Introduction

INTRODUCTION

Digital image processing becomes progressively more essential in the medical domain and health care (Semmlow and Griffel, 2014). For disease diagnosis or pathological study, medical imaging is involved to create images and obtain significant information about the biological structures or body functions using specialized modalities and techniques. Biomedical signal/image analysis and processing are one of the most imperative visualization and interpretation processes in biology and medicine.

Recently, various powerful algorithms and instruments for acquiring, detecting, transmitting, storing, analyzing, processing and displaying images have been developed (Rangayyan, 2004). Consequently, scientists and physicians can attain quantitative measurements that support medical diagnoses and scientific hypotheses. In addition to the original medical imaging modalities such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), MR angiography (MRA), Ultrasound, Positron Emission Tomography (PET) and X-ray (Pan, 2010), nowadays other imaging modalities such as endoscopy or radiography are equipped with digital sensors. Moreover, microscopic images are commonly used in medicine and biology for cells/tissues structure representation.

Medical images are extremely cooperative for accurate diseases diagnosis, pathological lesion detection, supports the human body anatomy and to deduce different problems in the medical domain. Typically, digital images are composed of individual pixels which have discrete color/brightness values. These images are then efficiently processed and objectively evaluated after their acquisition and transmission if required. To transmit these images to many places at the same time, communication networks and protocols are to be used. Such systems and protocols are the Picture Archiving and Communication Systems (PACS) and the Digital Imaging and Communications in Medicine (DICOM) protocol; respectively (Erberich et al., 2007).

To acquire and extract accurate information from the medical images, analysis and processing biomedical image data is to be executed. Therefore, complex processing procedures are to be performed concerning several phases, such as data acquisition, preprocessing, segmentation, feature extraction, classification, clustering and registration. New technologies for medical data acquisition and storage provided large datasets for statistical analysis, which requires efficient pattern recognition methods. Image classification systems have received a recent boost and become one of the most interesting research areas. Medical image classification has an important role for diagnosis, treatment and medical teaching (Sonka et al., 2014). Additionally, medical images’ clustering involves finding a structure in a cluster with data having no label, which is important for example to recognize damaged areas in tissues. Various procedures have been developed for clustering in different fields such as medicine, engineering, data
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mining (Liu et al., 2011). Nevertheless, there is no standard technique of clustering for ideal results for all of the medical imaging applications.

The main concern of the current chapter is to introduce the different modalities used for medical images acquisition and the concept of the medical image analysis/processing. Besides presenting the concept of medical image processing and analysis, classification and clustering with various applications in the medical domain are also explained.

BACKGROUND

Medical Image Modalities

Medical imaging is concerning with numerous technologies to view the human body for diagnoses and monitor medical conditions. Consequently, wide variety of modalities in medical imaging techniques can be employed. Each modality provided different information about the organ/area of the body under study or treatment, which related to possible disease/injury. The imaging modality selection for a targeted

Table 1. Comparison between common medical imaging modalities

<table>
<thead>
<tr>
<th>Instrument/Concept</th>
<th>Limitations that Affect Its Image Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Magnetic Resonance Imaging (MRI)</td>
<td>• Implanted medical devices that contain metal may malfunction or cause problems during an MRI exam. • MRI cannot image classifications and bone and cannot always distinguish between cancerous and non-cancerous anomalies.</td>
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<tr>
<td>• Uses radio waves and magnetic field to create detailed images of organs and tissues. • MRI highly efficient in diagnosing a number of conditions by showing the difference between normal and diseased soft tissues of the body. • MRI uses strong magnetic fields to cause water molecules to resonate. It is very good at imaging soft tissues, such as the heart, lungs, liver and other organs.</td>
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<tr>
<td>Computed Tomography (CT)</td>
<td>• Enable to view very fine details in soft tissues such as muscles or ligaments (MRI might be more appropriate in such situations). • Patient motion during a CT scan can cause the images to be “blurry”. • Metal artifacts in the body can cause ‘streaks’ in the image. Flat tumors may also be harder to image with a CT scan.</td>
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<tr>
<td>• Combines multiple X-ray projections taken from different angles to produce detailed cross-sectional images of areas inside the body. • CT images allow physicians to get precise, 3-D views of certain parts of the body, such as soft tissues, the pelvis, blood vessels, the lungs, the brain, the heart, abdomen and bones. • CT is often the preferred method of diagnosing many cancers, such as liver, lung and pancreatic cancers.</td>
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<tr>
<td>X-RAY</td>
<td>• The two dimensional nature of the images can lead to false positives. • Technicians often take two images, one from the front and one from the side. • Not good for distinguishing anomalies in dense tissue. • The resolution of an x-ray is not very high.</td>
</tr>
<tr>
<td>• Uses ionizing radiation to produce images of a person’s internal structure by sending X-ray beams through the body, which are absorbed in different amounts depending on the density of the material. • Radiation Therapy is a type of device which also utilizes X-rays, gamma rays, electron beams or protons.</td>
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<tr>
<td>Ultrasound (Medical Sonography or Ultrasongraphy)</td>
<td>• Ultrasound can be blocked by bone, and so is not useful in imaging past the ribs of the chest. • Ultrasound imaging will not be useful for evaluating the digestive. • The clarity of an ultrasound attenuates as it passes through tissue (not useful for imaging deep within the body). • The resolution of an ultrasound is fairly limited. • The accuracy of an ultrasound depends to a large degree on the skill of the technician and radiologist.</td>
</tr>
<tr>
<td>• Uses high frequency sound waves to create images inside the body. • The ultrasound machine sends sound waves into the body and is able to convert the returning sound echoes into a picture. • Ultrasound technology produces audible sounds of blood flow, allowing medical professionals to use both sound and visuals to assess a patient’s health.</td>
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clinical study requires medical insights specific to organs under study (Giedd et al., 1999; Gohagan et al., 2005; Linton et al., 2014; Turkington et al., 2014; Nørgaard et al., 2014; Dey et al., 2015; Hore et al., 2015). Figure 1 illustrates the different modalities that can be used for medical imaging with referring to the body part under test by each device.

A comparison between some of these modalities and their limitations that affects the image is demonstrated in Table 1.

For more reliable and accurate assessment, the images from different multiple modalities can be considered using medical images fusion (Singh and Khare, 2014; James and Dasarathy, 2014).

**Medical Image Analysis and Processing**

Biomedical image processing refers to the provision of digital image processing for biomedical sciences. Image analysis considered high-level image processing, while, low-level processing refers to techniques which can be realized without prior knowledge on the specific images content (Deserno, 2011). Image processing can be considered as the transformation of an image into another modified (enhanced) image. On the other hand, image analysis is the transformation of an image to produce information representing a description for the original image. Thus, the main purpose of the image processing is to produce images which are more reliable and simple for subsequent analysis.

Medical images are used to derive coherent visualizations and models. Image analysis sequence starts from the acquisition, proceeds to restoration and segmentation to conclude with analysis. The steps of biomedical image processing are addressed as follows: i) image formation: start from medical image
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Figure 2. Image processing modules

![Image Processing Modules](image)

capturing to digital image matrix formation, ii) image visualization (image enhancement): manipulates the image matrix to obtain optimized output of the image, iii) image analysis: includes all the steps of processing, which are used for quantitative measurements as well as abstract interpretations of biomedical images and iv) image management: includes techniques that provide the efficient storage, communication, transmission, archiving, and access (retrieval) of image data as well as including telemedicine methods. These modules of the image processing are demonstrated in Figure 2.

From Figure 2, it is clear that image analysis requires a priori knowledge of the nature and content of the images. This knowledge about the image is further integrated into algorithms at a higher level of abstraction. Thus, image analysis process of is very precise. High-level image processing consists of schemes at the texture, region, object, and scene levels (Xu et al., 2002).

It is obvious that image analysis techniques entail features extraction to aid in the object’s identification and to emphasize the image information at particular level. Afterwards, description (feature selection) can be performed to extract the attributes that result in some quantitative information of interest. Features selection is also important for data size reduction. Subsequently, the extracted features are aggregated into a list which acts as the input to a clustering algorithm. Clustering algorithms then presents a depiction of the grouping structures which discovered within the objects. This description consists of a list containing labeled clusters to which it has been assigned. Thus, after features extraction, the features are organized into groups (clusters) of approximately shared features.
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Segmentation methods are used to isolate the desired object from the scene. Thus, measurements can be performed on it subsequently. Segmentation partitions the image into its constituent connected regions or objects. The segmentation level to which the subdivision is carried depends on the problem being solved (Tsechpenakis et al., 2007; Dey et al., 2012; Samanta et al., 2012; Roy et al., 2014). In medical image processing, the segmentation is performed for example to discriminate between healthy anatomical structures and pathological tissues. Depending on the level of feature extraction required after segmentation, the segmentation procedure can be categorized into pixel, edge, and texture or region-oriented or hybrid (combination of single procedures).

According to the image analysis steps in Figure 2, the classification/detection task is to be executed after the segmentation step. Classification is to assign particularly specified classes of objects to all connected regions obtained from the segmentation process.

Image analysis mainly engages feature extraction and selection, clustering, segmentation, representation and description, classification or recognition (Lotufo et al., 2011).

MAIN FOCUS OF THE CHAPTER

Based on the previous detailed description of the image analysis steps, it is clear that both image clustering and classification play significant role in the image analysis/processing module. Therefore, this chapter focuses on an extensive representation for the clustering/classification of the medical images supported with related literatures.

Clustering

Clustering involves finding a structure in a cluster with data having no label. It is the process of assigning a cluster label for every object. Therefore, it is required to search on a specific label to find out which objects belong to it. However, based on the used clustering paradigm, there are other ways of describing the discovered structure. These paradigms become an open research domain to suggest different assumptions and approaches. Such clustering paradigms are:

1. Hierarchical clustering (HCA), which produces a tree-like description of the clustering structure. Cutting the tree at any level produces a partition of the objects (Thies et al., 2003; TamijeSelvy et al., 2011),
2. Graph-theoretic clustering, which views the objects as nodes in a weighted network, or graph (Cordella et al., 2005; Peng et al., 2013),
3. Mixture Models clustering, which assumes the objects as generated by a mixture of probability distributions (Penny and Friston, 2003; Greenspan et al., 2006),
4. Partitional clustering, where clusters are disjoint partition of objects. An object belongs to only one cluster (Gath and Iskof, 1995), and
5. Fuzzy clustering, where an object possesses varying degrees of membership with more than one cluster (Tabakov, 2006; Mahmoud et al., 2013).
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Extensive studies were conducted concerning medical images clustering applications. Dey’s team has extensive work on segmentation based clustering. In 2012, they employed Fuzzy C-Means (FCM) for blood vessels segmentation in retinal images to provide early glaucoma detection/diagnosis. The authors compared the results of an expert ophthalmologist hand-drawn ground-truths and segmented image using the proposed method. The experimental results established that the segmented blood vessels have with sensitivity, specificity, PPV, PLR and accuracy of 99.62%, 54.66%, 95.08%, 219.72 and 95.03%, respectively (Dey et al., 2012). Additionally, Dey et al., (2013) proposed appropriate selection of the Region of Non-Interest based on Fuzzy C-Means (FCM) clustering for segmentation and Harris corner detection, to improve retention of diagnostic value lost in watermarking to embed ownership information. Afterwards, the present watermark is embedded in the selected area of RONI based on alpha blending technique. The results prove that the generated watermarked image achieved acceptable level of imperceptibility, where the distortion was compared to the original image. The Peak signal-to-noise ratio (PSNR) of the original image versus the watermarked image was calculated to prove the efficacy of the proposed method. Bose et al., (2013) proposed to images segmentation using multi-threaded programming and k-means clustering. Parts of images were considered as a thread and k-means clustering was used to segment them on every thread. The proposed method results were compared to segmentation results without multithreading. The obtained results were very much promising. Azween et al., (2014) proposed an ensemble clustering algorithm with supervised classification of clinical data for untimely coronary artery disease diagnosis.

Zhou et al. (2014) introduced medium mathematics system to process fuzzy information for image segmentation. The authors established the medium similarity measure based on the measure of medium truth degree (MMTD) and used the pixel correlation and its neighbors to identify the medium membership function. An improved FCM medical image segmentation algorithm based on the MMTD which considered some spatial features was employed. The experimental results proved that the proposed algorithm was robust to noise than the standard FCM, with more certainty and less fuzziness. Thus, the authors suggested employing the proposed method to segment the medical images efficiently in various applications.

Classification

Image classification research aspires to find images representations to be automatically used for images categorization into a finite set of classes. Generally, algorithms for image classification requires pre-processing, which involve relevant features extraction and images segmentation into sub-components based on some prior knowledge about their context. Medical image classification plays an important role in diagnosis and treatment. An extensive explanation of the different classifiers with applied example is introduced in Chapter 2. Thus, in the current chapter the most common classifiers for the medical applications are mentioned, such as:

1. Neural network (NN) classifier, which neural networks are data driven self-adaptive methods in which they can adjust themselves to the data, without any explicit specification of functional or distributional form with the underlying model (Tech and Korrapati, 2010),

2. Support Vector Machines (SVM), which is a binary classifier (classify two classes) by finding the maximum separating hyper plane between the two classes (Vanitha and Venmathi, 2011) and
3. **Neuro Fuzzy classifier**, where Neuro fuzzy systems are fuzzy systems that uses artificial NNs theory in to determine their properties (fuzzy sets and fuzzy rules) by processing data samples (Bhardwaj and Siddhu, 2013).

Previous studies were very useful to conduct several classifiers in medical image classification applications as follows. Zacharaki et al. (2009) investigates pattern classification methods to distinguish between different types of brain tumors, namely primary gliomas from metastases, and also for grading of gliomas. A computer-assisted classification method combining conventional MRI and perfusion MRI was developed and used for differential diagnosis using Support Vector Machines (SVMs) with recursive feature elimination. The proposed method consisted of several steps: region of interest (ROI) definition, feature extraction, feature selection and classification. Tumor shape and intensity characteristics as well as rotation invariant texture features, were the extracted features. 102 brain tumors histologically images were involved in this study. The binary SVM classification accuracy, sensitivity, and specificity, assessed by leave-one-out cross-validation, were respectively 85%, 87%, and 79%. Multi-class classification was also performed via one-versus-all voting scheme.

Othman et al. (2011) used discrete wavelet transformation to obtain the feature related to MRI images. An advanced kernel based schemes such as SVM for the classification of volume of MRI data as normal and abnormal was deployed. In the same year, Vanitha and Venmathi (2011) develop an automatic tool to identify microbiological types without human supervision. The Bacteriophage typing and the fluorescent imaging methods were used to extract representative feature profiles. The bacterial types were identified by human experts by reading the feature profiles. These methods were time consuming and prone to errors. The bacterial image features were extracted, and then the SVM was used for classifying the Bacterial types. Results proved that the SVM have high approximation capability and much faster convergence.

Hosseini and Zekri (2012) conducted an extensive review for the adaptive neuro-fuzzy inference system (ANFIS) classifier for medical image classification during the past 16 years. The authors revealed that the ANFIS is a fuzzy inference system (FIS) implemented in the framework of an adaptive fuzzy neural network. It joins the FIS explicit knowledge representation with the artificial neural networks learning power. Thus, the ANFIS integrates best features of fuzzy systems and neural networks. A brief comparison with other classifiers, main advantages and drawbacks of this classifier are investigated.

**FUTURE RESEARCH DIRECTIONS**

Image processing have many purposes such as i) image enhancement to reduce the noise or sharpening images, ii) pattern recognition for automatic detection of a certain shape/texture in the images and identify objects, iii) data reduction to easily handled and interpreted information, e.g., the reduction of an image to a set of objects, features, or a set of measurements, iv) image synthesis, which refers to reconstructing a three-dimensional scene from two-dimensional images, v) combination of images (fusion), refers to combining images of two different modalities (types) from the same scene involves registration, and vi) Data compression to reduce the images size and speed up image transmission across a network.

There are major challenges in biomedical image processing that can be addressed and to be considered as future points and recommendations to be covered by researches as follows.
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- **Semantic Gap**: Refers to the inconsistency between the cognitive interpretation of a diagnostic image by the physician (high level) and the simple structure of discrete pixels, which is used in computer programs to represent an image (low level). Thus, it is difficult to formulate a priori knowledge, using medical images that can be integrated directly and easily into automatic algorithms of image processing. In the medical domain, there are three main aspects hindering bridging this gap, namely (Lotufo et al., 2011): i) Heterogeneity of images: it can be largely eliminated using correction algorithms, but this runs the risk of destroying the subtle features of the real image (Lee, 1983), ii) Unknown delineation of objects: where the biological structures cannot be separated from the background due to the diagnostically or therapeutically relevant object is represented by the entire image. This leads to segmentation problem even if the objects were definable in the biomedical images. This problem is due to the shape or borderline itself is represented fuzzily or only partly. In addition to these medical images inherent properties, which complicate their high-level processing, special requirements related to the process has its limitations, where iii) Robustness and reliability of algorithms (medical process): it is required that images which cannot be processed correctly, must be automatically, rejected and withdrawn from further processing. Consequently, all images that have not been rejected must be evaluated correctly.
- Texture analysis plays a supportive rather than a comprehensive role in the future of medical image interpretation. The robustness of texture analysis makes it particularly attractive for monitoring disease progression or treatment response with time.
- Features selection is a recommended step for size and consuming time reduction.
- Fuzzy c-means (FCM) is one of the trendy clustering algorithms for medical image segmentation. However, FCM is highly vulnerable to noise due to not considering the spatial information in image segmentation, which needs to be resolved for efficient segmentation.
- Automatic medical image classification is a progressive field in image classification, and it is expected to be more developed in the future with further new algorithms.
- Automatic diagnosis is a promising can assist pathologists by providing second opinions and reducing their workload. These automated system need to cover all medical imaging aspects and to replace all manual or semi-automated existing systems (where, currently, segmentation is often carried out manually by experienced clinicians or radiologists).
- Image fusion is a promising process.
- More focus should direct to processing images (data) in four dimensional (4D) domains.
- On-line medical images atlases can be found for many medical domains including dermatology, ophthalmology, radiology, cytopathology and gastroenterology. The complete volume of medical image data is valuable for numerous challenges and opportunities.

**CONCLUSION**

Medical imaging domain gains its importance with the increasing need to automated and efficient diagnosis in a short period of time. It is a promising plays a significant role in medical diagnosis, treatment, executing, and evaluating surgical and radiotherapeutical procedures. The extracted information from the medical images captured by various modalities may include geometric models of anatomical structures, functional descriptions of anatomical structures, or diagnostic assessment. Most medical imaging modalities provided data in two spatial dimensions (2D) as well as in time. In addition, data in three
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Spatial dimensions (3D) as well as in time (called 4D) are becoming common and promising trend. The large amount of data involved necessitates the identification or segmentation of the objects of interest before further analysis can be made. The result of this segmentation process is the grouping or labeling of pixels into meaningful regions or objects.

Additionally, medical image retrieval system is to provide a tool for radiologists to retrieve the images similar to query image in content. Classification is an essential part in retrieval system that utilizes image processing, pattern recognition and classification methods in order to distinguish between normal and abnormalities due to tumor. Support Vector Machines using the correlation kernel, Polynomial kernel, Gaussian kernel and Radial basis function (RBF) kernel all pay important role in each application and provide satisfactory results. SVM proved its efficiency over neural networks and RBF classifiers. Unlike neural networks, SVM model does not need hypothesizing number of neurons in the middle layer or defining the centre of Gaussian functions in RBF. SVM uses an optimum linear separating hyperplane to separate two set of data in a feature space. This optimum hyperplane is produced by maximizing minimum margin between the two sets. Conversely, Neural network techniques are more useful in automatically analyzing the images by training the networks. Data mining techniques are also playing equal role in keeping the image databases and making analysis on the set of images.

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