

CONTENT-BASED RETRIEVAL OF BIOMEDICAL IMAGES USING ORTHOGONAL FOURIER-MELLIN MOMENTS

A Thesis

*Submitted In Partial Fulfillment of the Requirements
for the Award of the Degree of*

MASTER OF ENGINEERING

In

COMPUTER SCIENCE AND ENGINEERING

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June, 2018**

CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, "*Content-based retrieval of biomedical images using orthogonal Fourier-Mellin moments*", in partial fulfillment of the requirements for the award of degree of Master of Engineering in *Computer Science and Engineering* submitted in Computer Science and Engineering Department of Thapar Institute of Engineering and Technology, Patiala, is an authentic record of my own work carried out under the supervision of *Dr. Ashutosh Aggarwal* and refers other researcher's work which are duly listed in the reference section.

The matter presented in the thesis has not been submitted for award of any other degree of this or any other University.

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ACKNOWLEDGEMENT

I would like to express my grateful thanks to my supervisor **Dr. Ashutosh Aggarwal**. This work would not have been possible without his encouragement and guidance. I thank my supervisor for his time, patience, discussion and valuable comments. Their enthusiasm and optimism made this experience both rewarding and enjoyable.

I am equally grateful to **Dr. Maninder Singh**, Professor and Head of Computer Science and Engineering Department, an excellent teacher and a well-credited researcher, who always encouraged us to keep going with the work.

I will be failing in my duty if I don't express my gratitude to **Dr. S.S. Bhatia**, Senior Professor and Dean of Academic Affairs, Thapar Institute of Engineering and Technology, for making all the provisions of infrastructure such as library facilities, computer labs equipped with net facilities, immensely useful for learners to equip themselves with latest in the field.

I am also thankful to entire faculty and staff members of Computer Science and Engineering Department for their direct-indirect help and cooperation, which made my stay at Thapar Institute of Engineering and Technology memorable.

Date: June, 2018

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ABSTRACT

Biomedical imaging field is growing enormously from last decade. The medical images have been used and stored continuously for diagnosis as well as research purposes. For real-time retrieval of medical images from such storage repositories there is a grave need of an effective and efficient biomedical image indexing and retrieval approach. In this quest, this thesis work presents a new approach for the retrieval of CT and MR images using orthogonal Fourier-Mellin moments (OFMMs). OFMMs have excellent information representation capability that enables them to pack the entire image information in very less number of coefficients. This property makes the proposed approach not only effective but also computationally very efficient and most favourable among all the existing approaches. The proposed approach has been tested and compared with numerous existing, state-of-the-art as well as recently published biomedical indexing and retrieval approaches on four standard databases namely, Emphysema CT, NEMA CT, OASIS MRI and NEMA MRI. Additional experiments have been conducted to analyse the noise robustness ability of the proposed and all the compared approaches. The reported results show a significant increase in the retrieval rate of the proposed approach over all the existing approaches on noise free Emphysema CT and OASIS MRI medical databases and noisy images of all the test medical databases.

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ABBREVIATIONS

CBIR	Content-Based Image Retrieval
MIR	Medical Image Retrieval
TBIR	Text-Based Image Retrieval
CBMIR	Content-Based Biomedical Image Retrieval
ROIs	Region of Interests
LBP	Local Binary Patterns
ORIMs	Orthogonal Rotation Invariant Moments
OFMMs	Orthogonal Fourier-Mellin Moments
ORITs	Orthogonal Rotation Invariant Transforms
ICM	Inner Circle Mapping
OCM	Outer Circle Mapping
OCR	Optical Character Recognition
APR	Average Precision Rate
ARR	Average Retrieval Rate
mAP	Mean Average Precision
NEMA	National Electrical Manufacturers Association
DB	Database
OASIS	Open Access Series of Imaging Studies
CT	Computed Tomography
MRI	Magnetic Resonance Imaging

Chapter 1

Content-Based Biomedical Image Retrieval System

The usage of biomedical images during diagnosis of a patient in hospitals is increasing rapidly. The biomedical images can be in the form of X-ray, computed tomography (CT), magnetic resonance imaging (MRI), etc. Due to the rapid increment in biomedical images, it is becoming a more challenging task to diagnose a patient in clinics and hospitals. Hence, there is a need to have a more accurate and effective searching, indexing and retrieving techniques for the proper diagnosis. Moreover, it cannot be achieved without a proper arrangement of the biomedical images data. To cope up with such type of situations a new technique named content-based image retrieval (CBIR) system comes into the existence. CBIR systems have benefited the collection and management of continually increasing biomedical images as well as the medicine, R&D department, and education. CBIR systems work on the principle to retrieve the most relevant images from an already existing image database on the basis of their primary (e.g. color, texture & shape) or semantic features [1]. To develop robust and efficient medical image retrieval (MIR) system, extraction of appropriate visual features like shape, color, and texture plays a significant role. These features (especially textures) provide the salient information from medical images in an efficient manner.

The organization of this chapter is divided into five sections. Section 1.1 presents an overview of the image retrieval and different types of the image retrieval systems. Section 1.2 describes about the content-based biomedical image retrieval systems and their areas of application. Section 1.3 describes about the architecture of the CBMIR systems and the steps involved during the retrieval of the biomedical images. Section 1.4 describes the challenges in existing CBMIR systems. Section 1.5 describes the contributions of the research work. Lastly the chapter included the organisation of the thesis file in section 1.6.

1.1 Image Retrieval

Vast and rapid changes have been seen in the field of information technology. Nobody is untouched by the taste of this technology. To capture the images with help of the digital cameras have become a very easy and to capture the images with digital devices have become the routine of daily lives. The storage has become cheap with the expansion of the internet so that the size of the digital image collection is getting increased day by day. To retrieve the images from various domains, browsing tools are needed desperately. The images should be browsed and retrieved according to the concerned subjects like clothing, fashion, medicine, buildings or architect etc. To retrieve or browse the image many retrieval systems have been developed and are being used. There are two types of the retrieval systems which are being used by users to browse or retrieve the images: 1) Text-based image retrieval 2) Content-based image retrieval

1.1.1 Text-Based Image Retrieval (TBIR)

Text-based image retrieval (TBIR) involves searching on the bases of automatic or manual annotation of the image [2-3]. In addition, the searching links with the metadata or keywords associated with the query image. Google images are one of the most common example of the TBIR systems. TBIR is fast but sometimes faces a challenging task to describe the entire visual cues of an image in the form of keywords and thus the process of retrieval may end up with the irrelevant images. With the help of existing technologies, it is easy to have the textual description about the images but requires humans to manually annotate the each image in the database. Moreover, it is not possible to have the manual annotation in the case of very large databases and automatically generated images. Furthermore, the annotation process is usually not providing the efficient results because different users have the different perception to describe an image and generally, do not make the systematic annotation. The unsystematic way of annotation degrades the performance of the TBIR systems. To address all these shortcomings of TBIR the CBIR systems are introduced [4-5].

1.1.2 Content-Based Image Retrieval (CBIR)

CBIR is also called as QBIR that is “**query by the image content**”. CBIR is introduced to allow users to search images from large databases which match closely with their query image [6]. In CBIR system the search involves retrieving the results

on the bases of the visual features of the query image rather than to keywords or metadata associated with it. The visual features of an image can be its shape, intensity, color, size etc. To develop robust and efficient CBIR system, extraction of appropriate visual feature plays a significant role. The visual feature descriptors of an image can be categorized into two types as the local feature descriptors [7] and the global feature descriptors [8]. In local feature descriptors, an image is divided into overlapping blocks and information within each block is obtained by exploring the neighbours in different directions. Features of each block are appended together to form a feature vector of the entire image. In global feature descriptors, the entire image is considered as a single unit for the purpose of feature extraction.

1.2 Content-Based Biomedical Image Retrieval (CBMIR)

The significance of biomedical image in hospitals and health centres is growing consistently, making the process of diagnosis more effective as well as patient friendly. Now with the advancement in the imaging technology; it is become easier to detect the diseases earlier with a précising way, can diagnosis with the more cure, less invasive and the worthful results can be closely monitored [9]. The number of images produced digitally is expanding strongly among various departments like radiology, endoscopy, dermatology, MRI, HRCT, X-rays, cardiology etc. Management and admittance to these digital medical images repositories become a challenging task. Most of the accesses to these systems are based on the patient identification or study characteristics like description, modality. Retrieval of digital medical images can be as text-based and content-based methods. So far, a variety of retrieval of medical image systems has been developed using text-based or content-based methods or with a combination of these methods.

1.2.1 Application Areas of CBMIR

CBMIR systems are applied in various biomedical applications for the purpose of clinical diagnosis and decision making. At present, picture achieves and communication systems (PACS) are used in many hospitals and radiology departments in a large scale [10]. The biomedical application of CBIR systems are as:

- PACS (picture archiving and communication system)
- IRMA (image Retrieval for Medical Applications)
- SPIRS (Spine Pathology and image Retrieval System)

- MIMS (spine x-ray images in the sagittal plane)
- Image Map
- ASSERT (Automatic Search and Selection Engine with Retrieval Tools)
- Web MIRS system
- Cervigram Finder system

1.3 The Architecture of CBMIR

In the CBMIR systems, the task of retrieval is performed by the mean of the visual cues associated with the image itself. The visual cues can be a color, shape or the texture related to an image. A standard CBMIR system works on the bases of two stages as:

- ❖ Off-line feature extraction i.e. data insertion
- ❖ Online image retrieval i.e. query processing

In off-line feature extraction, the low-level feature descriptors like color, texture, shape of each image in the database are extracted and stored in the form of a multidimensional database called as the “feature database”. These feature databases can also be named as the image signature. Due to the compact size of an image signature, it is essay to manage it rather than to manage the properties of the entire image.

In online image retrieval, the user will submit a query to the system in the form of a sketch related to the object or an image itself. The system employs the same feature extraction technique as employs earlier in the off-line mode. After that, a similarity measure is applied to find out the distance between the feature vector of a query image and already known feature vector database. On the bases of similarity measures, the ranking of all the existing images in the database is done to retrieve out the top most relevant images according to the query image. A relevance feedback to the retrieval system can be given by a user to learn about the level of user satisfaction. Figure 1.1 explains the architecture [11] of the CBMIR system.

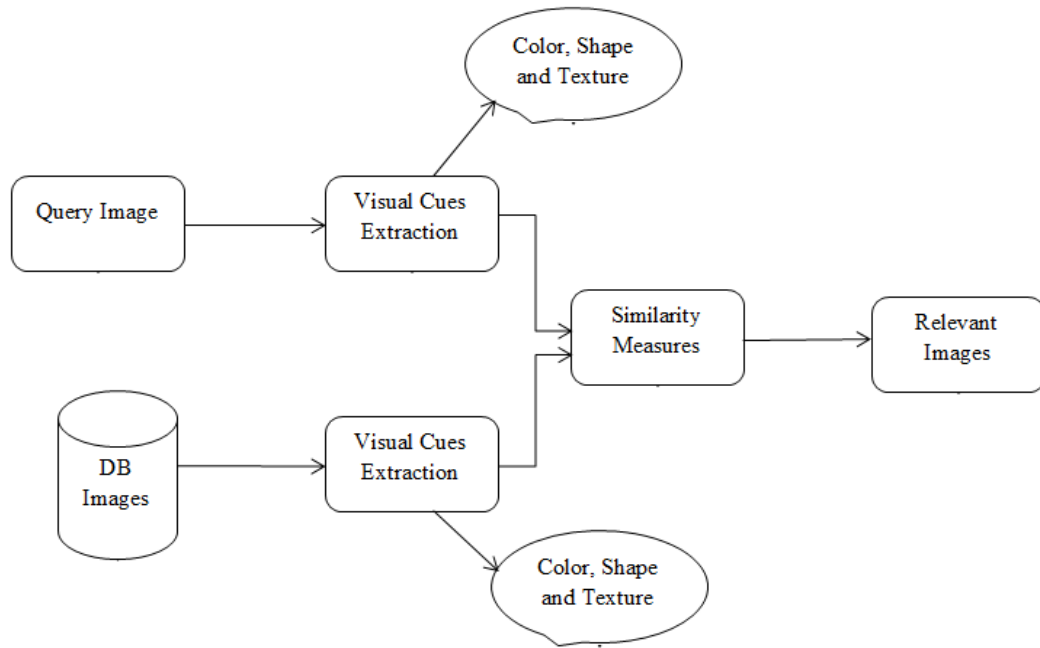


Figure 1.1: Architecture of the CBMIR System

1.3.1 Content-Based Biomedical Image Retrieval Process

CBMIR works into six main steps to perform the task of image retrieval. The description of these steps is given below.

❖ Image acquisition

To acquire a digital image from the image database, the first step is the image acquisition. The image database is a huge collection of structural images. The type and number of images to retrieve totally depends upon the choice of the user.

❖ Image pre-processing

Image pre-processing is a way of representing an image into a more meaningful and attractive way. Extraction, analysis and recognition of an image, filtration, normalization and the segmentation all are the basic elements of the image pre-processing process. Image segmentation is often used for the portioning of a digital image into the multiple parts so that these parts can be used further for the significant representation of the portioned regions or the entire object [12].

❖ Feature extraction

Feature extraction is the basic aspect of any retrieval system. The efficiency of any retrieval system is depend on the type of features chosen and up to which mark the chosen features are able to distinguish among different image classes (discriminating capability). A good feature descriptor must comprises the nature to be invariant to rotation, scaling and various illumination variations. Although with all these properties a descriptor must have the higher discriminating power. Sometimes the system compromises the degree of discrimination while maintaining a balance between all above-mentioned aspects of a good feature descriptor. The visual feature descriptors of an image can be categorized into two types as the local feature descriptors and the global feature descriptors. Global feature descriptor means to consider the entire image as a whole, while local descriptors represent the visual features of a particular region or object used to describe the image, can be referred as a region based visual descriptor. The visual descriptors of an image can be its color, shape and texture.

Colors are the one of the most important visual descriptor of an image and used to make the gray scale images more pleasant to eyes, easier to analyze and understand. Colors are basically a composition of three primary RGB i.e. RED, GREEN, and BLUE colors. The process of extraction involves the three phases as: 1) To define a proper color space for the required purpose. 2) To select the appropriate color extraction method. 3) To have the similarity measures.

RGB, HSV, YIQ, CIE, L^*U^*V are the common color spaces used in the various applications. Color edge [13], color histograms [14], color moments [15], color correlogram [16] etc. are the commonly used color descriptors. The rest description about the colors can be seen in [17].

Shape signifies the idea to have a description of the region of interests (ROIs) in an image. ROIs can lie within the local or global region of any query image. Shape descriptors are classified into the two categories as region based [18] and boundary based [19]. In region-based, all the pixels inside an image are used for its shape representation. Moment descriptors are generally used for the region based representation purpose. The boundary based methods only exploit the boundary values of the input shape. These techniques include area, perimeter, compactness, eccentricity etc. for the shape representation.

Texture is a visual pattern exhibiting the property of homogeneity which has a similar kind of pattern. Texture contains properties like coarseness, contrast, directionality, line likeness etc., Texture signifies about the natural feature of a pattern like the texture of hair, brick, skin, brick and wood etc. [20].

In our work, we are using both shape and texture visual feature descriptors to examine the phenomenon of variations occur among the different regions of body organs at local as well as global view during the retrieval of biomedical images.

❖ **Similarity measures**

The process of matching the query image with the images of the used database is termed as the similarity measure or distance measure. Similarity measures have a great impact on the performance of the CBMIR systems. In this process the low-level feature descriptors (color, texture, shape) of each image in the database are extracted and stored in the form of a multidimensional database called as the “feature database”. After that, the same technique of feature extraction is employed on the query image to acquire a specific feature vector space. Then, a similarity measure is applied to find out the distance between the feature vector of a query image and already known feature vector database. On the bases of similarity measures, the ranking of all the database images is done to find out the top most relevant images according to the query image. The Euclidian distance, Canberra distance etc. are often used as the distance measures in the medical applications. Moreover, it is not suggested to use these distance measures each and every time. The selection of the distance measure depends on the type of application. In this thesis work, extended Canberra distance has been used as a distance measure.

❖ **Resultant retrieved**

This involves the process of retrieving the most relevant images from the database in the accordance with the query image. From the ranking of database images, the top most relevant images are retrieved as a resultant. The retrieval will be on the bases of the threshold value (η). In our work we are using $\eta = 100$ means that the output will be the topmost 100 relevant biomedical images having almost or exact features according to the given query image [21].

❖ User interface and feedback

This step involves the user's interaction with the working system. A feedback is given back to the system for the purpose of the refinement in searching process. Feedback can either be positive or negative depends on the user satisfaction level. Hence the feedback plays a major role to make a system more efficient.

1.4 Challenges in CBMIR

The amount of information produced visually in the scope of the medical study demonstrates the role of developing new, alternative methods to complement the text. CBMIR technique plays a crucial role for the physician to assist decision-making process by retrieving out the relevant images from the large archives. However, the incorporation of this technology to solve practical medical problems is a goal yet to be present. Some of the open do research issues for the usage of CBIR in medicine are identified as:

- There is need to have fast feature extraction as well as indexing techniques to control the gradually increasing amount of medical images facts to shorten the gap between the numerical nature of the character and semantic meaning of images.
- The lack of communication between the developer and the experts in the medical field, which is directly linked to the usage and performance of CBIR systems and there exist a semantic gap between the features extracted by the machine i.e. the low-level features and features extracted according to the human perception i.e. the high-level features.
- The shape-based descriptors are supposed to find out fine detailing in medical image retrieval. Moreover, most of existing content-based image retrieval systems do not prefer to make the use of full shape descriptor as they work on the principle to use either the indirect correlates of the shape descriptors which are not as much capable to capture the desired classification granularity.
- Tools that can automatically extract semantic features from images are desperately required.
- The insufficiency of huge image datasets free of charge with defined query topics and standards compromises the retrieval quality of CBIR systems.

1.5 Contributions of the Research Work

The main objective of the present research work is to develop a new orthogonal Fourier Mellin moments i.e. OFMMs-based approach for the content-based retrieval of CT and MRI images. In this regard, we carried out a thorough literature survey of different state-of-the-art as well as recently published local feature extraction techniques for the content-based retrieval of biomedical images. All the local feature descriptors have proved to be promising and good image retrieval approaches. However, these schemes suffer from high computational cost, large feature vector length and poor discrimination power. Therefore, we successfully employ an OFMMs-based framework for addressing all these shortcomings of the existing local image retrieval approaches. The major outcomes of our research work are:

- Development of new OFMMs-based approach for retrieval of CT and MRI images. The proposed approach uses OFMMs superior feature representation ability to extract global features from CT and MR images.
- Detailed comparative performance analysis of our proposed approach with the existing as well as the recently published feature descriptors such as LBDP, LWP, LNIP, LNIP, etc., is presented.
- Additional experiments are presented to analyze the noise robustness ability and the computational efficiency of the proposed as well as the compared methods.
- All the presented experiments establish the supremacy of the proposed approach over the existing methods.

1.6 Organization of the Thesis File

The thesis file is organized as follows:

Chapter 2: This chapter provides the detailed review of the different CBIR techniques for the retrieval of biomedical images. The complete description about the state-of-the-art as well as recently published local feature extraction techniques for the content based retrieval of biomedical images and closely related applications has been discussed in this chapter.

Chapter 3: This chapter represents the problem statement and its solution using our proposed approach in this thesis work.

Chapter 4: This chapter defines the proposed framework for OFMMs-based CT and MRI image retrieval system. As OFMMs are the subclass of the ORIMs(orthogonal rotational invariant moments), the chapter initially presents an overview of ORIMs and their mathematical background. Then the complete description about OFMMs considered in our research work and their general properties which make them suitable for the content-based image retrieval system has been discussed in this chapter.

Chapter 5: This chapter introduces the computational framework employed to test the performance of proposed approach in comparison with the recent and state-of-the-art retrieval methods. The chapter gives the description about the types of datasets, performance measures, similarity measures etc. used for the experimental work. The computational efficiency of all the methods has been computed to find out which method has fastest retrieval rate among all the methods. Additional experiments have been performed to analyse the noise robustness abilities of all the methods.

Chapter 6: Finally, chapter 6 summarizes the thesis work and presents the possible scope for extension of our proposed work in near future.

Chapter 2

Literature Review

Recent studies have shown that medical image retrieval (MIR) is one of the active research areas in the field of biomedical image processing. One of the main reason is the expansion and hasty growth of various medical modalities such as ultrasound (US), X-Ray, computed tomography (CT) and magnetic resonance imaging (MRI) to provide the accurate diagnosis of a disease. Therefore, it is highly desirable to organize the biomedical image data in a structured manner for efficient access, search and retrieval of medical images for clinical purpose.

To develop a robust and efficient MIR system, extraction of appropriate features like color, shape, and texture plays a significant role. Colors are the one of the most important visual descriptor of an image and used to make the gray scale images more pleasant to eyes, easier to analyze and understand. Colors are basically a composition of three primary RGB i.e. RED, GREEN, and BLUE colors. RGB, HSV, YIQ, CIE, L^*U^*V are the common color spaces used in the various applications. The rest description about the colors can be seen in [17]. Shape signifies the idea to have a description of the region of interests (ROIs) in an image. ROIs can lie within the local or global region of any query image. Shape descriptors are classified into the two categories as region based [18] and boundary based [19]. Texture is a visual pattern exhibiting the property of homogeneity which has a similar kind of pattern. Texture consist the properties like coarseness, contrast, directionality etc., Texture signifies about the natural feature of a pattern like the texture of hair, brick, skin, brick and wood etc., [20]. Among these three categories, it has been observed that the, texture- based features are widely adopted and popular among the medical research community across all over the globe [22]. This is because, medical images are rich in texture information. Every body organ has different texture of underlying tissues cells in it. So, texture-based feature descriptors are more capable to extract useful information in comparsion to other category of features. The texture-based feature descriptors can further be categorized into two classes as local texture feature descriptors and global texture feature descriptors.

In local feature descriptors, an image is divided into overlapping blocks and information within each block is obtained by exploring the neighbors in different directions. Features of each block are appended together to form a feature vector of the entire image. In global feature descriptors, the entire image is considered as a single unit for the purpose of feature extraction. The description of how the content-based image retrieval systems work with different feature extraction techniques is detailed in [23-26]. The work done in the initial days for the retrieval of CT and MRI images is mentioned in [27]. The PACS (Picture archiving and communication system) [28], IRMA (Image retrieval for medical applications) [29], SPIRS (Spine pathology and image retrieval system [30] etc., are the most popular content-based medical image retrieval systems (MIR).

In the initial days, local binary pattern (LBP) [31] has been introduced as a local feature descriptor for the purpose of the texture synthesis. LBP achieves very appreciable results in texture synthesis because of its simple working strategy. As LBP works in the local structure of an image the researchers adopted the idea to use LBP in the biomedical areas like to analyze the microstructure of the different body organs of the X-ray, CT, MRI images. Now with the help of LBP, it became easier to analyze the region of disorder and proper diagnosis can be provided to a patient. LBP has given a new insight into the research areas like face recognition [32], Analysis of Pulmonary Emphysema [33] and Facial Paralysis [34] etc., Because of its uniform direction working strategy, the results expected under the difficult lighting conditions, noise conditions, pose conditions, ageing of the images etc. are not that much satisfactory. To deal with such type of conditions LBP is further extended to its various variants in different application areas.

To cope up the lightning conditions Tan and Triggs introduced a new local feature extraction technique named Local ternary patterns (LTP) [35] as a three-valued code formation method. A constant user-defined threshold value is added to convert the binary code values as a 3-valued code formation. With the help of LTP, it becomes easier to analyze the different patterns under difficult noise, aging and lighting conditions. Due to these superior abilities, the use of LTP is further extended in medical application [36] for the purpose to detecting abnormal smear cells , for classifying pain states starting from facial features etc.,

LTP solves partially the problem of being less sensitive to noise and still suffer from the mechanism to recover the corrupted patterns. Hence most of the times both LBP and LTP choose to work with the corrupted structures without making any efforts to recover them. Moreover, the selection of constant user-defined threshold value to achieve better results in various lighting conditions is a very crucial step. LTP has proven itself as a better descriptor over the LBP but scenarios like threshold selection etc. limit its performance. Hence there is still a need to have some modification in local binary and ternary methods to have the overall better performance. With the advancement in the medical equipment and increased number of medical modalities, the complexity of information in the medical images has also increased. Thus only texture-based features are not capable enough to extract all the information present in the medical image. Therefore, the need of how is to design multi-dimensional or hybrid feature descriptor which can extract different types of information such as edge, structural as well as textual information at the same time from the given medical image. In this quest various (hybrid) feature descriptors have been proposed lately. Some of the prominent methods are described as follows:

LBP and LTP can only work by exploring the edge information either in a positive direction or in a negative direction. A new method named local tetra patterns (LTrPs) [37] is introduced to improve the performance of both the methods by exploring the edge information in more than the two directions. LTrPs encode the edge information in the selected four directions to have the better retrieval of biomedical images. LTrPs have the extraordinary power to explain the spatial structure of the body organs in a more accurate and detailed way. The only problem with LTrPs is that it has very high feature vector length.

Another variant of LBP i.e., the local Quinary patterns (LQPs) [38] have been introduced as advancement over all the earlier proposed local patterns. The LQP uses the five-valued code pattern to extract the more detailing structure of the biomedical images. Two constant user-defined threshold values are added to convert the extracted patterns into five coded formats. LQPs have shown better performance but like LTP they also suffer from the problem of threshold selection and high dimensionality. The LQPs are further extended to local quantized extrema patterns (LQEPs) [39].

In LQEP, the extrema operations are applied over the directional geometric structures of the input image for the better image retrieval. To overcome the high dimensionality problem, Murala and Wu introduced a new method of feature extraction named Local co-occurrence ternary patterns (LTCoP) [40]. LTCoP works as a rotational invariant local feature descriptor in comparison to the earlier mentioned methods. LTCoP simply encodes the co-occurrence of the similar ternary edges which are calculated based on the grey values of the central pixel and the surrounding pixels. Because of the advancement of the LTCoP over the LBP and its different variants, it has been widely used in the MRI images analysis systems. However, the high time complexity of LTCoP method is its limiting factor.

Apart from the code format, all the existing methods have almost same working methodologies to encode the relationship between a center pixel and its surrounding neighbors. To change the trend of these working methodologies, Murala and Wu further proposed a new approach called local mesh edge ternary patterns (LMePs) [41] especially for the retrieval of CT and MR images. LMeP simply encodes the relationship among the surrounding neighbors and extract better edge information as compared to LBP and all existing variants. The problem with LMeP is the high computational cost while dealing with the non-uniform patterns. To deal with the high computational complexity of LMeP, it was further extended to a new method named Local Mesh Peak Valley edge patterns (LMePVPs) [42]. LMePVP encodes the relationship among the neighboring pixels using local mesh peak edge patterns (LMePEP) and local mesh valley edge pattern (LMeVEP). The LMePEP and LMeVEP can also be referred as the first order derivatives and the second order derivatives. Like LTP, LMePVP is also a ternary pattern and have better spatial information and less sensitivity towards the noise.

All the above mentioned methods extract relationships between neighboring pixels and center pixel in 2D plane. A new method called spherical symmetric three-dimensional local ternary pattern (SS-3D-LTP) [43] performs the same operation however in 3D view for the natural, texture and biomedical image retrieval applications. SS-3D-LTP is an extension of LTP from 2D to 3D. The SS-3D-LTP have the advantage to encode the relationship between the central

pixel to its neighboring pixels in a selected five directions with an aim to convert the input 2D image to the 3D plane with the help of the Gaussian filter bank. From the 3D view of the body organs, the physicians can analyze the region of disorder more quickly, in an effective way.

To further enhance the discrimination power and to reduce the high dimensionality of feature vector, a similar set of approaches has been proposed by Dubey et al. (LWP [44], LDEP [45], LBDISP [46] and LBDP [47]) for CT image retrieval applications. Authors have employed either wavelet or divided the image into bit planes to encode the differences between the neighbors and the center pixel. The LWP is designed to utilize the both relationship encoding techniques i.e. among local neighbors as done in LMeP and also between the centre pixel and its local neighbors as done in LBP. In LWP, local wavelet decomposition technique is used to encode the relationship among the local neighboring pixels. After that, a comparison between the decomposed values and transformed centre pixel value is done to produce a binary pattern. The size of the feature vector is invariant to the radius of the local neighborhood. LWP has the lower retrieval time, computational time and high discrimination power as compared to LBP and its existing variants.

Local diagonal extrema patterns (LDEP) [45] only consider the diagonal elements around a central pixel to construct the extrema patterns and hence reduces the curse of dimensionality over existing LBP and its variants. This is because only the limited numbers of diagonal elements are selected in LDEP to construct the extrema patterns. Hence LDEP has proven itself as a compact, high discriminative and efficient over all the existing method for the retrieval of the CT images.

Local bit-plane dissimilarity pattern (LBDISP) [46] encodes the local dissimilarity between a central pixel and its surrounding pixels at a bit plane level. The dimension of the descriptor simply depends upon the number of neighbors only. LBDISP are preferable to analyse and retrieve out the images of different body organs more effectively than the earlier ones. LBDISP have almost nearer time complexity as the LDEP and better discrimination rate.

Following the same trend, Deep et al introduced two new retrieval techniques called local mesh ternary patterns (LMeTP) [48] and directional local ternary quantized extrema (DLTerQEPs) [49] to extend the standard LBP and LTP functionality for a 2D image in the selected directions for the retrieval of MRI and CT image. LMeTP encodes the grey scale relationship among the neighbors for a given centre pixel with selected three directions of mesh patterns. In addition, LMeTP simply uses the ternary patterns from the mesh patterns of an image to encode better spatial structural information of the medical images. LMeTP advances the performance of the content-based biomedical retrieval systems.

DLTerQEP [49] extracts the information between any pair of neighbors along the selected directions of the horizontal, vertical, diagonal, anti-diagonal (HVDA₇) structure of an image. It uses the ternary patterns from the horizontal, vertical, diagonal, anti-diagonal (HVDA₇) structure of the directional local extrema pattern values of an image and provides more spatial structure information for the better retrieval. DLTerQEP provides a vast improvement in the discrimination power. DLTerQEPs patterns are further extended to local quantized extrema quinary pattern (LQEQRyP) [50] for the better image retrieval.

Verma and Raman also proposed two new retrieval methods namely local tri-diagonal patterns (LTDP) [51] local neighborhood difference patterns (LNDP) [52] to achieve better retrieval performance over the LBP and all its variants by encoding all the possible information associated with each pixel in an image. Both have the capabilities to extract more accurate and systematic features from an input image in comparison to the existing methods.

LNDP simply encodes the mutual relationship among the neighboring pixel to create the local patterns and tries to overcome the problem of information redundancy. LNDP has numerous advantages like easy computation methodology, feasible dimensionality for the real-time retrieval systems, face recognition applications etc., and has better performance over earlier local patterns.

After that, a new variant called local neighborhood intensity pattern (LNIP) [53] has been introduced for the natural image retrieval and face recognition applications. In LNIP, the information contained in the adjacent neighbors of a

particular pixel is encoded to extract the binary patterns. The extraction of binary patterns can be done in two ways, i.e. either as the sign of the intensity difference or as the magnitude of intensity difference with respect to adjacent neighbors. In the end, these sign and magnitude values of the patterns are concatenated together to provide more resistance to illumination changes. Recently Local directional gradient pattern (LDGP) [54] has been observed in the literature. LDGP extracts the relationship between the high order derivatives of the centre pixel in four different directions to compute the local pattern. LDGP has the low feature vector length in the comparison to the earlier existing methods. This low feature vector length reduces the feature extraction and matching time during the retrieval. Hence LDGP has least time complexity in the comparison to the earlier proposed methods.

All the above-mentioned methods are local feature descriptors and have proved to be good image retrieval approaches. The local feature descriptors give good performance, but they are vulnerable and insufficient to give similar performances in scenarios where the query images have been degraded either by noise or by some transformations like rotation, scaling or translation etc. Also, some of the methods have very large feature size and are very computation intensive. Thus, in order to achieve maximum throughput in retrieving medical images of different body organs, we cannot rely only on local features. The global information of an image plays a very crucial role in differentiating between images of different body parts. Hence in this research work, we are shifting the idea of local feature descriptors to the global one and propose a new image retrieval approach for the retrieval of CT and MR images based on orthogonal Fourier-Mellin moments (OFMMs). The OFMMs offers several advantages over the existing local feature descriptor methods which make them very suitable for this application. More insight into properties and working of OFMMs is presented in Chapter 4.

2.1. Overview of Existing Methods

2.1.1. Local Binary Pattern (LBP)

The local binary pattern (LBP) was proposed by Ojala et al. [31] for the purpose of texture classification. LBP had success in terms of speed and there was no need to tune any parameter. This made LBP very useful and popular in many applications like face recognition, object tracking, medical imaging etc. For a given input grey scale image, the LBP pattern is calculated by constructing a local window around each pixel of the image to encode the intensity difference relationship between a central pixel of the local window and all its neighboring pixels. The number of neighboring pixels depends on the value of radius (R). If $R = 1$, it means that 8 neighbors will be lying on the circumference of the circle around the central pixel. The value obtained from the intensity difference is replaced with the binary number either 0 or 1. Thus a binary code of a specific length is obtained for the selected central pixel, to get an LBP map. The weights are assigned to the obtained binary values as described in Eq. (2.1).

$$\text{LBP}(N, R) = \sum_{i=1}^N 2^{i-1} \times D_1(I_i, I_c) \quad (2.1)$$

$$D_1(I_i, I_c) = \begin{cases} 1, & I_i \geq I_c \\ 0, & \text{otherwise} \end{cases} \quad (2.2)$$

To construct a feature vector for the entire image a histogram concatenation is done for all possible obtained LBP maps as described in Eq. (2.3).

$$\text{Hist_LBP} = \sum_{i=1}^X \sum_{j=1}^Y D_2(\text{LBP}(I_i, I_c), L) \quad (2.3)$$

$$D_2(a_1, a_2) = \begin{cases} 1, & a_1 = a_2 \\ 0, & \text{otherwise} \end{cases} \quad (2.4)$$

where $L \in [0, (2^N - 1)]$, I_i and I_c are the intensity values of the neighboring pixel and central pixel.

2.1.2. Local Ternary Pattern (LTP)

Tan and Triggs extended the LBP from the two-valued code to three-valued code. A user-defined threshold value t is used in combination with the LBP two-valued code to convert into the three-valued code.

The LTP is three-valued code is defined as:

$$\vec{F}(x, g_c, t) = \begin{cases} +1, & x \geq g_c + t \\ 0, & |x - g_c| < t \\ -1, & x \leq g_c - t \end{cases} \quad (2.5)$$

where t is a threshold value, values $g_c - t$ and $g_c + t$ are considered to be as the low and high range of values. The values lie in the lower range of the low are replaced as -1 , values in the upper range to the high value replaced by $+1$ and the rest of the values are considered to be as 0 . In LTP the threshold value is a user-defined value. LTP values are more resistant to noise and invariance to the grey level transformation. To construct a feature vector for the entire image a histogram concatenation is done for all possible obtained LTP maps as described earlier in LBP.

2.1.3. Local Quinary Patterns (LQP)

Local quinary patterns are proposed as another variant of LBP for the purpose of medical image analysis. To encode the intensity difference relationship between a particular central pixel (g_c) to all its neighboring pixels, LQP uses the five code format instead of binary or ternary format. The standard expression to replace the binary code format into the quinary format is as:

$$\vec{f}(x, t_1 t_2) = \begin{cases} +2, & x \geq g_c + t_2 \\ +1, & g_c + t_1 \leq x < g_c + t_2 \\ 0, & g_c - t_1 \leq x < g_c + t_1 \\ -1, & g_c - t_2 \leq x < g_c - t_1 \\ -2, & otherwise \end{cases} \quad (2.6)$$

where t_1 and t_2 are two user-defined constant threshold values, x denotes the particular neighboring pixel. The quinary patterns obtained from the above equation are further split into four binary patterns as:

$$b_c(x) = \begin{cases} 1, & x = c \\ 0, & else \end{cases} \quad (2.7)$$

The four binary patterns are obtained by considering the values of c from $-2, -1 + 1, -2$. To construct a feature vector for the entire image a histogram concatenation is done for all possible obtained binary patterns as described earlier in LBP. The more detail can be found in [38].

2.1.4. Local Quantized Extrema Pattern (LQEP)

LQEPs are proposed by the Rao and Rao as an extension over local quinary patterns (LQPs) for the natural images retrieval. The idea to integrate the local

quinary patterns (LQP) and directional local extrema pattern (DLEP) is proposed to design the local quantized extrema patterns. The LQP simply computes the directional geometric features from the given query image. These directional geometric features are collected in horizontal (H), vertical (V), diagonal (D) and antidiagonal (A) directions of a central pixel; combinations of these antidiagonal forms a HVDA₇ geometric structure of the given pattern.

Then, the extrema operations are employed on the obtained directional geometric structures to construct a feature vector of an appropriate size. The steps to be followed during the LQEP construction are as:

Input: Query image; **Output:** Top relevant images

- Load the given query image.
- Compute the HVDA₇ pattern for the selected center pixel.
- Compute the values of local extrema patterns in selected $0^\circ, 45^\circ, 90^\circ$ and 135° directions.
- Calculate the LQEP of 12-bit with four directional extrema.
- Construct the histogram for 12-bit LQEP.
- Compute the feature vector by appending all LQEP histograms.
- Apply distance measure between the feature vectors of the query image and images existing in the database.
- Retrieve the similar images on the bases of distance measure.

In this way the LQEP patterns are computed from the given input image. The more detail can be found in [39].

2.1.5. Local Tetra Patterns (LTerP)

LTerP uses the direction of the centre gray pixel to describe the spatial structure of the local texture. LTerP encodes the relationship between a centre pixel (g_c) and its surrounding pixels in the selected horizontal and vertical directions with the help of first-order derivatives as:

$$I_{hori}^1(g_c) = I(g_{k_{hori}}) - I(g_c) \quad (2.8)$$

$$I_{verti}^1(g_c) = I(g_{k_{verti}}) - I(g_c) \quad (2.9)$$

On the bases of first order derivatives, the possible directions for the central pixels are calculated.

The standard equation to compute the possible directions for the central pixel is as:

$$I_{Dir}^1(g_c) = \begin{cases} 1, & I_{hori}^1(g_c) \geq 0, & I_{verti}^1(g_c) \geq 0 \\ 2, & I_{hori}^1(g_c) < 0, & I_{verti}^1(g_c) \geq 0 \\ 3, & I_{hori}^1(g_c) < 0, & I_{verti}^1(g_c) < 0 \\ 4, & I_{hori}^1(g_c) \geq 0, & I_{verti}^1(g_c) < 0 \end{cases} \quad (2.10)$$

The Eq. (2.10) shows that there are possibly four directions to convert an input image into the tetra patterns.

The second order derivative is calculated as:

$$LTrP^2(g_c) = \left\{ f_3 \left(I_{Dir}^1(g_c), (g_c) \right), f_3 \left(I_{Dir}^1(g_c), I_{Dir}^1(g_2) \right) \dots, \right. \\ \left. \dots f_3 \left(I_{Dir}^1(g_c), I_{Dir}^1(g_p) \right) \right\} \Bigg|_{p=8} \quad (2.11)$$

$$f_3 \left(I_{Dir}^1(g_c), I_{Dir}^1(g_p) \right) = \begin{cases} 0, & I_{Dir}^1(g_c) = I_{Dir}^1(g_p) \\ I_{Dir}^1(g_c), & else \end{cases} \quad (2.12)$$

Eq. (2.11) and Eq. (2.12) show about the 8-bit tetra pattern construction for each central pixel. After that, all the obtained patterns are further split into four parts on the bases of possible four directions correspond to center pixel. The computed tetra patterns are further split into the three binary patterns and for a single direction say 1 as:

$$LTerP^2|_{Direction_{2,3,4}} = \sum_{p=1}^P 2^{(p-1)} \times f_4(LTerP^2(g_c)) \Bigg|_{Direction_{2,3,4}} \quad (2.13)$$

$$f_4(LTerP^2(g_c))|_{Direction_{2,3,4}} = \begin{cases} 1, & if \ LTerP^2(g_c) = \emptyset \\ 0, & else \end{cases} \quad (2.14)$$

In the same fashion, the three more tetra patterns will be computed for the remaining 2^{th} , 3^{th} and 4^{th} directions and are converted to the binary patterns. Thus total 12 binary patterns are formed after exploring all four directions. For getting more precise results, 13^{th} binary pattern is calculated by considering the values after magnitude of the horizontal and vertical directions by using the first order derivatives as:

$$M_{I_{(g_p)}^1} = \sqrt{I_{(0^\circ)}^1(g_p)^2 + I_{(90^\circ)}^1(g_p)^2} \quad (2.15)$$

$$LP = \sum_{p=1}^P 2^{(P-1)} \times f_1 \left((M_{I_{(g_p)}^1} - M_{I_{(g_c)}^1}) \right) \Big|_{P=8} \quad (2.16)$$

Hence a feature vector of length 2^p has been constructed from the p neighbors. At the end, a histogram construction is done to represent the entire image, using equation as:

$$H_s(l) = \frac{1}{N_1 \times N_2} \sum_{j=1}^{N_1} \sum_{k=1}^{N_2} f_5(PTN(j, k), l) \quad (2.17)$$

$$f_5(x, y) = \begin{cases} 1, & \text{if } x = y \\ 0, & \text{else} \end{cases} \quad (2.18)$$

where $l \in [0, p(p-1) + 2]$ and $N_1 \times N_2$ represents about the size of the input image. The more detail can be found in [37].

2.1.6. Local Ternary Co-occurrence Patterns (LTCoP)

The idea of LBP and LTP has been used to introduce LTCoP for the retrieval of biomedical images. LTCoP is a ternary code (0,1,2) method and uses the first order derivation in selected eight directions to encode the ternary co-occurrence patterns from the query image. LTCoP is calculated as:

$$LTCoP = \left[f_3 \left(I_{P,R}^1(g_1), I_{P,R+1}^1(g_1) \right), f_3 \left(I_{P,R}^1(g_2), I_{P,R+1}^1(g_2) \right), \dots, \right. \\ \left. \dots, f_3 \left(I_{P,R+1}^1(g_p), I_{P,R+1}^1(g_p) \right) \right] \quad (2.19)$$

$$f_3(x, y) = \begin{cases} 1, & \text{if } x = y = 1 \\ 2, & \text{if } x = y = 2 \\ 0, & \text{else} \end{cases} \quad (2.20)$$

where $p = 8$, $I_{P,R}^1(g_i)$ and $I_{P,R+1}^1(g_i)$ are the ternary values in the selected eight directions and these values are computed as:

$$\check{I}_{P,R}(g_i) = I_{P,R}(g_i) - I_{P,R}(g_c); \quad i = 1, 2, \dots, p \quad (2.21)$$

$$\check{I}_{P,R+1}(g_i) = I_{P,R+1}(g_i) - I_{P,R}(g_c); \quad i = 1, 2, \dots, p \quad (2.22)$$

where $\check{I}_{P,R}(g_i)$ and $\check{I}_{P,R+1}(g_i)$ are the first order derivatives corresponding to the given central pixel (g_c). After that these values of first order derivatives are further converted into the sign of derivatives as:

$$I_{P,R}^1(g_i) = \check{f}_1 \left(\check{I}_{P,R}(g_i) \right) \quad (2.23)$$

$$I_{P,R+1}^1(g_i) = \check{f}_1 \left(\check{I}_{P,R+1}(g_i) \right) \quad (2.24)$$

Following the trend of LTP, the obtained ternary patterns are further split into the binary patterns. To construct a feature vector for the entire image a histogram concatenation is done for all possible obtained LTCOP maps. The complete description of LTCOP is in [40].

2.1.7. Local Mesh Patterns (LMeP)

In contrast to all the earlier proposed methods, LMeP encodes the relationship among the neighboring pixels for a particular central pixel in an image. The standard equation to encode the LMeP is as:

$$LMeP_{p,R}^j = \sum_{i=1}^p 2^{(i-1)} \times f_1(g_{\alpha|R} - g_{i|R}) \quad (2.25)$$

$$\alpha = 1 + \text{mod}((i + p + j - 1), p) \quad (2.26)$$

where j is the LMeP index and $\text{mod}(x, y)$ returns the remainder for x/y operation. Eq. (2.26) shows that for p neighbors the possible LMeP patterns will be $\binom{p}{2}$ i.e. for $p = 8$, there are possible four LMeP patterns for the given image and it depends upon the user's choice that with how many patterns he wants to work. For p neighboring pixels the length of feature vector will be 2^p . After computing the local pattern (PTN) the entire image is represented by constructing a histogram as:

$$H_s(l) = \frac{1}{N_1 \times N_2} \sum_{j=1}^{N_1} \sum_{k=1}^{N_2} f_2(PTN(j, k), l) \quad (2.27)$$

where $l \in [0, p(p-1) + 2]$ and $N_1 \times N_2$ defines the size of the query image. A feature vector of length 2^p will be obtained after appending all the histograms.

$$f_2(x, y) = \begin{cases} 1, & \text{if } x = y \\ 0, & \text{else} \end{cases} \quad (2.28)$$

The detailed description of the method is available in [41].

2.1.8. Local Mesh Peak Valley Edge Patterns (LMePVEP)

LMePVEP is the extension over the LMeP. In LMePVEP, the forward and backward first order derivatives are used to compute the relationship among the neighbors for a given central pixel (g_c). The LMePVEP is a ternary pattern (0,1,2) and its values are further these ternary values are split into two binary patterns as local mesh peak edge pattern (LMePEP) and local mesh valley edge

pattern (LMeVEP). Both the binary patterns will have the values ranging from 0 to 255. In the end, the histograms corresponding to each of the pattern are appended together to obtain a feature vector for the given image. After that the comparison of query image with the each image of database is done to retrieve the images based on the best matches. The rest description about LMePVEP is in [42].

2.1.9. Spherical Symmetrical Three Dimensional Local Ternary Pattern (SS-3D-LTP)

SS-3D-LTP is the extension over the LTP. SS-3D-LTP has the advantage to encode the relationship between the central pixel and its neighboring pixels along the five selected directions in 3D representation of given 2D image. The 3D representation is obtained by stacking together gaussian images of the input image. The gaussian images are calculated as:

$$L(\sigma) = g(x, y, \sigma) * I(x, y) \quad (2.29)$$

where $*$ is the convolution operator and σ is the standard deviation of the gaussian filter. The value of σ is varied to construct multiresolution or multiscale gaussian filter bank, $g(x, y, \sigma)$.

For any central pixel $L_c(\sigma_2)$ the neighbors are calculated as:

$$V_{|P=8} = \begin{cases} V(L_0(\sigma_2)), (L_1(\sigma_2), L_2(\sigma_2), L_3(\sigma_2), L_4(\sigma_2), L_5(\sigma_2), L_6(\sigma_2), L_7(\sigma_2)); \\ \quad \text{at } \alpha = 1 \\ V(L_2(\sigma_1)), (L_c(\sigma_1), L_6(\sigma_1), L_6(\sigma_2), L_6(\sigma_3), L_c(\sigma_3), L_2(\sigma_3), L_2(\sigma_2)); \\ \quad \text{at } \alpha = 2 \\ V(L_5(\sigma_1)), (L_c(\sigma_1), L_1(\sigma_1), L_1(\sigma_2), L_1(\sigma_3), L_c(\sigma_3), L_5(\sigma_3), L_5(\sigma_2)); \\ \quad \text{at } \alpha = 3 \\ V(L_4(\sigma_1)), (L_c(\sigma_1), L_0(\sigma_1), L_0(\sigma_2), L_0(\sigma_3), L_c(\sigma_3), L_4(\sigma_3), L_4(\sigma_2)); \\ \quad \text{at } \alpha = 4 \\ V(L_3(\sigma_1)), (L_c(\sigma_1), L_7(\sigma_1), L_7(\sigma_2), L_7(\sigma_3), L_c(\sigma_3), L_3(\sigma_3), L_3(\sigma_2)); \\ \quad \text{at } \alpha = 5 \end{cases} \quad (2.30)$$

where $L_0, L_1, L_2 \dots L_7$ are the neighbors of L_c and $L(\sigma_1), L(\sigma_2), L(\sigma_3)$ are the three gaussian images of input image I . The 0.5, 0.55, and 0.6 are the optimum values of σ_1, σ_2 and σ_3 respectively. After finding the neighbors in five different directions i.e. $\alpha = 1$ to 5 local ternary patterns are constructed as:

$$\begin{aligned}
& f(x, y) \\
& = \left\{ \begin{array}{l} \left(\begin{array}{l} \vec{f}(l_0(\sigma_2) - l_c(\sigma_2)), \vec{f}(l_1(\sigma_2) - l_c(\sigma_2)), \vec{f}(l_2(\sigma_2) - l_c(\sigma_2)), \\ \vec{f}(l_3(\sigma_2) - l_c(\sigma_2)), \vec{f}(l_4(\sigma_2) - l_c(\sigma_2)), \\ \vec{f}(l_5(\sigma_2) - l_c(\sigma_2)), \vec{f}(l_6(\sigma_2) - l_c(\sigma_2)), \vec{f}(l_7(\sigma_2) - l_c(\sigma_2)) \end{array} \right) \\ \text{at } \alpha = 1 \\ \left(\begin{array}{l} \vec{f}(l_2(\sigma_1) - l_c(\sigma_2)), \vec{f}(l_c(\sigma_7) - l_c(\sigma_2)), \vec{f}(l_6(\sigma_1) - l_c(\sigma_2)), \\ \vec{f}(l_0(\sigma_2) - l_c(\sigma_2)), \vec{f}(l_6(\sigma_3) - l_c(\sigma_2)), \\ \vec{f}(l_c(\sigma_3) - l_c(\sigma_2)), \vec{f}(l_2(\sigma_3) - l_c(\sigma_2)), \vec{f}(l_2(\sigma_2) - l_c(\sigma_2)) \end{array} \right) \\ \text{at } \alpha = 2 \\ \left(\begin{array}{l} \vec{f}(l_5(\sigma_1) - l_c(\sigma_2)), \vec{f}(l_c(\sigma_1) - l_c(\sigma_2)), \vec{f}(l_1(\sigma_1) - l_c(\sigma_2)), \\ \vec{f}(l_1(\sigma_2) - l_c(\sigma_2)), \vec{f}(l_1(\sigma_3) - l_c(\sigma_2)), \\ \vec{f}(l_c(\sigma_3) - l_c(\sigma_2)), \vec{f}(l_5(\sigma_3) - l_c(\sigma_2)), \vec{f}(l_5(\sigma_2) - l_c(\sigma_2)) \end{array} \right) \\ \text{at } \alpha = 3 \\ \left(\begin{array}{l} \vec{f}(l_4(\sigma_1) - l_c(\sigma_2)), \vec{f}(l_c(\sigma_1) - l_c(\sigma_2)), \vec{f}(l_0(\sigma_7) - l_c(\sigma_2)), \\ \vec{f}(l_0(\sigma_2) - l_c(\sigma_2)), \vec{f}(l_0(\sigma_3) - l_c(\sigma_2)), \\ \vec{f}(l_c(\sigma_7) - l_c(\sigma_2)), \vec{f}(l_4(\sigma_3) - l_c(\sigma_2)), \vec{f}(l_4(\sigma_2) - l_c(\sigma_2)) \end{array} \right) \\ \text{at } \alpha = 4 \\ \left(\begin{array}{l} \vec{f}(l_3(\sigma_1) - l_c(\sigma_2)), \vec{f}(l_1(\sigma_2) - l_c(\sigma_2)), \vec{f}(l_2(\sigma_2) - l_c(\sigma_2)), \\ \vec{f}(l_3(\sigma_2) - l_c(\sigma_2)), \vec{f}(l_4(\sigma_2) - l_c(\sigma_2)), \\ \vec{f}(l_5(\sigma_2) - l_c(\sigma_2)), \vec{f}(l_6(\sigma_6) - l_c(\sigma_2)), \vec{f}(l_7(\sigma_2) - l_c(\sigma_2)) \end{array} \right) \\ \text{at } \alpha = 5 \end{array} \right) \quad (2.31)
\end{aligned}$$

After the construction of the patterns, each pattern is further split down into the two patterns as LTP_{upper} and LTP_{lower} . The SS-3D-LTP for a particular selected direction is as:

$$SS - 3D - LTP_{\alpha, P, R} = \sum_{q=0}^{P-1} V_{(upper, lower)} q^{2^q} \quad (2.32)$$

At the end of the method, five LTP_{upper} and five LTP_{lower} patterns are appended together to form a feature vector. The rest description of the method is available in [43].

2.1.10. Local Wavelet Patterns (LWP)

The LWP is designed to utilize the both relationship encoding techniques i.e. among local neighbors as done in LMeP and also between the centre pixel and its local neighbors as done in LBP. In LWP, local wavelet decomposition technique is used to encode the relationship among the local neighboring pixels. After that, a comparison between the decomposed values and transformed centre pixel value is

done to produce a binary pattern. The steps to be followed during LWP construction are as:

- Compute the local neighboring pixels of any given pixel in such a way that all the neighboring pixels must be residing at the equal distance from the centre pixel. Only those pixels will be chosen as the central pixel whose all local neighboring pixels are residing within the dimensions of the given image.
- The next step is to apply local wavelet decomposition technique to encode the intensity based relationship existing among the neighboring pixels of the selected pixel.
- After that same decomposition technique is employed to encode the relationship between the centre pixel and its neighborhood elements.
- A center pixel transformation technique is applied to have the proper matching between the boundary limits of center and local wavelet decomposed values and these values are further used to construct a binary array of N (number of neighbors).
- At the end, local wavelet pattern feature vector of size 2^N is obtained for the given image.

In this way, the LWP patterns are computed for the given input image. The rest description of the method can be found in [44].

2.1.11. Local Diagonal Extremas Patterns (LDEP)

LDEP is introduced as an alternative to tackle the high feature dimensionality issues existing in earlier. In LDEP, the relationship between the central pixel and its local diagonal neighbors is encoded to construct the desired pattern. The information among the local diagonal neighbors is encoded by calculating the values and indexes of the local diagonal extremas using first-order local diagonal derivatives. With the help of first-order local diagonal derivatives, LDEP calculates its local diagonal extremas i.e. maxima and minima values. The relationship of these local diagonal maxima and minima with the center pixel is used further to construct the LDEP descriptor. The LDEP pattern for and central pixel $p^{i,j}$ having $I^{i,j}$ intensity values and $\varphi_{\max}, \varphi_{\min}$ is the local maxima and minima respectively is defined as:

$$LDEP^{i,j} = (LDEP_1^{i,j}, LDEP_2^{i,j}, LDEP_3^{i,j}, \dots, LDEP_{dim}^{i,j}) \quad (2.34)$$

where $\dim$ is the maximum length of the LDEP pattern and $LDEP_k^{i,j}$ is the k^{th} element of the $LDEP^{i,j}$ pattern. The mathematical equation to calculate the k^{th} element as:

$$LDEP_k^{i,j} = \begin{cases} 1, & \text{if } k = (\varphi\max + 8\lambda) \text{ or } k = (\varphi\max + 4 + 8\lambda) \\ 0, & \text{otherwise} \end{cases} \quad (2.35)$$

where λ is the extrema-central relationship factor. The LDEP pattern always consist the values of two 1's and rest as 0's. The location of 1's is calculated on the basis of indices of extremas and type of relationship between the extremas and the central pixel. LDEP patterns for the whole image are constructed as:

$$LDEP = (LDEP_1, LDEP_2, LDEP_3 \dots, LDEP_{\dim}) \quad (2.36)$$

where $LDEP_k$ is the k^{th} element and its value is computed as:

$$LDEP_k = \frac{1}{(m1 - 2R)(m2 - 2R)} \sum_{i=R+1}^{m1-R} \sum_{j=R+1}^{m2-R} LDEP_k^{i,j} \quad (2.37)$$

The rest description of the method can be found in [45].

2.1.12. Local Bit-Plane Dissimilarity Pattern (LBDISP)

LBDISP decomposes the local neighborhood into bit-planes to find the dissimilarity map by computing the dissimilarity between the center and its neighbors at each bit-plane. After that, the local bit-plane dissimilarity patterns (LBDISP) are constructed for an input image by exploiting the relationship of center with dissimilarity map. The number of neighbors defines the dimension of the descriptor. Binary patterns obtained from LBDISP encoding in a particular bit-plane (t^{th}) plane for the (k^{th}) neighbor of a particular central pixel are computed as:

$$D_k^{i,j} \Big|_{t \in [1, N] \ \& \ k \in [1, B]} = \begin{cases} 0, & \text{if } I_k^{i,j,t} = I^{i,j,t} \\ 1, & \text{otherwise} \end{cases} \quad (2.38)$$

where $t \in [1, B]$ and $k \in [1, N]$, the neighboring values are calculated as:

$$D_k^{i,j} \Big|_{k \in [1, N]} = \sum_{t=1}^B 2^{t-1} \times D_k^{i,j,t} \quad (2.39)$$

After encoding a relationship between the central pixel and its neighbors, histograms are computed to construct the final feature vector for the entire image.

The histograms are constructed as:

$$H(\gamma) = \sum_{i=R+1}^{m1-R} \sum_{j=R+1}^{m2-R} \begin{cases} 1, & \text{if } \gamma = \sum_{k=1}^N 2^{K-1} \times LBDISP_K^{i,j} \\ 0, & \text{otherwise} \end{cases} \quad (2.40)$$

$$LBDISP_K^{i,j} \big|_{k \in [1,N]} = \begin{cases} 1, & \text{if } D_k^{i,j} \geq D^{i,j} \\ 0, & \text{otherwise} \end{cases} \quad (2.41)$$

The complete description of the method is in [46].

2.1.13. Local Bit Plane Decoded Patterns (LBDP)

In LBDP, the difference between the intensity value of center pixel and local bit-plane transformed values is calculated to obtain the binary patterns. These computed values are further decomposed into the local bit planes for the further processing. LBDP uses the local bit-plane transformation method to encode the relationship among neighbors in each bit-plane separately. Then the relationship of center pixel with each transformed values is encoded. After that the computed values are decoded further to construct a feature vector for the query image. The framework for the LBDP is as:

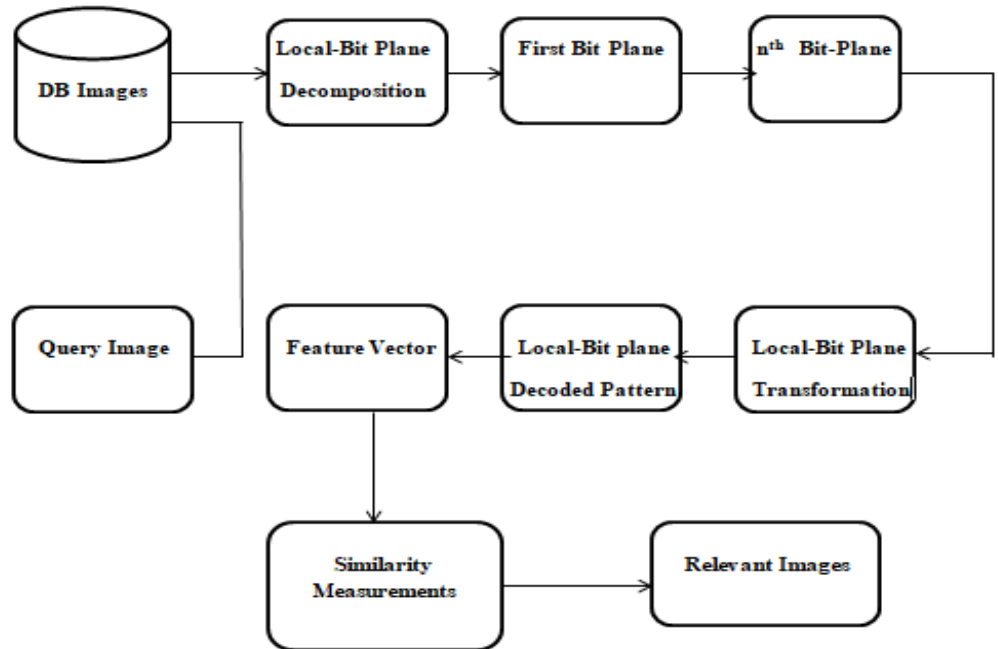


Figure 2.1: Framework for LBDP

2.1.14. Directional Local Ternary Quantized Extrema Patterns (DLTerQEPs)

DLTerQEPs encodes the local information between the centre pixel and any pair of neighbors in the selected four directions as $0^\circ, 45^\circ, 90^\circ, 135^\circ$. The method encodes the ternary patterns from the $HVDA_7$ structure of the DLTerQEPs patterns of an image. These ternary patterns from the image are extracted using local extrema and directional geometrical structures. The directional local extremas for the local pattern neighborhood of an image are computed as:

$$LDEV(q, r) = \sum_{q=1}^{k_1} \sum_{r=1}^{k_2} \left[I(q, r) - I \left(1 + \text{floor} \left(\frac{k_1}{2} \right), 1 + \text{floor} \left(\frac{k_1}{2} \right) \right) \right] \quad (2.42)$$

where $k_1 \times k_1$ is the size of the input image. After that, the $HVDA_7$ structure is used to compute the feature vector from the LDEV values. In the end, four directional ternary extrema coding (DTEC) values are collected at different threshold values as generally done in local ternary patterns. After that, the obtained ternary patterns are further split into the two binary patterns as LTP_{upper} and LTP_{lower} . The values for LTP_{upper} are calculated as:

$$\vec{F}_2(x, g_c) = \begin{cases} 1, & \text{if } (x \leq (\text{threshold} = 2)); \\ 0, & \text{if } (x \geq \text{threshold}); \end{cases} \quad (2.43)$$

LTP_{lower} are computed as:

$$\vec{F}_2(x, g_c) = \begin{cases} 1, & \text{if } (x \leq (\text{threshold} = -2)); \\ 0, & \text{if } (x \geq \text{threshold}); \end{cases} \quad (2.44)$$

After computing all these values a final directional ternary extrema coding (DTEC) will be constructed as a collective array of all the values corresponding to LTP_{upper} and LTP_{lower} .

DTEC is represented as:

$$DTEC(I(g_c)) = \begin{bmatrix} DTEC1(|I(g_c)|)|_{0^\circ}, DTEC1(|I(g_c)|)|_{45^\circ}, \dots \\ DTEC1(|I(g_c)|)|_{90^\circ}, DTEC1(|I(g_c)|)|_{135^\circ} \\ DTEC2(|I(g_c)|)|_{0^\circ}, DTEC2(|I(g_c)|)|_{45^\circ}, \dots \\ DTEC2(|I(g_c)|)|_{90^\circ}, DTEC2(|I(g_c)|)|_{135^\circ} \end{bmatrix} \quad (2.45)$$

After that all the obtained values are easily converted to the unique DLTerQEP values simply by multiply with the binomial.

The DLTerQEP values are computed as:

$$DLTerQEPs_{\alpha,p} = \sum_{w=0}^{p-1} DTEC_{\left(\frac{upper}{lower}\right),w} * 2^w \quad (2.46)$$

The complete image is represented by constructing a histogram for all patterns obtained. The more detail can be found in [49]. DLTerQEPs are further extended to local quantized extrema quinary pattern (LQEQtyP) [50] for the better biomedical image retrievals.

2.1.15. Local Neighborhood Difference Pattern (LNDP)

LNDP encodes the mutual relationship of all the neighboring pixels in a binary pattern with respect to each pixel in the image. In LNDP, comparison of each neighboring pixel is done with two most adjacent and appropriate pixels to compute the relationship. These two most adjacent neighborhood pixels can either be in vertical or horizontal direction pixels, the closest neighboring pixel matters. After that a binary number is assigned to each encoded relationship. In the same trend, binary number for each neighboring pixel is calculated and finally a histogram construction is done to represent the given image in the form of LNDP patterns. For neighboring pixel (I_n) and centre pixel (I_c) LNDPs are computed as:

$$K_1^n = I_8 - I_n, \quad K_2^n = I_{n+1} - I_n, \quad \text{for } n = 1 \quad (2.47)$$

$$K_1^n = I_{n-1} - I_n, \quad K_2^n = I_{n+1} - I_n, \quad \text{for } n = 2, 3, \dots, 7 \quad (2.48)$$

$$K_1^n = I_{n-1} - I_n, \quad K_2^n = I_1 - I_n, \quad \text{for } n = 8 \quad (2.49)$$

where k_1^n and k_2^n are the difference of each neighborhood pixel with two other neighborhood pixels, each neighboring pixel is decoded into a binary number on the bases of these two difference values.

$$f_3(k_1^n, k_2^n) = \begin{cases} 1, & \text{if } k_1^n \geq 0 \text{ and } k_2^n \geq 0 \\ 1, & \text{if } k_1^n < 0 \text{ and } k_2^n < 0 \\ 0, & \text{if } k_1^n \geq 0 \text{ and } k_1^n < 0 \\ 0, & \text{if } k_1^n < 0 \text{ and } k_2^n \geq 0 \end{cases} \quad (2.50)$$

LNDP for a given centre pixel is computed from the above binary values as follows:

$$LNDP(I_c) = \sum_{n=1}^8 2^{n-1} \times f_3(k_1^n, k_2^n) \quad (2.51)$$

Each pixel will be represented by a unique binary number, and finally, a histogram is constructed to represent the image in a form of LNDP. The detailed description of the method is available in [52].

2.1.16. Local Diagonal Gradient Pattern (LDGP)

LDGP is a local descriptor used to encode the relationship of the neighboring pixel in a higher order without losing any discriminative information. LDGP encodes the higher order derivative for any centre pixel with respect to the selected four directions $0^\circ, 45^\circ, 90^\circ$ and 135° in order to compute the micro patterns of the given image. LDGP of order n^{th} for any image is computed as:

$$\begin{aligned} LDGP^n(R_0) \\ = \{C(I_0^{n-1}(R_0), I_{45^\circ}^{n-1}(R_0)), \{C(I_0^{n-1}(R_0), I_{90^\circ}^{n-1}(R_0)), C(I_0^{n-1}(R_0), \\ I_{135^\circ}^{n-1}(R_0)), C(I_{45^\circ}^{n-1}(R_0), I_{90^\circ}^{n-1}(R_0)), C(I_{45^\circ}^{n-1}(R_0), I_{135^\circ}^{n-1}(R_0)), ..., \\ C(I_{90^\circ}^{n-1}(R_0), I_{135^\circ}^{n-1}(R_0))\} \end{aligned} \quad (2.52)$$

where $C(...)$ encodes the pair of $(n-1)^{th}$ derivative directions of the reference central pixel as:

$$C(I_\theta^{n-1}(R_0), I_\alpha^{n-1}(R_0)) = \begin{cases} 1, & \text{if } I_\theta^{n-1}(R) \\ 0, & \text{else} \end{cases} \quad (2.53)$$

The detailed description of the method is available in [54].

2.1.17. Local Neighborhood Intensity Patterns (LNIP)

LNIP computes the relative intensity difference between a selected pixel and the center pixel by considering its adjacent neighbors and generate a sign and a magnitude pattern. For signed pattern (I_c), the sign of the relative difference between one of the neighbors of center pixel (I_i) and its corresponding adjacent neighbors is calculated. The sign Binary pattern $B_{1,i}$ corresponding to a center pixel (I_i) are computed as:

$$B_{1,i}(k) = \text{sign}(S_i(k)I_i) \quad (2.54)$$

Similarly, another binary pattern $B_{2,i}$ of the same size corresponding to the center pixel considering the same neighboring pixels is encoded as:

$$B_{2,i}(k) = \text{sign}(S_i(k)I_c) \quad (2.55)$$

$$\text{sign}(a, b) = \begin{cases} 1, & a \geq b \\ 0, & \text{else} \end{cases} \quad (2.56)$$

where $k = 1$ to M and to analyse the structural variation between the both the obtained patterns the XOR operation is performed over them as:

$$D_1 = \text{XOR}(B_{1,i}, B_{2,i}) \quad (2.57)$$

$$B((I_i, I_c)) = \begin{cases} 1, & \#(D_1 = 1) \geq \frac{1}{2}M \\ 0, & \text{else} \end{cases} \quad (2.58)$$

$$\text{LNIP}_s(I_c) = \sum_{i=1}^8 2^{i-1} \times B(I_i, I_c) \quad (2.59)$$

where $\frac{1}{2}M$ is the required threshold value and M is the size of a constructed pattern for the sign difference values. In the same way, the final sign pattern is computed for all the pixels in the whole image and histograms are constructed to represent each pixels pattern in the form of a single feature vector. For magnitude patterns, the mean deviation is used to find out the corresponding values as:

$$M(I_i, T_c) = \text{sign}(M_i, T_c) \quad (2.60)$$

$$\text{LNIP}_M(I_c) = \sum_{i=1}^8 2^{i-1} \times B(I_i, I_c) \quad (2.61)$$

where T_c is the threshold value and M_i is any magnitude patterns of length M and are calculated as:

$$M_i = \frac{1}{M} \sum_{K=1}^M |S_i(k) - I_i| \quad (2.62)$$

$$T_c = \frac{1}{8} \sum_{i=1}^8 |I_i, I_c| \quad (2.63)$$

At the end histogram of magnitude patterns are calculated and two final histograms.

The values of $LNIP_S(I_c)$ and $LNIP_M(I_c)$ are concatenated to construct a final feature vector as:

$$Hist = [Hist^{LNIP_S}, Hist^{LNIP_M}] \quad (2.64)$$

The complete description about the LNIP can be seen in [53].

Chapter 3

Problem Statement

From the past years, the advancement in the information technology has turned the world around us into the digital one. With help of technology, it is become easier to capture, store and share the digital images. To maintain the proper storage of the captured digital images it is needed to have an organized system. The storage of images in such a way leads to the formation of the bulky database. The various naming schemas have been introduced to store the relevant images into a particular storage space or device like to name a folder related to the images insides it, make easier to retrieve the images. Moreover just to have a proper database is not the sufficient solution. The problem arises when people demand to retrieve the images related to a particular color, shape and texture etc. like “images of a red apple”. This is because the different people may have the different perception about the color of an apple; a person can be a color blind and results to the poor retrieval performance. The poor performance is because to retrieve such kind of the images is generally done manually by looking into all the images in the database until the satisfactory results are not found. The process of looking into each image is time-consuming. Although the size of the database is not possessed to be same in each and every time. The task of manual retrieval of images is only possible in the case of the small DBs. The big firms (medical firms) cannot afford to spend their valuable time and money in manual retrieval tasks because to retrieve a bigger database can take an hour, a day or week to retrieve the desired results. Hence there is a need to have a system that can work in a quick and efficient approach than the traditional approach. The content-based image retrieval systems are introduced to address all these shortcomings of existing methods. With the help of CBIR systems, it is become easier to have automation in the field of the image storage and retrieval. The image retrieval plays an important role in the various application domains like in architecture, to find out the similar architect according to the query image, tourism, to find out the all the relevant places according to the query image, police stations, to have a proper criminal identification, medicines, historical research, fingerprint identification, and engineering etc. [50]

Among all these domains, the CBIR systems prove their beneficial impacts in the medicine. With the advancement of the imagining devices, daily the millions of images have been generated in the hospitals to diagnose the patients. The sources to generate these biomedical images can be an X-RAY, CT scan or the MRI etc. The usage of these biomedical images can be served for the following tasks as:

- For teaching purpose in medical institutions for giving the students an actual idea about the region of the disorder.
- In R & D department by the researchers to generate the new patterns from the existing ones.
- To diagnose, a doctor can compare the captured image with the image of healthy organs to have a proper idea of the problem and its cure.

CBMIR systems have brought the great advancement in the biomedical image retrieval application but still suffering the problem of the “semantic gap”. Semantic gap is basically a gap exists between the low-level visual feature descriptor of the image and the actual visual perception of the image. Moreover, for the development of robust and efficient medical image retrieval (MIR) system, extraction of appropriate visual features like shape, color, and texture plays a significant role. These features provide the salient information from medical images in an efficient manner. The visual feature descriptors of an image are of two types as the local feature descriptors and the global feature descriptors. Global feature descriptor means to consider the entire image as a whole, while local descriptors represent the visual features of a particular region or object used to describe the image.

Local descriptors have been used in a variety of medical as well as closely related applications like face recognition, texture synthesis, fingerprint recognition etc. All local feature descriptors have proved to be good image retrieval approaches. The local feature descriptors give the good performance, but they are vulnerable and insufficient to give similar performances in scenarios where the query images have been degraded either by noise or by some transformations like rotation, scaling or translation etc. Also, some of the methods are failed to recover the corrupted patterns and hence opt to work with the corrupted patterns without make any efforts to recover them. Moreover after so many advancements in working methodologies of the local

descriptors they still seems to be struggling while maintaining a balance between the low feature length and high discrimination power, are computation intensive. Thus, in order to achieve maximum throughput in retrieving medical images of different body organs, we cannot rely only on local features. The global information of an image plays a very crucial role in differentiating between images of different body parts.

Hence we are shifting the idea of local feature descriptors to the global one and propose a new image retrieval approach for the retrieval of CT and MR images based on orthogonal Fourier-Mellin moments (OFMMs). The OFMMs offers several advantages over the existing local feature descriptor methods which make them very suitable for this application and gives the best throughput among all the existing local methods and help to reduce the "semantic gap". The complete description about OFMMs considered in our research work and their general properties which make them suitable for the content-based retrieval of CT and MRI images is in chapter 4.

Chapter 4

Proposed Framework for OFMMs-Based CT and MR Image Retrieval System

Orthogonal rotation invariant moments (ORIMs) are the scalar quantities which characterize a function and capture its significant properties. More specifically, ORIMs correspond to the projection of the function (or signal) on a specific basis function (kernel function), where the type or characteristic of the basis function gives the name to the moment. ORIMs possess several useful properties which made them highly successful in image processing applications and in optics applications. The orthogonal Fourier-Mellin moments (OFMMs) are inherited from the family of ORIMs. In this thesis, our focus is to use OFMMs to develop a novel approach for the content-based retrieval of the CT and MR images. OFMMs advance the performance of CBIR systems in terms of its superior image representation capability and high robustness towards noise. In addition, OFMMs have the characteristics to be invariant towards geometric transformations such as rotation, scaling and translation (RST). OFMMs in comparison to other very popular classes of ORIMs such as Zernike moments (ZMs) and pseudo Zernike moments (PZMs) is more computationally efficient and gives more number of features for same value of order. Thus, in our proposed work, we decided to work with the OFMMs for the content-based retrieval of the CT and MR images.

The organization of this chapter is divided into two sections. Section 4.1 presents an overview of ORIMs and their mathematical background. Section 4.2 describes about the OFMMs considered in our research work and their general properties which make them suitable for the content-based image retrieval system.

4.1. Orthogonal Rotation Invariant Moments (ORIMs)

Orthogonal rotation invariant moments (ORIMs) are a class of geometric invariants obtained by projecting the input signal onto a unit circular disk [55-56]. They are characterized by some basis functions, also referred to as ORIMs kernel functions and the moments of the input signal are obtained by its convolution with the ORIMs

kernel functions. The standard equation required for the ORIMs to represent a continuous function $f(x, y)$ on a unit disk in the polar domain with circular harmonic order p and repetition q is defined by:

$$A_{pq} = \lambda \int_0^{2\pi} \int_0^1 f(r, \theta) V_{pq}^*(r, \theta) dr d\theta \quad (4.1)$$

The equivalent form of Eq.(4.1) in the Cartesian domain can be written as:

$$A_{pq} = \lambda \iint_{x^2+y^2 \leq 1} f(x, y) V_{pq}^*(x, y) dx dy \quad (4.2)$$

where $p = 0, 1, 2, \dots$; and $q = 0, \pm 1, \pm 2, \dots$, λ or $\frac{(p+1)}{\pi}$ is the normalization constant and function $V_{pq}^*(x, y)$ represents the complex conjugate of the ORIMs basis function $V_{pq}(x, y)$ given as:

$$V_{pq}(x, y) = V_{pq}(r, \theta) = R_{pq}(r) e^{jq\theta} \quad (4.3)$$

where

$$r = \sqrt{x^2 + y^2}, \quad j = \sqrt{-1}, \quad \theta = \tan^{-1}(y/x), \quad \theta \in [0, 2\pi] \quad (4.4)$$

The radial polynomial $R_{pq}(r)$ takes on different forms for different families of ORIMs such as ZMs, PZMs, OFMMs, etc. [57]. The magnitude of ORIMs is invariant to rotation and with appropriate transformations the ORIMs coefficients can be made scale and translation invariant. The kernel functions of ORIMs are orthogonal and complete over the unit disk. That is,

$$\iint_{x^2+y^2 \leq 1} V_{pq}(x, y) V_{p'q'}^*(x, y) dx dy = \frac{1}{\lambda} \delta_{pp'} \delta_{qq'} \quad (4.5)$$

where δ_{pq} is the Kronecker delta, i.e., $\delta_{pq} = 1$, if $p = q$, and zero, otherwise. The orthogonality and the completeness of the kernel function enables the reconstruction of the signal using the expression:

$$\hat{f}(x, y) = \sum_{p=0}^{p_{max}} \sum_q A_{pq} V_{pq}(x, y) \quad (4.6)$$

where p_{max} is the maximum order of the moments, and the value of q depends on the different types of ORIMs.

4.1.1. Derivation of ORIMs for Digital Images

Eq. (4.2) reflects ORIMs as the continuous function $f(x, y)$. Since we can't work with the continuous images, there is a desperate need to convert these images into the digital one which are discrete in nature. In this section, a computational framework for the derivation of ORIMs for digital images has been presented. The ORIMs of order p with repetition q for a digital image $f(i, k)$ of size $N \times N$ is written as:

$$A_{pq} = \lambda \sum_{i=0}^{N-1} \sum_{\substack{k=0 \\ x_i^2 + y_k^2 \leq 1}}^{N-1} f(i, k) V_{pq}^*(x_i, y_k) \Delta x \Delta y \quad (4.7)$$

where Δx and Δy are the sampling intervals in the x and y directions and (x_i, y_k) is the normalized coordinate location on the unit disk corresponding to pixel (i, k) computed as:

$$x_i = \frac{2i + 1 - N}{D}, \quad y_k = \frac{2k + 1 - N}{D} \quad (4.8)$$

$$\Delta x = \Delta y = \frac{2}{D} \quad (4.9)$$

for all $i, k = 0, 1, 2, \dots, N - 1$. The Eq. (4.7) is also referred to as the zeroth order approximation [58, 59] of Eq. (4.2)

Rewriting Eq. (4.7) after using Eq. (4.9) we get:

$$A_{pq} = \frac{4\lambda}{D^2} \sum_{i=0}^{N-1} \sum_{\substack{k=0 \\ x_i^2 + y_k^2 \leq 1}}^{N-1} f(i, k) V_{pq}^*(x_i, y_k) \quad (4.10)$$

Similarly, Eq. (4.6) assumes the form

$$\hat{f}(i, k) = \sum_{p=0}^{p_{max}} \sum_q A_{pq} V_{pq}(x_i, y_k) \quad (4.11)$$

The value of D (diameter of the circle) is depending upon the mapping technique used to map the $N \times N$ image over the circular unit disk. The mapping techniques are of two types.

❖ Inner Circle Mapping (ICM)

Figure 4.1 represents the mapping of square image onto the circular disk. In ICM the mapping is done in such a fashion that center of the image must be transformed to origin of the unit circular disk. Moreover, all the pixel coordinates must be normalized interior to the range of circular disk. One drawback associated with this form of mapping is loss of information in the form of corner pixels that are not included in computation of moments. This is because of the constraint $x_i^2 + y_k^2 \leq 1$ imposed for calculation of ORIMs. Thus only those pixels can participate for the calculation of ORIMs whose centers fall interior to the unit circle. The pixels whose centers do not meet with this condition are excluded from the computation of ORIMs. Thus, a perfect mapping of the square image to the circular domain is not achieved and the circular boundary of the unit disk is approximated in a zig-zag pattern as represented in Fig. 4.2. Thus in ICM, the value of diameter (D) must be equal to the dimension of the square image (N). Therefore, for this mapping technique Eq. (4.10) can be computed as:

$$A_{pq} = \frac{4\lambda}{N^2} \sum_{i=0}^{N-1} \sum_{\substack{k=0 \\ x_i^2 + y_k^2 \leq 1}}^{N-1} f(i, k) V_{pq}^*(x_i, y_k) \quad (4.12)$$

❖ Outer Circle Mapping (OCM)

Figure 4.3 represents the mapping of square image into the circular disk. In OCM the image of size $N \times N$ is mapped inside the unit circular disk. This mapping technique assures that there is no loss of information during computation of moments and thus all information of the square image can be preserved during moment computation. Hence for OCM the value of diameter (D) is equal to the diagonal of square image ($N\sqrt{2}$). Therefore, for OCM Eq. (4.10) can be written as:

$$A_{pq} = \frac{2\lambda}{N^2} \sum_{i=0}^{N-1} \sum_{\substack{k=0 \\ x_i^2 + y_k^2 \leq 1}}^{N-1} f(i, k) V_{pq}^*(x_i, y_k) \quad (4.13)$$

In outer circle mapping, the value of $r = 1.0$ i.e. $x_i^2 + y_k^2 = 1$ is not obtained for any pixel location and the maximum value of $r = 1 - \frac{1}{N}$ is achieved at the pixels located

at four vertices of the square image. Also, the ORIMs computed using outer circle mapping are more accurate as compared to inner circle mapping. This results in a much better quality of reconstructed image even for the zeroth order approximation. For that reason, the outer circle mapping has been widely preferred over inner circle mapping in various image processing applications [58, 59].

However, we use inner disk mapping for the computation of OFMMs. This is because the majority of the portion in the medical images is the black background which is completely irrelevant towards the computation of OFMMs values. The ROI (region of interest) or the body part captured by in the medical image is placed at the center of the image with surrounding black background. Using outer circle approach in such sort of images would affect the accuracy of the moment values and would further deteriorate the retrieval rates of the proposed method.

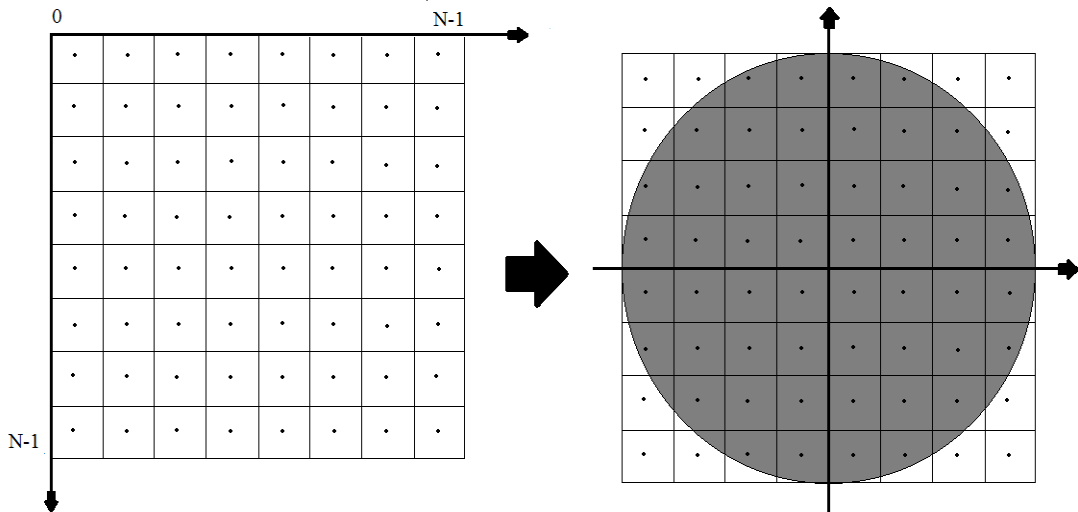


Figure 4.1: Mapping of an image onto the unit circular disk (ICM)

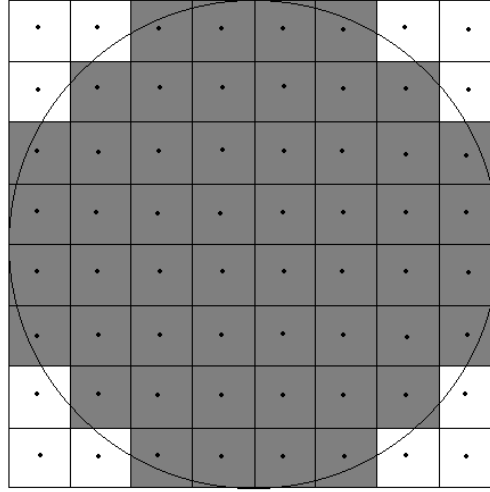


Figure 4.2: Inscribed circular disk approximated by square grids

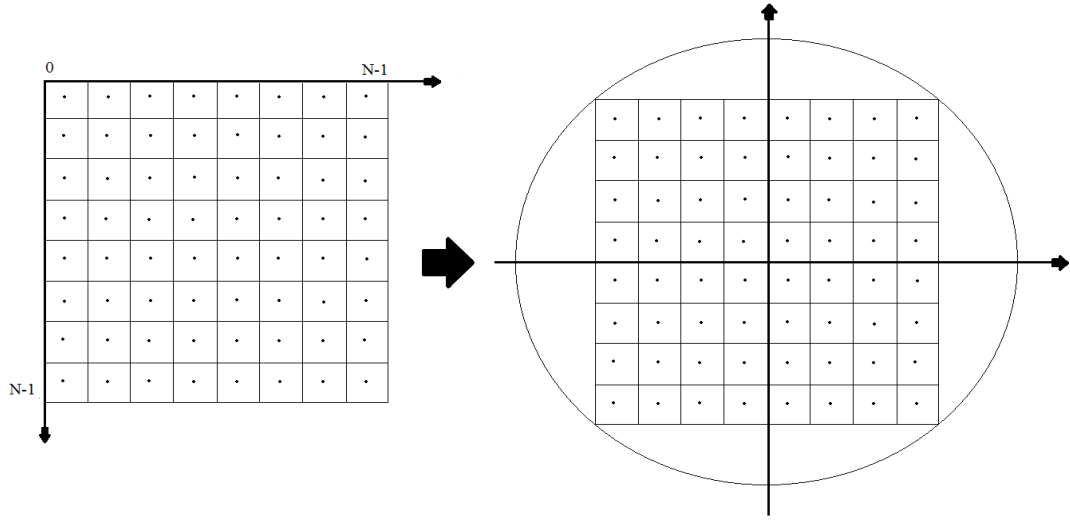


Figure 4.3: Mapping of an image into the unit circular disk (OCM)

4.2. Orthogonal Fourier-Mellin Moments (OFMMs)

OFMMs are introduced by Sheng and Shen in 1994 [60]. OFMMs hold several useful properties which made them highly successful in pattern classification [61], optical character recognition(OCR) [62], object recognition [63], image denoising [64], image super resolution [65] etc. The standard zeroth order approximation for the OFMMs is in Eq. (4.10) and their radial part $R_{pq}(r)$ is defined as:

$$R_{pq}(r) = R_p(r) = \sum_{s=0}^p (-1)^{p+s} \frac{(p+s+1)!}{s! (p-s)! (s+1)!} \quad (4.14)$$

where $R_p(r)$ signifies the radial part of the OFMMs is independent from the repetition function q . The standard equation to find out the total OFMMs coefficient (L) for order p_{max} is as:

$$L = (p_{max} + 1)(q_{max} + 1) \quad (4.15)$$

OFMMs are complex numbers. The real and imaginary parts of OFMMs are given as follows:

$$Re(A_{pq}) = \frac{4(p+1)}{\pi N^2} \sum_{i=0}^{N-1} \sum_{k=0}^{N-1} f(x_i, y_k) R_p(r_{ik}) \cos q\theta_{ik} \quad (4.16)$$

$$Img(A_{pq}) = \frac{4(p+1)}{\pi N^2} \sum_{i=0}^{N-1} \sum_{k=0}^{N-1} f(x_i, y_k) R_p(r_{ik}) \sin q\theta_{ik} \quad (4.17)$$

The magnitude of the OFMMs is obtained as:

$$|A_{pq}| = \sqrt{Re^2(A_{pq}) + Img^2(A_{pq})} \quad (4.18)$$

4.2.1. Properties of OFMMs

OFMMs possess several useful properties which made them highly successful in various image processing applications. A few of these properties which are relevant to our proposed work on image retrieval have been explained in this section.

❖ Rotation Invariance

The magnitude of the OFMMs coefficients, i.e., $|A_{pq}|$ is invariant to the image rotation. Let us consider $f(x, y)$ is the original image and after rotating this original image by an angle α in the counter clockwise direction, $f^r(x, y)$ will be the rotated image. The condition to be meet between the original and the rotated image in polar coordinates is as:

$$f^r(r, \theta_1) = f(r, \theta) \quad (4.19)$$

where

$$\theta_1 = \theta + \alpha \quad (4.20)$$

Using Eq. (4.1), the OFMMs for the original image $f(x, y)$ and rotated image $f^r(x, y)$ can be computed as:

$$A_{pq} = \lambda \int_0^{2\pi} \int_0^1 f(r, \theta) V_{pq(OFMMs)}^*(r, \theta) dr d\theta \quad (4.21)$$

$$= \lambda \int_0^{2\pi} \int_0^1 f(r, \theta) R_{pq(OFMMs)}(r) e^{-jq\theta} dr d\theta$$

$$\begin{aligned} A_{pq}^r &= \lambda \int_0^{2\pi} \int_0^1 f^r(r, \theta_1) V_{pq(OFMMs)}^*(r, \theta_1) dr d\theta_1 \\ &= \lambda \int_0^{2\pi} \int_0^1 f^r(r, \theta_1) R_{pq(OFMMs)}(r) e^{-jq\theta_1} dr d\theta_1 \end{aligned} \quad (4.22)$$

Substituting Eq. (4.19) and $d\theta_1 = d\theta$ in Eq. (4.22) we get:

$$\begin{aligned} A_{pq}^r &= \lambda \int_0^{2\pi} \int_0^1 f(r, \theta) R_{pq(OFMMs)}(r) e^{-jq(\theta+\alpha)} dr d\theta \\ &= \lambda \int_0^{2\pi} \int_0^1 f(r, \theta) R_{pq(OFMMs)}(r) e^{-jq\theta} e^{-jq\alpha} dr d\theta \\ &= e^{-jq\alpha} \left[\lambda \int_0^{2\pi} \int_0^1 f(r, \theta) R_{pq(OFMMs)}(r) e^{-jq\theta} dr d\theta \right] \end{aligned} \quad (4.23)$$

From Eq. (4.21) we can rewrite Eq. (4.23) as:

$$A_{pq}^r = A_{pq} e^{-jq\alpha} \quad (4.24)$$

$$|A_{pq}^r| = |A_{pq}| \quad (4.25)$$

Equations (4.24) and (4.25) prove that on rotation, OFMMs hardly acquires a phase shift but their magnitudes remain unchanged, i.e., magnitudes of OFMMs coefficients of the rotated and the original image are same.

❖ Orthogonality

As given in Eq. (4.5), the OFMMs kernel functions are orthogonal and complete over the interior of the unit disk. The orthogonality feature of OFMMs gives them several useful characteristics. Firstly, the moments are non-redundant, i.e., every moment captures unique information about the input signal; thus, fewer moments are required

to represent the input signal. Secondly, the reconstruction accuracy of OFMMs increases with the increase in number of moments. Consequently, every signal can be precisely reconstructed by using a set (possibly infinite) of these moments.

❖ Noise Robustness

The OFMMs for digital images are computed as a result of the summation process in Eq. (4.10). The summation process neutralizes the effect of the additive noise existing in the image. This leads to the robustness of OFMMs to the noise. Thus, the OFMMs coefficients computed from the noisy image don't differ much in comparison to those obtained from noise-free images.

4.2.2. Proposed Framework

The success of any content-based image retrieval method highly depends on its capability to accurately represent image features in minimum possible values. OFMMs are highly popular for their superior image representation capabilities in noise-free and even under noisy conditions. Thus, the above mentioned properties of OFMMs make them highly suitable for the retrieval of CT and MR images. Figure 4.4 represents the flowchart of the proposed OFMMs-based retrieval system.

Following pseudo-code will help in understanding the proposed framework as:

Input: Medical image of size $N \times N$, Precomputed OFMMs basis functions V_{pq}^* ,
Maximum order p_{max}

Output: OFMMs based feature vector

Step 1: Load the image I.

Step 2: Convolution of Precomputed OFMMs basic functions with input image to get A_{pq} , where $p \in \{0,1 \dots p_{max}\}$, $q \in \{0,1 \dots q_{max}\}$ and $q_{max} = p_{max}$.

Step 3: Determine magnitude of all OFMMs moments i.e., compute $|A_{pq}|$.

Step 4: Form a feature vector by concatenating all $|A_{pq}|$.

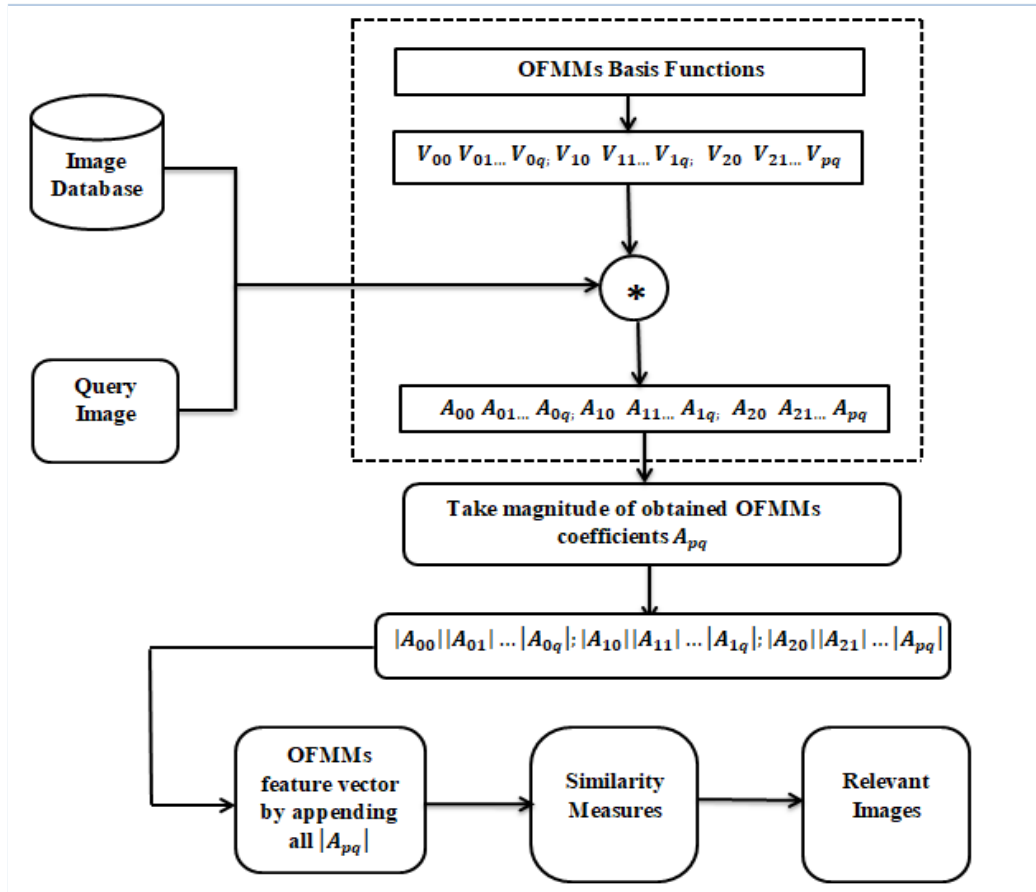


Figure 4.4: Flowchart for the proposed framework

Chapter 5

Experimental Framework and Results

This chapter introduces the computational framework employed to test the performance of proposed approach in comparison with the recent and state-of-the-art retrieval methods. Table 5.1 presents the name and abbreviations of all the methods used for their comparison with the proposed OFMMs-based approach. All the methods have been implemented in MATLAB 2014. Figure 5.1 shows the flowchart of the proposed retrieval system framework.

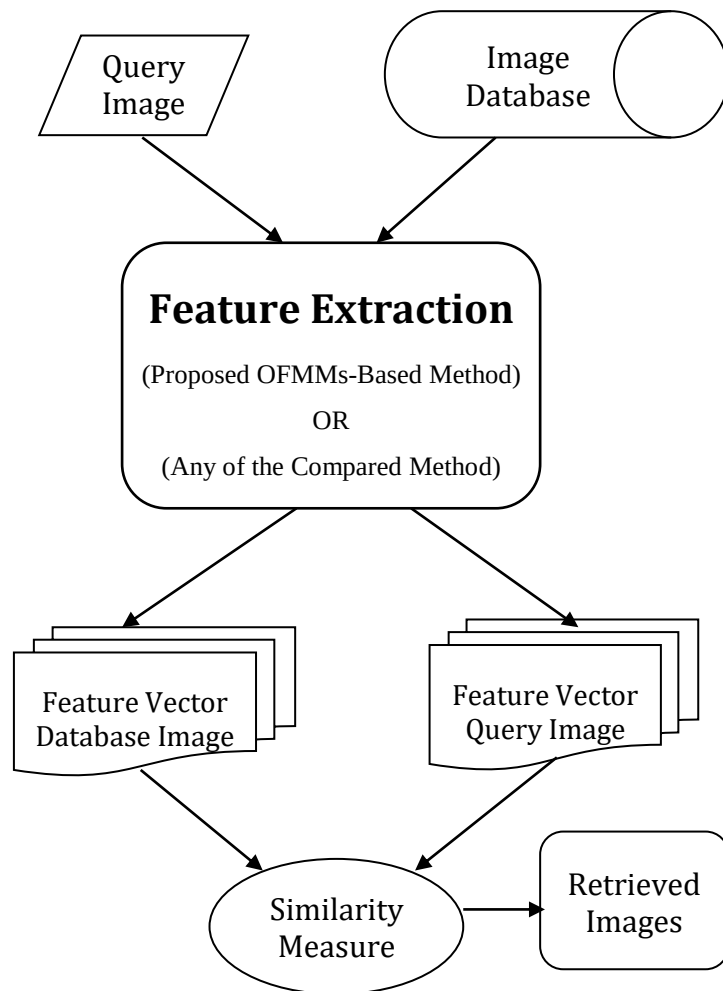


Figure 5.1: Flowchart of the retrieval system framework

Table 5.1: Name and Abbreviations of all the compared methods

S.No.	Abbreviation	Method Name	Reference	Year
1	LBP	Local Binary Pattern	[31]	2002
2	LTP	Local Ternary Pattern	[35]	2009
3	LTrP	Local Tetra Patterns	[37]	2012
4	LQryP	Local Quinary Patterns	[38]	2012
5	LTCoP	Local Ternary Co-Occurrence Patterns	[40]	2013
6	LMeP	Local Mesh Patterns	[41]	2014
7	LMePVEP	Local Mesh Peak Valley Edge Patterns	[42]	2014
8	SS-3D-LTP	Spherical Symmetric 3D Local Ternary Patterns	[43]	2015
9	LWP	Local Wavelet Pattern	[44]	2015
10	LDEP	Local Diagonal Extrema Pattern	[45]	2015
11	LQEP	Local Quantized Extrema Patterns	[39]	2015
12	LBDISP	Local Bit-Plane Dissimilarity Pattern	[46]	2016
13	LBDP	Local Bit-Plane Decoded Pattern	[47]	2016
14	LMeTP	Local Mesh Ternary Patterns	[48]	2016
15	DLTerQEP	Directional Local Ternary Quantized Extrema Pattern	[49]	2016
16	LQEQryP	Local Quantized Extrema Quinary Pattern	[50]	2017
17	LTDP	Local Tri-Directional Patterns	[51]	2017
18	LNDP	Local Neighborhood Difference Pattern	[52]	2017
19	LNIP	Local Neighborhood Intensity Pattern	[53]	2017
20	LDGP	Local Directional Gradient Pattern	[54]	2017

5.1 Similarity Measure

The performance of a retrieval system depends not only on effective features but also on strong similarity (or classification) measures. Among the several similarity measures, the Extended Canberra distance is very popular and widely used in retrieval applications. Also, in [66] it was shown that the classification performance of Extended Canberra distance is much superior to other similarity measures. Therefore, in our experiments, we use Extended Canberra similarity measure to compare the feature vectors of the query image with that of database images. The mathematical formulation of Extended Canberra distance is as follows:

$$D_{ECD}(t, Q) = \sum_{\tau=1}^{dim} \frac{|F^Q(\tau) - F^t(\tau)|}{(F^Q(\tau) + \mu^Q) + (F^t(\tau) + \mu^t)}, \quad (5.1)$$

where,

$$\mu^Q = \frac{1}{dim} \sum_{\tau=1}^{dim} F^Q(\tau), \quad \mu^t = \frac{1}{dim} \sum_{\tau=1}^{dim} F^t(\tau) \quad (5.2)$$

and dim is the dimension of the feature vectors, $F^Q(\tau)$ and $F^t(\tau)$ is the τ^{th} element of the feature vectors of query image Q and database image t , respectively.

5.2 Performance Measures

In the proposed work, every image in the database is used as a query image. The performance of each retrieval method is measured using four performance measures namely average precision rate (APR), average retrieval rate (ARR), F_score and mean average precision (mAP). The mathematical formulation for each of these performance measures is given as follows

$$APR (\%) = \frac{\text{number of relevant images retrieved}}{\text{total number of images retrieved } (\eta)} = \frac{100}{\omega} \sum_{i=1}^{\omega} \frac{r(DB_i)}{\eta}, \quad (5.3)$$

$$\begin{aligned} ARR (\%) &= \frac{\text{number of relevant images retrieved}}{\text{total number of relevant images in the database}} \\ &= \frac{100}{\omega} \sum_{i=1}^{\omega} \frac{r(DB_i)}{g(DB_i)}, \end{aligned} \quad (5.4)$$

$$F_score (\%) = \frac{2 \times ARP \times ARR}{ARP + ARR}, \quad (5.5)$$

$$mAP (\%) = \frac{100}{\omega} \sum_{i=1}^{\omega} \sum_{\eta=1}^{g(DB_i)} \frac{r(DB_i)}{\eta}, \quad (5.6)$$

where, ω denotes the image count in the database DB , $r(DB_i)$ and $g(DB_i)$ are the number of relevant images retrieved and the number of relevant ground truth images available for the i^{th} query image, respectively.

5.3 Datasets

In order to analyze the performance of our proposed OFMMs-based approach for biomedical image retrieval, experiments have been conducted on four different medical databases namely Emphysema CT database [67] and NEMA CT database [68] for CT image retrieval and OASIS MRI database [69] and NEMA MRI database [70] for MRI image retrieval. All these databases are available in public domain and can be downloaded easily.

5.3.1 Emphysema CT Database

The Emphysema CT database was created to classify the healthy lung tissue from the emphysematous tissue. This is required for the diagnosis of chronic obstructive pulmonary disease (COPD). The Emphysema CT database consists of 168 tissue images collected from 39 different subjects. The images in this database is divided into three categories (or classes) which include Normal tissue (NT), Centrilobular Emphysema (CLE), and Paraseptal Emphysema (PSE) containing 59, 50 and 59 images, respectively. Figure 5.2(a) shows one sample image from each category.

5.3.2 NEMA CT Database

The National Electrical Manufacturers Association (NEMA) created this database consisting of CT images of various body parts in order to aid in the use of medical images for research and diagnosis purposes. We considered the CT0001, CT0003, CT0021, CT0030, CT0031, CT0053, CT0054, CT0057, CT0060, and CT0083 cases of this database in this work. We collected 600 CT images from this database and

categorized it into 10 categories having 54, 70, 66, 50, 15, 60, 52, 104, 60 and 69 images. Figure 5.2(b) shows one sample image from each category.

5.3.3 OASIS MRI Database

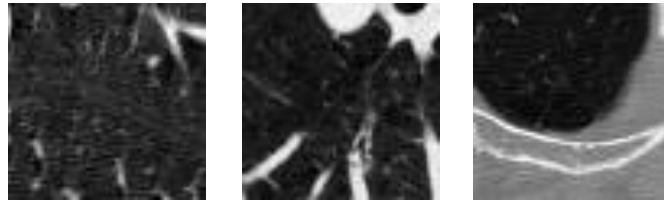
The Open Access Series of Imaging Studies (OASIS) is an MR image dataset consisting of a cross-sectional collection of 416 MR images from the same number of subjects, aged between 18 to 96 years. These set of images are grouped into four categories with 125, 104, 91, and 96 images, respectively, depending upon the size and shape of ventricular seen in the MR image. A sample image from each category of database is shown in Fig. 5.2(c).

5.3.4 NEMA MRI Database

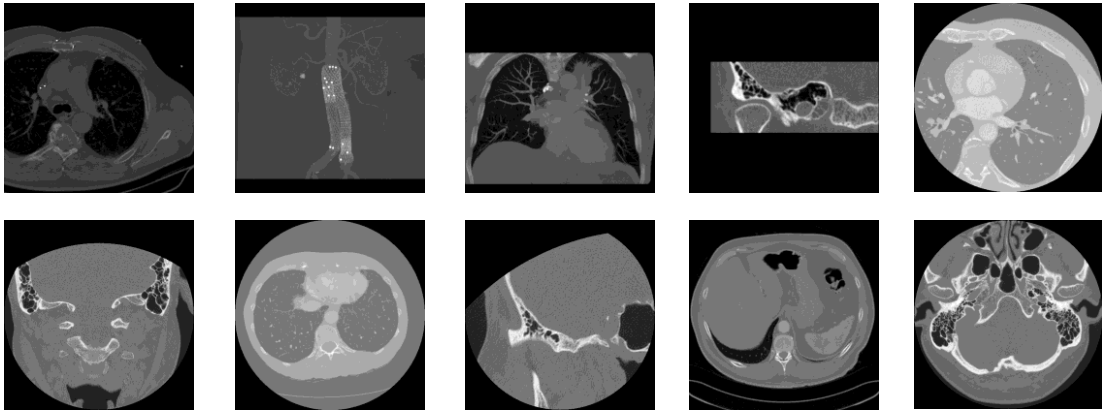
Similar to NEMA CT database, this database is also created by the National Electrical Manufacturers Association (NEMA) containing MR images of various body parts. We collected 372 MR images from this database and categorized it into 5 categories having 72, 100, 76, 59 and 65 images. Figure 5.2(d) shows one sample image from each category.

These four databases would not only test the ability of the proposed and all the compared methods to encode different forms of textural information observed in CT and MR images but also their ability to effectively represent the changes in shape at global and local scale.

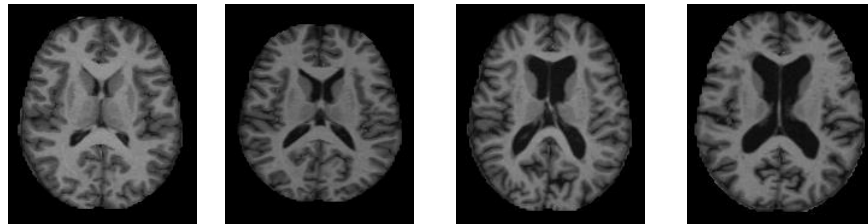
For instance, the Emphysema CT database and OASIS MRI database contains images of same body part, i.e., lung and brain, respectively. Thus, for any method to give high retrieval performance on these databases requires the ability to (accurately) discriminate among images that might seem similar overall but are altogether different due to the variation in shape that exists locally in them. On the other hand, in case of NEMA CT and NEMA MRI databases which contain images of different body parts, the (said) method should possess superior information representation capability to (accurately) discriminate among images that are altogether different in its overall representation, i.e., at global scale. Table 5.2 summarizes the four databases considered in our experimental framework in terms of number of images, size of each image, number of classes, and images in each class, etc.



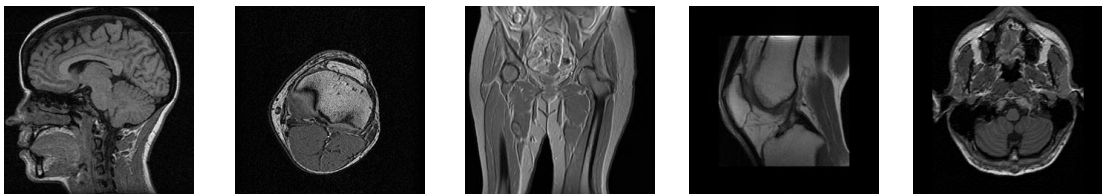
(a)



(b)



(c)



(d)

Figure 5.2: Sample image from (a) Emphysema CT database, (b) NEMA CT database, (c) OASIS MRI database and (d) NEMA MR database

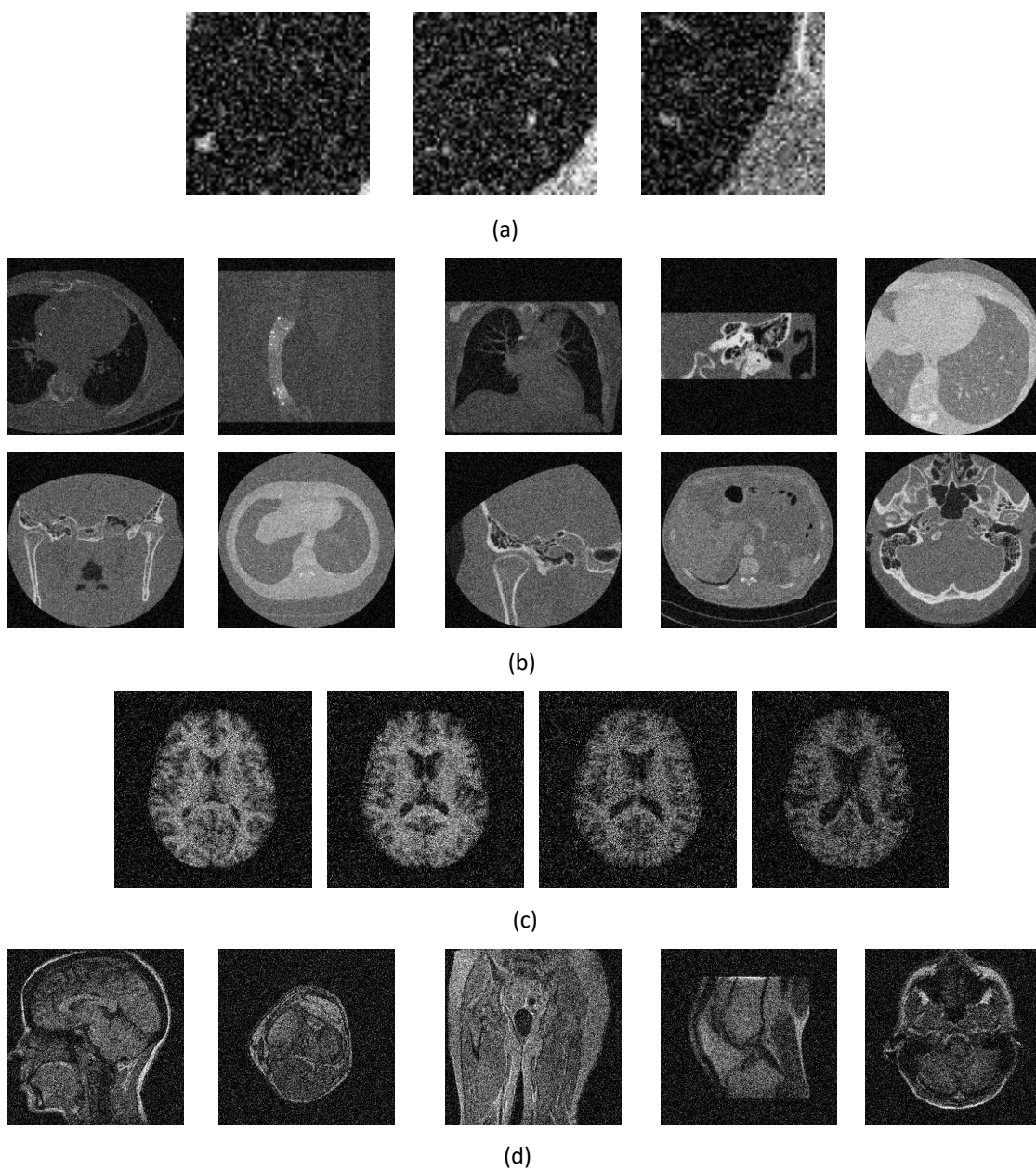


Figure 5.3: Sample noisy image from (a) Emphysema CT database, (b) NEMA CT database, (c) OASIS MRI database and (d) NEMA MR database

5.3.5 Noisy Databases

Besides experimenting on the above mentioned databases, additional experiments have been performed in our work to test the effectiveness of the proposed OFMMs-based approach under noisy conditions and to demonstrate its superiority over the existing approaches of biomedical image retrieval. In this process, a new copy of each of the four databases has been created consisting of noisy images. The noisy images are obtained by corrupting the original noise-free images with additive white Gaussian noise with zero mean and $\sigma \in [5,50]$. The procedure for creating the noisy database is shown below. In these set of experiments, all the methods are trained on noise-free images, whereas, all the noisy images are passed as query images to test the noise robustness capability of the proposed and the compared approaches. Figure 5.3 shows sample noisy images from each of the four test databases.

Input: Noise – free database DB

Output: Noisy database NDB

Procedure: Let L be the number of images in DB

```

for( $i = 1; i \leq L; i++$ )
{
     $image = DB(i)$ ;
    Add white Gaussian noise ( $\eta$ ) of zero mean and standard deviation
     $\sigma \in [5,50]$ 
     $noisy\_image = image + \eta(0, \sigma)$ 
     $NDB(i) = noisy\_image$ ;
}

```

Table 5.2: Summary of databases used in the experimental framework

S. No.	Database	No. of Images	Image Size	No. of Classes	Images/Class
1	Emphysema CT	168	61×61	3	{59,50,59}
2	NEMA CT	600	512×512	10	{54, 70, 66, 50, 15, 60, 52, 104, 60, 69}
3	OASIS MRI	416	208×208	4	{125,104,91,96}
4	NEMA MR	372	256×256	5	{72,100,76,59,65}

5.4 Experimental Results

This section provides several experiments to demonstrate the effectiveness of the proposed method and compare its results with the existing methods mentioned in Table 5.1. For all these approaches, we have taken a window size of 3×3 with $(P, R) = (8, 1)$. For the proposed OFMMs-based approach, the order (p) of OFMMs has been set to 3 which gives a total of 16 features.

5.4.1 Experiments on Noise-Free Databases

❖ Results on Emphysema CT Database

Figure 5.4 shows the graphs comparing the retrieval performance of the proposed OFMMs-based approach with the existing approaches as function of number of top matches (η) over Emphysema CT database. Summarization of these values for $\eta = 100$ has been shown in Table 5.3. From the table it can be observed that proposed approach has significantly outperformed all the existing approaches with average gain in retrieval rates of 12.87%, 7.50%, 9.48% and 10% for *ARR*, *APR*, *F_score* and *mAP*, respectively. The maximum gain in retrieval rates of 16.70%, 9.76%, 12.33% and 14.78% by the proposed approach in terms of *ARR*, *APR*, *F_score* and *mAP*, respectively, has been observed over LDGP, followed by LNIP and so on. On the contrary, out of all the compared methods, LBDISP has shown the best performance with retrieval rates of 77.69%, 43.48%, 55.75%, 62.20%, which are very near to those of our proposed approach.

❖ Results on NEMA CT Database

Table 5.4 summarizes the retrieval performances as well as % age improvement in retrieval rates of the proposed OFMMs-based approach over the existing approaches on NEMA CT database in terms of *ARR*, *APR*, *F_score* and *mAP*, respectively for top 100 matches, i.e. for $\eta = 100$. The graph for the proposed and all the compared methods has been shown in Figure 5.5. From the table, it can be observed that the retrieval rates for the proposed approach are less than majority of the compared approaches. The LMePTerP approach has shown best performance among all the existing as well as proposed OFMMs-based approach with retrieval rates 64.98% (*ARR*), 96.36% (*APR*), 77.62% (*F_score*) and 98.55% (*mAP*). On the other hand, performance of the proposed method is observed to be better than LWP, LBDP

and LBDISP, only, with the retrieval rates of 54.03% (*ARR*), 81.24% (*APR*), 64.90% (*F_score*) and 87.89% (*mAP*) respectively.

❖ Results on OASIS MRI Database

The retrieval performance of the proposed and all the compared methods corresponding to different number of top positions have been shown in Table 5.5 and Fig. 5.6. The proposed OFMMs-based approach achieved maximum retrieval rates of 40.17% (*ARR*), 42.52% (*APR*), 41.31% (*F_score*), and 51.09% (*mAP*), closely followed by the LBDISP approach which gave the highest retrieval performance of 37.89% (*ARR*), 40.35% (*APR*), 39.08% (*F_score*), and 45.81% (*mAP*), among all the compared methods. The proposed method once again outperformed all the methods with average improvement of 9.86% (*ARR*), 10.28% (*APR*), 10.06% (*F_score*), and 13.58% (*mAP*). Similar observations can be observed from the graphs shown in Fig. 5.6, depicting the retrieval performances of the proposed and the compared approaches at different top positions.

❖ Results on NEMA MRI Database

Figure 5.7 shows the *APR*, *ARR* and *F_score* graphs comparing the retrieval performance of the proposed OFMMs-based approach with the existing approaches as function of number of top matches (η) over NEMA MRI database. Summarization of these values for $\eta = 100$ has been shown in Table 5.6. The existing approaches performed reasonably well with the higher retrieval rates to those obtained by the proposed approach. The *ARR* and *mAP* values of LBP, LTP, LTrP, LTCoP, LNIP, LTDP, LMeP, LMePVEP, LNDP, LDGP, LQEP and DLTerQEP have been observed to be 100%, whereas, the *APR* and *F_score* values have been observed to be 77.06% and 87.04%. Among all the compared methods, the retrieval performance of LWP has been observed to be the lowest with retrieval rates of 53.04% (*ARR*), 71.51% (*APR*), 60.91% (*F_score*), and 86.68% (*mAP*) respectively. The proposed approach gave retrieval performance of 62.49% (*ARR*), 83.42% (*APR*), 71.45% (*F_score*), and 91.35% (*mAP*) only better than the LWP.

From the above presented results, we draw three conclusions:

1. In comparison to Emphysema CT database, the retrieval rates on NEMA CT database are quite high. This is because, each class of NEMA CT database

contains CT images of different body part in contrast to Emphysema CT database whose each class contains the CT images of lung tissues. Since, it is much easier to distinguish between the CT images of different body parts as compared to different lung tissues, there are an increased number of misclassifications in Emphysema CT database as compared to NEMA CT database, and thus, resulting into higher retrieval rates on NEMA CT database.

2. Similarly, the retrieval rates on NEMA MRI database are quite high in comparison to OASIS MRI database. The reason for high retrieval rates on NEMA MRI database is attributed to the reduced misclassifications among different classes of the database. The database contains only five classes each containing MR images of different body part. There is hardly any ambiguity while classifications as classes are very well distant from each other, which can also be observed from Fig. 5.2(d). The query results of the proposed OFMMs-based method on Emphysema CT, NEMA CT, OASIS MRI and NEMA MRI databases have been shown in Fig. 5.8, respectively.
3. Lastly, the proposed method gave best retrieval rates on OASIS MRI and Emphysema CT database in comparison to all the existing and state-of-the-art methods. Whereas, in case of NEMA CT and NEMA MRI database the retrieval performance of the proposed approach is observed to be lower than the compared approaches. The reason for reduced performance on NEMA CT and NEMA MRI database is attributed to the nature of images as mentioned in above two points. Also the size of images in these databases is quite large in comparison to Emphysema and OASIS MRI database. Since, the size of image is large, extracting more OFMMs coefficients from such images would surely enhance the retrieval rates of the proposed approach.

5.4.2 Experiments on Noisy Databases

One of the biggest advantage of OFMMs is that their values are robust to image noise, i.e. under noisy conditions their values are similar or very close to the original values (noise-free). This property of OFMMs is very useful in real life scenario where the images are noisy in nature. In such situations OFMMs will be able to perform accurate image retrievals without getting affected by noise. To compare the noise

robustness capabilities of the proposed and the existing approaches, various experiments have been performed on noisy CT and MRI images.

Tables 5.7-5.10 summarize the retrieval performances of the proposed OFMMs-based approach over the existing approaches on noisy Emphysema CT, noisy NEMA CT, noisy OASIS MRI and noisy NEMA MRI databases, respectively, in terms of *ARR*, *APR*, *F_score* and *mAP*, for top 100 matches. Even in the presence of noise, the proposed approach obtained retrieval rates of 79.82% (*ARR*), 45.03% (*APR*), 57.58% (*F_score*), and 62.39% (*mAP*) on noisy Emphysema CT database, 74.12% (*ARR*), 48.51% (*APR*), 58.64% (*F_score*), and 76.52% (*mAP*) on noisy NEMA CT database, 30.39% (*ARR*), 33.76% (*APR*), 31.98% (*F_score*), and 35.75% (*mAP*) on noisy OASIS MRI database, and 76.32% (*ARR*), 56.82% (*APR*), 65.14% (*F_score*), and 78.82% (*mAP*) on noisy NEMA MRI database, which are close to (80.34% (*ARR*), 45.31% (*APR*), 57.94% (*F_score*), and 62.35% (*mAP*)), (97.24% (*ARR*), 68.03% (*APR*), 80.05% (*F_score*), and 99.12% (*mAP*)), (40.17% (*ARR*), 42.52% (*APR*), 41.31% (*F_score*), and 51.09% (*mAP*)), and (100% (*ARR*), 80.30% (*APR*), 89.07% (*F_score*), and 100% (*mAP*)), obtained on noise-free images of Emphysema CT, NEMA CT, OASIS MRI and NEMA MRI databases, respectively. The proposed method because of its noise resilient property achieved an average improvement in retrieval rates of 17.11% (*ARR*), 9.87% (*APR*), 12.52% (*F_score*), and 23.74% (*mAP*) on noisy Emphysema CT database, 54.12% (*ARR*), 36.98% (*APR*), 44.05% (*F_score*), and 65.33% (*mAP*) on noisy NEMA CT database, 8.33% (*ARR*), 6.29% (*APR*), 7.24% (*F_score*), and 10.30% (*mAP*) on noisy OASIS MRI database, and 27.70% (*ARR*), 45.34% (*APR*), 35.18% (*F_score*), and 49.55% (*mAP*) on noisy NEMA MRI database over all the compared approaches. A comparison between the retrieval performances (*F_score* values at $\eta = 100$) of the proposed and all the compared methods on both noisy and noise-free images of four test databases has been presented in Fig. 5.9. From the figure, it can be observed that all the compared methods witnessed a significant drop in their retrieval rates (in comparison to noise-free images) on all four noisy test databases indicating their inability to retrieve images under noisy conditions. The drop in retrieval rates of the proposed approach is insignificant as compared to those attained by the existing approaches. These results clearly support the fact that the OFMMs values are robust to image noise and their values are least affected in comparison to the existing approaches under noisy

conditions. Figure 5.10-5.13 shows the graphs depicting the retrieval performance of the proposed OFMMs-based approach and the other existing methods as function of number of top matches on noisy Emphysema CT database, noisy NEMA CT database, noisy OASIS MRI database, and noisy NEMA MRI database, respectively. Figure 5.14 illustrates the query results of the proposed method on four noisy test databases.

Table 5.3: Comparison of retrieval rates of the proposed and the existing techniques for top 100 matches (*i. e.* $\eta = 100$) on Emphysema CT database
All values are in percentages (%)

Performance Measure	ARR	APR	F_score	mAP	<i>Improvement</i> = ((OFMMs – COMPARED METHOD))			
					ARR	APR	F_score	mAP
Proposed	80.34	45.31	57.94	62.35				
LBDISP	77.69	43.48	55.75	62.20	2.65	1.83	2.19	0.15
LWP	74.46	41.35	53.17	57.08	5.88	3.96	4.77	5.27
LTCOP	70.08	39.15	50.24	57.39	10.26	6.16	7.70	4.96
DLTerQEP	69.64	39.63	50.51	50.72	10.70	5.68	7.43	11.63
LBDP	68.69	38.04	48.97	56.41	11.65	7.27	8.97	5.94
LQEQRyP	68.67	38.98	49.73	51.44	11.67	6.33	8.21	10.91
LQEP	68.00	38.32	49.02	48.91	12.34	6.99	8.92	13.44
LTP	66.99	37.53	48.11	53.20	13.35	7.78	9.83	9.15
LBP	66.98	37.53	48.11	52.41	13.36	7.78	9.83	9.94
LMeP	66.68	37.27	47.81	53.72	13.66	8.04	10.13	8.63
SS-3D-LTP	66.12	36.98	47.43	55.61	14.22	8.33	10.51	6.74
LMeTP	65.82	36.83	47.23	52.41	14.52	8.48	10.71	9.94
LTrP	65.61	36.86	47.20	50.95	14.73	8.45	10.74	11.40
LMePVEP	65.45	36.70	47.03	50.96	14.89	8.61	10.91	11.39
LDEP	65.34	36.56	46.89	49.61	15.00	8.75	11.05	12.74
LQryP	65.21	36.51	46.81	51.47	15.13	8.80	11.13	10.88
LNDP	65.10	36.52	46.80	48.86	15.24	8.79	11.14	13.49
LTDP	64.62	36.16	46.37	48.02	15.72	9.15	11.57	14.33
LNIP	64.61	36.20	46.40	47.99	15.73	9.11	11.54	14.36
LDGP	63.64	35.55	45.61	47.57	16.70	9.76	12.33	14.78
Average Improvement					12.87	7.50	9.48	10.00

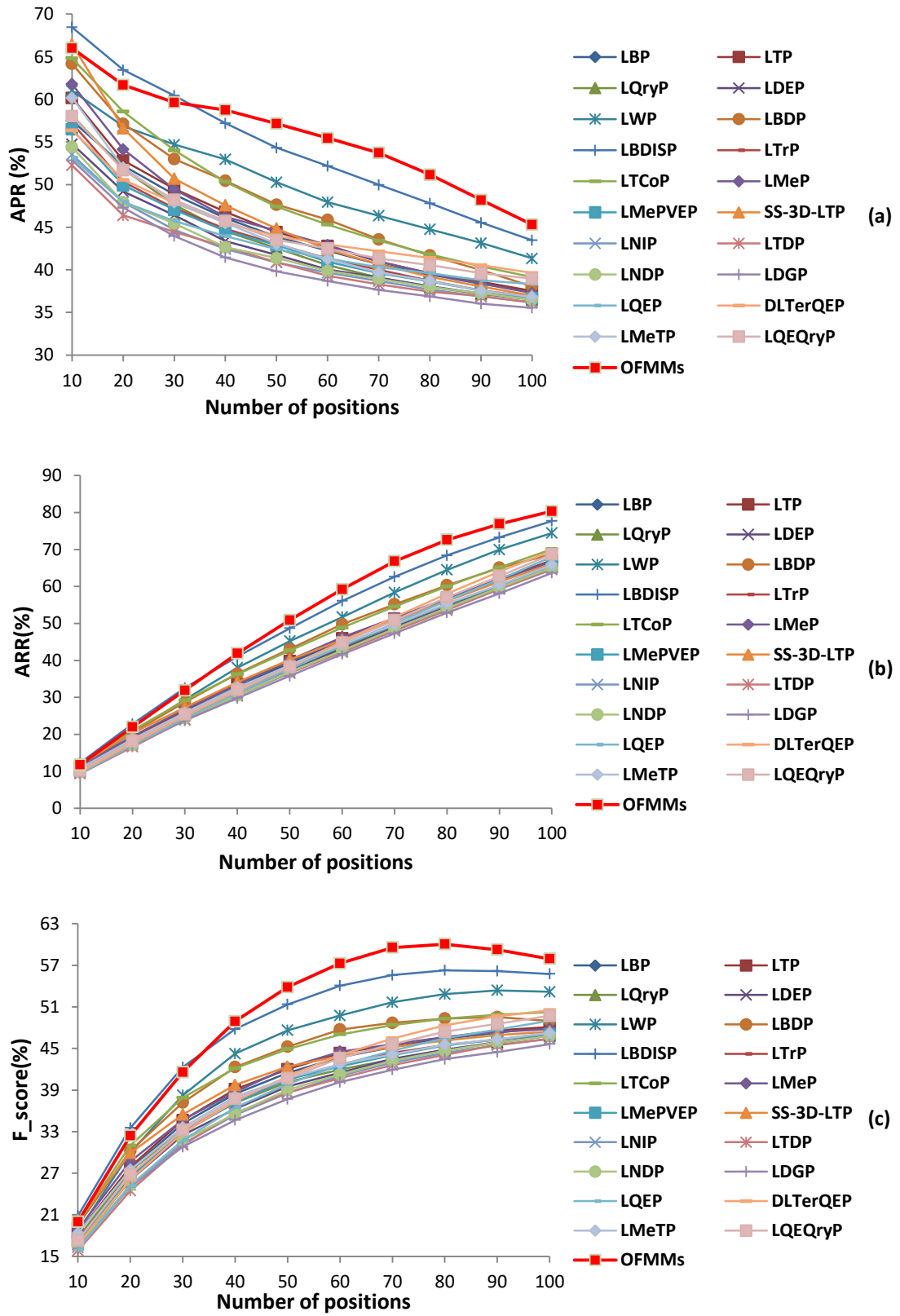


Figure 5.4: Comparison of the proposed method with other existing methods in terms of (a) *APR*, (b) *ARR*, and (c) *F_score* as function of number of top matches (η) on Emphysema CT database

Table 5.4: Comparison of retrieval rates of the proposed and the existing techniques for top 100 matches (*i.e.* $\eta = 100$) on NEMA CT database.
All values are in percentages (%)

Method	Feature vector	<i>APR</i>	<i>ARR</i>	<i>F_score</i>	<i>mAP</i>
LMePTerP	1536	64.98	96.36	77.62	98.55
DLTerQEP	8192	64.92	96.45	77.61	99.00
LQEP	4096	64.70	96.43	77.44	98.96
LQEQerP	16384	64.65	95.83	77.21	98.56
LMeP	768	64.64	96.19	77.32	98.12
LNDP	256	64.62	96.42	77.38	98.07
SS-3D-LTP	2560	64.62	95.92	77.22	98.43
LTP	512	64.52	95.99	77.17	98.83
LTDP	768	64.50	96.18	77.21	98.50
LTrP	3328	64.26	95.92	76.96	97.92
LQP	1024	64.00	95.27	76.56	98.48
LDGP	64	63.98	95.52	76.63	97.27
LNIP	512	63.93	95.45	76.57	97.68
LDEP	24	63.72	95.02	76.28	97.23
LTCoP	512	63.55	95.47	76.31	98.36
LMePVEP	1024	62.91	93.51	75.22	97.43
LBP	256	62.25	94.19	74.96	97.85
OFMMs	16	54.03	81.24	64.90	87.89
LWP	256	52.76	80.37	63.70	89.89
LBDP	256	50.06	76.91	60.64	84.45
LBDISP	256	45.20	71.14	55.28	82.41

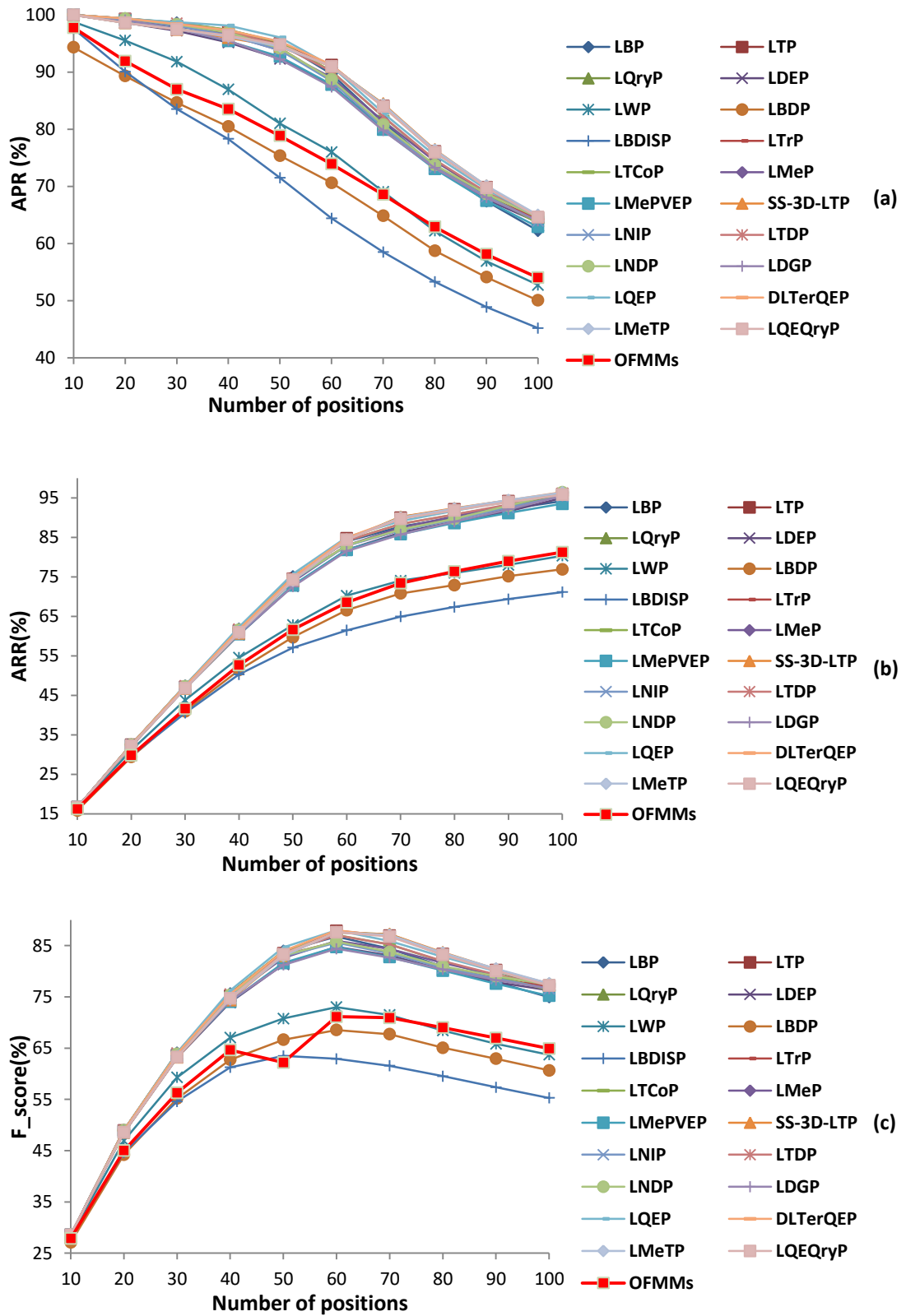


Figure 5.5: Comparison of the proposed method with other existing methods in terms of (a) *APR*, (b) *ARR*, and (c) *F_score* as function of number of top matches (η) on NEMA CT database

Table 5.5: Comparison of retrieval rates of the proposed and the existing techniques for top 100 matches (*i. e.* $\eta = 100$) on OASIS MRI database
All values are in percentages (%).

Performance Measure	<i>ARR</i>	<i>APR</i>	<i>F_score</i>	<i>mAP</i>	<i>Improvement = (OFMMs – COMPARED METHOD)</i>			
Proposed	40.17	42.52	41.31	51.09	<i>ARR</i>	<i>APR</i>	<i>F_score</i>	<i>mAP</i>
LBDISP	37.89	40.35	39.08	45.81	2.28	2.17	2.23	5.28
LTCOP	33.30	35.51	34.37	40.73	6.87	7.00	6.94	10.36
LQP	32.69	34.78	33.70	40.26	7.48	7.74	7.61	10.83
SS-3D-LTP	31.84	33.84	32.81	39.58	8.33	8.68	8.50	11.51
LTDP	30.99	33.12	32.02	38.17	9.18	9.40	9.29	12.92
LNIP	30.88	33.00	31.90	38.29	9.29	9.52	9.41	12.80
LBDP	31.18	32.87	32.01	42.40	8.98	9.65	9.31	8.69
LTP	30.76	32.79	31.74	38.20	9.40	9.73	9.57	12.89
LNDP	30.75	32.75	31.72	38.30	9.42	9.76	9.59	12.79
LMeP	30.26	32.29	31.24	37.84	9.91	10.23	10.07	13.25
LBP	30.29	32.26	31.25	37.13	9.87	10.26	10.07	13.96
LQEQerP	29.94	31.74	30.82	36.37	10.22	10.78	10.49	14.72
LMePTerP	29.46	31.37	30.39	37.32	10.71	11.15	10.92	13.78
DLTerQEP	29.43	31.15	30.27	35.87	10.74	11.37	11.05	15.22
LTrP	29.04	30.84	29.92	36.66	11.12	11.68	11.39	14.43
LMePVEP	28.33	30.19	29.23	35.49	11.84	12.33	12.08	15.60
LDGP	28.08	29.92	28.97	33.60	12.09	12.60	12.34	17.49
LDEP	27.84	29.51	28.65	33.39	12.33	13.01	12.66	17.71
LQEP	27.61	29.38	28.47	33.13	12.56	13.13	12.84	17.96
LWP	25.65	27.12	26.36	31.66	14.52	15.40	14.95	19.43
<i>Average Improvement</i>					9.86	10.28	10.06	13.58

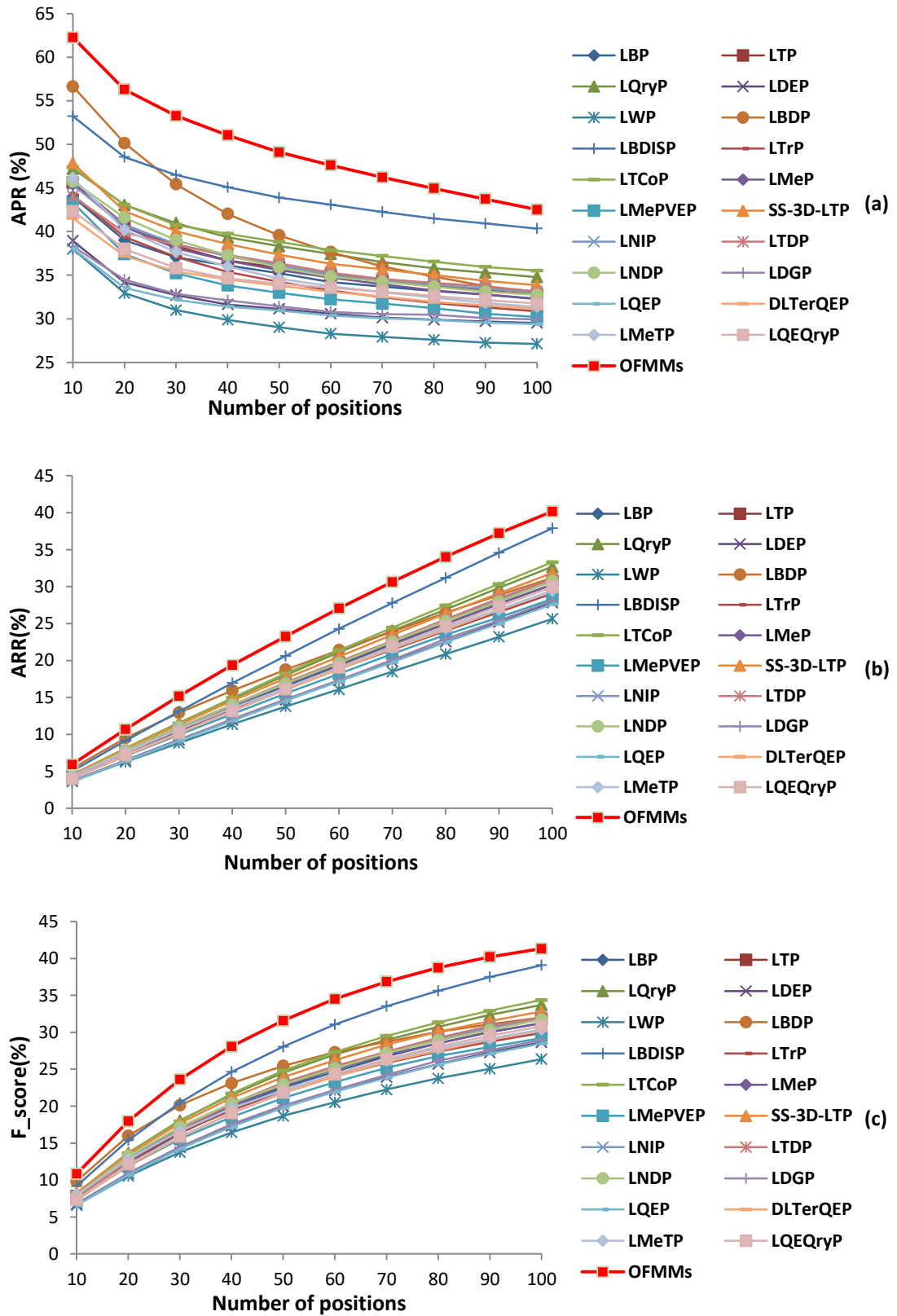


Figure 5.6: Comparison of the proposed method with other existing methods in terms of (a) *APR*, (b) *ARR*, and (c) *F_score* as function of number of top matches (η) on OASIS MRI database

Table 5.6: Comparison of retrieval rates of the proposed and the existing techniques for top 100 matches (*i. e.* $\eta = 100$) on NEMA MRI database
All values are in percentages (%).

Method	Feature vector	<i>APR</i>	<i>ARR</i>	<i>F_score</i>	<i>mAP</i>
LBP	256	77.06	100.00	87.04	100.00
LTP	512	77.06	100.00	87.04	100.00
LTrP	3328	77.06	100.00	87.04	100.00
LTCoP	512	77.06	100.00	87.04	100.00
LMeP	768	77.06	100.00	87.04	100.00
LMePVEP	1024	77.06	100.00	87.04	100.00
LNIP	512	77.06	100.00	87.04	100.00
LTDP	768	77.06	100.00	87.04	100.00
LNDP	256	77.06	100.00	87.04	100.00
LDGP	64	77.06	100.00	87.04	100.00
LQEP	4096	77.06	100.00	87.04	100.00
DLTerQEP	8192	77.06	100.00	87.04	100.00
LBDISP	256	77.05	99.99	87.03	99.99
LQEQerP	16384	76.06	98.83	85.96	99.86
LMePTerP	1536	76.06	98.80	85.95	99.77
LQP	1024	75.95	98.79	85.88	99.80
LDEP	24	74.96	97.90	84.91	99.63
SS-3D-LTP	2560	73.51	96.22	83.34	98.87
LBDP	256	63.36	83.80	72.16	93.93
OFMMs	16	62.49	83.42	71.45	91.35
LWP	256	53.04	71.51	60.91	86.68

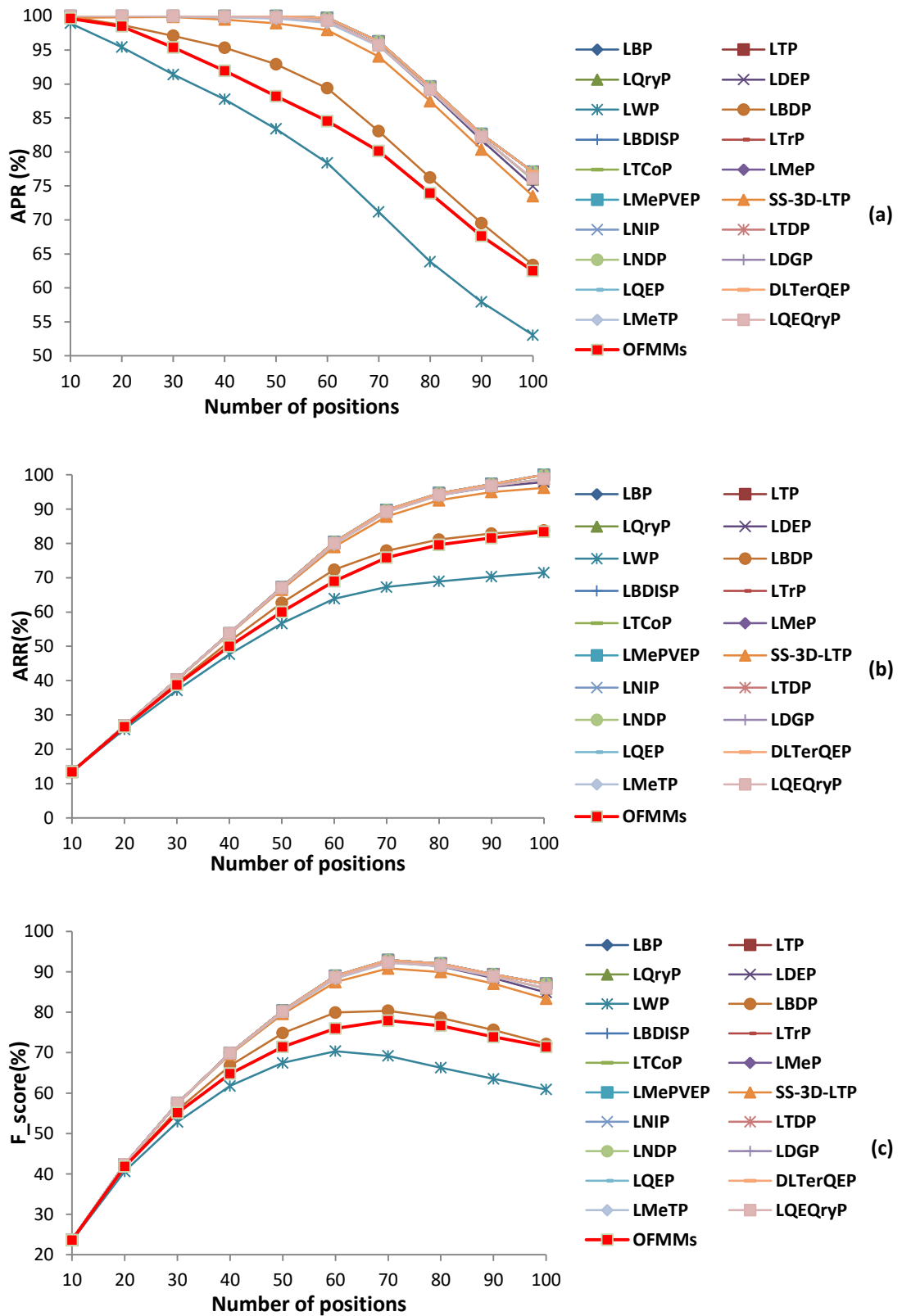


Figure 5.7: Comparison of the proposed method with other existing methods in terms of (a) *APR*, (b) *ARR*, and (c) *F_score* as function of number of top matches (η) on NEMA MRI database

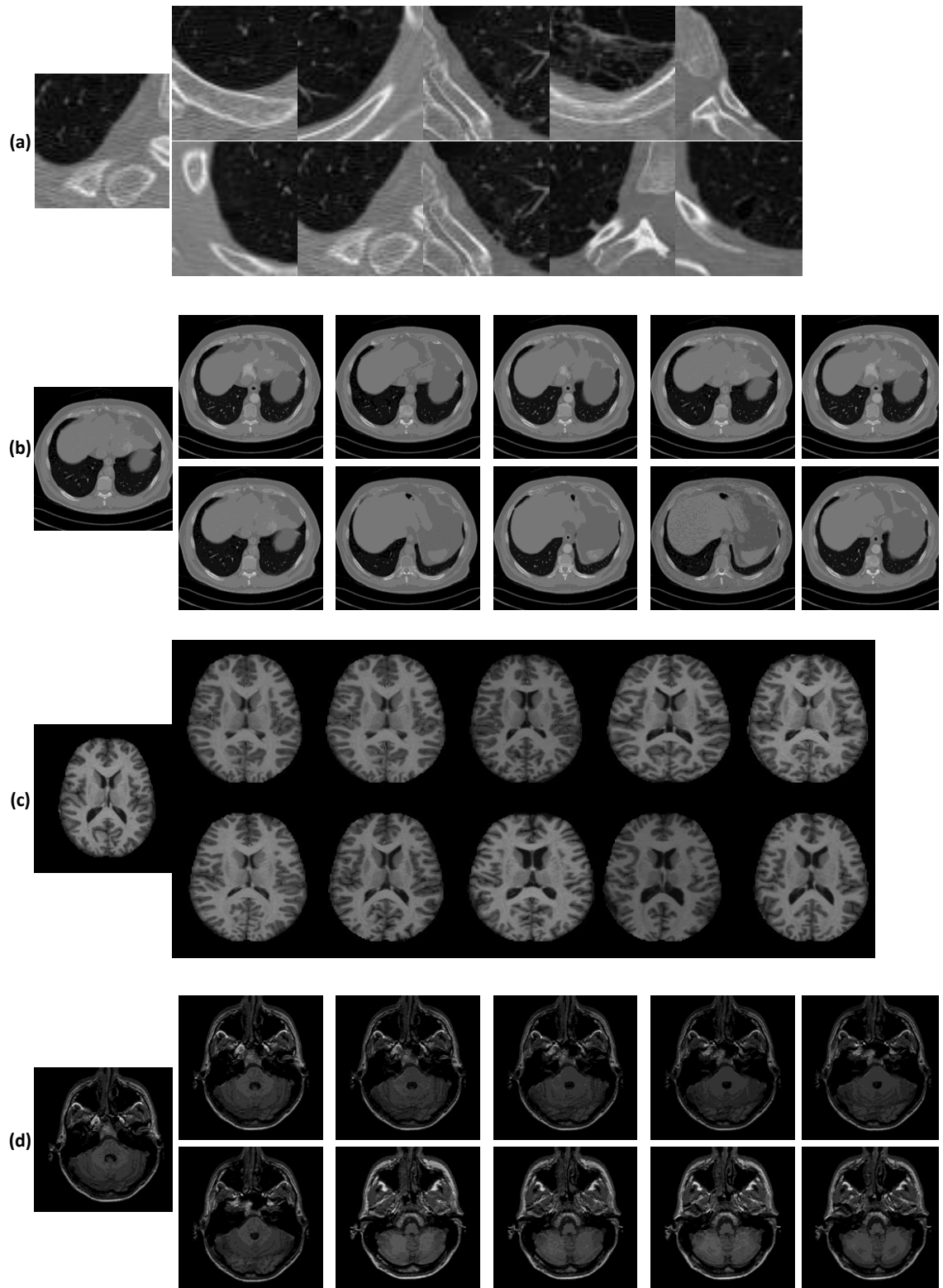


Figure 5.8: Query results of the proposed method on (a) Emphysema CT database, (b) NEMA CT database, (c) OASIS MRI database, and (d) NEMA MRI database

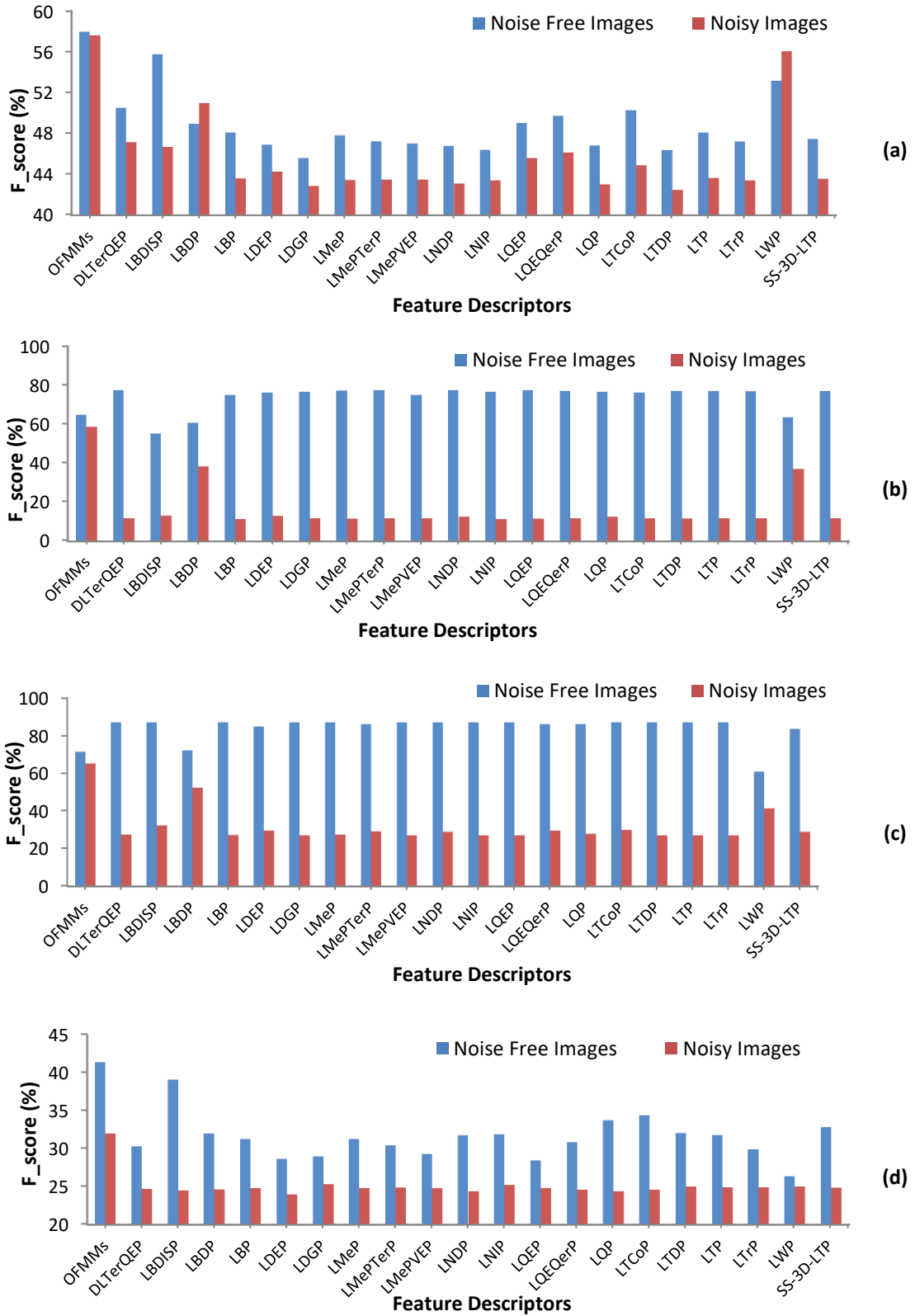


Figure 5.9: Comparison of the proposed method with other existing methods in terms of F_score (for top 100 matches) on noisy and noise-free images of (a) Emphysema CT database, (b) NEMA CT database, (c) NEMA MRI database and (d) OASIS MRI database

Table 5.7: Comparison of retrieval rates of the proposed and the existing techniques for top 100 matches (*i. e.* $\eta = 100$) on Emphysema CT database
All values are in percentages (%).

Performance Measure	<i>ARR</i>	<i>APR</i>	<i>F_score</i>	<i>mAP</i>	<i>Improvement = (OFMMs – COMPARED METHOD)</i>			
Proposed	79.82	45.03	57.58	62.39	<i>ARR</i>	<i>APR</i>	<i>F_score</i>	<i>mAP</i>
LWP	78.26	43.63	56.03	57.06	1.55	1.40	1.55	5.33
LBDP	71.41	39.64	50.98	52.41	8.41	5.39	6.59	9.98
DLTerQEP	64.85	37.02	47.13	41.42	14.97	8.01	10.45	20.97
LBDISP	64.86	36.47	46.69	40.55	14.96	8.56	10.89	21.84
LQEQerP	64.08	36.05	46.14	39.71	15.74	8.98	11.43	22.68
LQEP	63.15	35.64	45.56	39.32	16.66	9.39	12.01	23.07
LTCop	62.51	35.02	44.89	40.27	17.31	10.01	12.68	22.12
LDEP	61.22	34.68	44.28	35.60	18.59	10.35	13.30	26.80
LBP	60.51	34.08	43.61	36.55	19.30	10.95	13.97	25.84
LTP	60.72	34.06	43.64	37.24	19.09	10.97	13.94	25.15
LMeP	60.35	33.94	43.45	37.43	19.47	11.09	14.13	24.96
LMePVEP	60.50	33.93	43.48	35.52	19.31	11.10	14.09	26.87
LTrP	60.30	33.92	43.41	35.86	19.51	11.11	14.16	26.53
SS-3D-LTP	60.90	33.90	43.55	36.48	18.91	11.3	14.02	25.91
LNIP	60.42	33.84	43.38	35.22	19.40	11.19	14.20	27.17
LMePTerP	60.90	33.84	43.50	34.33	18.92	11.19	14.07	28.06
LNDP	59.96	33.61	43.08	34.95	19.86	11.42	14.50	27.44
LQP	60.22	33.44	43.00	34.08	19.60	11.59	14.58	28.31
LDGP	59.67	33.43	42.85	34.57	20.14	11.60	14.73	27.82
LTDP	59.38	33.07	42.48	34.36	20.43	11.96	15.09	28.03
<i>Average Improvement</i>					17.11	9.87	12.52	23.74

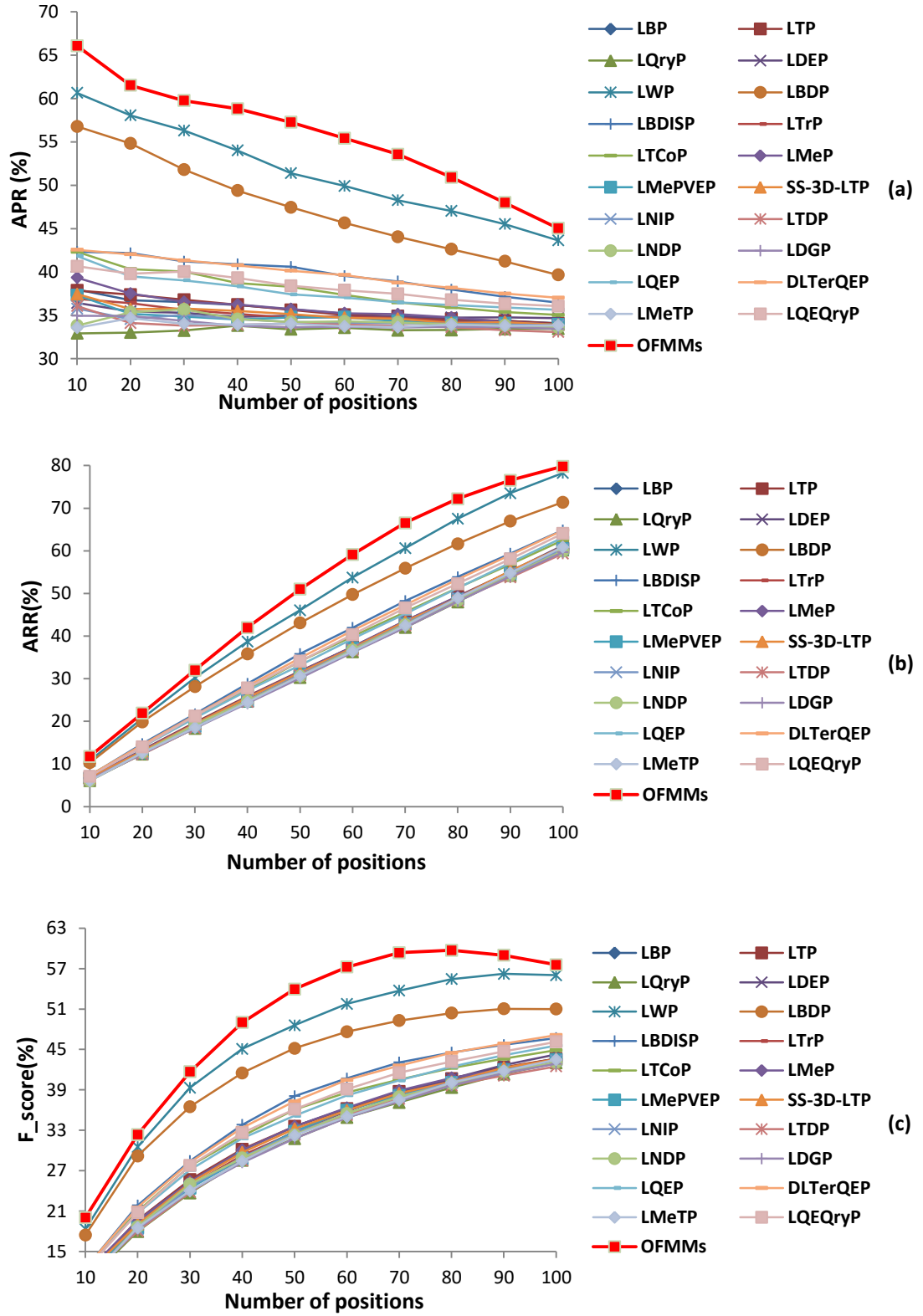


Figure 5.10: Comparison of the proposed method with other existing methods in terms of (a) *APR*, (b) *ARR*, and (c) *F_score* as function of number of top matches (η) on noisy Emphysema CT database

Table 5.8: Comparison of retrieval rates of the proposed and the existing techniques for top 100 matches (*i. e.* $\eta = 100$) on NEMA CT database
All values are in percentages (%).

Performance Measure	<i>ARR</i>	<i>APR</i>	<i>F_score</i>	<i>mAP</i>	<i>Improvement = (OFMMs – COMPARED METHOD)</i>			
Proposed	74.12	48.51	58.64	76.52	<i>ARR</i>	<i>APR</i>	<i>F_score</i>	<i>mAP</i>
LBDP	47.11	32.57	38.51	35.83	27.01	15.94	20.13	40.69
LWP	46.51	31.03	37.23	31.00	27.61	17.48	21.41	45.52
LDEP	18.39	10.27	13.18	9.48	55.74	38.24	45.46	67.05
LBDISP	19.05	10.11	13.21	9.71	55.08	38.40	45.43	66.81
LNDP	16.42	10.09	12.50	7.88	57.70	38.42	46.14	68.64
LQP	18.45	9.73	12.74	8.83	55.68	38.78	45.90	67.70
SS-3D-LTP	16.75	9.24	11.91	8.77	57.38	39.27	46.73	67.75
LTP	16.80	9.18	11.87	8.87	57.32	39.33	46.77	67.65
LMePVEP	16.81	9.18	11.87	8.69	57.32	39.33	46.77	67.83
LMePTerP	16.67	9.18	11.84	8.61	57.46	39.33	46.80	67.92
LQEQerP	16.67	9.18	11.84	8.68	57.46	39.33	46.80	67.85
LTrP	17.03	9.16	11.91	9.03	57.10	39.35	46.73	67.49
LTCop	16.77	9.14	11.83	8.72	57.35	39.37	46.81	67.80
DLTerQEP	16.68	9.10	11.77	8.66	57.45	39.41	46.87	67.87
LDGP	17.28	9.05	11.88	8.99	56.84	39.46	46.76	67.53
LTDP	16.59	8.97	11.64	8.70	57.53	39.54	47.00	67.82
LQEP	16.55	8.93	11.60	8.52	57.57	39.58	47.04	68.01
LMeP	16.66	8.91	11.61	7.67	57.46	39.59	47.03	68.85
LBP	16.59	8.79	11.49	9.22	57.54	39.72	47.15	67.30
LNIP	16.24	8.67	11.31	8.01	57.88	39.83	47.33	68.51
<i>Average Improvement</i>					54.12	36.98	44.05	65.33

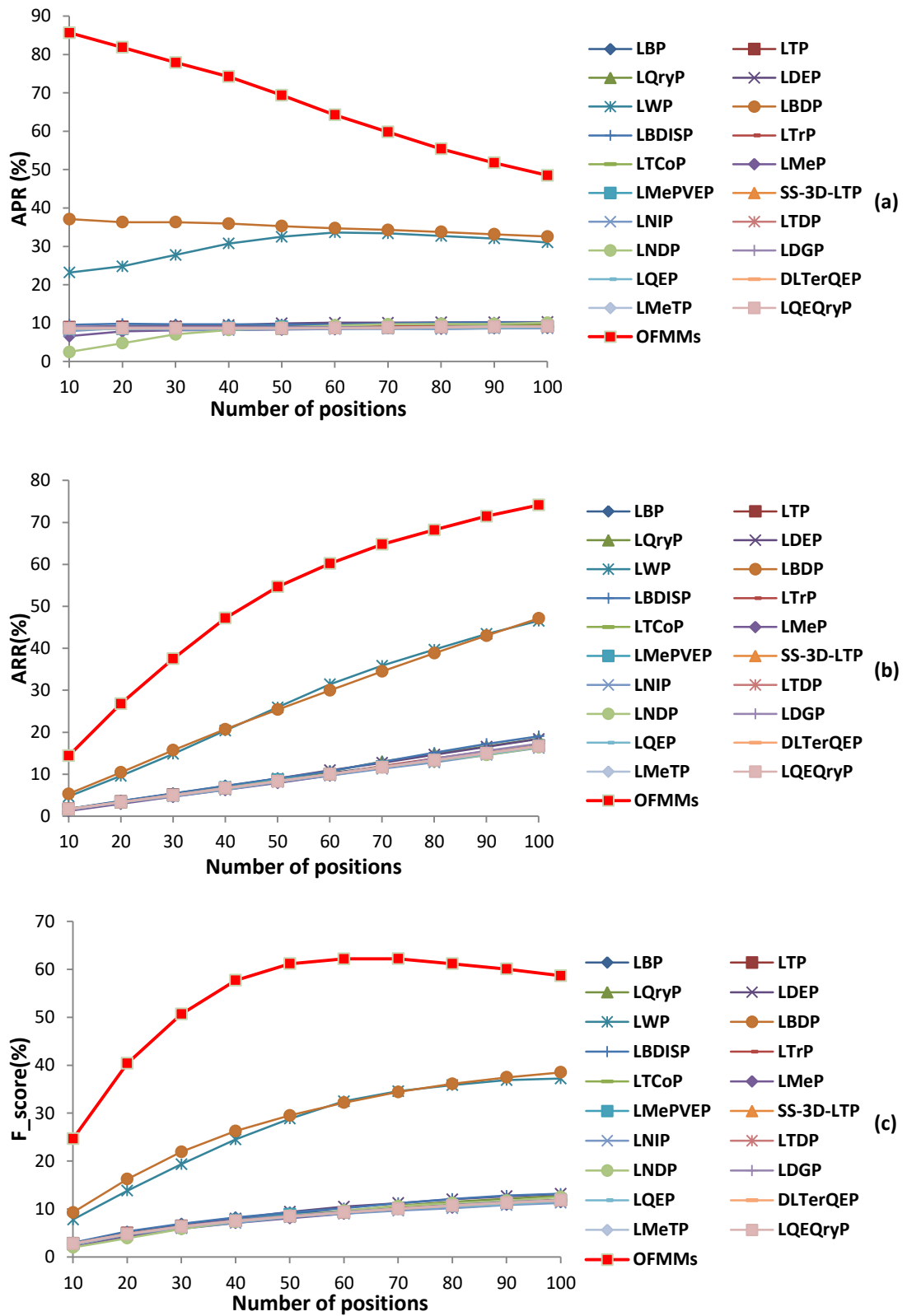


Figure 5.11: Comparison of the proposed method with other existing methods in terms of (a) *APR*, (b) *ARR*, and (c) *F_score* as function of number of top matches (η) on noisy NEMA CT database

Table 5.9 Comparison of retrieval rates of the proposed and the existing techniques for top 100 matches (*i. e.* $\eta = 100$) on noisy OASIS MRI database.
All values are in percentages (%).

Performance Measure	<i>ARR</i>	<i>APR</i>	<i>F_score</i>	<i>mAP</i>	<i>Improvement = (OFMMs – COMPARED METHOD)</i>			
Proposed	30.39	33.76	31.98	35.75	<i>ARR</i>	<i>APR</i>	<i>F_score</i>	<i>mAP</i>
LDGP	24.11	26.60	25.30	26.35	6.27	7.16	6.69	9.40
LNIP	24.01	26.55	25.21	26.47	6.38	7.21	6.77	9.28
LTDP	24.06	26.06	25.02	26.08	6.33	7.69	6.96	9.68
LTrP	24.04	25.84	24.91	25.91	6.35	7.92	7.08	9.85
LMePTerP	24.00	25.77	24.85	25.81	6.39	7.99	7.13	9.95
LMeP	23.95	25.70	24.80	25.62	6.43	8.06	7.19	10.13
LTP	24.15	25.60	24.85	25.40	6.24	8.16	7.13	10.35
LBP	24.01	25.59	24.78	25.49	6.38	8.17	7.21	10.26
LWP	24.47	25.56	25.00	25.76	5.92	8.20	6.98	9.99
LMePVEP	24.07	25.55	24.79	25.70	6.32	8.21	7.20	10.05
LQEP	24.05	25.55	24.78	25.43	6.33	8.21	7.21	10.32
SS-3D-LTP	24.17	25.54	24.84	25.55	6.22	8.22	7.15	10.20
DLTerQEP	23.95	25.50	24.70	25.41	6.43	8.25	7.28	10.34
LQEQerP	23.95	25.32	24.62	25.24	6.44	8.44	7.37	10.52
LTCop	23.90	25.27	24.57	25.37	6.49	8.49	7.42	10.39
LNDP	23.78	24.99	24.37	25.07	6.60	8.77	7.61	10.68
LBDISP	24.31	24.72	24.51	24.75	6.08	9.04	7.47	11.00
LQP	24.02	24.67	24.34	24.80	6.37	9.09	7.65	10.95
LBDP	24.97	24.28	24.62	24.89	5.42	9.48	7.36	10.86
LDEP	24.03	23.89	23.96	24.02	6.35	9.87	8.02	11.73
<i>Average Improvement</i>					8.33	6.29	7.24	10.30

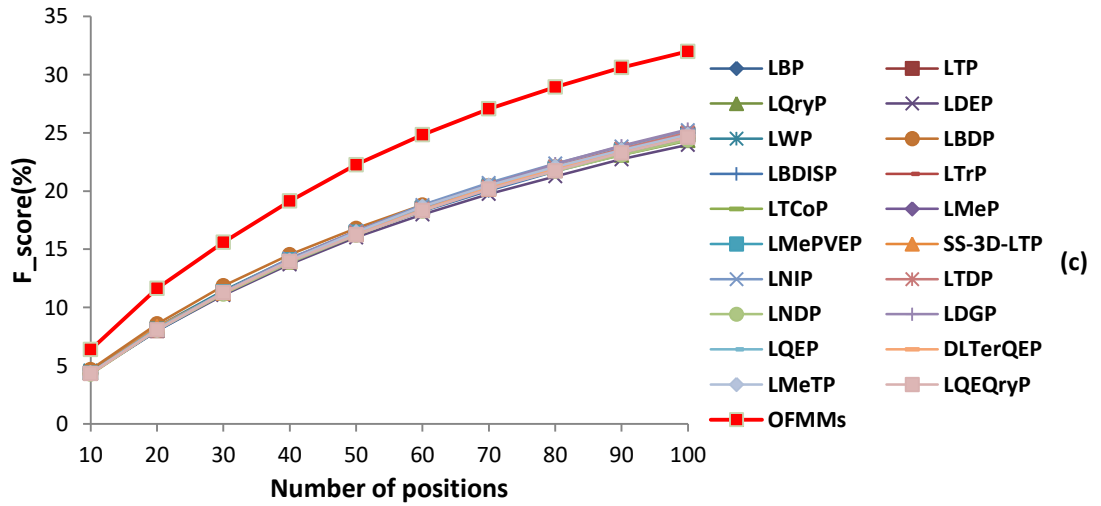
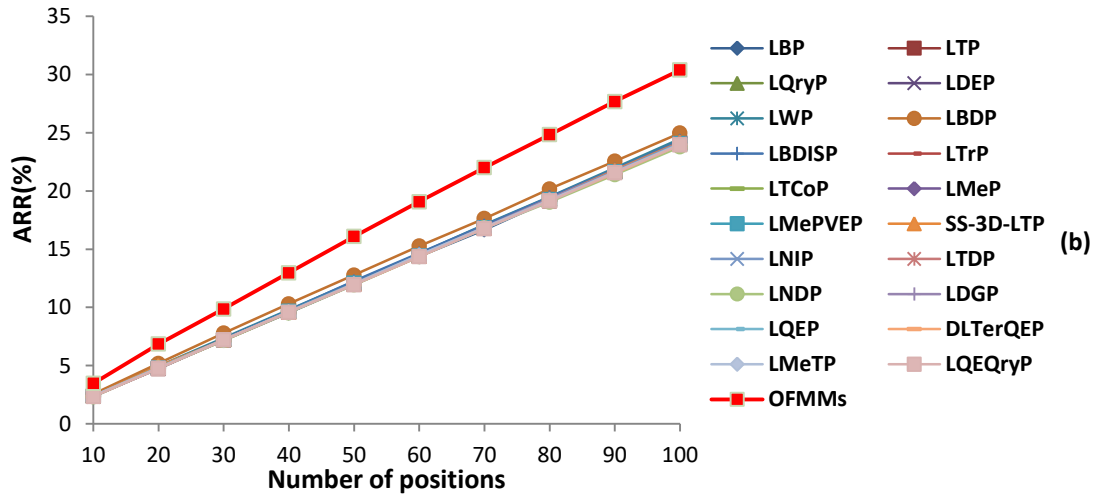
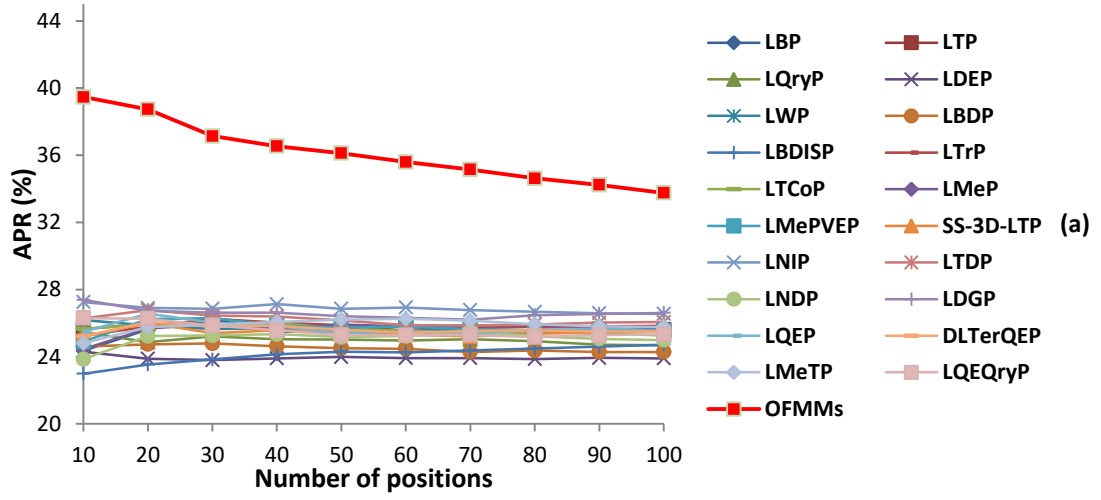


Figure 5.12: Comparison of the proposed method with other existing methods in terms of (a) *APR*, (b) *ARR*, and (c) *F_score* as function of number of top matches (η) on noisy OASIS MRI database

Table 5.10: Comparison of retrieval rates of the proposed and the existing techniques for top 100 matches (*i. e.* $\eta = 100$) on noisy NEMA MRI database.
All values are in percentages (%).

Performance Measure	<i>ARR</i>	<i>APR</i>	<i>F_score</i>	<i>mAP</i>	<i>Improvement = (OFMMs – COMPARED METHOD)</i>			
Proposed	76.32	56.82	65.14	78.82	<i>ARR</i>	<i>APR</i>	<i>F_score</i>	<i>mAP</i>
LBDP	60.54	46.20	52.40	50.17	15.78	10.62	12.74	28.65
LWP	46.34	37.33	41.35	42.04	29.98	19.48	23.79	36.78
LBDISP	34.91	29.98	32.26	30.05	41.41	26.84	32.88	48.76
LTCoP	30.36	29.33	29.84	29.92	45.95	27.48	35.30	48.90
LDEP	29.84	28.96	29.39	27.08	46.47	27.86	35.75	51.74
LQEQerP	30.04	28.83	29.42	27.04	46.28	27.99	35.72	51.78
LMePTerP	29.45	28.69	29.06	26.90	46.86	28.13	36.07	51.92
SS-3D-LTP	29.56	28.28	28.91	28.06	46.76	28.53	36.23	50.75
LNDP	29.90	27.92	28.88	28.14	46.41	28.90	36.26	50.68
LMeP	27.37	27.20	27.29	26.92	48.95	29.61	37.85	51.90
DLTerQEP	27.33	27.20	27.26	26.92	48.98	29.62	37.87	51.90
LBP	27.28	27.14	27.21	27.14	49.04	29.68	37.93	51.68
LQP	28.36	27.05	27.69	26.63	47.95	29.77	37.45	52.18
LDGP	26.96	26.94	26.95	26.95	49.35	29.87	38.19	51.87
LMePVEP	26.90	26.89	26.90	26.88	49.42	29.92	38.24	51.94
LTP	26.89	26.89	26.89	26.88	49.43	29.93	38.25	51.94
LNIP	26.89	26.88	26.88	26.88	49.43	29.93	38.25	51.94
LTDP	26.89	26.88	26.89	26.88	49.43	29.93	38.25	51.94
LTrP	26.88	26.88	26.88	26.88	49.43	29.94	38.26	51.94
LQEP	26.88	26.88	26.88	26.88	49.43	29.94	38.26	51.94
<i>Average Improvement</i>					27.70	45.34	35.18	49.55

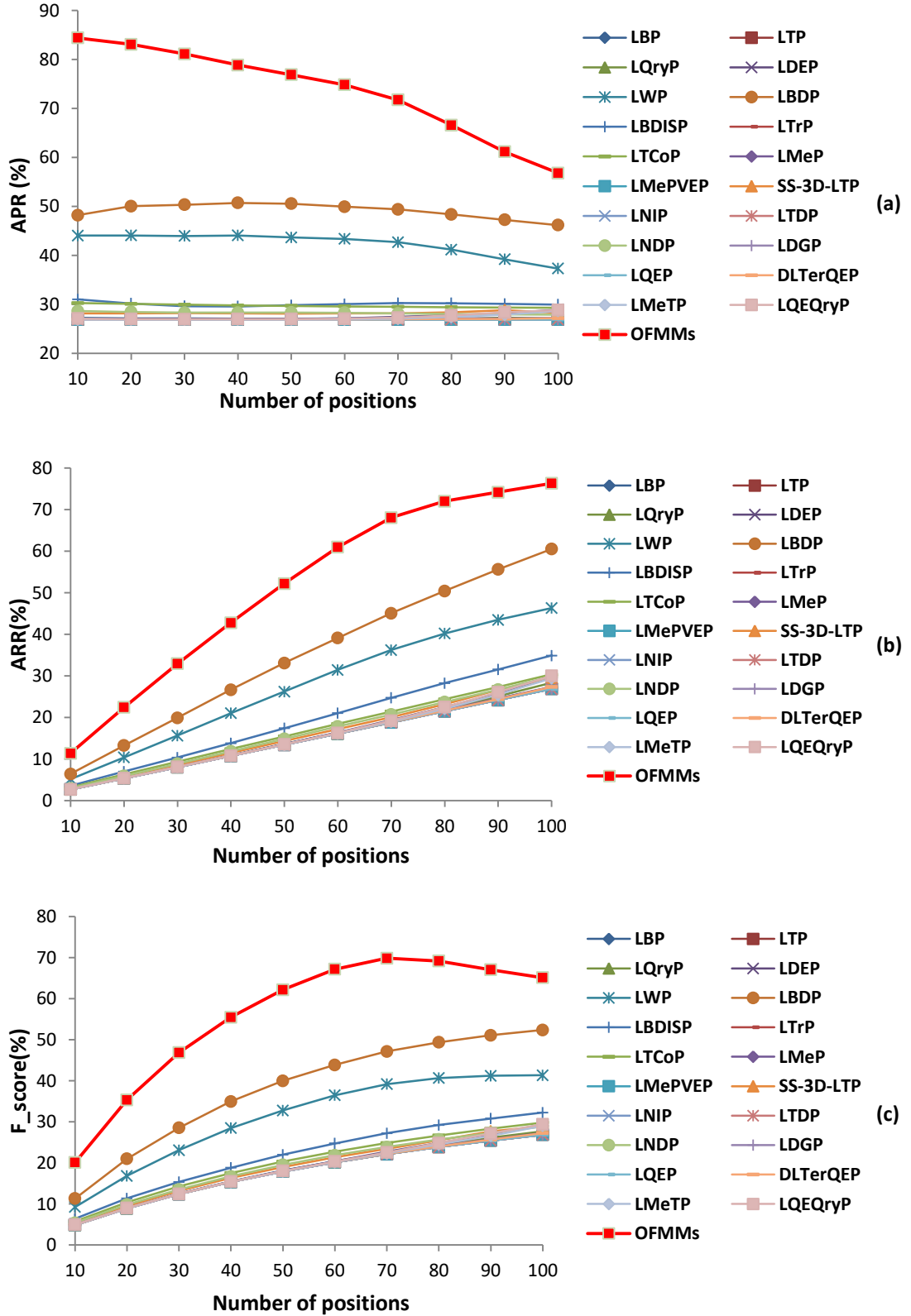


Figure 5.13: Comparison of the proposed method with other existing methods in terms of (a) *APR*, (b) *ARR*, and (c) *F_score* as function of number of top matches (η) on noisy NEMA MRI database

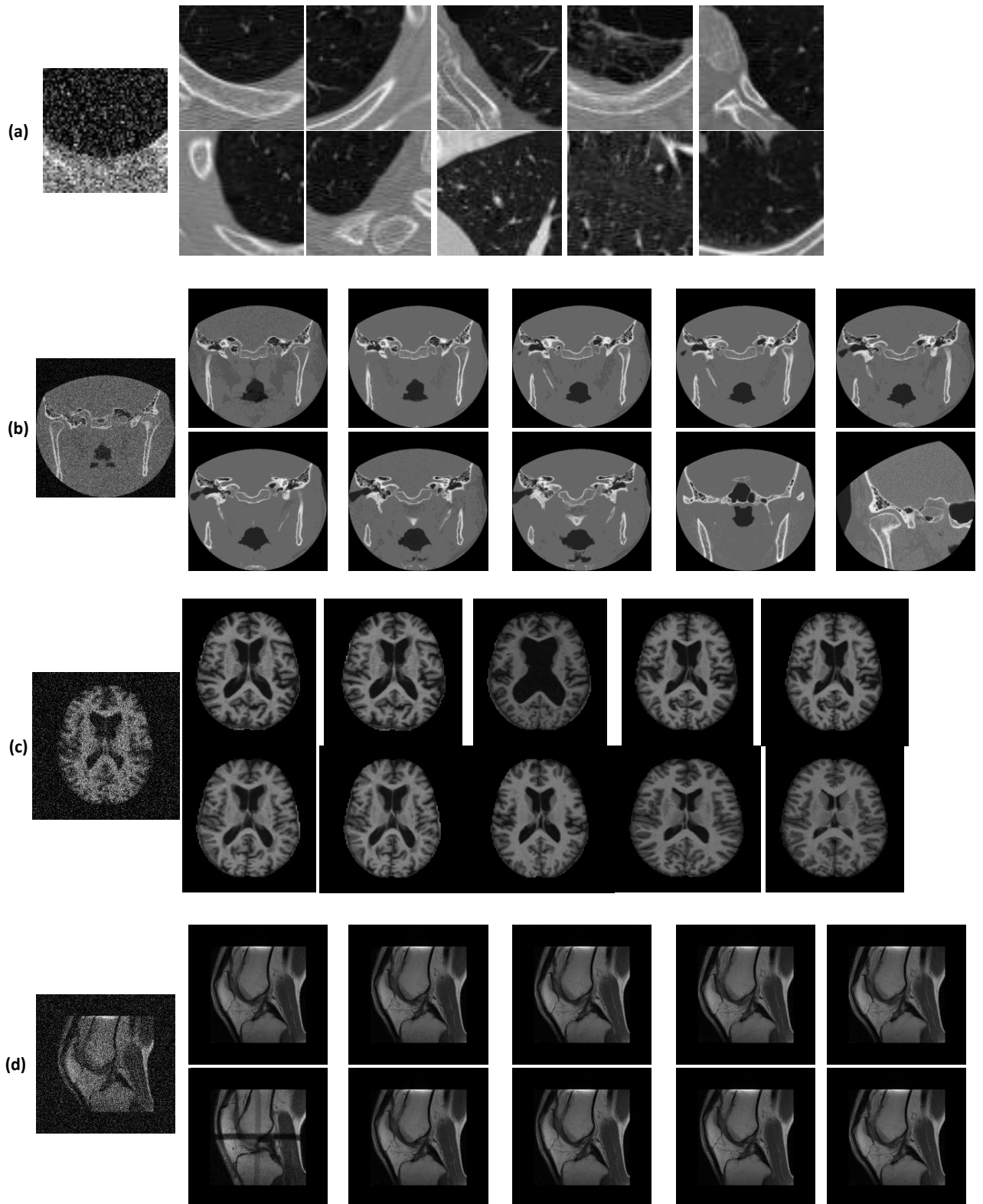


Figure 5.14: Query results of the proposed method on (a) noisy Emphysema CT database, (b) noisy NEMA CT database, (c) noisy OASIS MRI database, and (d) noisy NEMA MRI database

5.5 Computational Efficiency

Biomedical image retrieval requires methods which are effective as well as computationally efficient. Such methods should provide real time response, i.e., the time associated with the retrieval of medical images should be very less. The computational time for any retrieval system depends on two phases: 1) Feature Extraction Phase and 2) Retrieval (Classification) Phase. The feature extraction phase involves CPU time spent on extracting features from the query and the databases images. The feature extraction time depends on the size of the image. The bigger the image is, higher will be its feature extraction time. The classification phase involves the CPU time spent on matching the features of the query image with those of database images. The classification time depends on the number of features extracted by the method. The feature vector with large dimensionality would take more time in determining the similarity/dissimilarity between query and database images. Table 5.11 shows the comparison of the feature vector length of the proposed and all the compared approaches for a given query image.

Table 5.11: Comparison of feature vector length of the proposed and all the compared approaches for a given query image

S.No.	Method	No. of features	Increase in Feature size in comparison to proposed OFMMs-based approach (B/A)
A	OFMMs	16	
B	LDEP	24	1.50 times
	LDGP	64	4 times
	LBDISP	256	16 times
	LNDP	256	16 times
	LBDP	256	16 times
	LWP	256	16 times
	LBP	256	16 times
	LTP	512	32 times
	LTCoP	512	32 times
	LNIP	512	32 times
	LMeP	768	48 times
	LTDP	768	48 times
	LQP	1024	64 times
	LMePVEP	1024	64 times
	LMePTerP	1536	96 times
	SS-3D-LTP	2560	160 times
	LTrP	3328	208 times
	LQEP	4096	256 times
	DLTerQEP	8192	512 times
	LQEQR	16384	1024 times

From the table it can be observed that the proposed OFMMs-based approach uses least number of features as compared to the existing approaches. All the existing methods have much larger feature dimensionality as compared to the proposed approach with increase in feature size in order of 16 to 1024 times. The LQEQerP method has the highest number of features, i.e., 16384 features, which are 1024 times higher than the proposed OFMMs-based approach. The comparison of feature extraction time and retrieval time (in seconds) of the proposed approach with the existing biomedical image retrieval approaches over all four test databases i.e., Emphysema CT, NEMA CT, OASIS MRI and NEMA MRI has been given in Table 5.12. The feature extraction time is computed by calculating the total time required to extract features from all the images of the database. The retrieval time over a particular database is computed by finding the total time required to match each image of that dataset with remaining images. The image content in a database has no effect on the execution times of any method. Thus, the execution times for noisy databases are similar to those of noise-free databases. Since, each of the four test databases vary in the number and size of the images, a separate comparison between the execution times of the proposed and the existing methods on each of the four test databases has been shown in Table 5.12. From the table it can be observed that the total CPU time for the proposed method is lowest among all other compared (and existing) methods. Therefore, it can be deduced that the proposed OFMMs-based approach gives the best retrieval rates in minimum computation time in comparison to all the existing state-of-the-art biomedical retrieval approaches. Figure 5.15 shows the diagrammatic comparison between the proposed and all the compared approaches in terms of the total CPU time (feature extraction time + retrieval time) spent for retrieval of CT and MR images over Emphysema CT, NEMA CT, OASIS MRI and NEMA MRI databases, respectively.

Table 5.12: CPU elapse time (sec) during feature extraction and retrieval of images over Emphysema-CT, and OASIS-MRI databases using LBP, ULBP, LDEP, Mb-LBP, and the proposed OFMMs-based feature descriptors

Feature Descriptors	Feature Extraction Time (A)				Retrieval Time (B)				Total CPU time (A+B)			
	Emphys ema CT	NEMA CT	OASIS MRI	NEMA MRI	Emphys ema CT	NEMA CT	OASIS MRI	NEMA MRI	Emphys ema CT	NEMA CT	OASIS MRI	NEMA MRI
OFMMs	0.26	65.42	7.49	10.14	0.11	1.46	0.67	1.17	0.37	66.88	8.16	11.31
LDEP	0.62	156.13	17.87	24.20	0.18	1.86	1.10	1.42	0.8	157.99	18.97	25.62
LDGP	0.20	51.38	5.88	7.96	0.33	4.33	2.02	3.07	0.53	55.71	7.9	11.03
LBDISP	1.05	265.07	30.33	41.09	0.98	11.51	6.01	7.25	2.03	276.58	36.34	48.34
LNDP	0.58	146.43	16.76	22.70	0.98	11.51	6.01	7.25	1.56	157.94	22.77	29.95
LBDP	0.68	171.88	19.67	26.64	0.98	11.51	6.01	7.25	1.66	183.39	25.68	33.89
LWP	0.39	98.25	11.24	15.23	0.98	11.51	6.01	7.25	1.37	109.76	17.25	22.48
LBP	0.34	85.03	9.73	13.18	0.98	11.51	6.01	7.25	1.32	96.54	15.74	20.43
LTP	0.47	117.54	13.45	18.22	2.01	20.54	12.32	12.26	2.48	138.08	25.77	30.48
LTCoP	1.00	252.74	28.92	39.17	2.01	20.54	12.32	12.26	3.01	273.28	41.24	51.43
LNIP	1.90	477.18	54.60	73.96	2.01	20.54	12.32	12.26	3.91	497.72	66.92	86.22
LMeP	0.76	190.27	21.77	29.49	2.45	30.21	15.02	16.41	3.21	220.48	36.79	45.9
LTDP	1.20	302.54	34.62	46.89	2.45	30.21	15.02	16.41	3.65	332.75	49.64	63.3
LQP	0.90	226.25	25.89	35.07	3.81	41.68	23.36	21.98	4.71	267.93	49.25	57.05
LMePVEP	1.27	318.63	36.46	49.39	3.81	41.68	23.36	21.98	5.08	360.31	59.82	71.37
LMePTerP	1.37	343.45	39.30	53.23	4.89	60.46	29.98	31.38	6.26	403.91	69.28	84.61
SS-3D-LTP	2.50	629.75	72.06	97.61	7.93	93.82	48.62	43.03	10.43	723.57	120.68	140.64
LTrP	31.19	7848.78	898.11	1216.56	10.50	121.70	64.38	51.80	41.69	7970.48	962.49	1268.36
LQEP	0.81	202.86	23.21	31.44	12.77	147.91	78.30	63.01	13.58	350.77	101.51	94.45
DLTerQEP	0.83	210.02	24.03	32.55	21.33	271.52	130.81	118.62	22.16	481.54	154.84	151.17
LQEQerP	1.53	385.55	44.12	59.76	45.78	510.18	280.68	252.26	47.31	895.73	324.8	312.02

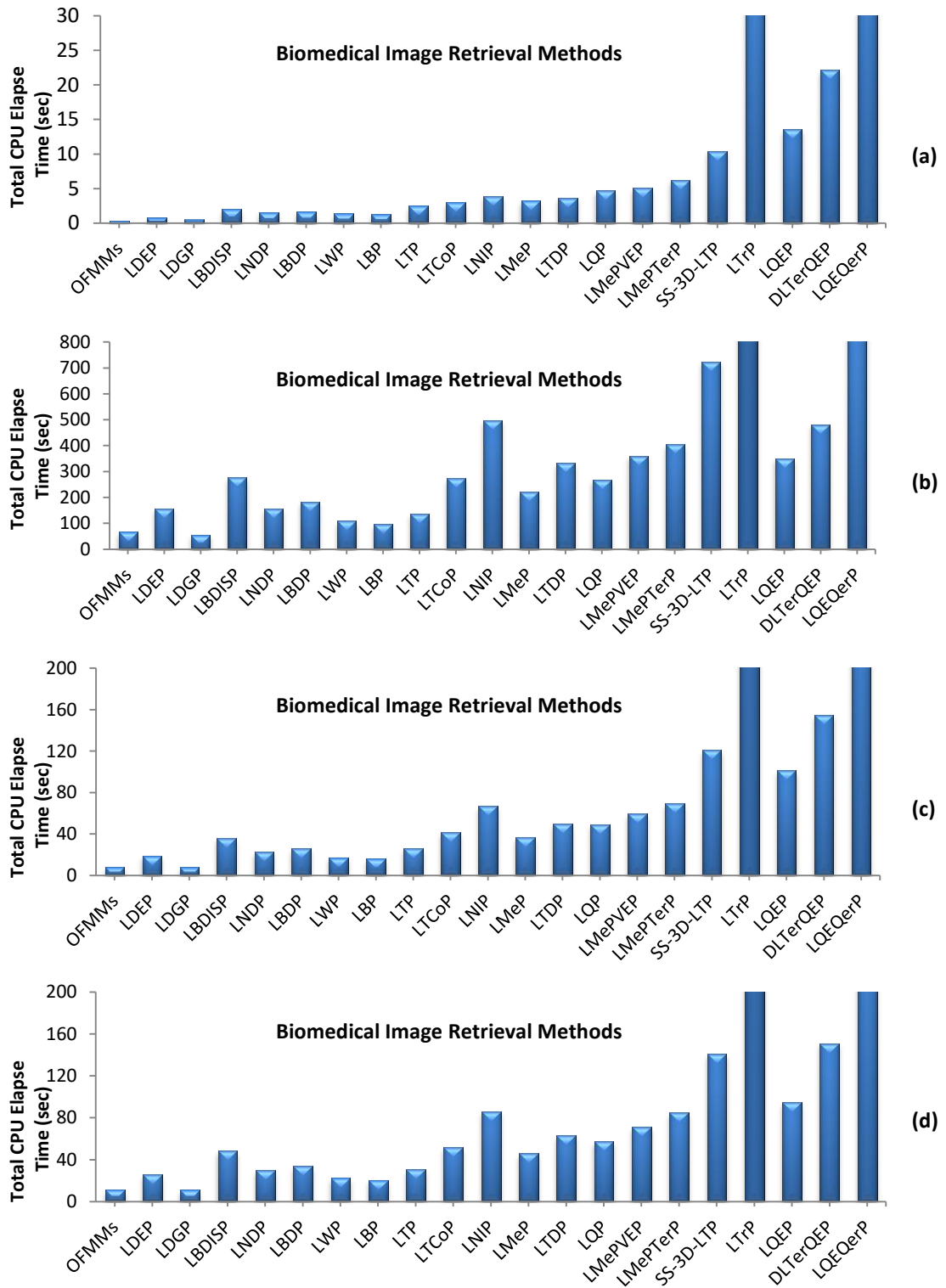


Figure 5.15: Comparison of total CPU Elapse time (sec) for the proposed and the existing biomedical image retrieval approaches over (a) Emphysema CT database, (b) NEMA CT database, (c) OASIS MRI database, and (d) NEMA MRI database

Chapter 6

Conclusion and Future Work

This chapter summarizes the thesis work in and presents the possible scope for extension of our proposed work in near future.

6.1 Conclusion

The CBMIR systems have been designed to provide the required information at the right time, the right place to the right persons with a motive to enhance the quality and efficiency of the care process. To develop a robust and efficient CBMIR system, extraction of appropriate visual features like shape, color, and texture plays a significant role. The visual feature descriptors of an image can be categorized into two types as the local feature descriptors and the global feature descriptors. Local binary pattern (LBP) is the one of the oldest and popular local feature descriptor method and it has given a new insight into the field of medical applications. LBP is further extended to its various variants to improve its functionality. LBP and all its variants have given very promising results in the large variety of application areas but methods still seems struggling while working in the scenarios where the query images have been degraded either by noise or by some transformations like rotation, scaling or translation etc. Also, some of the methods have very large feature size, poor discrimination power and are very computation intensive. Thus, in order to achieve maximum throughput in retrieving medical images of different body organs, we cannot remain stick to the local feature methods. The global information of an image plays a very crucial role in differentiating between images of different body parts.

Hence in our research work, we are shifting the idea of local feature descriptors to the global one and propose a new biomedical image retrieval approach images using orthogonal Fourier-Mellin moments (OFMMs). OFMMs are orthogonal moments and highly robust towards image noise. The noise resilience property of OFMMs makes them perfectly suitable for retrieval of real-life images that are generally degraded by the presence of noise. Exhaustive experiments performed on noisy and noise-free images of four standard databases namely Emphysema CT database, NEMA CT database, OASIS MRI database and NEMA MRI database substantiates the capability

of the proposed approach to accurately retrieve both CT and MR images even under noisy conditions. The retrieval performance of the proposed method has been compared with a large number of existing and state-of-the-art biomedical image retrieval approaches in terms of four performance measures namely *ARR*, *APR*, *F_score* and *mAP*. After the thorough analysis of the obtained results, it was observed that the proposed approach achieved very superior retrieval rates over all the compared approach on all four test databases. Especially in case of noisy images, all the existing approaches struggled to give good retrieval rates and witnessed a huge drop in their retrieval performances in comparison to those on noise-free images. The proposed approach, on the other hand, gave stable performance under noisy conditions. The biggest advantage of the proposed approach in comparison to the existing state-of-the-art biomedical retrieval approaches is its superior retrieval performance using a minimum number of features. Thus, the proposed method has proved to be both effective and computationally efficient for the retrieval of CT and MR images.

6.2 Future Work

This thesis work is focused on the content-based image retrieval for MRI and CT databases. Content-based biomedical image retrieval scheme presented in our thesis are promising still there is significant scope for future research. This research work improves the understanding of various techniques for feature extraction and similarity measurement which aids medical image retrieval and advances the state-of-the-art through its contributions. Three main aspects can be extended in future work as:

- Among all the visual descriptors of an image, colors are the most intuitive, effective and obvious feature. Moreover the colored images are easy to analyze and understand. From the results, it is seen that the proposed method has been proved to be both effective and computationally efficient for the retrieval of grey scale images. Hence the first aspect that we can extend in future is to use the proposed OFMMs-based method for the retrieval of colored images.
- OFMMs have the characteristics to be invariant towards geometric transformations such as rotation, scaling and translation (RST). The noise resilience property of OFMMs makes them perfectly suitable for retrieval of real-life images that are generally degraded by the presence of noise. The

second aspect that can be extend in future is to use enhanced properties of orthogonal rotation invariant transforms (ORITs) and orthogonal Fourier-Mellin moments (OFMMs) for the better image retrieval.

- OFMMs prove themselves as an efficient feature descriptor with a minimum feature vector length and high discrimination power. Hence the third aspect is to use proposed OFMMs based method for the retrieval of different biomedical modalities like HRCT, X-rays, cardiology etc. in future.

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