CHAPTER 1

1. INTRODUCTION

1.1. INTRODUCTION

This research is concerned with the study and analysis of sonographic images, image mining methods of identifying appendicitis to improve the efficiency and effectiveness of the diagnosis and detection process of acute appendicitis using image mining on sonographic images. Image mining is more than an extension of data mining to image domain. It is an interdisciplinary endeavor that draws upon expertise from computer vision, image processing, image acquisition, image retrieval, data mining, machine learning, database and artificial intelligence. Advances in image acquisition and storage technology have led to tremendous growth in very large and detailed image databases. Analysis of images will reveal useful information to the human users. Image mining deals with the extraction of implicit knowledge, image data relationships or other patterns not explicitly stored in the images. [Zhang et al., 2002].

1.2. IMAGE MINING

Image mining has led to tremendous growth significantly to large and detailed image databases. The most important areas belonging to image mining are: image knowledge extraction, content-based image retrieval, video retrieval, video sequence analysis, change detection, model learning and object recognition. Two different types of input data for knowledge extraction from an image collection are original image and symbolic description of the image [Rokia Missaoui et al., 2005]. Discovering knowledge from data stored in alphanumeric databases, viz relational databases, has been the focal point of much work in data mining. However, with advances in secondary storage capacity, coupled with a relatively low storage cost, more and more non-standard data is being accumulated and one category of
“non-standard” data is image data. There is currently a very substantial collection of image data that can be mined to discover a new and valuable knowledge.

The central research issue in image mining is how to preprocess image sets so as to represent in a form that supports the application of data mining algorithms [Ashraf Elsayed et al., 2009]. Advances in image acquisition and storage technology have led to great growth in very large and detailed image databases [Zaiane et al., 1998]. A huge amount of image data is generated in our daily life as medical image like CT images, Cardiogram images, MR images, Mammogram images, Xray images and Ultrasound Images etc. These images involve a great number of useful and implicit information that is difficult for users to discover. Image mining can automatically discover this implicit information and patterns from the high volume of images. Research in image mining can be broadly classified into two main directions. The first direction involves domain-specific applications where the focus is to extract the most relevant image features into a form suitable for data mining [Hsu et al., 2000, Fayyad et al., 1996, Kitamoto 2001]. The second direction involves general applications where the focus is to generate image patterns that may be helpful in understanding the interaction between high level human perceptions of images and low level image features [Hsu et al., 2002, Ordonez et al., 1999, Zaiane et al., 1998].

1.2.1. Characteristics of Image Mining

As an interdisciplinary research field, image mining has its own following characteristics: Dependence on spatial information is vital for interpretation of image content but there isn’t such requirement in traditional data mining. Interpretation of image contents is achieved through high level semantic that is generated by knowledge reasoning. Complexity of the image mining process not only analyzes and discovers a mode, but it also has to deal
with the operations related to mining system such as image retrieval, indexing, and storing, which play important roles in the final mining results and all these processes add difficulties to image mining [Rajendran et al., 2009].

The main characteristics of image mining system in literature are: color, shape and texture features. The color feature extraction procedure includes color image segmentation. For this purpose ideas from the procedure described in image retrieval by color semantics with incomplete knowledge are adopted [Corridoni et al., 1998]. First the standard RGB image is converted as L*u*v* image, where L* is luminance, u* is redness greenness, and v* is approximately blueness yellowness [Zaiane et al., 1998]. Twelve hues that are used as fundamental colors are yellow, red, blue, orange, green, purple, and six colors an obtained as linear combinations of them. Five levels of luminance and three levels of saturation are identified. This results that every color is transferred into one of 180 references colors. After that, clustering in the three dimensional feature space is performed by using the K-means algorithm [Jain 1991]. Then the image is segmented as N regions, every region is presented in extended chromaticity space.

The Quasi-Gabor filter is explored to present the image texture features. The image is characterized with 42 values by the calculation of the energy for each block defined by a combination of one of 6 frequencies 1, 2, 4, 8, 16 and 32; and one of 7 orientations 0°, 36°, 72°, 108°, 144°, 45° and 135° [Mira et al., 2002]. A procedure based on function approximated shape representation using dynamic programming with multi-resolution analysis is adopted [Mori et al., 1999].
1.2.2. Image Mining Process

In the process of image analysis and information extraction, segmentation algorithms are used to partition the image into regions which are spatially continuous, disjoint and homogenous. A region is defined as a set of continuous pixels, with two dimensional distributions, representing uniformity related to some attribute. A segmentation algorithm uses primarily region growing, edge detection or combination of both [Marcelino Pereira Dos Santos Silva et al., 2008]. The fundamental challenge in image mining is to determine how low-level pixel representation contained in an image or an image sequence can be effectively and efficiently processed to identify high-level spatial objects and relationships. Typical image mining process involves preprocessing, transformations and feature extraction, mining, evaluation and interpretation and obtaining the final knowledge. Various techniques from existing domains are also applied to the image mining and include the object recognition, learning, clustering and classification [Hassan 2005]. The remote sensing image-mining process is an interactive one; once it demanded the sample selection, model building and rating, context evaluation and return to specific points of the process among others [Marcelino Pereira Dos Santos Silva et al., 2008].

Figure 1. Image mining process [Zhang et al., 2002]
Figure 1 shows the image mining process. The images from an image database are first preprocessed to improve their quality. These images then undergo various transformations and feature extraction to generate the important features from the images. With the generated features, mining can be carried out using data mining techniques to discover significant patterns. The resulting patterns are evaluated and interpreted to obtain the final knowledge, which can be applied to applications.

1.2.3. Current State of Image Mining Research

Zhang et al., (2002) conduct research in real-world application of image mining involving satellite images. Satellite images are an important source of information and one useful application of satellite images is to examine the paths and trends of forest fires over the years, thereby enabling firefighters to have a better understanding of the behavior of such forest fires in order to combat these fires effectively. In order to achieve thus, the following steps had been followed by them.

1. An efficient and effective spatial clustering technique for large-scale multi-resolution incremental clustering that are adaptable in dynamic environment
2. An image indexing scheme is based on cluster-related semantic concepts to achieve high level image retrieval in the satellite image database
3. Fire cluster information to discover any spatial and temporal trends and patterns of fire development in terms of scale, area, duration and location

The mining of fire patterns from satellite images involves the following 6 steps which correspond to the information-driven framework level:

1. **Image processing.** In the lowest pixel level, image processing technique is used to extract the spatial location information of fire spots. The spatial location of a fire spot
is represented by its altitude and longitude in the map. Such spatial information is stored in the HotSpot database.

2. **Database integration.** The commercial satellite typically generates 2 to 3 images of a specified location every day and the extracted fire locations of each image i.e., the latitude and longitude are stored in an individual table of the HotSpot database.

3. **Spatial clustering.** FASTCiD is an efficient clustering method that has been developed by Zhang et al., (2002) for the large dynamic spatial databases. The cluster label of each fire spot is obtained after applying the clustering process.

4. **Semantic cluster concept generation.** FASTCiD allows to obtain the information regarding the spatial layout, the area and the density of a specific cluster automatically. Based on this information, one can define a few semantic cluster concepts such as center cluster, left cluster, dense cluster, sparse cluster, big cluster and small cluster.

5. **Semantic concept image indexing and retrieval.** After the generation of cluster semantic concepts, semantic concept indexing of HotSpot images is built to support high-level image retrieval based on these semantic concepts. Examples of such image retrieval are: retrieval of all the HotSpot images which have dense cluster in the center of the image, and retrieval of all the HotSpot images in which the clusters located in the left and lower corners are all small ones.

6. **Trends and patterns mining.** Finally, it is desirable to produce some spatial and temporal trends and patterns of the forest fire. To this end, Zhang et al., (2002) have explored the fire cluster information to discover any spatial and temporal trends and patterns of fire development in terms of scale, area, duration and location. These trends and patterns are potentially useful for better understanding of the behavior of the forest fires.
1.2.4. Issues in Image Mining

By definition, image mining deals with the extraction of image patterns from a large collection of images. Clearly, image mining is different from low-level computer vision and image processing techniques because the focus of image mining is an extraction of patterns from large collection of images, whereas the focus of computer vision and image processing techniques are understanding and/or extracting specific features from a single image. While there seems to be some overlapping between image mining and content-based retrieval, image mining goes beyond the problem of retrieving relevant images. In image mining, the goal is the discovery of image patterns that are significant in a given collection of images. Perhaps, the most common misconception of image mining is nothing more than just applying existing data mining algorithms on images. This is certainly not true because there are important differences between relational databases and image databases [Zhang et al., 2001].

In relational databases, the data values are semantically meaningful. For example, age 35 is well understood. However, in image databases, the data values themselves may not be significant unless the context supports them. For example, a grey scale value of 46 could appear darker than a grey scale value of 87 if the surrounding context pixel values are all very bright. Another important difference between relational databases and image databases is that the implicit spatial information is critical for interpretation of image contents but there is no such requirement in relational databases. As a result, image miners try to overcome this problem by extracting position-independent features from images first before attempting to mine useful patterns from the images. A third important difference deals with the image characteristics of having multiple interpretations for the same visual patterns. The traditional data mining algorithm of associating a pattern to a class will not work well here. A new class
of discovery algorithms is needed to cater to the special needs in mining useful patterns from images [Zhang et al., 2001].

Image mining denotes the synergy of data mining and image processing technology to aid the analysis and understanding in an image-rich domain. It is an interdisciplinary endeavor that draws upon the expertise in computer vision, image processing, image retrieval, data mining, machine learning, database and artificial intelligence [Burl, 1999]. Broadly speaking, image mining deals with the extraction of implicit knowledge, image data relationship, or other patterns not explicitly stored in the images and between image and other alphanumeric data.

Clearly, image mining is different from low-level computer vision and image processing techniques. The focus of image mining is the extraction of patterns from a large collection of images, whereas the focus of computer vision and image processing techniques are understanding and/or extracting specific features from a single image. While there seems to be some overlapping between image mining and content-based retrieval, image mining goes beyond the problem of retrieving relevant images. In image mining, the goal is the discovery of image patterns that are significant in a given collection of images and the related alphanumeric data.

Image mining is another term for pattern recognition. In pattern recognition, the objective is to recognize some specific patterns; whereas in image mining, the aim is to generate all significant patterns without prior knowledge of what patterns may exist in the image databases. Another key difference is in the types of patterns examined by the two research fields. In pattern recognition, the patterns are mainly classification patterns where as
in image mining, the patterns types are more diverse. It could be classification patterns, description patterns, correlation patterns, temporal patterns, and spatial patterns. Finally, pattern recognition deals only with pattern generation and pattern analysis. In image mining, this is only one aspect of image mining.

Image mining deals with all aspects of large image databases which implies that the indexing scheme, the storage of images, and the retrieval of images are all of concern in an image mining system. In agricultural studies, topics like precision agriculture and crop modeling will be addressed, in environmental studies; the topic of spatial/temporal scales is still an ongoing issue for research. Health issues concern the quantitative modeling of epidemics of a various kind and hydrology focuses on model-based geostatistics for rainfall prediction [Umamaheshwaran et al., 2007]. Increasing the number of image archives has made image mining an important task because of its potential to discover useful image patterns and relationships from a large set of images. A framework for extracting knowledge from a sequence of images has been proposed by Hsu et al., (2001).

1.3. APPLICATIONS OF IMAGE MINING

Image mining is a future trend, although it is a new research area, its development shows great potential, as far as now its application has expanded to various domains and gained good results. Mining on medical images is to acquire valuable knowledge and modes, which can later be used for discovering abnormal situations not consistent with the previous common modes. This can act as a reference and help doctors diagnose diseases. A new image mining technique for brain tumor classification using pruned association rule, which combines the low-level features extracted from images and high level knowledge from specialists. The method can classify the CT scan brain images into three categories namely
normal, benign and malign. It can assist the physicians for efficient classification with multiple keywords per image to improve the accuracy. The experimental result on pre-diagnosed database of brain images showed 96% and 93% sensitivity and accuracy respectively [Manoranjan Dash et al., 2005].

Image mining can also be used on satellite cloud imagery, [Asanobu Kitamoto, 2002] use Self-Organizing Feature Map neural network to do image clustering on typhoon image collections, and use the data mining methods to analyse typhoon patterns and predict typhoon. Edward applied a new clustering method to build up a system that is used for detecting copying unauthorized image on the internet. The system first clusters similar images, then indexes each cluster and it achieves [Chang et al., 1999].

Image Mining in natural scene recognition: Aura Conci et al., (2001) have presented a method that considers patch appearances and its relationships in the form of adjectives and prepositions for natural scene recognition. Many of the existing scene categorization approaches only employ patch appearances or co-occurrence of patch appearances to conclude the scene categories, but the relationships among patches remain ignored.

In this approach, each image is represented as a spatial pyramid, from which a collection of patch appearances with spatial layout information are obtained. Then they apply a feature mining approach to get discriminative patch combinations. The extracted patch combinations can be interpreted as adjectives or prepositions, which will be used for scene understanding and recognition [Bangpeng Yao et al., 2009].
Information extraction using mining techniques from remote sensing image is rapidly gaining attention among researchers and decision makers because of its potential in application oriented studies. Jothi Venkateswaran et al., (2010) have discussed that the combination of various techniques such as statistical, decision, parametric and association rules help in extracting information effectively from remote sensing image rather than applying any single method. Shah et al., (2010) have presented a new feature set, obtained by integrating independent component analysis and wavelet transformation for image information mining in geospatial data.

Manoranjan Dash et al., (2005) have discussed an image mining application of Egeria detection. Egeria is a type of wild plant found in various lands and water regions over San Joaquin and Sacramento deltas in USA. The challenge is to locate a view to accurately detect the weeds in new images. Their solution contributes two new aspects to image mining. First aspect is application of view selection to image mining: View selection is appropriate when a specific learning task is to be learned. Second aspect is automatic view selection for accurate detection: Authors have used association rule mining to automatically select the best view and their results show that the selected view outperforms other views including the full view.

Manjula Devi et al., (2009) have proposed a universal steg analysis using histogram, discrete fourier transform and SVM. The stego image has irregular statistical characteristics as compare to cover image. Using histogram and DFT, the statistical features are generated to train One-Class SVM to discriminate the cover and stego image. Currently government and private agencies use remote sensing imagery for ample applications from military application to farm development. The images may be sensitive to light and some might not.
Remote sensing image classification is one of the most significant application domains for remote sensing. Some of the image classification algorithms have proved good precision in classifying remote sensing data. Perumal et al., (2010) compared the different classification methods and their performances and concluded that mahalanobis classifier; a supervised learning classification technique performed the best.

Magnetic resonance imaging is the traditional method to perform fruit grading and applying image processing on fruit grading is a current trend. Image processing technique can avoid the depredation of fruit compared to traditional methods. Chu-Hui Lee et al., (1997) modified primary k-means algorithm which perform efficiently at image segmentation and investigated how to select a better number of clusters automatically and fine-tuning of k-means algorithm especially for apple grading.

1.4. OBJECTIVES

Image mining is the current trend, and although it is a new research area, its development shows great potential. Its application has expanded to various domains such as medicine, agriculture, satellite and gained good results. Mining on medical images is to acquire valuable knowledge and modes, which can later be used for discovering abnormal situations not consistent with the previous common modes. This can act as a reference and help doctors in diagnosing diseases. Valuable information can be hidden in images and the need for image mining is high in view of the fast growing amount of image data.

The main objective of this research is to design and develop an automatic appendicitis detection system using image mining on sonographic images. The objectives of this research have been:
1. To study and analyse sonographic images in detail, image mining on sonographic images and diagnosis methods of appendicitis disease

2. To design the concepts to carry out image mining on sonographic images of the patient’s abdomen

3. To identify the concepts to improve the efficiency and effectiveness of the diagnosis of appendicitis using sonographic image mining

4. To design and develop a software prototype to prove the above concepts

5. To test the software prototype

### 1.5. THESIS ORGANISATION

This thesis describes diagnosis of appendicitis in sonographic images using Euclidean Distance Technique. The design approach of automatic appendicitis detection system is to develop a tool to improve the efficiency and effectiveness of diagnosing an acute appendicitis in sonographic images.

Chapter 1 presents an introduction to image mining, its characteristics and process, current state of image mining research, issues and it also describes the general applications in various domains and objectives of the research.

Chapter 2 highlights a four-level information-driven framework for image mining systems, various methods available from literature, historical background, related work, algorithms and techniques that are frequently used in image mining, namely object recognition, image retrieval, image indexing, image classification and clustering, association rule mining and neural network.
Chapter 3 describes the overview of acute appendicitis, various existing methods for appendicitis diagnosis, related work in appendicitis and historical background of appendicitis. It also explains sonographic scanner machine and advantages of ultrasound image.

Chapter 4 presents image based distance measuring methods such as distance transform, euclidean distance, chamfer distance, geodesic distance, manhattan distance, city block distance and chess board distance. It also describes measuring the distance between two points in an image.

Chapter 5 details the design and development of the automatic appendicitis detection system using image mining technique. The developed system encompasses modules for the following functions: image capturing, image preprocessing, image enhancement, image extraction, image classification, image segmentation and similarity distance measure.

Chapter 6 discusses the results obtained by testing the tool with the test data and real data from sonologist.

Chapter 7 describes testing evaluation of performance of the system and validation results. The validation of results are expressed using four measures: mean, variance, standard deviation and standard errors. It also demonstrates the confusion matrix that helps in determining the performance of the proposed method in terms of accuracy, recall and precision.

Chapter 8 concludes the research, describes the contributions and limitations, and presents recommendation for future research.