



# An efficient and robust approach for biomedical image retrieval using Zernike moments



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## ABSTRACT

Success of any image retrieval system depends heavily on the feature extraction capability of its feature descriptor. In this paper, we present a biomedical image retrieval system which uses Zernike moments (ZMs) for extracting features from CT and MRI medical images. ZMs belong to the class of orthogonal rotation invariant moments (ORIMs) and possess very useful characteristics such as superior information representation capability with minimum redundancy, insensitivity to image noise etc. Existence of these properties as well as the ability of lower order ZMs to discriminate between different image shapes and textures motivated us to explore ZMs for biomedical retrieval application. To prove the effectiveness of our system, experiments have been carried out on both noise-free and noisy versions of two different medical databases i.e. Emphysema-CT database for CT image retrieval and OASIS-MRI database for MRI image retrieval. The proposed ZMs-based approach has been compared with the existing and recently published approaches based on local binary pattern (LBP), local ternary patterns (LTP), local diagonal extrema pattern (LDEP), etc., in terms of various evaluation measures like ARR, ARP,  $F_{score}$ , and  $mAP$ . The results after being investigated have shown a significant improvement (10–14% and 15–17% in case of noise-free and noisy images, respectively) in comparison to the state-of-the-art techniques on the respective databases.

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## 1. Introduction

In this era with ever increasing number of hospitals and medical institutions, the number of biomedical images related to patient diagnosis is growing drastically. Efficient utilization of this database for search and retrieval of medical images is very important for accurate patient diagnosis and for any further R&D (research and development) in medical sciences. To meet this requirement, content-based image retrieval (CBIR) systems were introduced.

CBIR systems search and retrieve images based on the visual contents of an image such as color, texture, shape, and spatial layout, etc. Such sort of information about an image is stored in the form of image features (local or global). Global features represent the visual features of an entire image as whole, whereas the local features represent the visual features of regions or objects to

describe an image. Accuracy of any retrieval system highly depends on the type of features used and their capability to distinguish among different image classes/groups. The detailed survey about various feature extraction techniques employed in CBIR systems can be found in [1–5].

Since, medical images exists in various formats, in this paper, the retrieval of only computed tomography (CT) and magnetic resonance imaging (MRI) images is performed. Initial works for retrieval of CT and MRI images can be seen in [6]. They have used bit plane histogram and hierarchical bit plane histogram along with the cumulative distribution functions for this purpose. In [7], a system for classification of benign and malignant breast masses based on texture and shape features in sonography images is proposed. Quellec et al. [8] proposed a medical retrieval system for diabetic retinopathy and mammographic databases. They used an optimized wavelet transform by adapting the wavelet basis within the lifting scheme framework and assign weights for each wavelet sub-band. Another work based on wavelet transform for brain image retrieval can be seen in [9]. The co-occurrence matrix based retrieval of CT and MRI images is proposed in [10]. A fast and robust local-structure-based region-of-interest (ROI) retrieval system for

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brain MRI images is given in [11]. Soreson et al. [12] provided a quantitative analysis of pulmonary emphysema in CT images based on LBP (local binary pattern). They have collaboratively used the LBP, joint LBP and intensity histograms for characterizing ROIs. Later, Peng et al. [13] developed a uniformity estimation method (UEM) for local brightness and structures to discover the pathological changes in the chest CT images. They extract features by proposing an extension of rotation invariant LBP and orientation difference of gradient vector to represent the brightness and structure in the image. Quddus et al. [14] proposed a method for retrieval of 2D MRI images in multimodal and noisy observations. Results for retrieval of 2D MRI brain images are better in terms of accuracy, speed, robustness and multimodality. Among the recent works for the retrieval of CT and MRI images includes the work of Murala and Wu [15–18]. Murala and Wu in [15] proposed a new feature extraction technique called local co-occurrence ternary patterns (LTCop) which encodes the co-occurrence of similar ternary edges in an image. Given a central pixel, the value of LTCop is calculated based on the first order derivatives in eight directions. The reported results show the superiority of their proposed approach in comparison to techniques like LBP, LDP (local directional pattern), LTP (local ternary pattern) etc. Later on, authors proposed another novel feature descriptor for biomedical image retrieval called local mesh patterns (LMeP) [16]. LMeP encodes the relationship among the surrounding neighbors for a given reference pixel in an image, contrary to LBP that encodes the relationship between the given reference pixel and its surrounding neighbors. This approach was further extended by authors in [17] to derive LMePVEP i.e. local mesh peak valley edge patterns. It was shown that LMePVEP demonstrated a significant improvement in terms of ARR and ARP as compared to LBP and LBP variants. Following the same trend, Dubey et al. in [19] proposed a technique called local diagonal extrema pattern (LDEP) for CT image retrieval. LDEP uses first order local diagonal derivatives to determine the values and indexes of the local diagonal extremas. These indexes are then used to form a feature descriptor for an entire image. To demonstrate the effectiveness and superiority of their approach, authors compared their results with those obtained by other state-of-the-art methods such as LMeP, LTCop, LTP, CSLBP, and LBP etc. and shown improved retrieval accuracy at reduced computational time. The biggest advantage offered by LDEP over other existing methods is its reduced dimensionality of feature vector, thus, offering higher performance using very less number of features.

However, like LBP and its multiple variants, LDEP is also a local feature extractor. While working on medical images of different body parts, the gross view of an image is very crucial for accurate identification, which the local features fail to capture. Therefore, due to the high dimensionality of feature vectors and lack of representation capability of local features extracted by LBP [20] and its different variants, we shifted our focus towards finding a global feature descriptor that can efficiently describe and represent image features (both shape and texture) for biomedical image retrieval purpose.

Among the numerous global feature descriptors existing in the literature, Zernike moments (ZMs) [21] are found to be very suitable for biomedical image retrieval application because of its useful characteristics such as excellent image representation capability, rotation (and scale) invariance, noise robustness, small feature size etc. All these properties of ZMs made it highly successful in various image processing and pattern recognition applications [22–43] including biomedical image enhancement/segmentation [43].

In this paper, we propose the use of ZMs for the retrieval of CT and MRI images and compare its performance with standard benchmark approaches like LBP, ULBP and the recently published state-of-the-art LDEP method on two standard test databases namely Emphysema-CT and OASIS-MRI database. Due to the superior

performance of LDEP approach over the other existing methods like LTP, LTCop, LMeP etc. as shown in [19], we therefore, compared our proposed ZMs-based approach with LDEP only. Additional experiments have been performed to test the effectiveness of the proposed ZMs-based approach under noisy conditions and to demonstrate its superiority (in terms of retrieval performance) over the existing and recently published approaches of biomedical image retrieval.

The rest of the paper is organized as follows. Section 2 describes various existing feature extraction methods for CT and MRI image retrieval. Section 3 describes the proposed ZMs-based system for retrieval of CT and MRI images. Section 4, presents the experimental set up and results obtained after using the proposed and the existing feature descriptors on two standard medical databases. Also, a comparative performance analysis of the proposed approach with recently published state-of-the-art approaches for biomedical image retrieval is presented. Section 5, presents the computational complexity of the proposed approach and all other compared feature descriptors for biomedical image retrieval application. Finally, conclusion is presented in Section 6.

## 2. Feature extraction methods

Feature extraction plays a very crucial role in the efficient working of any retrieval system both in terms of the retrieval accuracy as well as the computation time taken to achieve that accuracy. The goal of feature extraction part is to extract such features that can strongly represent an image using only little number of them. The local descriptors such as LBP, ULBP and LDEP are some of the well-known feature extraction techniques that have been used for retrieval of CT and MRI images. Thus, in the following section, we briefly discussed about the aforementioned techniques for biomedical image retrieval.

### 2.1. Local binary pattern (LBP)

The LBP operator proposed by Ojala et al. [20] is a benchmark approach for identification and classification of textural information in an image. LBP is a local feature descriptor as it compares the gray value of the central pixel with its surrounding neighbors. LBP value is the decimal equivalent of the binary code obtained by computing the difference in gray values of the central pixel with its neighboring pixels as described in Eqs. (1)–(2)

$$LBP_{N,R} = \sum_{n=0}^{N-1} T(P_n - P_c) 2^n \quad (1)$$

$$T(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where,  $P_c$  is the gray value of the central pixel,  $P_n$  is the gray value of the neighborhood pixel at radius  $R$  from its central pixel  $P_c$  and  $N$  is the number of neighborhood pixels surrounding the central pixel  $P_c$ .  $LBP_{8,1}$  is the most common form of LBP used in various image processing applications as well as for retrieval of CT and MRI images. In  $LBP_{8,1}$  8 neighbors are considered inside a  $3 \times 3$  window around the central pixel for computation of LBP value.

The key advantage of LBP is its simpler formulation and easy implementation but the high dimensionality of its feature vector restricts its use for many real time applications. For example,  $LBP_{8,1}$  provides a total of 256 features (corresponding to 256 binary codes obtained from 8 surrounding neighbors) from a single image. Hence, an extension of LBP known as uniform local binary pattern (ULBP) was proposed having all the properties of LBP but with reduced feature size. A local binary pattern is called uniform pattern when there exists at most two bitwise transitions i.e. from

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