of structural information [3].

The paper start on discussion in Section II Literature survey has been shown in section II. A discussion on GLCM Feature is presented in section IV. Finally, this papers ends with conclusion.

LITERATURE SURVEY

In this paper, a new Full-Reference (FR) 3D image quality assessment method to measure the distortions between the original and distorted images. The metric has taken into account some properties such as depth component, structure component and gradient component. The performance of the proposed metric is compared with other objective image quality assessment metrics. As a result an efficient 3D image metric that combines the depth information and structure information of images. The algorithm is evaluated on the popular Live Database and is shown to perform extremely well in terms of correlation with human perception [1]. In this paper, presents an application of gray level co-occurrence matrix to extract second order statistical texture features for motion estimation of images. The Four features namely, Angular Second Moment, Correlation, Inverse Difference Moment, and Entropy. Extracting the features of an image by GLCM approach, the image compression time can be greatly reduced in the process of converting RGB to Gray level image when compared to other DWT Techniques, but however DWT is versatile method of compressing video as a whole. These features are useful in motion estimation of videos and in real time pattern recognition applications like Military & Medical Applications [4].In this paper, the textural properties of images provide beneficial information for discrimination purposes, it is appropriate to employ texture based algorithms for feature extraction. The Gray Level Co-occurrence Matrix (GLCM) method represents an extremely efficient technique of extracting second order statistical texture features. This algorithm has been validated using high resolution images and its performance is found to be adequate [5]. In this paper, the patronage of background textural details is especially crucial as they help to define the image structure. By using the GLCM model to extract second-order statistical features for the origination of an image textural measure. Results coincide that our proposed method is feasible and meaningful [6]. In this paper, a novel two stage framework for distortion-accomplished blind image quality assessment based on natural scene statistics. The proposed framework is modular in that it can be extended above the distortion-pool considered here, and each module introduced can be replaced by better-performing in the future. Here describe a 4-distortion demonstration of the proposed framework and show that it performs ambitious with the full-reference peak-signal-to-noise-ratio on the IQA database [7]. In this paper, a new two-step skeleton for no-reference image quality assessment based on natural scene statistics. Once trained, the skeleton does not require any knowledge of the distorting process and the framework is modular in that it can be extended to any number of distortions. Here depict the framework for blind image quality assessment and a version of this framework; the blind image quality index is evaluated on the LIVE image quality assessment database. In this paper, we discussed DIS and demonstrated that each distortion has a unique signature which can be characterized by the use of DIS and used this signature to categorized images into distortion categories. We also described how distortion-aware IQA may be undertaken using DIS [9]. In this paper, presents two feature extraction methods and two decision methods to retrieve images having some segment in them that is like the user input image. The features used are (dispute) variances of gray level co-occurrences and line angle- ratio statistics constituted by a 2-D histogram of angles between two intersecting lines and ratio of mean gray levels inside and outside the (domain expanded) region spanned to automatically construct ground truth image pairs for the relevance and irrelevance classes [10]. In this paper, image mining in the domain such as breast mammograms to categorized and detects the cancerous cells. Mammogram image can be categorized into normal, begin and damning class and to explore the feasibility of data mining approach. The image mining technique with the extraction of implicit knowledge and image with data relationship. The main goals of this method are to apply image mining in the domain such as breast mammograms to categorized and detect the cancerous tissues. Total of 24 features including histogram intensity features and GLCM features are extracted from mammogram image. In this paper, could assist the medical staff and improve the accuracy of detection. The extracted features from trace functional coupled with the GLCM classifier yielded the absolute accuracy of 95% compared to the other classifiers [12]. In this paper, a fuzzy based no-reference image quality assessment system by applying human perception and entropy of images. The proposed approach selects important features to reduce complexity of the system and based on entropy of feature vector the images are split into different clusters. To assign soft class labels to different images, continuous weights are estimated using entropy of mean opinion score (MOS) unlike the previous works where crisp weights were used. The concept of fuzzy relational classifier has been utilized in the paper to develop a no-reference image quality assessment technique of distorted and decompressed images [13].

PROBLEM IDENTIFICATION

As the size of digital information grows exponentially, large volumes of raw data need to be extracted. Nowadays, there are several methods to customize and manipulate data according to our needs. The most common method is to use Image Mining. Image Mining has been used for extracting implicit, legal and potentially useful knowledge from large volumes of raw data .The extracted knowledge must be accurate, readable, perspicuous, and ease of understanding. Image mining has been used in most new inter-disciplinary area such as database, artificial intelligence statistics, visualization, parallel computing and other fields. However, with the emergence of massive image databases, the traditional manual and image based search suffers from the following limitations:

Time Complexity: Manual remarks require too much time and are expensive to implement. As the number of images in a database grows, the difficulty in finding desired images increases. It is not feasible to manually annotate all attributes of the image content for large number of images.

Discrepancy of subjective perception: Manual remarks fail to deal with the discrepancy of subjective realization. The phrase, "an image says more than a thousand words," implies a Content-Based Approach to Image Database Retrieval that the textual characterization is not sufficient for depicting subjective perception. Typically, an image usually contains several objects, which convey specific information. To capture all knowledge, ideas, opinions, and feelings for the content of any images is almost impossible.

Image collection: There might be some problem in the image collection. If the fluorescence condition for each image is given, color balancing may be performed in the pre-processing step, in order to reduce the impact of mismatched color balance between the query and Train Database images.

Feature extraction: Its deal with the problem that it has only some descriptive parameters were chosen to characterize the homogeneity property of images. In the future, many other parameters of expositive statistics can be used. Along with this we can apply dimension reduction on extracted features to compensate the retrieval time as the size of the database is increased.

At last, if the feature identification and extraction can be associated with some knowledge of those retrieve image as a semantic feature, it could significantly improve the precision and recall of the images.

METHODOLOGY

In this section we will describe the method that we will use to extract the aspects of the object the image for quality assessment.

A. GLCM Feature

Gray Level Co-occurrence Matrix is a useful method to extract image texture feature. Which is adopted in this paper. It is the estimation of the conditional probability density function of the two order matrix of image. It studies the gray scale configuration of double pixel combination in an image, which can be understood as the statistical regularity of double pixels in a certain direction and with a certain distance.

The GLCM C_d of SAR image is defined as follows:

C_d[i, j]= |{ I[r, c]| I[r, c]|=i,
I[r+ dr, c+ dc]= j}| (1)

The normalized GLCM is defined as follows:

$$N_d = \frac{C_d[i,j]}{\sum_i \sum_j C_d[i,j]} \quad (2)$$

Various parameters can be calculated from the GLCM to describe the textural features.

The angle second moment:

$$\text{ASM} = \sum_i \sum_j \{N_d[i,j]\}^2 \quad (3)$$

The entropy:

$$\text{ENT} = -\sum_i \sum_j N_d[i,j] log N_d [i,j] \quad (4)$$

The contrast:

$$\text{CON} = \sum_i \sum_j (i-j)^2 N_d[i,j] \quad (5)$$

The homogeneity:

$$\text{HOM} = \sum_i \sum_j \frac{1}{1+(i-j)^2} N_d[i,j] \quad (6)$$

The Variance:

$$\text{VAR} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i-\mu)^2 \quad (7)$$

The Mean:

$$\text{MEAN} = \sum_{i=0}^{2N-2} i P_{x+y}(i) \quad (8)$$

The Dissimilarity:

$$\text{DIS} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i,j)|i-j| \quad (9)$$

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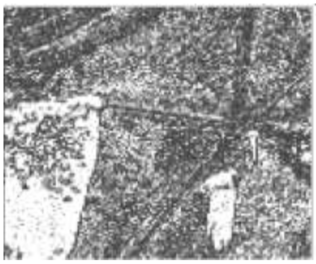
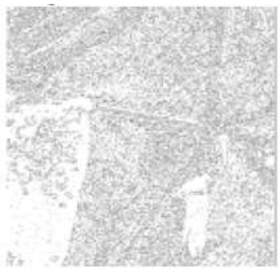
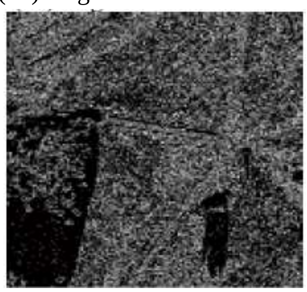
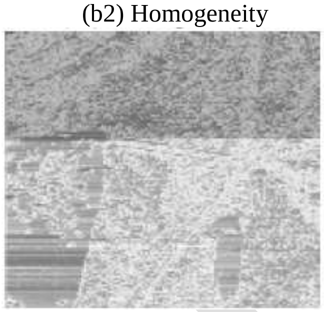
(a) Original Image





(b1) Angle second moment (b2) Homogeneity





(b3) Contrast (b4) Entropy

(b) Textural Images with different Texture Feature

Figure1: Images & Textural Images

Compared with the different textural images, the angle second moment have better performance than another three texture features for reflecting the texture characteristic more clearly. So angle second moment feature is chosen to reflect the image textural information [2].

B. Entropy Feature

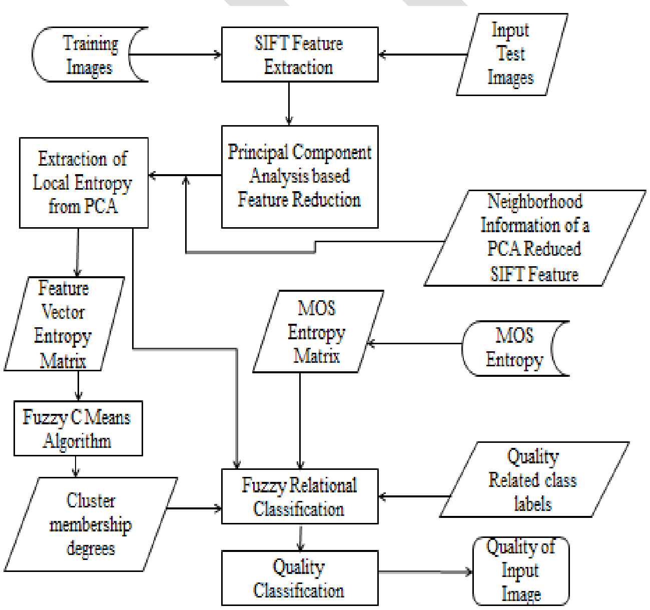


Figure 2: Feature entropy based image quality classification.

Utilizing human sensibility about the visual quality of the images, MOS entropies are computed and classified using algorithm and the following equation:

$X_{ij} = Y_{mi}$ for class j and

$X_{in} = \frac{1-Y_{mi}}{d-1}$ for other classes($n \neq j$)

where m_i is the MOS of i-th image, X_{ij} represents the class membership of i-th image to class j, d is the total number of classes and Y_{mi} stands for Shannon's entropy of image i, defined in the
below equation:

Y_{mi} =-z_{mi} $\log[z]$ where z_{xi}

and N is the total number of images.

Algorithm-1 (classifying MOS entropies)

Input: Five class labels: ''Excellent'', ''Good'', ''Average'', ''Bad'' and ''Poor'' with rank from high to low.

Begin

Step 1. Sort MOS entropy values of images in descending order

Step 2. Compute mean (M) of the Entropy data sets

Step 3. Denote maximum value of the data as Y_{max} and minimum value as Y_{min}.

Step 4. If entropy value of an image >= M and <= Y_{max} then Assign Class label to the image > ''Average'' (i.e. ''Excellent'',''Good'')

Else

Assign Class label to the image <= ''Average'' (i.e. ''Average'',''Bad'', ''Poor'')

Step 5. Set Y_{min}= M and compute new mean (m1) of the data having range Y_{max} to E_{min}

If entropy value of an image >= m1 and <= Y_{max} then Assign Class label to the image > ''Good'' (i.e. ''Excellent'')

Else

Assign Class label to the image <= ''Good'' (i.e. ''Good'' as classification under ''Average'' category is already done)

Step 6. Set Y_{max}=M and repeat step 5 with assignment of the class label of the image being changed to ''Bad''.

Step 7. Repeat step 5 and step 6 until all Entropy values are covered.

End.

C. Dimensionality Reduction Techniques

The calculation of the 7 texture measures for each GLCM will end up in a 24x8 feature vector, which is complicated to handle. A technique to resolve this problem is to use dimensionality reduction techniques. Principal Components Analysis and Linear Discriminant Analysis are the two most popular techniques used for dimensionality reduction. This paper discusses the use of PCA method for reducing the dimension of the feature vector.

Principal Component Analysis:

PCA is applied on this feature vector space, which facilitates in finding a set of the most representative projection vectors so that the projected samples maintains a large amount of information about original samples. An advantage of PCA is that around 90% of the total variance is contained in less than 10% of the dimensions.

D. Segregation of Feature of Interest in Any Image

1. Analysis of Candidate Image:

Having obtained the mean values for all the textural measures with the significant combinations of computational parameters, the next step is to classify the various pixels in the image. A 3x3 window is identified around every pixel in the image. For every window, compute the texture measures viz. energy, homogeneity, contrast, and variance. The texture measures are also evaluated with the specified displacement 1 with an orientation angle of 0_o. To summarize, each pixel will have two sets of texture feature vector that are calculated based on the chosen computational parameters.

2. Comparison with Reference Values:

The texture measures computed for every pixel are compared with their corresponding reference counterparts with a marginal tolerance. Depending on the outcome of the comparison, the pixels are classified as feature or background.

CONCLUSION

In this paper we discussed about the various approaches used to evaluate the quality of an image. The experimental result shows that the GLCM and SSIM methods are simple and are easy to implement. It can be very well observed that the proposed algorithm qualifies very well for identification and extraction of selected features.

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