

# CHAPTER 1

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## An Expert Local Mesh Correlation Histograms for Biomedical Image Indexing and Retrieval

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In this chapter, a new feature descriptor, local mesh correlation histograms (LMeCH) is proposed for content-based image retrieval (CBIR). The LMeCH integrates the local mesh patterns (LMeP) and grayscale joint histogram. Firstly, the LMeP features are extracted from the image and then the joint histogram is constructed between the LMeP and grayscale value of center pixel. The process of joint histogram is able to extract the efficient image features from the databases. The retrieval performance of the proposed method is tested on two bench mark OASIS-MRI and NEMA-CT biomedical image databases. The experimental results show a significant improvement in terms of precision, recall, average retrieval precision (ARP) and average retrieval rate (ARR) when compared with other standard image retrieval approaches on the same database.

## 1.1 Introduction

In recent times, the digital image processing gains its significant importance in many fields mainly in medicine. In day to day life, large amount of biomedical images are generated from hospitals, medical institutions and diagnostic centers etc. in the form of X-ray, ultrasound (US), computer tomography scan (CT-Scan), magnetic resonance imaging (MRI-Scan), etc. Hence, the biomedical database (image collection) is not useful unless it is organized to allow efficient access, search and retrieve. In medical occupation especially for medical students, it is not easy to understand the patients imaging reports. To solve the above problem, an expert system is required to help the doctor in the early stage of diagnosis, that is, the content based image retrieval (CBIR) system can be deployed to retrieve the similar images from record database by querying-in the current image. The results of the query along with associated patient history would help the medical students in arriving at the diagnosis. The "content-based" means, the search will analyze the actual contents of the image rather than the metadata. The CBIR system can filter images based on their content so it would provide better indexing and return more accurate results. The term "content" in this context might refer to color, shape, texture or any other information that can be derived from the image itself. The main goal in image retrieval is to select and retrieve the number of best matched images based on the query image. In the literature many similarity measures have been evolved based on experimental estimates. Vipparthi and Nagar [27, 29] and Subrahmanyam et al. [12] used four different similarity distance measures. The retrieval performance is extensively affected by different similarity measures. Here the least distance is being considered as more relevant image to the query. Likewise, the feature extraction is very prominent step in CBIR framework. The retrieval performance typically depends on the method used to extract features from raw images. The feature descriptors are either local or global. The local descriptor uses the features of a region or object, whereas; the global descriptor uses features of the whole image. In early years Manjunath et al. [9] has used intensity histogram based feature for biomedical image retrieval. However, their retrieval performance is very limited mainly on immense database due to lack of discriminative power. To solve this problem texture and local based retrieval were proposed. Texture is one of the most important characteristic of the image. Texture analysis is exten-

sively used in biomedical images due to its potential values. Many of the researchers use texture features for their research work; few of them are presented as follows. Scott and Shyu [21] have proposed entropy balanced statistical (EBS) k-d tree for biomedical image retrieval using high-resolution computed tomography (HRCT) lung image database. Cai et al. [2] have proposed a prototype design which supports an efficient content-based retrieval based on physiological kinetic features and reduces image storage requirements. Rahman et al. [20] have proposed a classification-driven biomedical image retrieval framework based on image filtering and similarity fusion by employing supervised learning techniques. Yang et al. [32] have proposed a boosting framework for distance metric learning that aims to preserve both visual and semantic similarities. Quéllec et al. [19] have proposed a system where, images are indexed in a generic fashion, without extracting domain-specific features. A signature is built for each image from its wavelet transform, these signatures characterize the distribution of wavelet coefficients in each sub-band of the decomposition. ElAlami [3] has proposed an unsupervised image retrieval framework based on rule base system using geometric moments (GMs) for features extraction. Lin et al. [7] have proposed fast K-means algorithm based on a level histogram for image retrieval.

In recent years, the local image features extraction attracting increasing attention in image retrieval. The local feature descriptor uses the visual features of regions or objects to describe the image. Many local descriptors are reported in the literature such as; Ojala et al. [18] have proposed local binary patterns which can show a better performance as well as less computational complexity for texture classification. LBP is succeeded in terms of performance and speed, this is reported in many research areas like texture classification [4, 18], face recognition [1], image retrieval [11, 14, 13, 10, 24, 27, 28, 26, 29, 30, 31, 25, 33]. Likewise, Vipparthi and Nagar [27] have proposed an expert image retrieval system using directional local XoR patterns. Similarly, Vipparthi and Nagar [28] have proposed multi-joint histogram based modelling for image retrieval application. Further, Vipparthi and Nagar [29] have proposed the directional local ternary pattern based on directional edges for image retrieval. The different LBP variant features for image retrieval, texture retrieval and object tracking applications have been proposed in (Subrahmanayam et al. [11, 14, 13, 10]). Su et al. [23] have proposed Region-based image retrieval system with heuristic pre-clustering relevance feedback using both Relevance feedback (RF) and region-based image retrieval (RBIR). Su et al. [22] have proposed an effective content-based video retrieval using pattern-indexing and matching techniques on basis of the discovered temporal patterns. Kilinc and Alpkocak [5] have proposed an expansion and re-ranking approach for annotation-based image retrieval from web by using term selection approach, which first expands the document using WordNet, and then selects descriptive terms among them. Laresé et al. [6] have proposed multiscale recognition of legume varieties based on leaf venation images. Yildizer et al. [34] have proposed an efficient content-based image retrieval using multiple support vector machines ensemble. Lin et al. [8] have proposed fast color-spatial feature based image retrieval methods using the K-means algorithm. The main advantages of the proposed method over the existing methods are given as follows:

- (1) The histogram of LMeP can be used to represent the textural and structural contents for image retrieval. However, LMeP cannot reflect the absolute values

of intensity. For some images such as CT scans, the intensity value (e.g. CT values) may be useful for diagnosis. Hence, in this chapter, we propose the method which collects the joint correlation between the center pixel gray value and LMeP.

- (2) The existing methods LTP, LDP, etc. collect the directional information from the images. Hence, all these methods are variant for the rotated databases. Whereas, the proposed descriptor can be rotational invariant by considering the rotational invariant two uniform patterns.
- (3) From the experimental results, it is proved that the proposed method outperforms the other existing methods in terms of average retrieval precision (ARP) and average retrieval rate (ARR) on benchmark biomedical databases.

The organization of this chapter is as follows: Section 1.1, presents the brief review of biomedical image retrieval and its literature work is given. In Section 1.2, the concise review of local patterns and proposed descriptor is presented. Section 1.3, presents the proposed descriptor frame work with similarity measurements. In Section 1.4, experimental results and discussion is presented. Based on the above summary this chapter is concluded in Section 1.5.

## 1.2 Local Patterns

### 1.2.1 Local Binary Patterns (LBP)

The concept of LBP was derived from the general definition of texture in a local neighborhood. LBP was successful in terms of speed and discriminative performance. For a given  $3 \times 3$  pixel pattern, the LBP value is calculated by comparing its center pixel value with its neighborhoods as shown below:

$$LBP_{N,R} = \sum_{i=0}^{N-1} 2^i \times f_1(p_i - p_c) |_{R=1,2,3} \quad (1.1)$$

$$f_1(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (1.2)$$

where  $N$  stands for the number of neighbors,  $R$  is the radius of the neighborhood,  $p_c$  denotes the grey value of the centre pixel and  $p_i$  is the grey value of its neighbors. The LBP encoding procedure from a given  $3 \times 3$  pattern is illustrated in Fig.(1.1).

### 1.2.2 Local Mesh Patterns (LMeP)

The LMeP [15] is computed by using neighborhoods at specified radius for a reference pixel. The calculation of LMeP patterns for a given pattern is shown in Fig.(1.1).

$$LMeP_{N,R} = \sum_{i=0}^{N-2} 2^i \times f_2(p_i - p_{i+1}) + 2^{N-1} \times f_2(p_{N-1} - p_{N-N}) |_{R=1,2,3} \quad (1.3)$$

$$f_2(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (1.4)$$

### 1.2.3 Local Mesh Correlation Histograms (LMeCH)

The standard LBP and LMePs have motivated us to propose LMeCHs. The LMeCH introduced a new methodology to calculate joint co-relation between LBP and LMeP. The LMeCH integrates the local mesh patterns (LMeP) and grayscale joint histogram. Firstly, the LMeP features are extracted from the image and then the joint histogram is constructed between the LMeP and the grayscale value of the central pixel. The LMeCH collects the correlation histogram using LMeP and uniform quantization on grayscale image. The computational complexity of the LMeP is reduced by using the uniform patterns. The process of joint histogram can extract the efficient image features from the databases. The general structure of constructing LBP, LMeP and the proposed approach (LMeCH) is shown in Fig.(1.1). The procedure of constructing LMeCH is shown in Fig.(1.2). In this chapter, the local patterns are calculated at specified radius ( $R = 1$ ). Further, the central pixel gray value is uniformly quantized into  $n$  levels. Each quantization level has the feature vector length  $2P$ . The LMeCH is calculated based on the quantized value of the central pixel.

The detailed explanation for correlation histograms calculation is illustrated as follows. The central pixel value of a given  $3 \times 3$  pattern is 180 as shown in Fig.(1.2). The neighboring pixels at radius one is "100 125 80 75 69 55 150 95". The binary mesh pattern for the neighborhoods are "0 1 1 1 1 0 1 0". The final mesh pattern value for the same is 94. The proposed descriptor uses uniform quantization for the central pixel gray value. Let us consider four quantization levels as shown in Fig.(1.2). The central pixel grey-value of  $3 \times 3$  pattern comes under the 3rd category of quantization level. Hence, the proposed descriptor histogram is constructed as shown in Fig.(1.2).

## 1.3 Feature Extraction

### 1.3.1 Proposed System Framework

Figure 1.3 illustrates the flowchart of the proposed descriptor, while its computation algorithm is given below:

### 1.3.2 Similarity Measurement

The retrieval performance not only depends on strong feature representation but also on good similarity or distance metric. In this chapter, four types of similarity distance measures are used as given below:

$$\text{Manhattan (L}_1\text{ or City - block) Distance} - D_s(Q_m, T_m) = \sum_{i=1}^{Lg} |f_{T_m, i} - f_{Q_m, i}| \quad (1.5)$$

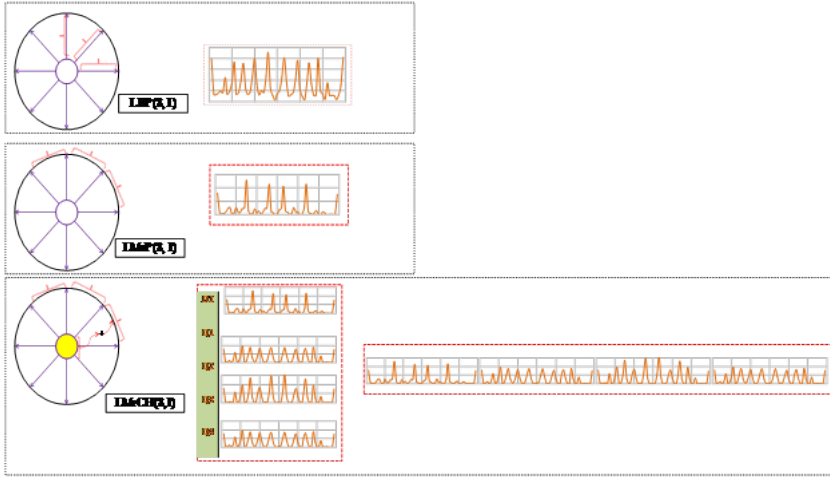


Figure 1.1: General structure of LBP, LMeP and LMeCH construction.

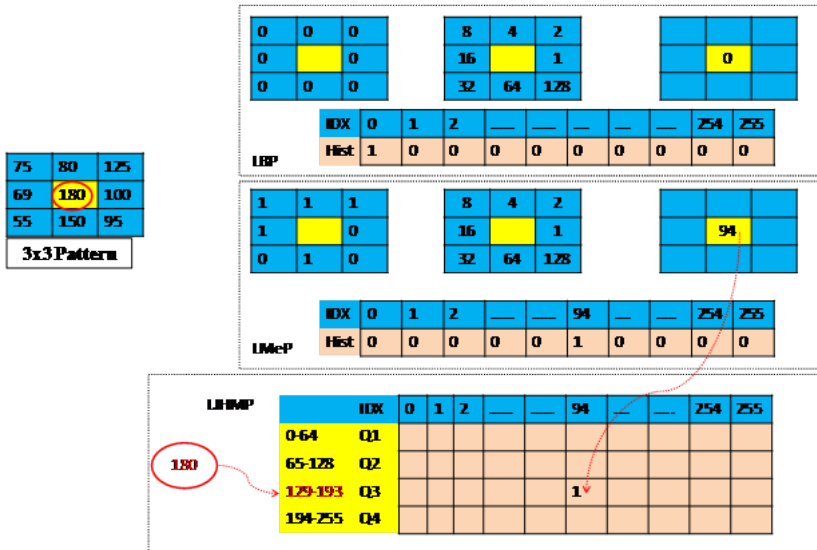


Figure 1.2: Calculation of LBP, LMeP and LMeCH for a given  $(P, R)$ .

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**Algorithm 1.1** Input: Image; Output: Retrieval results.

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*Step 1.* Load the image

*Step 2.* Divide the image into  $3 \times 3$  grids.

*Step 3.* Compute the local difference between neighbors for each central pixel and then convert to binary image.

*Step 4.* Construct the mesh pattern from *Step 3*.

*Step 5.* Quantize each central pixel grey value into four levels for a given image.

*Step 6.* Calculate correlation histogram between reference pixel and mesh pattern value.

*Step 7.* Construct the feature vector using quantized levels.

*Step 8.* Compute the similarities between query image and images in the database using Eq.(1.7).

*Step 9.* Retrieval images based on query image.

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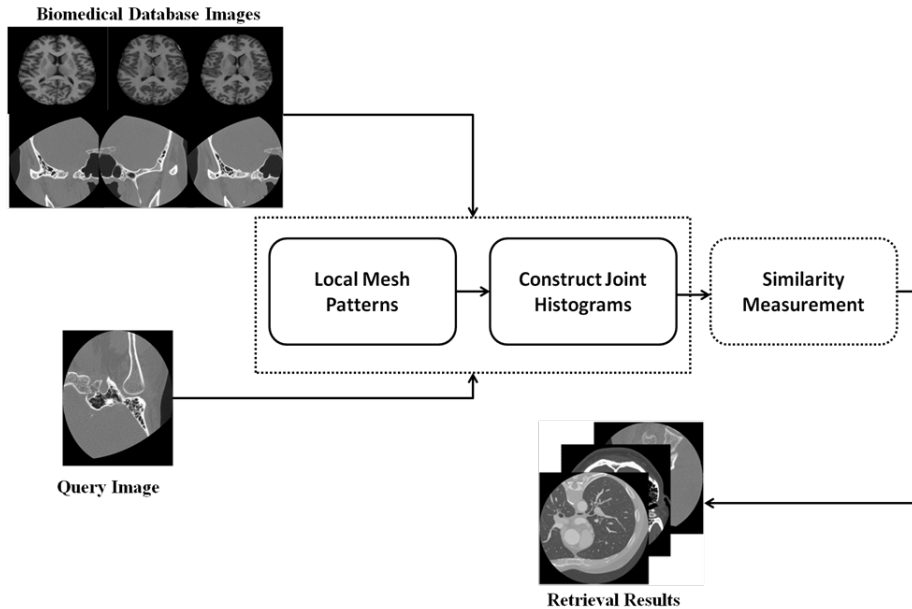


Figure 1.3: Proposed system framework.

$$\text{Euclidean } (L_2) \text{ Distance} - D_s(Q_m, T_m) = \left( \sum_{i=1}^{Lg} |f_{T_m,i} - f_{Q_m,i}|^2 \right)^{1/2} \quad (1.6)$$

$$\text{d1 Distance} - D_s(Q_m, T_m) = \sum_{i=1}^{Lg} \left| \frac{f_{T_m,i} - f_{Q_m,i}}{1 + f_{T_m,i} + f_{Q_m,i}} \right| \quad (1.7)$$

$$\text{Canberra Distance} - D_s(Q_m, T_m) = \sum_{i=1}^{Lg} \left| \frac{f_{T_m,i} - f_{Q_m,i}}{f_{T_m,i} + f_{Q_m,i}} \right| \quad (1.8)$$

where  $Q_m$  is the query image,  $Lg$  is feature vector's length,  $T_m$  is the image in the database;  $f_{T_m,i}$  is the  $i$ -th feature of image  $T_m$  in the database,  $f_{Q_m,i}$  is the  $i$ -th feature of the query image  $Q_m$ .

## 1.4 Experimental Results and Discussion

In order to analyze the performance of the proposed descriptor two experiments have been conducted on different biomedical image databases namely Open Access Series of Imaging studies (OASIS) [17] and National Electrical Manufactures association (NEMA) [16] datasets respectively. In both the experiments, each image in the database is used as the query image for performance evaluation.

The retrieval performance of the proposed descriptor is measured in terms of average precision, average retrieval precision (ARP), average recall and average retrieval rate (ARR) and are shown below.

The precision defined for the query image  $I_q$  is given below as follows:

$$P(I_q, n) = \frac{1}{n} \sum_{i=1}^{|DB|} |\psi(f(I_i), f(I_q))| \text{Rank}(I_i, I_q) \leq n \quad (1.9)$$

where  $n$  indicates the number of retrieved images,  $f(x)$  is the category of  $x$ ,  $\text{Rank}(I_i, I_q)$  returns the rank of image  $I_i$  (for the query image  $I_q$ ) among all images of  $|DB|$ .

Similarly, the recall is defined as follows

$$P(I_q, n) = \frac{1}{N_G} \sum_{i=1}^{|DB|} |\psi(f(I_i), f(I_q))| \text{Rank}(I_i, I_q) \leq n \quad (1.10)$$

where,  $N_G$  is the number of top matches considered and

$$\psi(f(I_i), f(I_q)) = \begin{cases} 1, & f(I_i) = f(I_q) \\ 0, & \text{otherwise} \end{cases} \quad (1.11)$$

In this approach, the average retrieval precision (ARP) (Eq.(1.12)) and the average retrieval rate (ARR) (Eq.(1.13)) are the bench mark for comparing results.



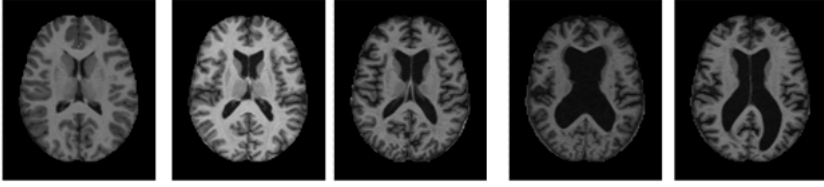


Figure 1.4: Some sample images from OASIS-MRI bio-medical image database.

$$ARP = \frac{1}{|DB|} \sum_{i=1}^{|DB|} P(I_i, n) \quad (1.12)$$

$$ARR = \frac{1}{|DB|} \sum_{i=1}^{|DB|} P(I_i, n) |_{n \leq N_G} \quad (1.13)$$

where  $|DB|$  is the total number of images in the database.

### 1.4.1 Experiment: 1

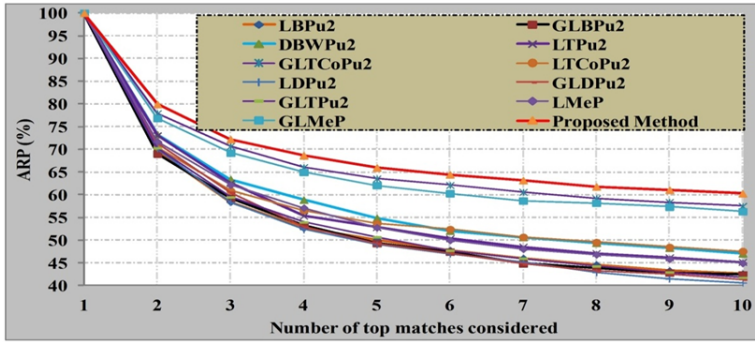
The Open Access Series of Imaging Studies (OASIS) dataset is used in this experiment. The OASIS database contains series of Magnetic Resonance Imaging (MRI). The OASIS dataset consists of 412 subjects aged between 18 to 90 years. The Complete detail of OASIS dataset is available in [17].

For image retrieval, the OASIS dataset is grouped into four different categories (124, 102, 89, and 106 images) based on the shape of ventricular in the images. The sample images of OASIS dataset is shown in Fig.(1.4).

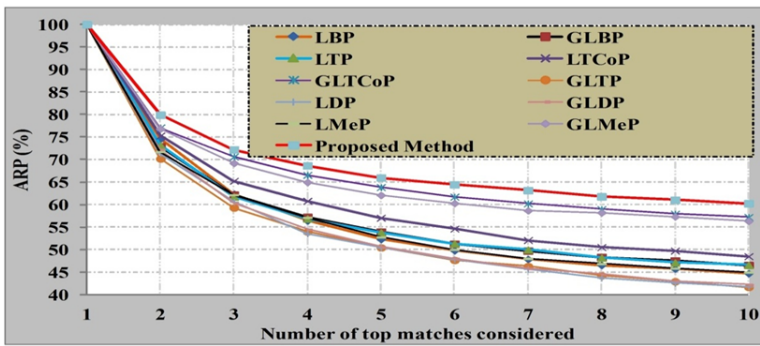
The retrieval performance of the proposed descriptor and other techniques with uniform pattern is shown in Fig.(1.5a). The retrieval performances of all the methods are shown in Fig.(1.5b). Similarly, Fig.(1.5c) illustrates the retrieval performance of the proposed method and other existing methods with rotational invariant features. The group wise retrieval performance of the proposed descriptor and other techniques with respect to ARP is tabulated in Table 1.1. From Fig.(1.5) and Table 1.1 it is evident that the proposed descriptor shows a significant improvement when compared with other state-of-the-art techniques. The retrieval performance of the proposed descriptor is calculated using four different similarity distance measures. The retrieval result for the same is shown in Fig.(1.6). The group wise retrieval performances with different similarity distance measures is shown in Fig.(1.7). From Fig.(1.6) and Fig.(1.7) it is evident that the  $d1$  distance measure shows a significant improvement when compared to other distance measures. The query results of the proposed descriptor on OASIS dataset is shown in Fig.(1.8).

### 1.4.2 Experiment: 2

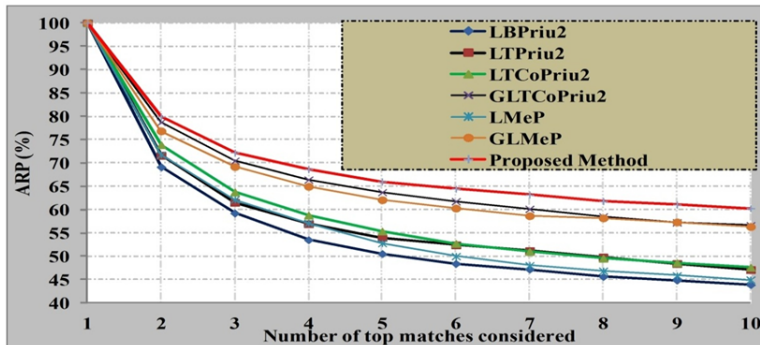
In this experiment, 681 CT scan images of different parts of human body are created by the National Electrical Manufactures Association (NEMA) [16]. The NEMA images



(a)



(b)



(c)

Figure 1.5: The retrieval performances of the proposed descriptor and other existing methods on OASIS database in terms of ARP.

Table 1.1: Group wise retrieval performance with respect to ARP on all the methods on OASIS database.

	<b>Group 1</b>	<b>Group 2</b>	<b>Group 3</b>	<b>Group 4</b>	<b>Total</b>
<b>LBPu2</b>	51.77	32.54	33.82	49.06	42.63
<b>GLBPu2</b>	54.43	37.94	26.51	46.03	42.42
<b>LTPu2</b>	53.38	38.23	36.61	53.39	45.81
<b>GLTPu2</b>	51.69	35.39	33.33	45.47	41.78
<b>LDPu2</b>	45.72	35.39	34.86	45.00	40.61
<b>GLDPu2</b>	45.88	39.80	37.19	43.49	41.37
<b>LTCu2</b>	55.88	40.29	36.56	57.35	47.57
<b>GLTCu2</b>	65.96	45.98	44.44	71.13	57.50
<b>DBWPu2</b>	52.74	37.74	34.38	60.00	47.05
<b>LBP</b>	54.91	34.80	33.96	51.79	44.72
<b>GLBP</b>	53.79	39.21	38.73	52.16	46.55
<b>LTP</b>	56.29	37.64	36.40	53.49	46.57
<b>GLTP</b>	51.53	35.09	33.38	45.09	41.60
<b>LDP</b>	46.29	36.37	36.82	45.56	41.80
<b>GLDP</b>	48.70	40.09	38.41	41.50	42.23
<b>LTCuP</b>	55.96	39.21	38.51	57.64	48.50
<b>GLTCuP</b>	65.16	45.09	44.07	71.41	57.22
<b>LBPriu2</b>	53.30	35.29	33.54	51.13	43.87
<b>LTPriu2</b>	56.85	38.82	37.30	53.39	47.12
<b>LTCuPriu2</b>	58.06	37.35	36.87	54.52	47.57
<b>GLTCuPriu2</b>	64.83	43.13	43.12	71.41	56.65
<b>LMePu2</b>	52.82	36.56	36.08	51.50	44.96
<b>GLMePu2</b>	66.12	44.90	43.38	68.30	56.34
<b>Proposed Method</b>	<b>70.32</b>	<b>45.49</b>	<b>42.35</b>	<b>77.73</b>	<b>60.26</b>

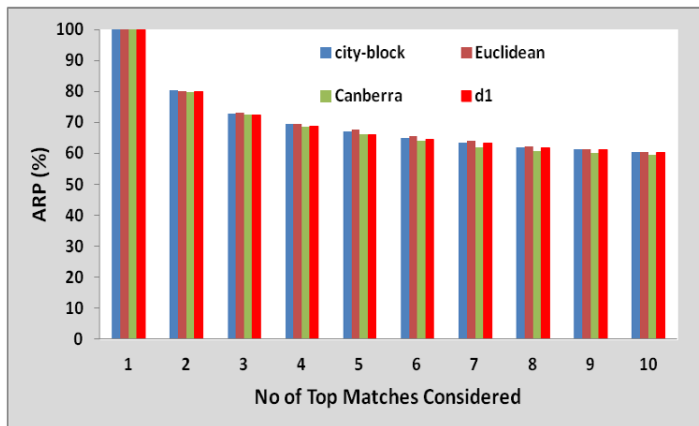


Figure 1.6: Retrieval performance of the proposed descriptor with different distance measures on OASIS database.

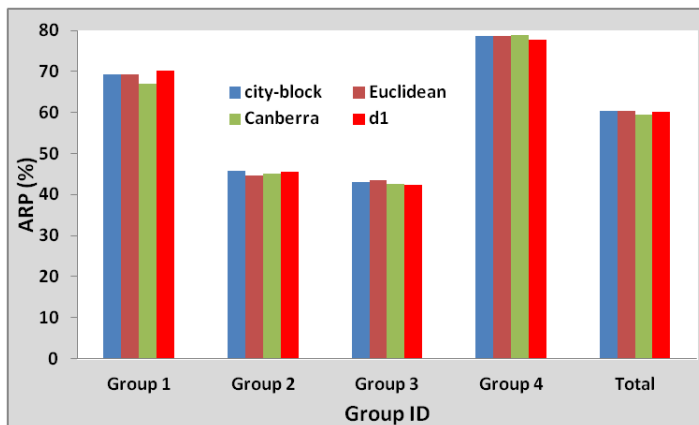


Figure 1.7: Retrieval performance of the proposed descriptor with different category ID's on OASIS database.

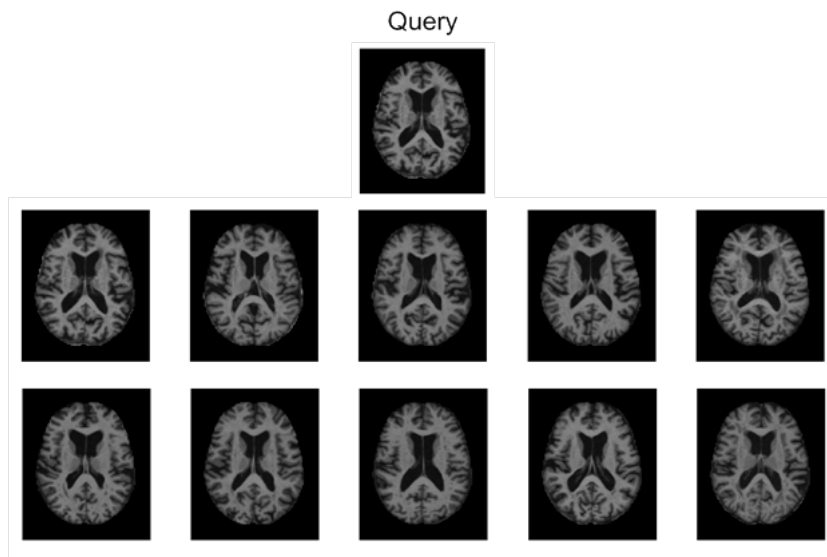


Figure 1.8: Query results of the proposed descriptor on OASIS-MRI database.

are grouped into 13 different categories (45, 59, 64, 29, 36, 18, 37, 14, 139, 46, 143, 33, and 36 images). Some sample NEMA-CT biomedical images are shown in Fig.(1.9).

The retrieval performance of the proposed descriptor is evaluated using ARP. The retrieval performance of the proposed descriptor (LMeCH) and other existing approaches are shown in Fig.(1.10). From Fig.(1.10) it is evident that the proposed descriptor shows a significant improvement in terms of their evaluatory measures. The retrieval performance of the proposed descriptor with different similarity distance measures as a function of number of top matches considered are shown in Fig.(1.11). From Fig.(1.11) it is clear that, the  $d1$  distance measure shows a significant improvement. The query results of the proposed descriptor are shown in Fig.(1.12). From all the

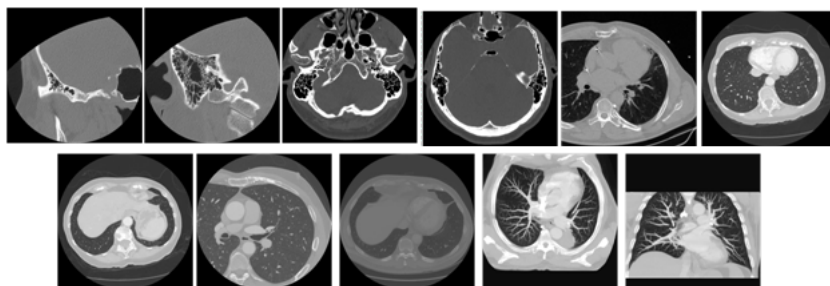
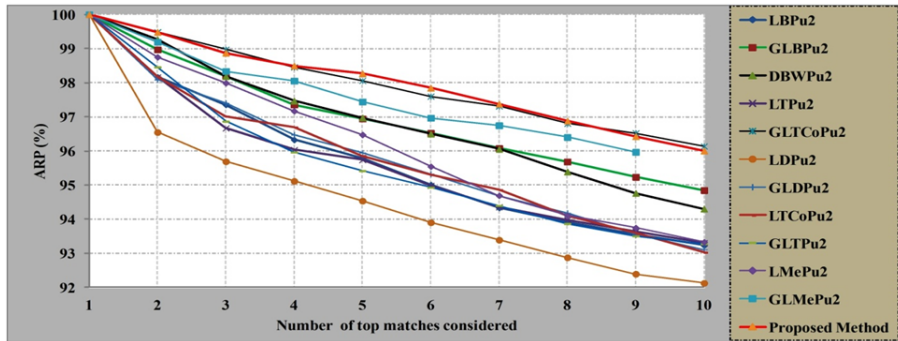
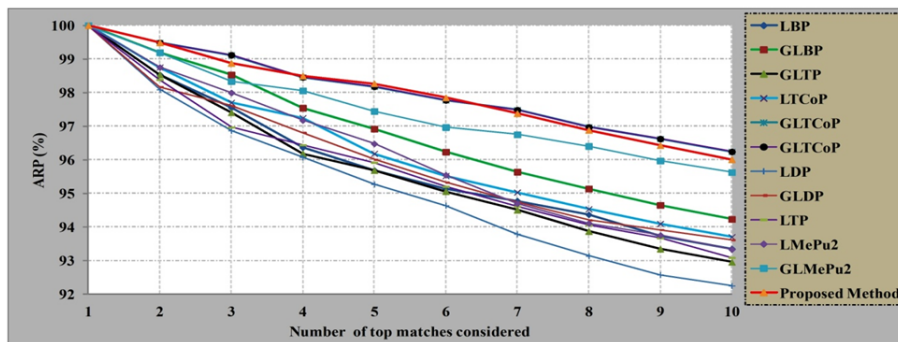


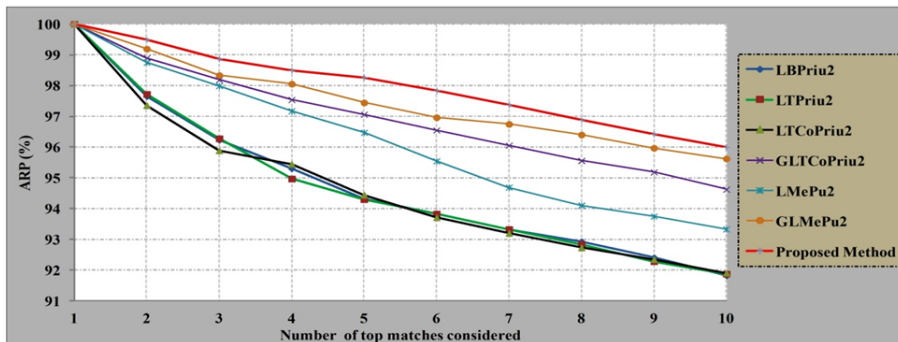
Figure 1.9: Sample images from NEMA-CT image database (One image from each category).



(a)



(b)



(c)

Figure 1.10: The retrieval performance of the proposed descriptor and other existing methods on NEMA-CT database in terms of ARP.

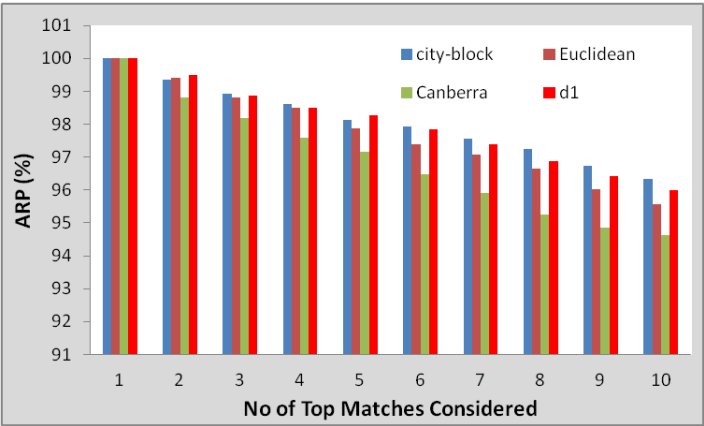


Figure 1.11: Comparison of Proposed descriptor on different distance measures on NEMA-CT database.

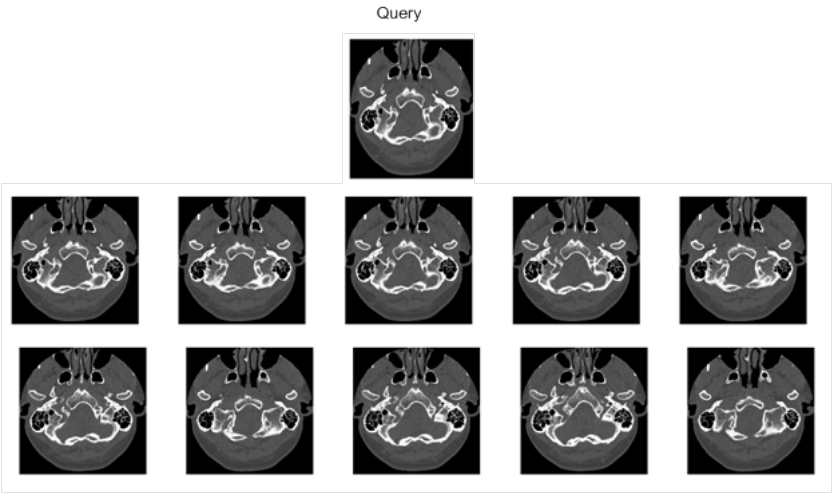


Figure 1.12: Query results of the proposed descriptor on NEMA-CT image database.

above experiments it is clear that, the proposed correlation histogram shows better retrieval performance for biomedical image retrieval application as compared to other state-of-the-art-techniques.

## 1.5 Conclusions

In recent years, the generation of biomedical images is increased tremendously from many sources. Hence, the biomedical database (image collection) needs an expert search engine to retrieve similar images from record database by querying-in the current image. The results of the query along with the associated patients' history would help doctors in the early stage of diagnosis.

In image retrieval, the feature extraction and similarity measurement are two major factors which determine the accuracy rate of the retrieval system. In this chapter, we mainly focused on designing / developing an expert feature extraction approach for bio-medical image retrieval system using local mesh correlation histogram (LMeCH).

The proposed LMeCH collects the joint correlation between the central pixel gray value and LMeP. The computational complexity of the LMeP is reduced by using the uniform patterns. The effectiveness of the proposed descriptor is tested on two biomedical image databases. The experimental results have proven that the proposed descriptor shows a significant improvement in terms of precision, recall, average retrieval precision (ARP) and average retrieval rate (ARR) as compared with the state-of-the-art techniques for image retrieval.

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