International Journal on Recent and Innovation Trends in Computing and Communication
Volume: 3 Issue: 2
ISSN: 2321-8169
724 - 730

A Review of Wavelet Based Fingerprint Image Retrieval

[1] Yashika Birdi, [2] Er.Jagroop Kaur
[1]M.Tech Scholar, University College of Engineering, Punjabi University,
Patiala, Punjab, India.
e-mail: yashika.birdi@gmail.com
[2]Assistant Professor, University College of Engineering, Punjabi University,
Patiala, Punjab, India.
e-mail: jagroop_80@rediff.com

Abstract: A digital image is composed of pixels and information about brightness of image and RGB triples are used to encode color information. Image retrieval problem encountered when searching and retrieving images that is relevant to a user's request from a database. In Content based image retrieval, input goes in the form of an image. In these images, different features are extracted and then the other images from database are retrieved accordingly. Biometric distinguishes the people by their physical or behavioral qualities. Fingerprints are viewed as a standout amongst the most solid for human distinguishment because of their uniqueness and ingenuity.
To retrieve fingerprint images on the basis of their textural features, by using different wavelets. From the input fingerprint image, first of all center point area is selected and then its textural features are extracted and stored in database. When a query image comes then again its center point is selected and then its texture feature are extracted. Then these features are matched for similarity and then resultant image is displayed.

Keywords: *Content Based Image Retrieval, Wavelets, Fingerprints, Feature Extraction, Texture Retrieval.*

*****

I. INTRODUCTION

Today there is continuously increase in digital images collections. Daily large numbers of images are produced, so a proper organization of images is required for fast and better retrieval. For this purposes image retrieval systems are designed. The image search becomes important due to popularity of various image search engines. In the previous decade, more data has been distributed in machine intelligible arrangements. In the then, a great part of the data in more established books, diaries and daily papers has been digitized and made machine intelligible. Enormous files of movies, music, pictures, satellite pictures, books, daily papers, and magazines have been made available for machine clients. Web makes it workable for the human to get to this colossal measure of data. The best test of the World Wide Web is that the more data accessible around a given subject, the more troublesome it is to place precise and applicable data. Most clients recognize what data they require, however are unsure where to discover it. Search engines can encourage the capacity of clients to spot such significant data. Information retrieval is the activity of obtaining information resources relevant to an information need from a collection of information resources. A large collection of images is referred to as image database. An image database is a system where image data are integrated and stored [1]. Image data include the raw images and information extracted from images by automated or computer assisted image analysis. An image retrieval problem is the problem encountered when searching and retrieving images that are relevant to a user's request from a database. To solve this problem, text-based and content-based are the two techniques adopted for search and retrieval in an image database. In text-based retrieval, images are indexed using keywords, subject headings, or classification codes, which in turn are used as retrieval keys during search and retrieval [2]. Textual information about images can be easily searched using existing technology, but requires humans to personally describe every image in the database. This is impractical for very large databases, or for images that are generated automatically, e.g. from surveillance cameras. It is also possible to miss images that use different synonyms in their descriptions. Systems based on categorizing images in semantic classes like "cat" as a subclass of "animal" avoid this problem, but still face the same scaling issues [3].

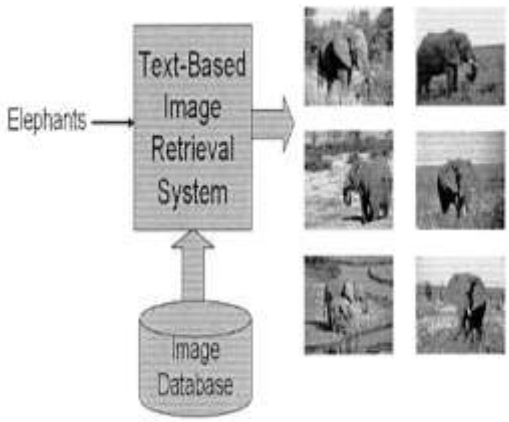

Figure 1.1: Text Based Image Retrieval

In different machine vision applications broadly utilized is the methodology of recovering sought pictures from a vast accumulation on the premise of features that can be consequently removed from the pictures themselves. These frameworks called CBIR (Content- Based Image Retrieval) have gotten escalated consideration in the writing of picture data retrieval since this field was begun years back, and subsequently an expansive scope of procedures has been proposed. The algorithms used in these systems are commonly divided into three tasks:

- Extraction
- Selection
- Classification

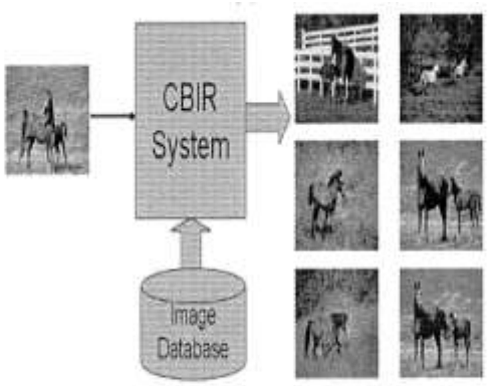

Figure 1.2: Content Based Image Retrieval

II. FEATURE EXTRACTION

Feature extraction is a means of extracting compact but semantically valuable information from images. This information is used as a signature for the image. Similar images should have similar signatures. If we look at the image shown in Figure 2.1, the white color and the texture of the building are characteristic properties. In a similar way, the sky can be described by its blue color. Furthermore, we can take the size of the objects in the image into account.

Figure 2.1 Example image for feature extraction

Representation of images needs to consider which features are most useful for representing the contents of images and which approaches can effectively code the attributes of the images. Feature extraction of the image in the database is typically conducted off-line so computation complexity is not a significant issue. This section introduces three features: texture, shape, and color, which are used most often to extract the features of an image.

- **Color**

  One of the most important features visually recognized by humans in images is color. Humans tend to distinguish images based mostly on color features. Because of this, color features are the most widely used in CBIR systems and the most studied in literature. Color is a powerful descriptor that simplifies object identification, and is one of the most frequently used visual features for content-based image retrieval. To extract the color features from the content of an image, a proper color space and an effective color descriptor have to be determined. The purpose of a color space is to facilitate the specification of colors. Each color in the color space is a single point represented in a coordinate system. Several color spaces, such as RGB, HSV, CIE L*a*b, and CIE L*u*v, have been developed for different purposes [4]. Although there is no agreement on which color space is the best for CBIR, an appropriate color system is required to ensure perceptual uniformity. Therefore, the RGB color space, a widely used system for representing color images, is not suitable for CBIR because it is a perceptually non-uniform and device-dependent system [5]. The most frequently used technique is to convert color representations from the RGB color space to the HSV, CIE L*u*v, or CIE L*a*b color spaces with perceptual uniformity. The HSV color space is an intuitive system, which describes a specific color by its hue, saturation, and brightness values. This color system is very useful in interactive color selection and manipulation. The CIE L*u*v and CIE L*a*b color spaces are both perceptually uniform systems, which provide easy use of similarity metrics for comparing color [6].

  After selecting a color space, an effective color descriptor should be developed in order to represent the color of the global or regional areas. Several color descriptors have been developed from various representation schemes, such as color histograms, color moments, color edge, color texture, and color correlograms.

- **Color Histogram**

  The most usually utilized strategy to speak to color feature of an image is the color histogram. A color histogram is a kind of structured presentation, where the tallness of each one bar speaks to a measure of specific color of the color space being utilized as a part of the image [4]. The number of receptacles relies on upon the quantity of colors there are in an image. The quantity of pixels in each one receptacle indicates y-hub, which demonstrates what number of pixels in an image is of a specific color. The color histogram cannot just effortlessly portray the worldwide and territorial appropriation of colors in an image, additionally be invariant to revolution about the perspective pivot.

ISSN: 2321-8169
724 - 730

- **Texture**

In the field of machine vision and image transforming, there is no obvious meaning of surface. This is on account of accessible composition definitions are based on surface examination systems and the features separated from the image. Be that as it may, composition can be considered rehashed examples of pixels over a spatial space, of which the expansion of commotion to the designs and their reiteration frequencies brings about compositions that can seem, by all accounts, to be arbitrary furthermore unstructured. Properties of homogeneity that don't come about because of the vicinity of just a solitary color or power. The diverse composition properties as saw by the human eye may be, for case, consistency, directionality, smoothness, and coarseness.

In real world scenes, texture perception can be far more complicated. Image textures have useful applications in image processing and computer vision. They include: recognition of image regions using texture properties, known as texture classification, recognition of texture boundaries using texture properties, known as texture segmentation, texture synthesis, and generation of texture images from known texture models.

Since there is no accepted mathematical definition for texture, many different methods for computing texture features have been proposed over the years. Unfortunately, there is still no single method that works best with all types of textures. According to Manjunath and Ma [7], the commonly used methods for texture feature description are statistical, model-based, and transform-based methods.

- **Shape**

One of the regular utilized features as a part of CBIR frameworks is the shape. State of an item is the trademark surface arrangement as spoke to by the layout or shape. Shape distinguishment is one of the modes through which human impression of the nature's turf is executed. It is essential in CBIR in light of the fact that it compares to district of diversions in images. They are boundary-based and region-based [8].

In region based techniques, all the pixels within a shape are taken into account to obtain the shape representation. Common region based methods use moment descriptors to describe shape [9]. Region moment representations interpret a normalized gray level image function as a probability density of a 2-D random variable.

III. TEXTURE ANALYSIS

This provides an introduction to texture. Following three different types of texture attributes are presented: spatial, frequency, and moment-based attributes.

- **Introduction to Texture**

Although no formal definition to texture exists, there are several of intuitive properties of texture, which are generally assumed to be true. Texture is a property of area, and therefore, its definition must involve gray values in a spatial neighborhood. The size of the neighborhood depends on the texture type, or the size of the primitives defining the texture. Texture involves also the spatial distribution of gray levels and therefore two-dimensional histograms or co-occurrence matrices are reasonable texture analysis tools. There are several properties, such as coarseness, contrast, and directionality, which play an important role in describing texture. Coarseness measures texture scale (average size of regions that have the same intensity), contrast measure vividness of the texture (depends on the variance of the gray-level histogram), and directionality gives the eventual main direction of the image texture. Texture analysis is important, since texture is useful in various applications such as automated inspection, medical image processing, remote sensing, defect detection and, similarity evaluation.

- **Texture Attributes**
- **Spatial Methods**
- **Co-occurrence matrix**

Gray level co-occurrence matrix (GLCM), originally introduced by Haralick [10] estimates image properties related to second-order statistics taking into account the spatial arrangement of gray-level primitives. Each entry (i,j) in GLCM corresponds to the number of occurrences of the pair of gray levels i and j which are a distance **d** apart in original image. Well-known statistics of the co-occurrence probabilities have been used to characterize properties of a textured region.

- **Auto-correlation function**

An important property of many textures is the repetitive nature of the placement of texture elements. The auto-correlation function of an image can be used to assess the amount of regularity as well as the fineness and coarseness of the texture. If the texture is coarse, then the auto-correlation function will drop slowly with distance; otherwise it will drop very rapidly. Formally, the autocorrelation function of an image I(x,y) is defined as follows [11]:

$$\rho(x,y)=\frac{\sum_{u=0}^{M}\sum_{v=0}^{N}I(u,v)I(u+x,V+y)}{\sum_{u=0}^{M}\sum_{v=0}^{N}I^2(u,v)} \tag{2.1}$$

ISSN: 2321-8169
724 - 730

Where *x*, *y* is the position difference in *u*, *v* direction, and *M*, *N* are the image dimensions.

- **Fractal dimension**

The fractal dimension gives a measure of the roughness of a surface. First we define a deterministic fractal in order to introduce some of the fundamental concepts. Self-similarity across scales in fractal geometry is a crucial concept. A deterministic fractal is defined using this concept as follows. If *A* is a bounded set in an Euclidean n-space, the set *A* is said to self-similar when *A* is the union of *N* distinct copies of itself, each of which have been scaled down by a ratio of *r*. The fractal dimension *D* is related to the number *N* and the ratio of *r* as follows:

$$D = \frac{\log N}{\log(1/r)} \qquad (2.2)$$

- **Frequency-based methods**
- **Power spectrum**

For the frequency-based approach a good solution is to partition the image into a set of non-overlapping *nxn* blocks and compute the power spectrum separately for each block. Maxima of the spectrum can be used as parameters for modeling texture properties. Each periodical pattern in the original spatial domain is represented by a peak in the power spectrum. Respectively, images including non-periodical or random patterns have a power spectrum in which peaks are not easy to detect.

- **Wavelet transform**

Gabor wavelet decomposition enables simultaneous localization of energy in both spatial and frequency domains. This localization has been shown to be optimal in the sense of minimizing the joint two-dimensional uncertainty in space and frequency.

- **Moment-based methods**

This introduces moment-based texture attributes. First the feature extraction for textured images using moments is explained. Then two sets of orthogonal moments, Zernike moments and Fourier-Mellon moments are described.

- **Texture feature extraction using moments**

In the moment-based method the texture features are obtained directly from the gray-level image f(x,y) by computing the moments of the image in local regions. The (p+q)th order moments of a function of two variables f(x,y). Let (i,j) be the pixel coordinates for which the moments are computed. Given a window width *W*, the coordinates are normalized to the range [-1, 1] and the normalized coordinates (xm, yn) are given by:

$$x_m = \frac{m-i}{W/2}, \quad y_n = \frac{n-j}{W/2} \qquad (2.3)$$

- **Co-occurrence matrix**

Gray level co-occurrence matrix (GLCM) [10], one of the most known texture analysis methods, estimates image properties related to second-order statistics. Each entry (*i*,*j*) in GLCM corresponds to the number of occurrences of the pair of gray levels *i* and *j* which are a distance **d** apart in original image.

Energy, also called Angular Second Moment and Uniformity, is a measure of textural uniformity of an image. Energy reaches its highest value when gray level distribution has either a constant or a periodic form. A homogenous image contains very few dominant gray tone transitions, and therefore, the **P** matrix for this image will have fewer entries of larger magnitude resulting in large value for the energy feature. In contrast, if the **P** matrix contains a large number of small entries, the energy feature will have smaller value. Entropy measures the disorder of an image and it achieves its largest value when all elements in **P** matrix are equal. When the image is not texturally uniform many GLCM elements have very small values, which imply that entropy is very large. Therefore, entropy is inversely proportional to GLCM energy. Contrast is a difference moment of the **P** matrix and it measures the amount of local variations in an image. Inverse difference moment measures image homogeneity. This parameter achieves its largest value when most of the occurrences in GLCM are concentrated near the main diagonal.

Energy	$\sum_i \sum_j P_d^2(i,j)$
Entropy	$\sum_i \sum_j P_d(i,j) \log P_d(i,j)$
Contrast	$\sum_i \sum_j (i-j)^2 P_d(i,j)$
Inverse Difference Moment	$\sum_i \sum_j \frac{P_d(i,j)}{\lvert i-j \rvert^2}, i \neq j$

Table 1: Features extracted from Gray Level Co-occurrence Matrix

- **Gabor Filters**

The human visual framework investigates the textural images by deteriorating the image into various sifted images, each of which contains power varieties over a tight scope of recurrence and introduction. In this way, the multi-channel separating methodology is naturally engaging, in light of the fact that it permits us to adventure contrasts in prevailing sizes and introductions in texture. Gabor channels have been utilized as a part of a few image examination applications including texture segmentation, defect detection, face recognition, motion tracking, and image retrieval.

Gabor function

The Gabor function is a complex exponential modulated by a Gaussian function. In its general form, the 2D Gabor function *g(x,y)* and its Fourier transform *G(u,v)* can be written as [12]:

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left[\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right]\right]\exp(2\pi jWx) \quad (2.4)$$

$$G(u,v) = \exp\left\{-\frac{1}{2}\left[\frac{(u-w)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}\right]\right\} \quad (2.5)$$

where *W* denotes the radial frequency of the Gabor function. The space constants σ_x and σ_y define the Gaussian envelope along the *x* and *y* axes.

- **Feature Representation**

The following feature representation is used in Netra image retrieval system [7]. Given an image *I(x,y)*, its Gabor wavelet transform is then defined to be:

$$W_{mn}(x,y) = \int I(x_1,y_1)g_{mn}*(x-x_1,y-y_1)dx_1dy_1 \quad (2.6)$$

where * indicates the complex conjugate. Assuming that the local texture regions are spatially homogeneous, and the mean μ_{mn} and the standard deviation σ_{mn} of the magnitude of the transform coefficients are used to represent the region for retrieval purposes.

$$\mu_{mn} = \iint |W_{mn}(x,y)dxdy|, and \;\; \sigma_{mn} = \sqrt{\iint (|W_{mn}(x,y)| - \mu_{mn})^2 dxdy} \quad (2.7)$$

A feature vector can be constructed using μ_{mn} and σ_{mn} as feature components.

IV. USAGE OF TEXTURE FEATURE IN BIOMETRICS

Biometrics, which alludes to the programmed distinguishment of people by their physical and/or behavioral qualities, has developed as an issue and actuating exploration field [13]. Actually, a few biometric applications have been received in non military personnel, business, and measurable regions. Customarily, the physical attributes utilized for human distinguishment incorporate among all these biometric qualities, fingerprints are viewed as a standout amongst the most solid for human distinguishment because of their uniqueness and ingenuity [14]. The finger impression's singularity implies that it is exceptional crosswise over people and over. Then again, the unique mark's ingenuity implies that the fundamental finger impression qualities don't change with time. The prevalence of finger impression based distinguishment has prompted the production of extensive scale databases. While the vast size of these accumulations bargains the retrieval speed, the clamor and the contortion that can be found in unique mark images might decrease the general retrieval exactness. Subsequently, both retrieval precision and rate assume an imperative part in the unique finger impression distinguishment process.

The fame of unique finger impression based distinguishment has prompted the production of vast scale databases. While the substantial size of these accumulations bargains the retrieval speed, the commotion and the twisting that can be found in unique finger impression images might decrease the general retrieval precision. Thusly, both retrieval exactness and rate assume an imperative part in the unique mark distinguishment process.

Programmed unique mark distinguishment frequently includes four steps:

- Acquisition
- Classification
- Identification
- Verification.

Unique finger impression obtaining alludes to the catch and representation of fingerprints. Unique mark grouping comprises in appointing an unique finger impression to a predefined class, while unique mark distinguishing proof is alluded to the retrieval of fingerprints that relates to a given unique finger impression question image (one-to-numerous examinations). At long last, unique finger impression confirmation is utilized to figure out if two unique finger impression images are the same or not (balanced examinations). Nonetheless, considering the huge size of the finger impression image databases and the computational expense of unique mark confirmation calculations, it is important to decrease the quantity of coordinated examinations amid finger impression check, looking for upgrades both in precision and retrieval velocity.

The textural examples that can be found in the focal area of fingerprints so as to create textural feature vectors utilized for unique finger impression indexing and retrieval. For that reason, we misuse the ability of distinctive sorts of well-known wavelet changes to incorporate both multiresolution and space-recurrence properties in a characteristic way. The unique finger impression images are then decayed into distinctive spatial/recurrence sub images and some measurable investigations unique finger impression inquiry image and the database images.

The texture features are extracted by different types of the wavelet transforms which include steerable wavelet, Gabor Wavelet Transform, Tree-Structured Wavelet Decomposition using orthogonal filter bank, and Tree-Structured Wavelet Decomposition using bi-orthogonal filter bank.

The most widely recognized approach to diminish the quantity of one-to-numerous correlations, amid finger impression recovery, is to parcel the database utilizing unique finger impression characterization systems which can be separated into two fundamental classifications: restrictive and constant characterization. The previous uses data identified with the example of edges and valleys found in fingerprints to segment the unique mark database into common selective canisters. In this sense, once the unique mark inquiry picture is grouped, the picture hopefuls are looked in the comparing canister. Further, this sort of methodology can be subdivided into four subcategories relying upon the kind of data utilized for select grouping, specifically, edge, introduction field, peculiarity, and structural-based data. In persistent characterization methodologies, unique finger impression pictures are spoken to by feature vectors. Similitude among unique mark pictures are created by the separation in the gimmick space of their comparing peculiarity vectors. This methodology is nearly identified with a finger impression database indexing issue. Edge based methodologies customarily utilize the data of the structure recurrence of the unique finger impression edges for arrangement purposes. [15] Considers the recurrence range of fingerprints, A wedge-ring indicator is utilized to parcel the recurrence area pictures into non-covering zones in which the pixel qualities are summed up to structure a feature vector. When the peculiarity vector is discovered, it is contrasted with the reference characteristic vectors of each of the classes and a further order is performed by utilizing a closest neighbor arrangement system. To catch the structure of finger impression edges, a few works create numerical models to describe the comparing pictures [16]. Chong et al. [17], for instance, B-splines bends to rough the state of the unique finger impression edges. At that point, comparative introduction edges are assembled together to get a worldwide shape representation of the fingerprints which is utilized for characterization.

Methodologies based on introduction fields utilize the neighborhood normal introductions of fingerprint edges to arrange fingerprints. [18] Utilize the square introduction fields of fingerprints and assurance measures to create the fingerprint feature vectors. For the purpose of feature dimensionality lessening, they consider a SOM neuronal system to enhance the generally speaking characterization precision.

Fingerprint singularities have been generally utilized for arrangement [19]. They can be characterized as the nearby districts where the fingerprint edges display some physical properties. Karu et al. [20] fingerprints to group them by considering the area and the quantity of the caught singularities.

Structural methodologies utilize the topology data of fingerprints for grouping purposes. Maio et al. [21] fragment a social chart model is made. A vague chart matching calculation is utilized to characterize fingerprint images.

Despite the fact that the pursuit spaces can be lessened in restrictive order approaches, there are a few inadequacies that should be viewed as: (1) a few fingerprints present properties of more than one class and subsequently they can't be allotted to only one receptacle, (2) regular appropriation of fingerprints is not uniform and in this manner, even by performing binning in the first database, the quantity of one-to-numerous examinations can at present be high – Cappelli et al. [22] demonstrated that the appropriation of utilized for binning are not simple to catch because of the vicinity of clamor, surrounding conditions, and so on.

Tan et al [23] analyzed two fingerprint ID methodologies based on: (a) characterization emulated by confirmation, and (b) indexing took after by check. Their characterization technique utilizes hereditary programming to produce composite administrators connected to a few features extricated from the fingerprint introduction fields. A Bayesian classifier is used to order the images. In any case, as issue of the retrieval process, a rundown of N fingerprint applicants is recovered and the confirmation methodology decides the correspondence. They presumed that the indexing-based methodology beats the arrangement strategy in the event that we consider the measure of the hunt spaces.

The above mentioned approaches reduce the search spaces by considering some fingerprint singularities [24]. Furthermore, the accurate detection of these singularities depends highly on the quality of the fingerprint images. Moreover, their definition often involves high computational costs that will affect directly the fingerprint recognition time. On the other hand, they both consider flash hashing for

 ISSN: 2321-8169
724 - 730

indexing purposes and we believe that by using metric access methods the query processing time can be improved. In this work, we will consider more specifically the textural information presented in fingerprints for feature extraction purposes, since it retains the discriminating power of fingerprints and can be directly associated to Metric Access Methods (MAM) for the data indexing.

V. CONCLUSION

The texture patterns that can be found in central region of fingerprints are studied which are used to generate textual feature vectors used for fingerprint indexing and retrieval. For that different types of well known wavelets are studied which are used to integrate both multi resolution and space frequency properties.The future work for the study is to implement the proposed system in order to illustrate the utility and suitability for applying different types of wavelets for fingerprints indexing and retrieval.

Further, the retrieval effectiveness of different image descriptors will be compared by analyzing the results in terms of precisions and recall curves. The future work also includes the use of more realistic fingerprints image databases. Further, the images will reflect real acquisition conditions. In the sense that images present abnormal distortions, including noise, significant rotations and translations.

VI. REFERENCES

[1] H. Tamura, and N. Yokoya, “Image Database Systems: A Survey,” Pattern Recognition, vol. 17, no 1, pp.29–49, Sep. 1984.

[2] S. Gerard, C. Buckely, “Term-Weighting Approaches in Automatic Text Retrieval,”Information Processing and Management, vol. 24, no.5, pp. 513-523, Jan. 1988.

[3] Y. Chen, J. Wang, “Image Categorization by Learning and Reasoning with Regions,” Journal of Machine Learning Research, vol. 5, pp. 913–939, May 2004.

[4] R. Gonzales, R. E. Woods, “Digital Image Processing,” 2nd Ed., New Jersey Prentice Hall, 2002

[5] T. Gevers and A. Smeulders, “Pictoseek: Combining color and shape invariant features for image retrieval,” IEEE Trans. Image Processing, vol. 9, no. 1, pp.102–119, Nov. 2000.

[6] Y. Haeghen,, J. Naeyaert, I. Lemahieu, and W. Philips, “An imaging system with calibrated color image acquisition for use in dermatology," IEEE Transaction on Medical Imaging, vol. 19, no. 7, pp. 722-730, June 2000

[7] B. Manjunath and W. Ma, “Texture features for Browsing and retrieval of image data,” IEEE transactions on pattern analysis and machine intelligence, vol. 18. No. 8, pp. 837-842, August 1996

[8] R. Datta, J. Li, and J. Wang, “Content-based image retrieval - approaches and trends of the new age,” ACM Computing Surveys, vol. 40, no. 2, Article 5, pp. 1-60 April 2008.

[9] C. Teh and T. Roland, “On image analysis by the methods of moments,” IEEE Trans. On Pattern Analysis and Machine Intelligence, vol. 10, no. 4, pp. 496-513, 1988.

[10] R.M. Haralick, K.Shanmugam, and I. Dinstein, “Textural Features for Image Classification”, *IEEE Trans. on Systems, Man and Cybernetics*, vol. SMC-3, no. 6, November 1973, pp. 610-621.

[11] M. Tuceryan, and A.K. Jain, *The Handbook of Pattern Recognition and Computer Vision (2nd Edition)*, by C.H. Chen, L.F. Pau, and P.S.P Wang (eds.), pp. 207-248, World Scientific Publishing Co., 1998

[12] A. Kumar, and K.H. Pang, “Defect Detection in Textured Materials using Gabor Filters”, *IEEE Transactions on Industry Applications*, vol. 38, no. 2, pp. 425-440, March/April 2002.

[13] A.K. Jain, A. Ross, S. Prabhakar, An introduction to biometric recognition, IEEE Transactions on Circuits and Systems for Video Technology 14 (1) (2004) 4–20.

[14] S. Pankanti, S. Prabhakar, A.K. Jain, On the individuality of fingerprints, IEEE Transactions on Pattern Analysis and Machine Intelligence 24 (8) (2002) 1010–1025.

[15] Fitz,Green, Fingerprint classification using a hexagonal fast fourier transform, Pattern Recognition 29 (10) (1996) 1587–1597.

[16] A.K. Jain, S. Minut, Hierarchical kernel fitting for fingerprint classification and alignment, ICPR 2 (2002) 469–473.

[17] Chong,Ngee,Jun,Gay, Geometric framework for fingerprint image classification, Pattern Recognition 30 (9) (1997) 1475–1488.

[18] Halici,Ongun, Fingerprint classification through self-organizing feature maps modified to treat uncertainties, Proceedings of the IEEE 84 (10) (1996) 1497–1512.

[19] L. Hong, A.K. Jain, Classification of fingerprint images, in: 11th Scandinavian Conference on Image Analysis, Kangerlussuaq, Greenland, 7–11 June, 1999.

[20] K. Karu, A.K. Jain, Fingerprint classification, Pattern Recognition 29 (3) (1999) 223–231

[21] D. Maio, D. Maltoni, A structural approach to fingerprint classification, in: ICPR ’96: Proceedings of the International Conference on Pattern Recognition, ICPR ’96, IEEE Computer Society, Washington, DC, USA, 1996, pp. 578–585. Volume III-Volume 7276.

[22] R. Cappelli, D. Maio, D. Maltoni, L. Nanni, A two-stage fingerprint classification system, in: WBMA ’03: Proceedings of the 2003 ACM SIGMM workshop on Biometrics methods and applications, ACM Press, New York, NY, USA, 2003, pp. 95–99.

[23] R.S. Germain, A. Califano, S. Colville, Fingerprint matching using transformation parameter clustering, IEEE Computational Science and Engineering 4 (4) (1997) 42–49.

[24] X. Tan, B. Bhanu, Y. Lin, Fingerprint identification: Classification vs. Indexing, in: Proceedings of the IEEE Conference on Advanced Video and Signal Based Surveillance, 2003, pp. 151–156.0