# MEDICAL IMAGE RETRIEVAL USING MOMENTS

**B.Jyothi[1], Y.Madhavee Latha[2], P.G.Krishna Mohan[3], V.S.K.Reddy[4]**

[1]Assoc.Prof, Department of Electronics and Communication, MallaReddy College of Engineering and Technology,A.P, India.

[2]Principal , Department of Electronics and Communication , MallaReddy Engineering College for Women. A.P, India.

[3]Professor, Department of Electronics and Communication JNTUH, HYD, A.P, India.

[4]Principal , Department of Electronics and Communication , MallaReddy College of Engineering and Technology, A.P, India.

## ABSTRACT

***Moments of images provide efficient local descriptors and have been used extensively in image analysis applications. Moments are able to provide invariant measures of shape. On this basis we propose an a new efficient retrieval system using region-based image retrieval system, finding region in the pictures using a new image segmentation method by improved mountain clustering (IMC) technique and features are extracted using a set of orthogonal set of moment functions for describing images The performance of the proposed moments is analyzed in terms of Recall Rate and Retrieval Accuracy. Experimental results demonstrate the superiority of clustering integration with pseudo pseudo-Zernike moments compared with individual features***.

**Index Terms -** Medical Image Retrieval, Improved Mountain Clustering, Pseudo-Zernike Moments.

## 1. INTRODUCTION

Medical images are important diagnostic evidence they can provide imperative information about anatomical pathology. The growth of Medical images in database is enormous in the past few years when the medical digital image equipments such as CT, MRI, and PET-CT are used in the clinic works [1]. The goals of medical information systems have often been defined to deliver the needed information to the right persons at the right time, the right place in order to improve the quality and efficiency of care process. Content Based Image Retrieval (CBIR) systems allow users to query based on the image content (color, texture, shape, etc.), which are analyzed and extracted automatically by computer to achieve the effective retrieval [2].Our goal is to develop an effective mechanism to overcome several limitations related to existing systems. On this basis we propose region-based image retrieval tool, finding region in the pictures using a new image-segmentation method by improved mountain clustering (IMC) technique and features are extracted using Pseudo-Zernike Moments. Experiment is done on the different medical images, satisfactory result is achieved.

In Content Based Image Retrieval (CBIR) systems feature can be extracted using image content (color, texture, shape, etc.). Now medical Images are mainly gray images for diagnostic gray scale images texture & shape feature are extracted. Image segmentation is well-known for its applications in exploratory pattern analysis [3] grouping, decision making and machine-learning situations for medical images. Under these limitations clustering methodology is appropriate for the exploration of interrelation among the data points to make an assessment of their structure. Clustering is basically collection or grouping of similar objects. Each cluster should be homogenous and objects belonging to the same group are similar to each other and each cluster should be different from other clusters. Clustering technique [4] can be hard or fuzzy. In a hard clustering algorithm, each object is allocated to a single cluster during its operation whereas, in a fuzzy clustering method a degree of membership is assigned to each object depending on its association with several other clusters.

Shape has been one of the most important and effective low level visual features in characterizing many pathologies identified by medical experts[6].Shape feature extraction has been one of the important research fields in the content-based medical image retrieval . Shape feature extraction [7] methods can usually divided into contour-based and region-based Contour-based shape feature extraction methods extract shape information from boundary of entity which contains boundary information [8]. However, region-based shape features extraction methods which extract the interior shape information [9] from all the pixels within entity in a medical image [10]. Commonly used contour-based shape feature extraction methods include Fourier , Wavelet , Curvature Scale Space Descriptors, Shape Signatures, Moments and function of Moments etc. Fourier Descriptor method [11] is one of the most elementary and widest used methods among these contour-based shape feature extraction methods.

The theory of moments including Hue-Moments [14] Legendre Moments, Wavelet Moments Zernike Moments and Krawachok Moments provides useful series expansion for the representation of object shapes. In the past decades, various moment functions due to their abilities to represent the image features have been proposed for describing images.Hu2 first derived a set of moment invariants, which are position, size and orientation independent. These moment invariants have been successfully used in the field of pattern recognition. However geometric moments are not orthogonal and as a consequence, reconstructing the image. Based on the theory of orthogonal polynomials, Teague6 has shown that the image can be easily reconstructed from a set of orthogonal moments, such as Legendre moments and Zernike moments. Teh and Chin7 evaluated various types of image moments in terms of noise sensitivity, information redundancy and image description capability; they found that Pseudo-Zernike moments (PZMs) have the best overall performance.
We are concentrating on the development of novel and efficient approaches for extracting information about shape region. In this paper, one could segment an image using an IMC method following set of extracted features using Pseudo-Zernike moments.
The organization of the paper is as follows. In Section 2, the Proposed Retrieval System is discussed. Feature Extraction and Similarity Measure are discussed in Section 3.Section 4 presents the Experimental results, finally conclusion are discussed in Section 5.

## 2. RETRIEVAL SYSTEM

CBIR has been proposed by the medical community for inclusion into picture archiving and communications systems (PACS) to provide an efficient search function to access the desired images. In medical research, researchers can use CBIR to find images with similar pathological areas and investigate their association. The perspective of present research is enable to retrieve similar images from an Image database for a given query image. The architecture of the proposed one is illustrated in fig (2.1).

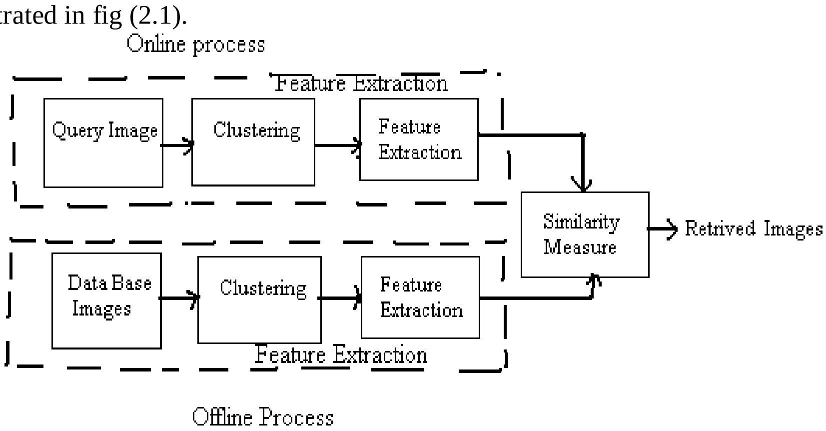


**Figure 2.1**: Proposed Retrieval System Architecture

In this paper, experimental data set contains 1000 images from Corel database of images, divided into 10categories, each category has 100 images. Experimental images covers a wealthy of content, including MRI.X-Ray, CT scan and so on. Selection of each type in the 80 images as training samples, 20 samples for testing.
Feature extraction is the most important task in the retrieval process in order to retrieve the relevant images from data. Accordingly in the proposed algorithm we designed shape feature vector by clustering and shape features are extracted for highest potential cluster using Pseudo Zernike Moments which is described as fallows.
Similarity measure is a function which computes the degree of similarity between a pair of text objects Our proposed system extract the primitive feature of a query image first and then compares the extracted features .The texture and shape feature vectors are extracted and the retrieval system combines these feature vectors, calculates the similarity between the combined feature vector of the query image and that of each target image in an image data base.

## 3. FEATURE EXTRACTION

### 3.1 Improved Mountain Clustering Technique

The mountain method, proposed by Yager and Filev [12], is a simple and effective algorithm as an approximate clustering.Chiu modified it by considering the mountain function on the data points instead of the grid nodes. Pal and Chakra borty [13].We proposed a scheme to improve the accuracy of the prototypes obtained by Yager's mountain method and Chiu's modified type. Moreover, Yager and Filev [14] applied the mountain method to the generation of fuzzy rules and Velthuizen et al. applied it for clustering large data sets such as the segmentation [15] of magnetic resonance images. In IMC, Mountain Clustering algorithm for estimating the number and location of cluster centers.

This algorithm is a grid based three-step procedure. In the first step, the hyperspace is discredited with a certain resolution in each dimension to obtain the grid points. The second step uses the dataset to construct the mountain function around all grid points. The third step generates the cluster centers by an iterative destruction of the mountain function. Though this method is simple, the computation grows exponentially with the dimension of hyperspace. In the n - dimensional hyperspace with m number of grid lines in each dimension, the number of grid points that must be evaluated .To overcome the computational complexity of this clustering technique, Azeem et al. presented the Modified Mountain Clustering technique which determines the cluster centers by an iterative destruction of the mountain function. Destruction of the mountain function implies reduction of potential values of the data points, which are nearer to the cluster center than a threshold. This iterative reduction in potential of all the data points with respect to the cluster center leads to loss of certain potential clusters. Because of iterative reduction, potential of some of the data points which can become a potential cluster center reduces to a degree to an extent that they lose the potential to become cluster center and hence we miss the corresponding cluster. The useful feature of the Improved Mountain Clustering is that its computational complexity is independent of the dimension and there is no need to specify a grid resolution.

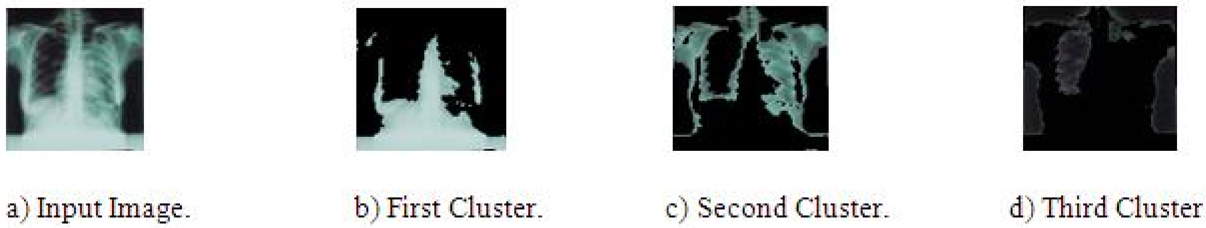


**Figure 3.1:** Improved Mountain clustering version-2 results

**3.2 Pseudo-Zernike Moments**

Shape is known to play an important role in human recognition and perception. Object shape features provide a powerful clue to object identity. Humans can recognize objects solely from their shapes. The significance of shape as a feature for content-based image retrieval can be seen from the fact that every major content-based image retrieval (CBIR) system incorporates some shape features in one form or another.

Image shape descriptors, as used in existing CBIR systems, can be broadly categorized into two groups namely, contour- and region-based descriptors. Contour-based shape descriptors use the boundary information of object shapes. Early work implemented object shapes via Fourier descriptors. Exploiting only information from the shape boundaries, contour-based shape descriptors thereby ignore potentially important information in the shape interior. In region-based methods, shape descriptors utilize information from both boundaries and interior regions of the shape. As the most commonly used approaches for region-based shape descriptors, moments and function of moments have been utilized as pattern features in a number of applications and. The theory of moments, including Hu moments, Legendre moments, wavelet moments, Zernike moments, and Krawtchouk moments, provides useful series expansions for the representation of object shapes.

Pseudo-Zernike moments consist of a set of orthogonal and complex number moments which have some very important properties. First, the pseudo-Zernike moments' magnitudes are invariant under image rotation. Second, pseudo-Zernike moments have multilevel representation capabilities. Third, pseudo-Zernike moments are less sensitive to image noise. In this paper, the pseudo-Zernike moments of an image are used for shape descriptor, which have better features representation capabilities and are more robust to noise than other moment representations.

Pseudo-Zernike moments consist of a set of complex polynomials that form a complete orthogonal set over the interior of the unit circle, $x^2 + y^2 \leq 1$. If the set of these polynomials is denoted by $\{V_{nm}(x, y)\}$, then the form of these polynomials is as follows

$$V_{nm}(x,y)=V_{nm}(\rho,\theta)=R_{nm}(\rho)\exp(jm\theta) \qquad \text{Eq.1}$$

Where $\rho = \sqrt{x^2 + y^2}$, $\theta = \tan^{-1}\left(\frac{y}{x}\right)$

Here n is a non-negative integer, m is restricted to be $|m| \leq n$ and the radial pseudo-Zernike polynomial $R_{nm}(\rho)$ is defined as the following

$$R_{nm}(\rho) = \sum_{s=0}^{n-|m|} \frac{(-1)^s (2n+1-s)!\,\rho^{n-s}}{s!(n+|m|+1-s)!(n-|m|-s)!} \qquad \text{Eq.2}$$

Like any other orthogonal and complete basis, the pseudo-Zernike polynomial can be used to decompose an analog image function f(x, y):

$$f(x,y)=\sum_{n=0}^{\alpha}\sum_{\{m:|m|\le n\}}A_{nm}Vnm(x,y) \quad \text{Eq.3}$$

Where $A_{nm}$ is the pseudo-Zernike moments of order n with repetition m, whose definition is

$$A_{nm}=\frac{n+1}{\pi}\iint_{x^2+y^2\le 1} f(x,y)V_{nm}^{*}(x,y)dxdy \quad \text{Eq.4}$$

It should be pointed out that in case of digital images, Eq. cannot be applied directly, but rather, its approximate version has to be employed. For instance, given a digital image of size M × N, its pseudo-Zernike moments are computed as

$$\hat{A}_{nm}=\frac{n+1}{\pi}\sum_{i=1}^{M}\sum_{j=1}^{N}h_{nm}(x_i,y_j)f(x_i,y_j) \quad \text{Eq.5}$$

Where the value of i and j are taken such that $x_i^2 + y_j^2 \le 1$, and

$$h_{nm}(x_i,y_j)=\int_{x_i-\frac{\Delta x}{2}}^{x_i+\frac{\Delta x}{2}}\int_{y_i-\frac{\Delta y}{2}}^{y_i+\frac{\Delta y}{2}}V_{nm}(n,m)dxdy \quad \text{Eq.6}$$

Where $\Delta x=\frac{2}{M}\ \Delta y=\frac{2}{N}$

$h_{nm}(x_i, y_j)$ can be computed to address the nontrivial issue of accuracy. In this research, we adopt the following formulas which are most commonly used in literature to compute pseudo-Zernike moments of discrete images

$$\hat{A}_{nm}=\frac{n+1}{\pi}\sum_{i=1}^{M}\sum_{j=1}^{N}V_{nm}^{*}(x_i,y_j)f(x_i,y_j)\Delta x\Delta y \quad \text{Eq.7}$$

**Shape feature representation**

Pseudo-Zernike moments are not scale or translation invariant. In our work, the scaling and translation invariance are firstly obtained by normalizing the image, and then $|\hat{A}_{nm}|$ is selected as shape feature set for image retrieval.
The pseudo-Zernike moments based shape feature vector is given by

$$F_S=\left(\left|\hat{A}_{00}\right|,\left|\hat{A}_{10}\right|,\left|\hat{A}_{11}\right|,\left|\hat{A}_{20}\right|,\ldots\ldots,\left|\hat{A}_{54}\right|\left|\hat{A}_{55}\right|\right) \quad \text{Eq.8}$$

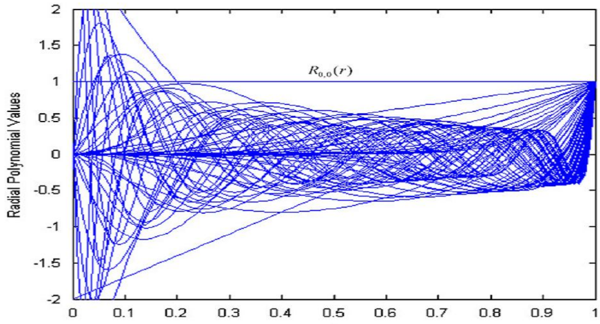


**Figure 3.2**. Graph of radial polynomials $R_{nm}(r)$ with orders $n$ =0 up to 10

## 4. SIMILARITY MEASURE

The similar images from the data base can be retrieved by using similarity measure[19]. Similarity measure is a function which computes the degree of similarity between a pair of text objects Our proposed system extract the primitive feature of a query image first and then compares the extracted features .The texture and shape feature vectors are extracted and the retrieval system[20] combines these feature vectors, calculates the similarity between the combined feature vector of the query image and that of each target image in an image data base, and retrieves a given number of the most similar target images. The shape feature similarity as follows.

$$S_{Shape}(Q,I)=\left(\sum_{i=0}^{5}\sum_{j}^{i}\left(\left|\hat{A}_{ij}^{Q}\right|-\left|\hat{A}_{ij}^{I}\right|\right)^2\right)^{\frac{1}{2}} \quad (9)$$

Where $|\hat{A}_{ij}^{Q}|$ and $|\hat{A}_{ij}^{I}|$ denote the shape feature of the query image Q and the target image I respectively. We calculate the similarity between the query image and each target image in the data base and then sort the retrieval results according to the similarity value.

## 5. EXPERIMENT AND ANALYSIS

In this paper, experimental data base covers ,brain tumor, tooth decay, lung cancer, tuberculosis etc. during the experiment the input images are Clustered through the Improved mountain clustering and features are extracted using pseudo-Zernike moments for maximum energy cluster in off line. We repeat the same procedure in online for query image. The retrieved highly efficient matching images sorted by based on above mention features. We used Retrieval Accuracy (RA) and Recall Rate (RR) as a performance measure I which the performance is improved by integrating clustering and shape representation using pseudo Zernike moments.

$$\text{Retrieval Accuracy} = \frac{\text{No. of relevant retrieved images}}{\text{Total no. of images in the database}} \times 100$$

$$\text{Precision} = \frac{\text{No. of relevant retrievad images}}{\text{Total no. of retrieved images}} \times 100$$

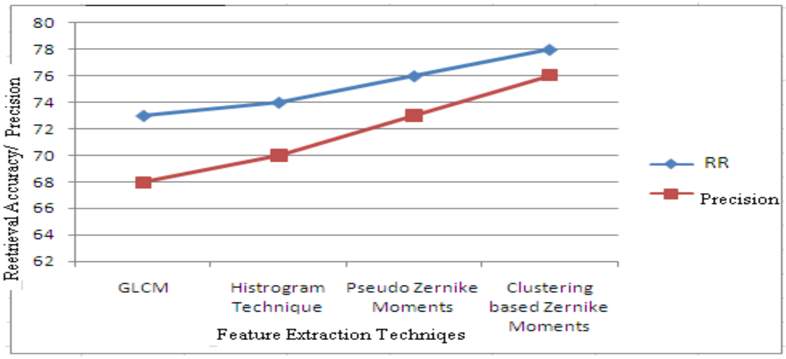


**Figure 4:** Retrieval Result

## 6. CONCLUSION

This paper presents a new and effective approach based on moments shape characteristics an integration with clustering technique. Through the image retrieval experiment, indicating that the use of clustering an integration with moments for feature representation, yields higher retrieval accuracy than the other conventional methods.

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