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# Image Quality Analysis Using Gray Level Co-Occurance Matrix (GLCM)

[1]Ayesha Siddika, [2]Md. Nesar Rahman, [3]Muhammad Shafiqul Islam, [4]MD. Shahajada, [5]Mahbub Ul Alam
[1]*Faculty, Dept. of CSE, World University of Bangladesh(WUB), Bangladesh.*
[2]*Student, Department of ICT, Bangladesh University of Professionals (BUP), Bangladesh*
[3]*Student, Department of ICT, Bangladesh University of Professionals (BUP), Bangladesh*
[4]*Senior Database Engineer, eGeneration Limited, Bangladesh*
[5]*Assistant Vice President, ITS Flora Telecom Limited*
*Corresponding Author: Ayesha Siddika*

*Gray level co-occurrence matrix has proven to be a powerful basis for use in texture classification. Various textural parameters calculated from the gray level co-occurrence matrix help understand the details about the overall image content.*
*The aim of this research is to investigate the use of the gray level co-occurrence matrix technique as an absolute image quality metric. The underlying hypothesis is that image quality can be determined by a comparative process in which a sequence of images is compared to each other to determine the point of diminishing returns. An attempt is made to study whether the curve of image textural features versus image memory sizes can be used to decide the optimal image size. The approach used digitized images that were stored at several levels of compression. GLCM proves to be a good discriminator in studying different images however no such claim can be made for image quality. Hence the search for the best image quality metric continues.*

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## I. Introduction

Images play a crucial role in today's age of succinct information. The field of image processing has exhibited enormous progress over past few decades. Generally, the images dealt in virtual environments or entertainment applications possess high fidelity resulting in large storage requirements. Images may undergo distortions during preliminary acquisition process, compression, restoration, communication or final display. Hence image quality measurement plays a significant role in several image-processing applications. Image quality, for scientific and medical purposes, can be defined in terms of how well desired information can be extracted from the image. An image is said to have acceptable quality if it shows satisfactory usefulness, which means discriminability of image content, and satisfactory naturalness, which means identify ability of image content. Digital storage of images has created an important place in imaging. Image quality metrics are important performance variables for digital imaging systems and are used to measure the visual quality of compressed images. The three major types of quality measurements are:

**Objective quality measurement**

The objective image quality measurement seeks to measure the quality of images algorithmically. A good objective measure reflects the distortion on image due to blurring, noise, compression and sensor inadequacy. Objective analysis involves use of image quality/distortion metrics to automatically perceive image quality; the most widely being used are "Peak Signal-to-noise Ratio PSNR" and "Mean Squared Error MSE". These methods provide mathematical deviations between original and processed images. The analysis depends on the number of images used in the measurement and the nature or type of measurement using the pixel elements of digitized images. Metrics have been defined either in spatial or frequency domain. These measurement techniques are easy to calculate, however they do not consider human visual sensitivities. They do not adequately predict distortion visibility and visual quality for images with large luminance variations or with varying content. It is believed that a combination of numerical and graphical measures may prove useful in judging image quality.

**Subjective quality measurement**

For several years, the image quality assessment (QA) has been performed subjectively using human observers based on their satisfaction. It depends on the type, size, range of images, observer's background and motivation and experimental conditions like lighting, display quality etc. The human visual system (HVS) is enormously complex with optical, synaptic, photochemical and electrical phenomena. The International Telecommunication Union (ITU) has recommended a 5-point scale using the adjectives bad, poor, fair, good and excellent. A numerical category scaling also can be used as an alternative, which is linear and hence more convenient to use. Subjective quality measurement techniques provide numerical values that quantify viewer's satisfaction, however are time-consuming and observer responses may vary. They provide no constructive methods for performance improvement and are difficult to use as a part of design process.

**Perceptual quality measurement**

The perceptual quality measurement techniques are based on models of human visual perception like image discrimination models and task performance based models. Ideally, they should be able to characterize spatial variations in quality across an image. Image quality measures (IQM) are figures of merit used for the evaluation of imaging systems or coding/processing techniques. Image quality measurement is still an unsolved problem today. There are at least two factors, which contribute to difficulty in finding a complete algorithm for image quality measurement. First factor being that there are many different kinds of noises and each can affect the quality of image differently. Secondly it is not simple to mathematically prove the quality of an image without human judgment. Image QA algorithms can as well be classified as "Full-reference" or bivariant, in which the algorithm has access to the perfect image, "No-reference" or univariant, in which the algorithm has access only to the distorted image and "Reduced-reference", in which the algorithm has partial information regarding the perfect image. All algorithms try to map the reconstructed image to some quantity that is positive and zero only when original and modified images are identical and also increases monotonically as the modified image looks worse. It is very useful to be able to automatically assess the quality of images when the number of images to be evaluated is large. Daly's visual difference predictor (VDP) is a popular bivariant tool to assess image quality.

## II. Related Literature Survey

Fuzzy c-means technologies: In this thesis paper Fuzzy c-means technologies include three major processes. The image capture process, feature extraction process and pattern analysis process, BS-88E Beauty Scope sensor is used to provide micro-hair quality images. The sampling location around the check was gently touched by the BS-88E Beauty Scope sensor. The cosmetician's suggestions for the best image quality are to wash the sampling location using water fast and then to wait for 15 minutes before capturing the skin image. By comparing to Gray level Co-occurrence Matrix and wavelet decomposition matrix method it doesn't require beauty sensors, it require skin image obtained from any source of digital camera. The beauty sensor is very costly as it consumes significant time. [1]

Diffusion Polarization: This method deals in this rehearse with detecting regions of damage and disease in the texture of different types of fruit and vegetable images. In this method, moments are used to estimate the components of the polarization image (mean intensity, polarization and phase) from images obtained with multiple polarizer angles. Using the polarization information and Fresnel theory characterization of the surface reflection based on spherical harmonic coefficients will be developed. They used the normalized cut method to segment surfaces into different regions developing on their surface reflectance properties. This method depends on the light variation and polarization but GLCM and WDM methods do not depend on the light and polarization. [2]

Skin feature extraction: It is a statistical method for skin texture analysis. It is only used for spot detection of the skin texture image by using ROI (Region of Interest). Using the Region of Interest they cannot extract the full skin diseases in the texture image. [3] it is one of the main important disadvantages of this method but in the GLCM and WDM methods, We can choose the image in any random pixels value, also we can use spot detection. We can choose any pixel value of the skin texture image and diagnose the disease using the skin texture image. [4]

Bidirectional imaging: It is also known as skin imaging method. This method captures significantly more properties of appearance than standard imaging. The observed of the skin's surface is greatly dependent on the angle of incident illumination and angle of observation. Specific protocols to and used to create the Rutgers Skin Texture database (clinical component). In GLCM and WDM methods, the texture image does not depend on the incident illumination and angle of observation. In case of replacement of this method, they use diffusion polarization method. [5]

Rietveld method: A Rietveld method is described which extracts information on crystal structure, texture and microstructure directly from two-dimensional synchrotron diffraction images. This is advantageous over conventional texture analysis that relies on individual diffraction peaks, particularly for low-symmetry materials with many overlapping peaks and images with a poor peak-to-background ratio. The method is applied to two mineralized biological samples with hydroxyl apatite fabrics: an ossified pachycephalosaurid dinosaur tendon and an Atlantic salmon scale. Both are measured using monochromatic synchrotron X-rays. The dinosaur tendon has very strongly oriented crystals with c-axes parallel to the tendon direction. The salmon scale displays a weak texture.

This research describes two new applications of synchrotron radiation to characterize crystallite orientation in highly heterogeneous biological apatite. A strong hydroxyl apatite. Alignment was confirmed for the dinosaur tendon, a weak texture in the salmon scale. Because of their heterogeneity and weak scattering. [6]

Wavelet Based Image Texture: In this paper Yongsheng Dong and Jinwen Ma proposed an efficient one-nearest neighbor classifier of texture via the contrast of local energy histograms of all the wavelet sub bands between an input texture patch and each sample texture patch in a given training set. They have investigated the supervised texture classification problem by contrasting the local energy histograms of all the wavelet sub-bands between an input texture patch and each sample texture patch in a given training set. The contrast is conducted with a discrepancy measure defined as a sum of the symmetries Kullback – Leibler divergences between the input and sample local energy histograms on all the wavelet sub-bands, and then the one-nearest-neighbor classifier is built [7].
Pros: The method proposed by Yongsheng Dong and Jinwen Ma are satisfactory in classification performance.
Cons: Weak in Classification accuracy.

Filtering Techniques: This paper show, the most major filtering approaches to texture feature extraction and perform a comparative study. Filtering approaches includes, Laws masks, ring/wedge filters, dyadic Gabor filter banks, wavelet transforms, wavelet packets and wavelet frames, quadrature mirror filters, discrete cosine transform, eigen filters, optimized Gabor filters, linear predictors, and optimized finite impulse response filters. These filtering keep the local energy function and the classification algorithm identical for most of the approaches [8]. For reference, comparisons with two classical non-filtering approaches, co-occurrence (statistical) and autoregressive (model based) features, are given. This paper is an attempt to present a ranking of the tested approaches based on extensive experiments.

Pros: The filter optimization approaches is a low feature count, thus many of the optimization schemes yields to computational characteristics.
Cons: The development of powerful texture measures that can be extracted and classified with a low computational complexity.

SVD Based Modeling: This paper introduces a new model for image texture classification based on wavelet transformation and singular value decomposition. The probability density function of the singular values of wavelet transformation coefficients of image textures is modeled as an exponential function. The model parameter of the exponential function is estimated using maximum likelihood estimation technique. Truncation of lower singular values is employed to classify textures in the presence of noise. Kullback-Leibler distance (KLD) between estimated model parameters of image textures is used to perform the classification using minimum distance classifier. The exponential function permits us to have closed-form expression for the estimate of the model parameter and computation of the KLD[9]. These closed-forms of expression reduce the computational complexity of the proposed approach. This Experiment shows, the proposed approach improves recognition rates using a lower number of parameters on large databases. The proposed approach achieves higher recognition rates compared to that of the other approaches like traditional sub-band energy-based approach, the hybrid IMM/SVM approach, and the GGD-based approach.
Pros: It significantly reduces memory space required for storing the features of training texture images. Main aim of employing SVD is to achieve higher recognition rates on larger databases, requiring less computation.
Cons: Statistical and Model-based approaches are more apt only for highly regular deterministic textures.

Linear Regression Model:The wavelet transform is an important multi resolution analysis tool which has already been commonly applied to texture analysis and classification. In this paper, a new approach to texture analysis and classification with the simple linear regression model based on the wavelet transform is presented and its good performance on the classification accuracy is demonstrated in the experiment [10].
Pros: Texture analysis and classification with the simple linear regression model based on the wavelet transform presented good performance on the classification accuracy. This model is natural and effective for more textures.
Cons: The classification rate is extremely affected by the noise. The energy of Gaussian noise spreading over the entire spectrum, affect the frequency channels with small energy, which leads to the sensitivity of the features.

Gaussian Mixtures: Texture classification generally requires the analysis of patterns in local pixel neighborhood. Statistically, the underlying processes are comprehensively described by their joint probability density functions (jPDFs).Framework is applicable to a wide variety of classification problems, such as industrial inspection, making the possible number of classes the more challenging problem[11]. Whereas making classes which leads to the more challenging problem. Achieving the representational-level invariance in the framework. Other plans include replacing the k-NN by its fuzzy counterpart, which has shown to perform well in industrial inspection tasks. Moreover, the investigation of other density estimators within this framework seems worthy. Finally, using unsupervised classification method can be applied to extend the framework.

Pros: Using the oriented difference filters, this framework avoids the quantization errors and its classification performance is applicable. The primary goal of this contribution is to circumvent the curse of dimensionality using GMM-based density estimation; extensions toward such non-linear steps are beyond the scope of this paper.

Cons: Using too low numbers of the decomposition levels may result in the loss of critical texture characteristics.

Dominant Neighborhood Structure: This paper introduce new global texture descriptor that is based on the texture DNS [12]. Texture features are obtained by generating an estimated global map representing the measured intensity. Similarity of any given image pixel and its surrounding neighbors within a certain window. This research, to enhance the classification performance of the proposed method. By increasing the classification accuracy can be explored through using other robust classifiers such as SVM.

Pros: The DNS features are robust to noise and rotation-invariant. The proposed method produces higher classification rates than the method in the case of the Outex database. The obtained classification rate when the method is applied to texture set with large number of classes (CUReT) is excellent and highly comparable to the fused CLBP approach that employs three times in the proposed method's of feature size.

Cons: To enhance the classification performance of the proposed method, increase the classification accuracy can be explored through using other robust classifiers.

Discrete Cosine Transforms: Texture can be considered as a repeating pattern of local variation of pixel intensities. In this texture classification, the goal is to assign an unknown sample image to a set of known texture classes. This paper attempted to classify 3 different types of textures using artificial neural networks and Evolving Fuzzy Neural Network (EFuNN).Compared to ANN, an important advantage of Neuro-fuzzy models is their reasoning ability (if-then rules) of any particular state [13].

Pros: Soft computing model are easy to implement and produce desirable mapping functions by training on the given data set. Choosing suitable parameters for the soft computing models is more or less a trial and error approach.

Cons: Optimal results will depend on the selection parameters.

Color image processing and texture analysis techniques: This paper indicate two color image processing and texture analysis techniques applied to meat images and assessment of error due to the use of JPEG compression at image capture. JPEG error analysis was performed by capturing TIFF and JPEG images, then calculating the RMS difference and applying a calibration between block boundary features and subjective visual JPEG scores. Both scores indicated high JPEG quality. Correction of JPEG blocking error was trialed and found to produce minimal improvement in the RMS difference. The texture analysis meth odds used were singular value decomposition over pixel blocks and complex cell analysis. The block singular values were classified as meat or non- meat by Fisher linear discriminate analysis with the color image processing result used as 'truth.' Using receiver operator characteristic (ROC) analysis, an area under the ROC curve of 0.996 was obtained, Demonstrating good correspondence between the color image processing and the singular values. The complex cell analysis indicated a 'texture angle' expected from human inspection. [14]

Model-based and feature-based methods: Texture analysis plays an important role in the automated visual inspection of texture images to detect their defects. For this purpose, in this paper model-based and feature-based methods are implemented and tested for textile images in a laboratory environment. The methods are compared in terms of their success rates in determining the defects. Because quality control is one of the most important parts in textile industry. [15]

In this paper, various texture analysis methods have been studied for defect inspection of textile fabrics. For each method, the effects of various parameters have been examined. Although many of the methods gave promising results, texture modeling using the 9$^{th}$ orders Markov Random Field model gave the best results. [15]

## III. Proposed Method: Features Based on Co-occurrence Matrix

We compute gray-level co-occurrence image matrices from gray-level images. From these matrices, we extract 2$^{nd}$ order statistical texture features, instead of having these directly from images. The difference between a gray-level image and the corresponding gray-level co-occurrence matrix is that the matrix has equal

number of rows and columns, and it is equal to the number of distinct gray-levels or pixel values in that image. It is a matrix, which describes the frequency of one gray-level appearing in a specified spatial linear relationship with another gray-level within the area of investigation.
Let us consider that an image contains $N$ gray-levels from 0 to $N$–1. Also, consider that $f(m, n)$ is the intensity at sample $m$, line $n$ of the neighborhood, then we can have the following co-occurrence matrix from the gray-level pixel values of the image,

| | | | |
|---|---|---|---|
| 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 |
| 0 | 2 | 2 | 2 |
| 2 | 2 | 3 | 3 |

**Fig. 1:** a 4 by 4 matrix

| $i/j$ | 0 | 1 | 2 | 3 |
|---|---|---|---|---|
| 0 | #(0,0) | #(0,1) | #(0,2) | #(0,3) |
| 1 | #(1,0) | #(1,1) | #(1,2) | #(1,3) |
| 2 | #(2,0) | #(2,1) | #(2,2) | #(2,3) |
| 3 | #(3,0) | #(3,1) | #(3,2) | #(3,3) |

**Fig. 1(a):** The number of co-occurrences of pixel *i* to the neighboring pixel value *j*.

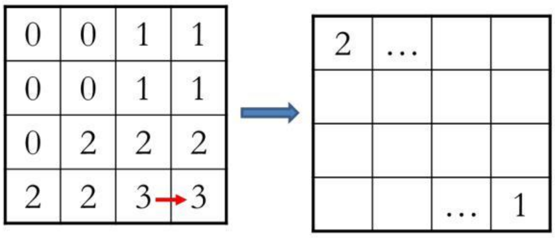


**Fig. 1(b):** Calculation for co-occurrence matrix for horizontal orientation

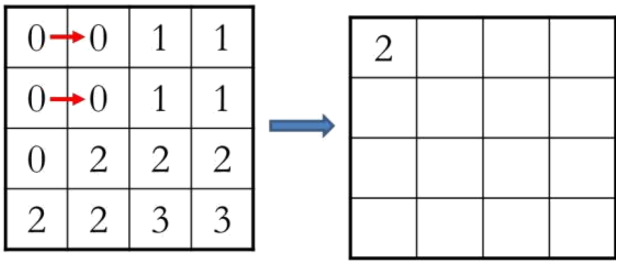


**Fig. 1(c):** Another step for computing the co-occurrence matrix

| | | | |
|---|---|---|---|
| 2 | 2 | 1 | 0 |
| 0 | 2 | 0 | 0 |
| 0 | 0 | 3 | 1 |
| 0 | 0 | 0 | 1 |

**Fig. 1(d):** The co-occurrence matrix for the image in (a)

## IV. Evaluation Features

In this thesis, I target four different features, which are computed from co-occurrence matrix. A number of features are extracted for an image from co-occurrence matrix and different applications exploited a few of these randomly. It is very essential to understand image features and their respective rational and impact on orientation. These features are presented as follows:

**Angular Second Moment (ASM)/ Energy feature**

The Angular Second Moment (ASM) is known as uniformity or energy or uniformity of energy. It measures the uniformity of an image. When pixels are very similar, the ASM value will be large. For an image of single color of no variation, the ASM values for different angles are the Angular Second Moment returns the sum of squared elements in the matrix. It is calculated according to the following equation,

$$\text{Energy} = \sum_{i=0}^{N-1} \sum_{J=0}^{N-1} {p_{ij}}^2 \qquad (1)$$

**Contrast feature**

The contrast is a measure of local intensity or gray-level variations between the reference pixel and its neighbor. In the visual perception of the real-world, contrast is determined by the difference in the color and brightness of the object and other objects within the same field of view. The contrast returns a measure of the intensity contrast between a pixel and its neighbor over the whole image. The contrast is also known as variance and inertia. The contrast is zero when the neighboring pixels have constant values. For example, for an image of single color of no variation, the contrast values for different angles are 0. It is calculated as,

$$\text{Contrast} = \sum_{i=0}^{N-1} \sum_{J=0}^{N-1} (i-j)^2 \, p_{ij} \qquad (2)$$

**Entropy feature**

The entropy is a difficult term to define. The concept comes from thermodynamics; it refers to the quantity of energy that is permanently lost to heat every time a reaction or a physical transformation occurs. The entropy cannot be recovered to do useful work. Because of this, the term can be understood as amount of irremediable chaos or disorder. Hence, in other words, the entropy can measure disorder or complexity of an image. It is a statistical measure of randomness that can be used to characterize the texture of the input image. It is maximal when all elements are equal. The high entropy image has a great contrast from one pixel to its neighbor. Complex textures tend to have high entropy. However, for an image of single color of no variation, the entropy values for different angles are 0. The equation of entropy is:

$$\text{Entropy} = \sum_{i=0}^{N-1} \sum_{J=0}^{N-1} p_{ij} \times \log(p_{ij}) \qquad (3)$$

**Inverse Difference Moment (IDM)/Homogeneity feature**

The Inverse Difference Moment (IDM) is usually called homogeneity that measures the local homogeneity of an image. The IDM feature obtains the measures of the closeness of the distribution of the matrix elements to its diagonal. The IDM is also influenced by the homogeneity of the image. Homogeneity relates to contrast of the texture. It has maximum value when all elements in the image are same. For an image of single color of no variation, the inverse difference moment feature values or different angles are 1. The IDM weight value is the inverse of the Contrast weight, with weights decreasing exponentially away from the diagonal. It provides a strong response at the central locations of the features of interest. The IDM is computed according to the following equation

$$\textbf{Homogeneity} = \sum_{i=0}^{N-1} \sum_{J=0}^{N-1} \frac{1}{1+(i-j)^2} p_{ij} \qquad (4)$$

## V. Experimentation

Earlier literature shows that GLCM textural features are used for category-identification of images representing different content. The various kinds of datasets relevant for analysis may include photomicrographs, aerial photographs of natural or man-made scenes, high altitude satellite pictures.

The primary objectives of the study were as follows:

**Objective 1:** To study if the textural features followed some specific trend as the quality of images increased.

**Objective 2:** To study if the orientation of the overall image content can be used to speculate the most appropriate choice of GLCM angle

This study focuses on digital images representing content ranging from simple text, periodic patterns, natural scenes, plants to human faces. Each dataset was formed by storing an image at five quality levels using jpeg compression technique and maintaining constant pixel resolution. This study is in a way unique from the earlier GLCM research works because it analyses different compressed versions of the same image. Quality level 1 signifies the poorest quality while quality level 5 is the best. The Irfanview application was used for this purpose, which is freely downloadable [Irfa04].

The given dataset comprised of four different images stored at five compression levels. The following table gives the memory sizes of each image:

**Table 1:** Dataset 1

| Image | Quality level 1 | Quality level 2 | Quality level 3 | Quality level 4 | Quality level 5 |
|---|---|---|---|---|---|
| Carpet | 6KB | 7KB | 8KB | 9KB | 13KB |
| (Fig. 2a-2e) | | | | | |
| Plant | 5KB | 6KB | 7KB | 8KB | 11KB |
| (Fig. 3a-3e) | | | | | |
| Water | 5KB | 7KB | 7KB | 8KB | 12KB |
| (Fig. 4a-4e) | | | | | |
| Student Union | 6KB | 7KB | 8KB | 9KB | 12KB |
| (Fig. 5a-5e) | | | | | |

A Sony digital camera DSC-F717, set at pixel resolution of 640x480, was used to take the pictures. Using the Irfanview application, all pictures were resampled at 160x120 sizes for faster computation. The lanczos filter was used for resampling which offers better quality at the cost of higher processing time.

**CARPET Image:**

**Fig. 2a:** Quality level 1

**Fig. 2d:** Quality level 4

**Fig. 2b:** Quality level 2

**Fig. 2e:** Quality level 5

**Fig. 2c:** Quality level 3
**Fig. 2:** Different quality level of carpet images

PLANT Image:

**Fig. 3a:** Quality level 1

**Fig. 3d:** Quality level 4

**Fig. 3b:** Quality level 2

**Fig. 3e:** Quality level 5

**Fig. 3c:** Quality level 3
**Fig. 3:** Different quality level of plant images

**WATER Image:**

**Fig. 4a:** Quality level 1

**Fig. 4d:** Quality level 4

**Fig. 4b:** Quality level 2

**Fig. 4e:** Quality level 5

**Fig. 4c:** Quality level 3

**Fig. 4:** Different quality level of water images

STUDENT UNION Image:

**Fig. 5a:** Quality level 1

**Fig 5d:** Quality level 4

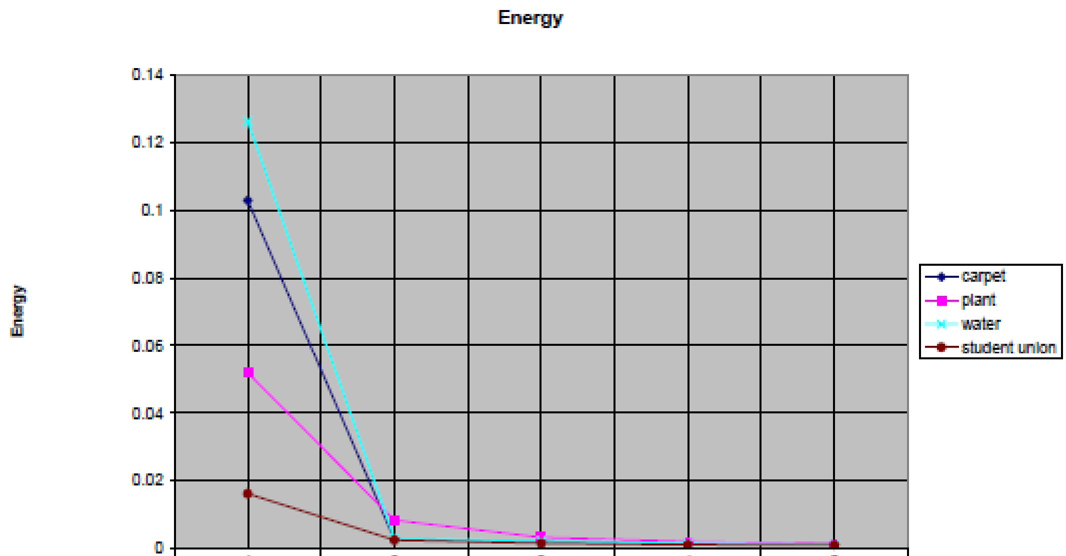
**Fig. 5b:** Quality level 2

**Figure 5e:** Quality level 5

**Figure 5c:** Quality level 3

**Fig. 5:** Different quality level of Student Union images

As discussed in the previous, radius and angle happen to be the crucial parameters for GLCM processing. In this experimentation, the radius was set to 1 and angle was set to 0°, and textural parameters for all the twenty images were calculated. Each run took approximately 2 minutes of processing time. Following plots were obtained for the four images.




| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| carpet | 0.102686 | 0.002737 | 0.002211 | 0.001757 | 0.001476 |
| plant | 0.051969 | 0.008506 | 0.003426 | 0.002214 | 0.001441 |
| water | 0.1262 | 0.003028 | 0.002334 | 0.00177 | 0.001292 |
| student union | 0.016295 | 0.002632 | 0.001708 | 0.001295 | 0.001167 |

Image size

**Fig. 6:** Energy Graph for different types of images

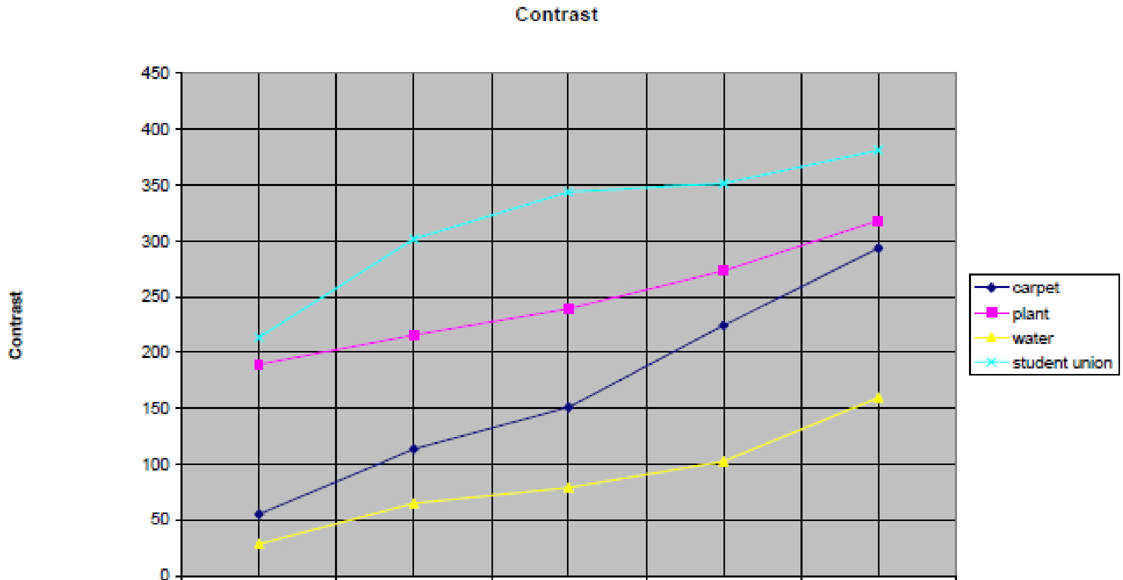
Based on my dataset 1, I find the following graphical result for four different types of image. Where each types of image has 5 different quality levels.

In Fig. 6 we show that energy of image varying according to the size of image.ASM or energy feature measure the uniformity or energy of an image. From the energy graph we show that, energy level is high for smallest size of image.

Here let consider 5 different quality level images of water, we show that for image of Q.L 5 to Q. L 2 their energy level is varying slightly. If we compare Q.L 2 and Q.L 5 we easily distinguish that for image Q. L 5 energy is very less than Q. L 2. Because image of Q.L 5 size is larger than Q. L 2. Now if clarify Q.L 1, we find that its energy level is higher than others image.

Similarly others images energy also decreased from Q.L 1 to Q.L 5. For this graph we also show that every types of images (like carpet, plant, student union, grass and flowers) energy level more high for quality level 1 because of small size and more less for Q. L 5 because of large size.

Now if we compare of each images we can easily find that energy level of water are more than other images. On the other hand images of student union consists lowest energy. So from this above graph we can easily decide that student union is high quality image and water is low quality image than others images.




| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| carpet | 55.09717 | 113.590671 | 150.896855 | 224.319706 | 293.362159 |
| plant | 189.30629 | 215.754194 | 239.403565 | 273.152622 | 318.245075 |
| water | 28.436688 | 64.825681 | 79.04696 | 102.456394 | 159.59371 |
| student union | 213.606395 | 301.669708 | 344.010065 | 351.473272 | 381.208912 |

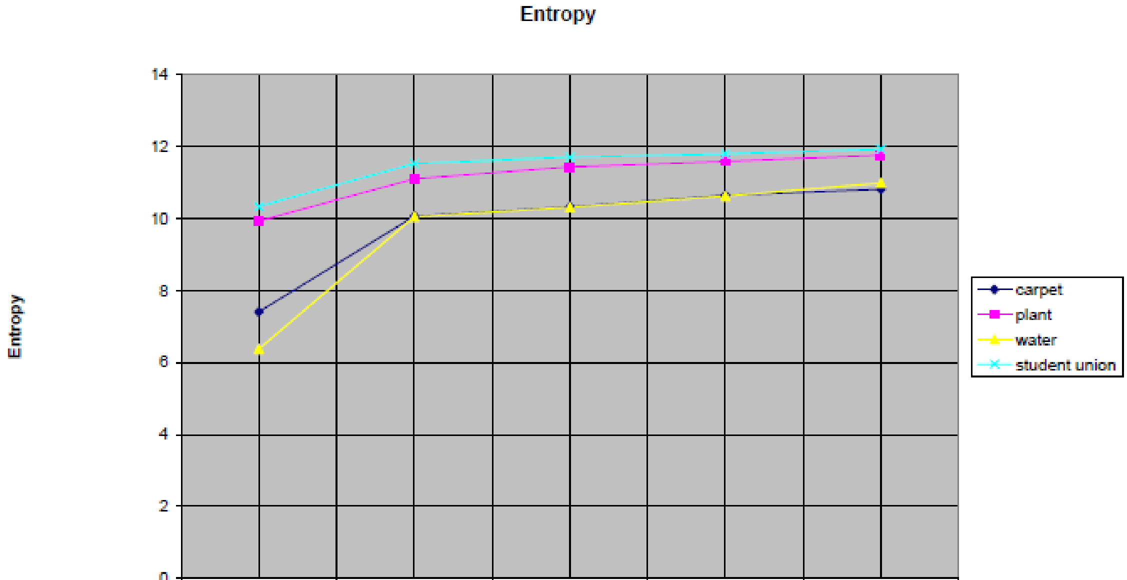
**Fig. 7:** Contrast Graph for different types of images

Based on my dataset 1, if we consider Fig. 7 we show that by this to graph we find contrast of different images. Contrast mainly measure the intensity of a pixel depends on the reference pixel to its nearest pixels over the whole image. If any image is single color then it has no variance and its contrast values of different angles are 0. That means contrast is 0 when the neighboring pixels have constant values. From this two graphs we show that contrast value increased or decreased depend on the image size. When image size is large then contras is high.

In the Fig. 7, if we consider carpet image (with 5 different quality levels) we show that between Q. L 1 to Q.L 3 they have different contrast and contrast increases from Q.L 1 to 3. Q.L 3 is more contrasted than Q.L 1 and Q.L 2. Because Q.L 3 is largest size than other two images. Again if we compare between Q.L 3 to Q.L 5, we easily distinguish that Q. L 5 is more contrasted than Q.L 3 and Q.L 4. Because size of Q.L 5 image is greater than the other images.

Similarly, we find contrast for my different 5 sets of images. Contrast is high when intensity is high and intensity depends on the size of image.

From the above graph, we analyst that student union is more contrasted and water is less contrasted than other images. So we can say that, student union is high quality image and water is low quality image (depend on my data set).




| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| carpet | 7.406133 | 10.069191 | 10.333392 | 10.647961 | 10.815329 |
| plant | 9.933953 | 11.102696 | 11.438641 | 11.591306 | 11.761552 |
| water | 6.375845 | 10.05058 | 10.317378 | 10.627258 | 10.989184 |
| student union | 10.33714 | 11.531338 | 11.70637 | 11.796799 | 11.927477 |

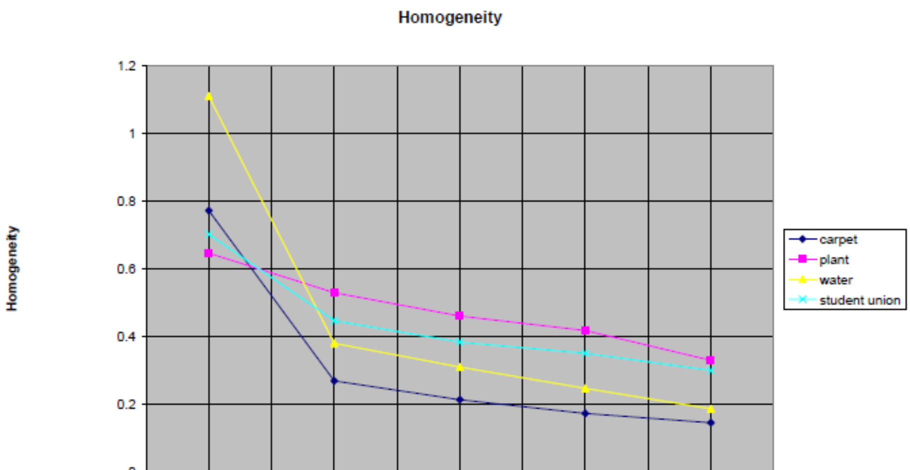
Image size

**Fig. 8:** Entropy Graph for different types of images

If we consider Fig. 8 here show entropy feature. This feature finds the disorder or complexity of image. It is maximal when all elements are equal. The high entropy image has a great contrast from one pixel to its neighbor. Complex texture tends to have high entropy. For a single color image it is 0 in different angle.

From my database 1, if we consider 5 different images of plant we show that entropy increased from Q.L 1 to Q. L 5. If we compare Q. L 1 and Q. L 2 we show that entropy increased rapidly from Q.L 1 to Q.L 2. Because Q.L 2 is more complex or disorder than Q.L 1. If we consider between Q.L 2 to Q.L 5 we show that entropy is varying slightly. Now if we compare 2 and 5, Q.L 5 is more complex than 2 because image of Q.L 5 is larger than Q.L 2 and other also in size.

For the other images of this given dataset we also show that entropy level is increased from Q.L 1 to Q.L 5 depend on the quality of images. From this above graph, we can say that student union consist best quality than other and carpet consist worst quality than other.




| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| carpet | 0.77259 | 0.269093 | 0.213785 | 0.172889 | 0.145548 |
| plant | 0.64665 | 0.529999 | 0.460994 | 0.417791 | 0.329586 |
| water | 1.110717 | 0.380352 | 0.309926 | 0.247085 | 0.186674 |
| student union | 0.702435 | 0.447129 | 0.383845 | 0.351082 | 0.299706 |

Image size

**Fig. 9:** Homogeneity Graph for different types of images

This Fig. 9 show the homogeneity of different images. Homogeneity is a GLCM features that measures the closeness of the distribution of matrix elements to its diagonal. It is the inverse of contrast. If any image is single color then it has no variance of pixel that means variance is 0 and homogeneity is 1.

In this graph, we show that homogeneity is decreased when image size is increased. Homogeneity is inverse of image size. If we consider water in 5 different qualities from Q.L 1 to Q.L 5, we show that homogeneity of Q.L 1 and Q.L 2 is varying rapidly. And homogeneity is decreased from Q.L 1 to Q.L 2 because closeness of diagonal pixels are decreased depend on the size of image and here image size of Q.L 2 is largest than Q.L 1. Now if we consider from Q.L 2 to Q.L 5 we must show that homogeneity is decreased very slightly. And Q.L 5 consist the lower homogeneity than Q.L 2 because here image size of Q.L 5 is largest than Q.L 2.

Similarly decrease homogeneity from Q.L 1 to Q.L 5 depends on their quality size.
For these above graph water consist more homogeneity and plant consist less homogeneity.

## VI. Analysis Result

The analysis showed that energy and homogeneity decrease with increasing image quality, whereas contrast and entropy showed consistent increase with increasing image quality for all of the images. There is no change in the sign of first derivative.

**Table 2:** Analysis of 4 GLCM features

| Radius | Angle | Energy | Contrast | Entropy | Homogeneity |
|---|---|---|---|---|---|
| 1 | 0 | Decrease with increasing image quality | Increase with increasing image quality | Increase with increasing image quality | Decrease with increasing image quality |

## VII. Conclusion

This thesis work attempted to investigate the use of GLCM textural parameters as an image quality metric. The proposed method discussed the relevance of radius and angle which happen to be the most crucial input parameters in GLCM processing. It can be concluded that the most appropriate value of radius for analysis would be one as closely spaced pixels are more likely to be correlated than those which are spaced far away. The radius which must be used in computing the GLCM may be obtained from the autocorrelation function of the image. The radius value at which the normalized autocorrelation function of the image becomes too small can serve as an upper bound on the value which may be used for computing the GLCM. No definite conclusion can be drawn regarding the value of angle. For most of the studies, it might be appropriate to calculate the textural parameters for all the four values of angle and use the average value. Thus GLCM happens to be a good discriminator in studying different images however no such claim can be made for image quality. The analysis of the results shows that the nature of the curve of textural parameter versus image size may not always follow a specific trend for chosen values of radius and angle. Performing exhaustive processing for all possible radius and angle values could be considered as an option and then choosing the most appropriate set of graphs. This however reduces the chances of automating the entire process. Hence the search for the best image quality metric continues.

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