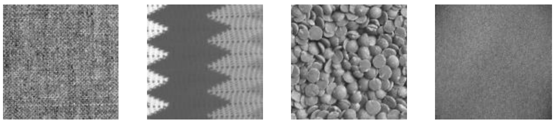
CHAPTER 1

Introduction

1.1 Background and motivation

Texture is one of the most important image characteristics [1-3]. It contains information about a spatial distribution of tonal variation. Tone is the various shades of gray, while texture involves the spatial distribution of gray tones [4]. Both tone and texture have dependent relationship. There are many texture definitions depending on research viewpoints or fields. We can divide the definitions into three groups according to natural, artificial, and mathematical perspectives. From natural perspective, texture is the property of all surfaces that humans may describe it as fineness, coarseness, granulation, or smoothness, and so on as shown in figure 1.1 [5]. In computer vision, texture is recognized as either natural or artificial quantity. Natural texture is found in real life while artificial texture is created by humans as shown in figure 1.2. Moreover, from the mathematical perspective, texture can be described as regular, near regular, irregular, near stochastic, or stochastic as shown in figure 1.3 [6]. Regular textures are composed of a periodic pattern where the color (or intensity) and shape of all elements are evenly repeated. In contrast, stochastic textures consist of a random pattern where the color (or intensity) and shape of all elements are randomly scattered over the image. However, textures are quite easy to identify by humans but they are still hardly described by machines. In addition, texture features are useful in recognition, segmentation, and classification of an object or image. For example, texture features are used to help diagnose abnormalities in medical images, identify bio-information, separate different regions in aerial photography, categorize horticulture, analyze the in-vivo skin, and etc.



Fine Coarse Grained Smooth

Figure 1.1 An example of textures in human observation.

Artificial Natural

Figure 1.2 An example of textures in computer vision.

Regular Near-regular Irregular Near-stochastic Stochastic

Figure 1.3 An example of textures in mathematical perspective.

1.2 Literature reviews

Texture analysis can be divided into four categories [3] including statistical approach, structural approach, signal processing approach, and model based approach. In statistical approach, texture features are computed based on the statistical distribution of image colors (or intensities) at specified relative pixel positions. Texture features can be created from the first-order statistics, second-order or higher-order statistics. An image histogram is an example of the first-order statistical which is simple to compute and has only rotation and translation invariant properties. The second order statistics investigate the relationship between a pair of pixels across the spatial domain of an image. A well-known second order statistical feature is a gray level co-occurrence matrix [4, 7]. The gray level run length [8] and local binary patterns [9] are the higher order statistical features that take the pixel relationships into account by only using the pixel pairs. For structure approach, texture features are described by texture elements and spatial placement rules. Texture elements can be a pixel value, a region with uniform gray levels, or a line segment. The placement rules can be obtained through modelling geometrical relationships between primitives or learning their statistical properties. An example application of structure approach is the texture synthesis [10]. In signal processing approach, filter banks are applied to the images. The texture features can be computed from the energy of the filter responses. Fourier transform, wavelet transform, and gabor filters are examples of the signal processing method. They are widely used in texture analysis such as in [11]. In model based approach, the model based methods include fractal models [12], autoregressive models [13 - 14], random field models [15], and the epitome model [16]. They generally use stochastic and generative models to represent images, with the estimated model parameters as texture features for texture analysis.

This research is focusing only on statistical approaches. The advantage of these texture features are that their computations perform only on a spatial domain. There are many researches using this method. Here, we mainly discuss a previous researches involving the GLCM and the fuzzy co-occurrence matrix.

Julesz [17] used a gray tone spatial dependence co-occurrence statistic in the texture discrimination experiments. The experimental results were summarized from the synthesis textures with different statistical, topological, or heuristic that were generated by the digital computer. The synthesis textures created from a lower order statistical distribution was easier than the one created from the higher order statistical distribution. Then, this proposed method was suitable for micro patterns. On the other hand, a weak discrimination was found on complex texture patterns.

Darling and Joseph [18] used statistics obtained from the nearest neighbor gray tone transition matrix to measure the difference area for satellite images. The experimental results were summarized from the classification of the lunar topographic and the clouds pattern based on the basis of their texture. The pattern recognition process was split into three tasks including preprocessing, features extraction, and classification. The preprocessing phase converts the original images to 8-bit gray scale ones and resizes into a small area by moving average of the initial element field. Then, the feature extraction phase computes the features set which consists of 300 to 400 logic units such as means, brightness variance, and relative frequency of each gray level. Finally, the six algorithms were used to derive decision functions consisting of forced learning, Bayes weights, error correction, iterative design, mean square error, and MADALINE as in classification phase. As a result, it was found that classification accuracy was related to the proportion of the input field filled by important distinguishing characteristics of the texture pattern. The natural textural patterns achieved the highest recognition levels.

Haralick [19] used the gray tone spatial dependence matrix, a function of the angular relationship between the neighboring resolution cells as well as a function of the distance between them, to classify the remotely sensed imagery. There were six sample images per category with nine general categories including scrub, orchard, heavily wooded, urban, sub-urban, lake, marsh, swamp, and railroad yard. The set of features consists of the angular second moment difference (ASMD), the angular second moment inverse difference (ASMID), the angular second moment (ASM), and the correlation between neighboring gray tones (COR). Each of these features is a function of the angle and distance between what we consider to be neighboring resolution cells. In this study, the data sets were divided into 1/8" x 1/8" from the standard 1:20,000, 9" x 9" aerial photography. Furthermore, the 48 features were considered in four angles 0°, 45°, 95°, and 135° at the distance of 1, 3, and 9 resolution cells. The number of features was reduced to 36 features by calculating the mean, range, and mean deviation of each type of features at a given distance over the four angles. As a result, the average classification accuracy was up to 81%. He concluded that his proposed method was able to recognize the micro texture patterns.

Haralick and Shanmugam [20] used numerical features which was calculated from the spatial gray tone dependence matrix to automatically analyze and identify the digitized photomicrographs of the pore structure of reservoir rocks. The set of texture features are the angular second moment (ASM), the correlation between neighboring gray tones (COR), the entropy (ENT), and the contrast (CONT). Before extracting the textural features, the data sets were normalized using equal probability quantization with 16 levels to eliminate the variations in the gray levels which might be resulted from variations in lighting, lens, film, developer, and other processing variables. As a result of linear discriminant function, the identification accuracy of the testing set on the 8 features was 89 percent. The researchers concluded that the proposed textural features were useful for describing the pore grain geometry of natural porous materials. They suggested that it may be possible to increase the recognition accuracy by using additional features and more powerful identification methods.

Haralick et al. [4] suggested a set of 28 textural features for image classification which was easily computed from each of the gray tone spatial dependence matrices. The properties of the features sets were tested on three difference kinds of image data which consist of the photomicrographs of sandstones, the 1:20000 panchromatic aerial photographs, and the Earth Resources Technology Satellite (ERTS) multi-special imagery. The identification accuracy from both the piecewise linear decision rule and the min-max decision rule was 89 percent for the photomicrographs, 82 percent for the aerial photographic imagery, and 83 percent for the satellite imagery. They concluded that the easily computable textural features probably have a general applicability for a wide variety of image classification applications. However, the gray tone normalization on the imagery and the use of features invariant under monotonic gray tone transformation are required since texture is independent of the tone. In additional of this study, the size of sub-images and the distance which should be used in computing the gray tone spatial dependence matrices were necessary to determine.

Haralick [7] reviewed various approaches and models for textural classification including statistical approach, optical transform, digital transform, textural edgeness, structural element, gray tone dependence matrices, run length, and autoregressive models. The textural data patterns were classified as being weak (coarse) or strong (fine). The coarse textural patterns more vary in spatial texture primitive interaction; the fine textural patterns have nonrandom spatial texture primitive relationship. In conclusion, the statistical approach works well for micro-pattern. The pure structure approach seems not to be widely used because it computes on complex primitive patterns. The researcher suggested using histograms of primitive properties and co-occurrence of primitive properties over the pure structural and statistical approaches.

Baraldi and Parmiggiani [21] studied the six statistical gray level co-occurrence matrices features including energy, contrast, variance, correlation, entropy, and inverse difference moment. The information utility of the six textural parameters was tested on an AVHRR image over Antarctica, 512 × 512 pixels in size. The textural pattern definitions were categorized as very high texture (mountains), high/medium texture (sea ice with floes), low texture (clouds) and no texture (continental ice). In conclusion, two parameters, energy and contrast, were most significant to discriminate among different texture surfaces. The energy increases with the frequency of primitive patterns, while the contrast increases with higher contrast values of primitive patterns.

Ong and Khoo [22] studied texture segmentation and classification for texture image using grey level co-occurrence probabilities (GLCP) and Support Vector Machine (SVM) as post-processing. The GLCP is a discrete function that represents joint probability. To reduce the computation time in GLCP feature extraction, the windows size was set to $M \times N$. The purpose of SVM is to map the feature vector into a higher dimensional feature space, and then create a separating hyper plane with maximum gap to group the GLCP. The GLCP feature space provide a quantitative definition on a different texture. SVM helps provide the optimum boundaries, reveal texture patterns, and reduce noise.

Barrera et al. [23] proposed the rotation-invariant texture feature based fuzzy inference system for regions classification that consists of city, sea, and forest in aerial image. The texture features used in this paper are homogeneity, contrast, and entropy, obtained from Circular co-occurrence matrix and Radial co-occurrence matrix, respectively, with 20 × 20 pixels sub-images. After that, these features are used to create the fuzzy rules (Finally, they created 15 fuzzy rules). The experimental results indicated the robust rotation-invariants features for describing the texture information (100% correct for complete images and 82.5% correct for individual region block images).

Tou et al. [24] introduced the reduction of computations for the gray level co-occurrence matrices (GLCM) method by reducing the matrix dimension namely 1-D GLCM. To reduce the GLCM dimension, the certain values of the matrices are combined. Therefore, the 1-D GLCM represents the difference of the gray tones between the pixel pairs. The classification experiments are tested on two data sets, Brodatz texture data set with 32 textures and CAIRO wood dataset with 5 species. The 16 textural features extracted from each 1-D GLCM are contrast, energy, entropy and homogeneity with the given spatial distance of one pixel and four difference directions 0, 45, 90, and 135 degrees. As a result, the recognition rates are 83.01 percent and 81.35 percent for 1-D GLCM and 2-D GLCM, respectively. The conclusion shows that the classification accuracy of 1-D GLCM was quite better than 2-D GLCM but less computations involved.

Chen et al. [25] proposed the 3D gray level Co-occurrence matrix (3D-GLCM) for iris recognition. The main procedures consist of iris preprocessing, iris feature extraction, and iris pattern matching. First, the iris images are scaled to 300×400 pixels and transformed RGB color to HSV color for localization, segmentation and coordinate transformation, and enhancement the region of interest (iris zone). Next, the region of interest of iris images are generated the 3D-GLCM with 0, 45, 90, and 135 degrees. Each 3D-GLCM is projected onto three 2D planes for computing the feature vector by using the modified texture feature equations that consists of contrast, homogeneity, energy, entropy, and correlation. Finally, the similarity of feature vector of training and testing are compared using normalized Euclidean distance. This experimental results showed that the performance of classification rate was 99.65%. Moreover, this proposed method was compared with the 2D-GLCM and non-projection method to indicate the outperformance of the classification.

Benco et al. [26] represented the combination of color information with the one dimensional gray level co-occurrence matrices called 1-D Color Level Co-occurrence Matrices (1D-CLCM). The CLCM computed from the difference color level of pixels pair in 13 directions neighborhoods. Then, the homogeneity was extracted from each of CLCM. The results of content based image retrieval were verified with the data set of 2,600 color images, 20 images for each texture categories, and 128×128 resolution size. Experimental results demonstrated that 1D-CLCM was more efficient compared to one dimensional and original GLCM for color image retrieval.

Although the GLCM is very popular, this method may not cover the uncertainties of the gray level in the image, the ambiguity created by the transform function and the vagueness in the region boundaries. In order to compute the GLCM, the gray level in the image has to be quantized. Furthermore, the texture is independent of the tone. The image with the same texture may be recognized as different kinds of tones in different human perception. Most people could easily say that the texture on the two images is the same even though one image is created with the light and thin tone whereas the other image is created with the dark and heavy tone. This is a common sense that image quantization should be invariant under monotonic gray tones transformations.

However, there are a few works involving with a fuzzy co-occurrence matrix. **Cheng et al**. [27] created the fuzzy co-occurrence matrix from the number of elements in the set of membership function values which are obtained by mapping all of the gray-tone values into the fuzzy domain with the standard S-function. They used it to compute threshold values which are used to segment images. The experimental results shown that the segmentation performs well on a wide variety of images with/without noises.

Jawahar and Ray [28] defined the fuzzy co-occurrence matrix as a two-dimensional frequency distribution of fuzzy gray values. The fuzzy gray values were created from a symmetrical triangular membership function. The s-norm was used in this study. The conclusion showed that the fuzzy statistics had been observed to perform better in representing the spatial gray distribution in a digital image.

Debahis and Sankar [29] considered each gray value in the image as a fuzzy number. The gray levels represented by fuzzy numbers are then used to calculate the gray level fuzzy histogram and fuzzy co-occurrence matrix similar to [28]. However, the author used an adaptive triangular membership function to calculate the fuzzy statistics. Then, they compare the results with the various image segmentation techniques such as crisp histogram, fuzzy histogram, adaptive fuzzy histogram and fuzzy co-occurrence matrices. They concluded that the segmentation which was resulted from a wide variety of images are similar. On the other hand, the qualitative results of image segmentation were suitable for low varies gray tone in primitive pattern.

Audrey et al. [30] proposed the texture classification using fuzzy color co-occurrence matrices. They defined fuzzy color sets of a color image instead of color levels. The membership degree of each fuzzy color set defined by its membership function, i.e., symmetrical Gaussian and triangular using the Euclidean distance between colors. Then, texture was presented by one fuzzy color co-occurrence matrix. They performed classification tests on Outex color texture datasets. This method reached the correct classification rates between 87.59% to 100%. They concluded that when the color information was analyzed, the texture was better described than when the color component levels were considered.

Kamal et al. [31] proposed fuzzy aura matrices to characterize texture images. The authors extended the aura concepts to the fuzzy framework by defining the fuzzy aura sets and aura measures. The fuzzy aura measures can use spatially variant neighborhoods. The membership functions used in this research were Gaussian and triangular. The fuzzy aura measures assumed no restrictions about the neighborhood shape, size, and spatial invariance. The experiments were test on Outex benchmark texture datasets. This method reached the best correct classification rates as 95.88% and 99.56% for gray levels and color levels texture dataset, respectively. They concluded that the fuzzy aura matrices computed with spatially variant neighborhoods often outperform other powerful texture descriptors on both gray levels and color images.

The membership functions in [27 - 31] cases have to be somehow created. This fuzzy-based method has an uncertainty in itself since the shape and the domain of the universe of discourse are not known. The summarized of literature reviews based on fuzzy set theory is shown in table 1.1.

From the ambiguity created by the transform function in a gray levels quantization process, the vagueness in the region boundaries, and the uncertainty of the previous fuzzy co-occurrence matrix, we proposed a new fuzzy co-occurrence matrix by incorporating the fuzzy clustering into GLCM. This method will help to improve the texture analysis since the shape and the density of the universe of discourse are included into the gray levels quantization process depending on fuzzy clustering methods. Both quantized image and membership planes are created at a result of fuzzy clustering.

Table 1.1 The summarized of literature reviews based on fuzzy set theory.

Year	Reference	Method	Membership function	Application
1997	Cheng et al. [27]	Fuzzy homogeneity vector and fuzzy co-occurrence matrix	Standard S-function	Image segmentation
1996	Jawahar and Ray [28]	Fuzzy histogram	Symmetrical triangular (s-norm)	Image analysis
2006	Debahis and Sankar [29]	Fuzzy histogram and fuzzy co-occurrence matrix	Adaptive triangular	Image segmentation
2015	L. Audrey et al. [30]	Fuzzy co-occurrence matrix	Gaussian and triangular	Texture classification
2015	H. Kamal et al. [31]	Fuzzy aura matrix	Gaussian and triangular	Texture classification

1.3 Purpose of the study

To develop a novel fuzzy co-occurrence matrix by incorporating a fuzzy clustering into gray level co-occurrence matrix.

1.4 Research rationale

The proposed fuzzy co-occurrence matrix is aimed at using in computational intelligence. It can allow machines to understand images based on texture features. Images can be interpreted by texture features such as area positioning in satellite photography, the abnormal area in medical diagnosis. Finally, the fuzzy co-occurrence matrix texture features are used in image recognition, segmentation, and classification with a wide variety of images.

1.5 Educational advantages

To obtain a novel fuzzy co-occurrence matrix for texture feature extraction.

1.6 Scope of the study

1.6.1 The gray tones quantization are 4, 8, 16, and 32 levels.

1.6.2 The orientations used to create the fuzzy co-occurrence matrix are 0°, 45°, 90°, and 135°.

1.6.3 The distances used to create the fuzzy co-occurrence matrix are 1, 2, 3, 4, and 5.

1.6.4 The properties of fuzzy co-occurrence matrix will be compared to the traditional GLCM.

1.6.5 The texture data sets are Brodatz, Kylberg, UIUC, and UMD.

1.7 Research methodology

1.7.1 Formulate the research problem.

1.7.2 Study and review related theories and literature

1.7.3 Develop the objectives

1.7.4 Create the research scopes

1.7.5 Design for the solution

1.7.6 Collect the textural data sets

1.7.7 Create an algorithm and develop software

1.7.8 Test and improve the performance of algorithm

1.7.9 Collect experimental results

1.7.10 Discuss, conclude, and prepare a thesis manuscript