# Zernike Moments with Contourlet Transform for Content based Image Retrieval

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**Abstract:** Content Based Image Retrieval systems based on shape using invariant image moments, viz., Moment Invariants and Zernike Moments are available in the literature. Moment Invariants and Zernike Moments are good at representing the shape features of an image. Therefore, an efficient and orthogonal moment based Content Based Image Retrieval system (CBIR) is needed. Legendre Moments is orthogonal, computationally faster, and can represent image shape features compactly. CBIR system using Exact Legendre Moments and Contourlet Transform is proposed in this work. The results of proposed CBIR model are robust, efficient and effectively reduce the retrieval time and also improve the retrieval accuracy significantly. When compared to the other moment based CBIR systems, it is found that, the performance measures such as precision and recall values are improved.

**Keywords**: CBIR, Contourlet Transform, Zernike Moments.

## Introduction

In recent years, Content-based image retrieval (CBIR) plays an important role because the digital image collection has been rapidly increasing the size of the image. Every day, the gigabytes of pictures generate in military and civilian equipment. By using CBIR effective browsing, indexing and retrieval can be obtained. Visual content (e.g. color, texture, shape) extraction is the basis of CBIR. There are three fundamental bases for Content Based Image Retrieval which are multidimensional indexing, retrieval system design and visual feature extraction. The color feature can be achieved by the techniques like averaging and histograms. The texture feature can be grasped by using transforms or vector quantization. The shape feature can be reached by using gradient operators or morphological operators. The color histogram for color feature and wavelet demonstration for texture and location info of an image. This decreases the handling time for retrieval of an image with more talented legislatures. The abstraction of color features from digital images depends on an understanding of the theory of color and the representation of color in digital images.

Building real-world systems involve regular user feedback during the development process, as required in any other software development life cycle. Not many image retrieval systems are deployed for public usage, save for Google Images or Yahoo! Images (which are based primarily on surrounding meta-data rather than content). There are, however, a number of propositions for real-world implementation. For brevity of space we are unable to discuss them in details, but it is interesting to note that CBIR has been applied to fields as diverse as Botany, Astronomy, Mineralogy, and Remote sensing. Since the early 1990s, content-based image retrieval has become a very active research area. Both commercial and research image retrieval systems. In the past decade, many image retrieval systems have been effectively developed [1]. Some of them are, IBM QBIC [2], VIRAGO System [3], Visual Seek System [4], WBIIS System [5] and Blob-world System [6] are some the prominent CBIR systems. Shape is one of the primary visual features in CBIR. Numerous shape descriptors have been proposed in the literature [7], [8]. These descriptors fall into two categories: contour-based and region-based descriptors. Contour-based shape descriptors use only the boundary information, ignoring the shape interior content while the region-based shape descriptors exploit interior pixels of the shape. Therefore, region-based shape descriptors can be applied to more general shapes. For CBIR a shape descriptor should be robust, compact, and easy to derive and match.

## Related Work

Content Based Image Retrieval (CBIR) systems based on shape using invariant image moments, viz., Moment Invariants (MI) and Zernike Moments (ZM) are available in the literature. MI and ZM are good at representing the shape features of an image. Therefore, an efficient and orthogonal moment based CBIR system is needed. Legendre Moments (LM) are orthogonal, computationally faster, and can represent image shape features compactly. In terms of these properties, we

propose the shape feature by using Exact Legendre Moments (ELM) with Contourlet transform. Orthogonal moments allow for accurate reconstruction of the image, and makes optimal utilization of shape information. Zernike Moments (ZM) are widely used in CBIR as shape descriptors [9, 10].
Zernike Moments have many desirable properties, viz., rotation invariance and robustness to noise. Legendre Moments (LM) are continuous and orthogonal moments, they can be used to represent an image with minimum amount of information redundancy. Many algorithms are developed for the computation of Legendre Moments [11], [12], but these methods focus mainly on 2D geometric moments. The following diagram illustrates the Extraction of Zernike Moment features.

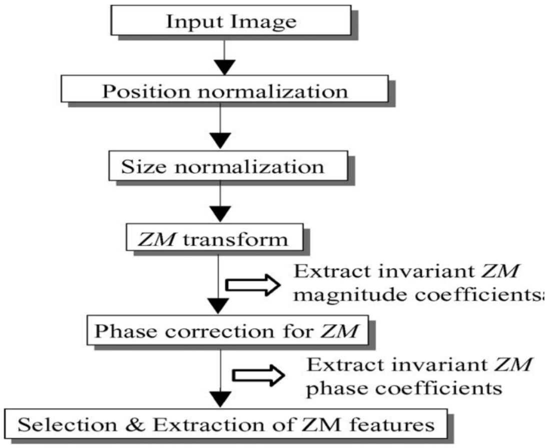



Fig. 1. Extraction of robust Zernike Moment features [13]

Zernike Moments (ZM) have many desirable properties, viz., rotation invariance and robustness to noise. Legendre Moments (LM) are continuous and orthogonal moments, they can be used to represent an image with minimum amount of information redundancy. Many algorithms are developed for the computation of Legendre Moments, but these methods focus mainly on 2D geometric moments. When they are applied to a digital image, a numerical approximation is necessary. Error due to approximation increases as the order of the moment increases. An accurate method for computing the Exact Legendre Moments (ELM) proposed by Hosney [14] is as follows.
Legendre moments of order $g = (p + q)$ for an image with intensity function $f(x, y)$ are defined as

$$L_{pq} = \frac{(2p+1)(2q+1)}{4}\int_{-1}^{1}\int_{-1}^{1} P_p(x)P_p(y)f(x,y)\,dxdy \tag{1}$$

$$P_p(X) = \sum_{k=0}^{p} a_{k,p}x^k = \frac{1}{2^p\, p!}\left(\frac{d}{dx}\right)^p\left[(x^2-1)\right]^p \tag{2}$$

$P(x)\,p$ obeys the following recursive relation

$$P_{p+1}(x) = \frac{(2p+1)}{(p+1)}xP_p(x) - \frac{p}{p+1}P_{p-1}(x) \tag{3}$$

The set of Legendre polynomials $\{P(x)\}p$ forms a complete orthogonal basis set on the interval [-1, 1]. A digital image of size $N$ ´ $N$ is an array of pixels. Centers of these pixels are the points $(xi, y_j)$. Recently Anjali Goyal, Anbarasa Pandian and Sudarvizhi [15], [16], [17] have discussed the feature based image retrieval system using Zernike Moments and also fusion of contoulet transform with Zernike Moments.

## Contourlet Transform

Contourlet Transform [18] is an extension of the wavelet transform which uses multi scale and directional filter banks [19]. The disadvantage of two-dimensional wavelets is their limited ability to capture directional information. To avoid this deficiency, a new method has been proposed which takes multiscale and directional representations that can capture the intrinsic geometrical structures such as smooth contours in natural images. Although the wavelet transform is powerful in representing images containing smooth areas separated with edges. It cannot perform well when the edges are smooth curves. New developments in directional transforms, known as Contourlets.

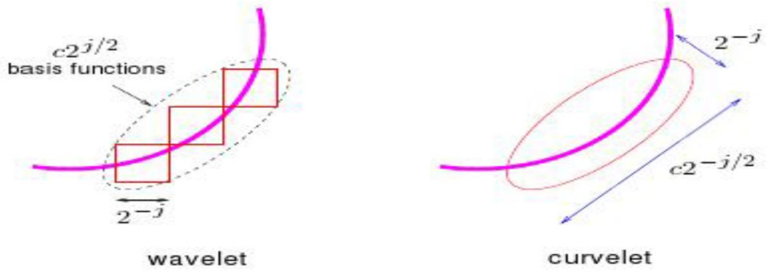



Fig. 2. Comparison of wavelet and curvelet [19]

The contourlet transform is composed of basis functions with different directions in multiple scales with flexible aspect ratios. This frame work forms a basis with small redundancy unlike other transforms. The basis element of the transforms oriented at various directions much more than few directions that are offered by other separable transform technique. The contourlet transform is a discrete extension of the curvelet transform that aims to capture curves instead of points, and provides for directionality. Contourlets not only possess the main features of wavelets (namely, multiscale and time-frequency localization), but also offer a high degree of directionality and anisotropy. The fundamental difference of contourlets with other multiscale directional systems is that the contourlet transform takes different and flexible number of directions at each scale, while achieving nearly critical sampling.

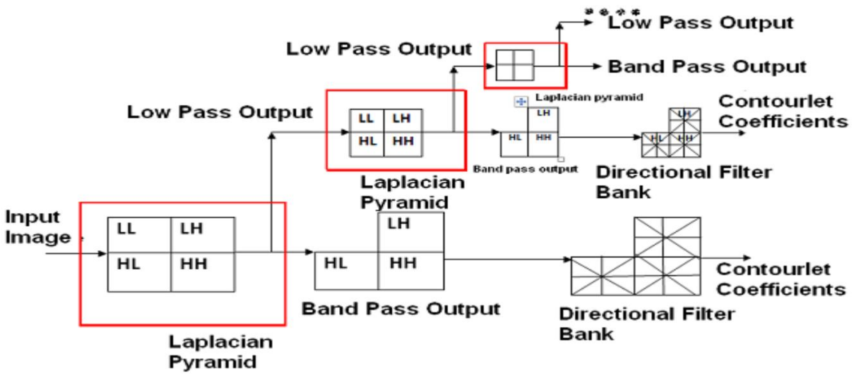



Fig. 3. Detailed sub-bands of all the decomposition levels of contourlet transform

First stage is low pass decomposition and second stage is DFB decomposition. The LP decomposition at each step generates a sampled low pass version of the original and the difference between the original and the prediction, resulting in a band pass image. Pyramidal Directional Filter Bank (PDFB), which decomposes images into directional sub-bands at multiple scales. The CT decomposes the original image into four sub-bands. The approximation sub-band preserves the information of the original image, and the detail sub-bands capture the intensity variations in all the directions.
After CT is applied on the image, contourlet coefficients from the detail sub-bands of all the decomposition levels are used to formulate the energy coefficients. The Standard Deviation ($\sigma_k$) and/or energy ($E_k$) of the CT decomposed image on each directional sub-band can be calculated by using,

$$\sigma_k = \sqrt{\frac{1}{NXN}\sum_{i=1}^{N=1}\sum_{j=1}^{N}\left(W_k\left(i,j\right)-\mu_k\right)^2} \quad (4)$$

$$E_k = \frac{1}{NXN}\sum_{i=1}^{N}\sum_{j=1}^{N}\left|W_k\left(i,j\right)\right|^2 \quad (5)$$

where, $W_k$ is the coefficients of $K^{th}$ contourlet decomposed sub-band, $\mu_k$ is the mean value of $K^{th}$ sub-band and $NXN$ is the contourlet decomposed sub-band.

## Proposed CBIR System

In this work, we are combining contourlet transform and Zernike Moments to find out the relative importance of the phase and magnitude of ZM in representing an image by contourlet transform. The scale and translation invariance of ZM can be obtained by normalizing the image using the geometrical moments. CBIR using contourlet and Zernike Moments technique is illustrated in the following block diagram. As the ZM moments are complex vectors, searching for similar images during query processing combines both magnitude and angle as a similarity measure; this similarity measure takes advantage of the strengths of both features for shape representation.

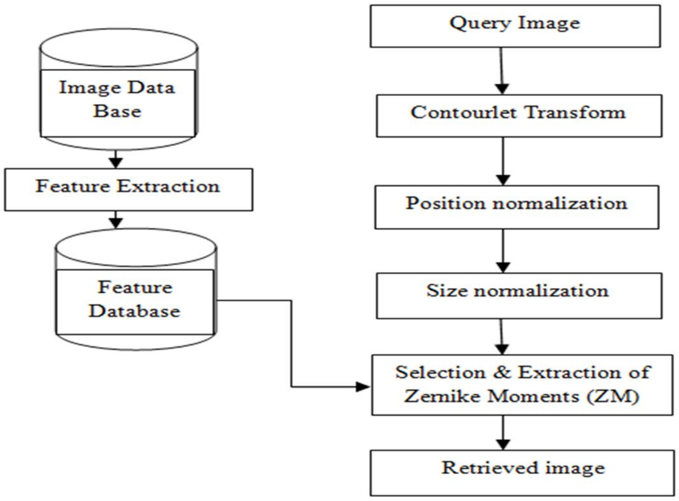



Fig. 4. Block diagram of the CBIR using Contourlet Transform and Zernike Legendre Moments

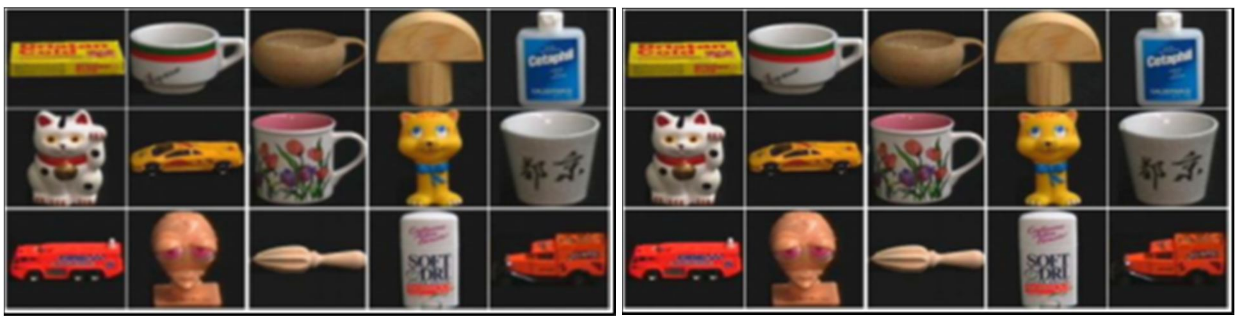
The basic procedure involved in the proposed CBIR system is that, the computation of ELM for the given image to form the feature vector and calculation of distance measure between the feature vectors of query and data base images. The retrieval of similar images based on minimum distance.

## Results and Discussion

For the performance analyses of the features selection methods two face images databases are used. They are COIL image database [20] and Georgia Tech (GT) face database [21]. The performance of the proposed system was checked by the following performance measures such as precision and recall. They are defined in terms of a set of retrieved images, such as the list of face images retrieved, and a set of the relevant images in the database (the list of all images on the database that belong to the same person). The standard definitions of these two measures are given by following equations.

$$Precision = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}}$$

$$Recall = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images retrieved in database}}$$



(a) (b)

Fig. 5: (a) Sample images from COIL image database, (b) Sample images from GT face image database

Retrieval performance of the proposed CBIR system is tested by conducting experiments on Corel shape database, COIL-20. It consists of 20 classes of images with each class consisting of 72 different orientations resulting in a total of 1440 images. All these gray scale images in the database are of the size 128×128. All images of all the 20 classes are used for experimentation. Moments up to order 4, 5, 6, 7, 8, and 9 are considered. It results in feature vectors of dimension 9, 12, 16, 20, 25, and 30 respectively for ZM.. The dimension of the feature vector is *seven* only for MI irrespective of the moment order. It is observed that the computation time is increasing with the size of the feature vector. Comparison of the retrieval performance of the proposed CBIR system with other moment based CBIR systems is presented in Table.

Table. 1. Retrieval performance of the proposed CBIR system with other moment based CBIR systems

| Method | Moment order | | | | | | |
|---|---|---|---|---|---|---|---|
| | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Moment Invariants | 45.32 | 45.32 | 45.32 | 45.32 | 45.32 | 45.32 | 45.32 |
| Zernike Moments | 49.41 | 52.15 | 52.56 | 53.41 | 53.65 | 54.35 | 54.67 |
| Proposed (ELM) | 58.76 | 59.01 | 61.21 | 62.45 | 63.89 | 64.56 | 65.89 |

In this method, the difference between an image and the reconstructed version based on a small set of its moments can be used to measure if the chosen set of moments contains sufficient information to serve as a good feature. Figure 6 illustrates the comparative average retrieval efficiency of the proposed CBIR system for various moments and moment orders.

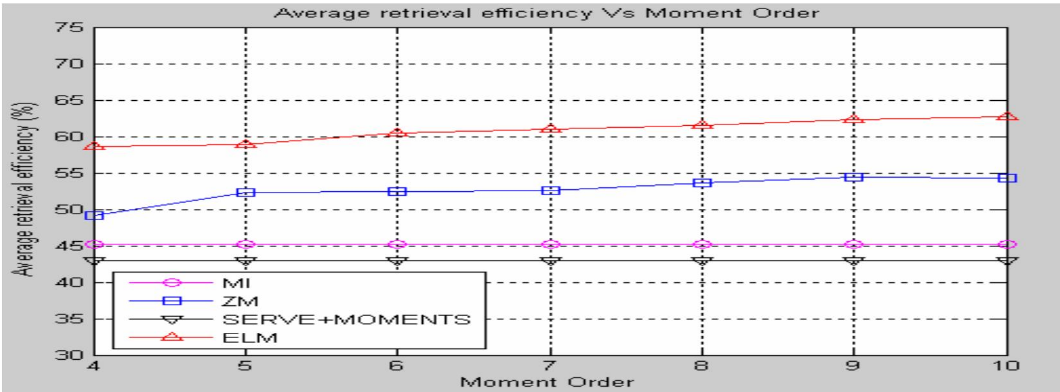



Fig.6. Average retrieval efficiency of the proposed CBIR system for various moments and moment orders.

## Conclusion

The increasing amount of digital images currently available, such as those on the internet or other media has prompted increased interests and a rapid development in content-based image retrieval. Finding the appropriate image features is critical for effective content-based image retrieval, which should also be robust to various changes in the images, such as those due to rotation, translation, scaling, or change in viewpoint. After carefully studying the literature on CBIR, we have proposed the CBIR model which extracts the features by contourlet transform and Zernike Moments. Based on the experimental results, we have concluded that contourlet and Zernike Moments can be used as robust features to extract shape for image retrieval. The comparison of the retrieval performance of the proposed CBIR system with other moment based CBIR systems were also carried out to prove its superiority.

## References

[1] Y. Rui, T. Huang, and S. Chang, Image retrieval: current techniques, promising directions and open issues, J. of Visual Communication and Image Representation, vol. 10,no.4,39-62, 1999.

[2] M. Flickner, H Sawhney, W. Niblack, J. Ashley, Q. Huang, B. Dom, M. Gorkani, J. Hafne, D. Lee, D. Petkovic, D. Steele and P. Yanker, “Query by Image and Video Content The QBIC System”, IEEE Computer, (1995), pp. 23-32.

[3] A. Gupta and R. Jain, “Visual information retrieval,” Communications of the ACM vol. 40, no. 5, (1997), pp. 70–79.

[4] J. R. Smith and S. F. Chang, "VisualSEEk: a fully automated content-based image query system", ACM Multimedia, (1996).
[5] J. Wang, G. Wiederhold, O. Firschein and S.Wei, "Content-based Image Indexing and Searching Using Daubechies Wavelets", International Journal on Digital Libraries (IJODL), vol. 1, no. 4, (1998), pp. 311–328.
[6] C. Carson, S. Belongie, H. Greenspan and J. Malik, "Blobworld: image segmentation using expectation-maximization and its application to image querying", IEEE Trans. Pattern Anal. Mach. Intell., vol. 8, No. 8, (2002), pp. 1026–1038.
[7] A. Khotanzad and Y. H. Hongs. Invariant image recognition by Zernike moments, IEEE Trans. on Pattern Analysis and Machine Intelligence, 12(5), 489-497, 1990.
[8] Chuang C.-H. and Kuo C.-C.J. Wavelet Descriptor of Planar Curves: Theory and Applications. IEEE Trans. on Image Processing, 5(1): 56-70,1996.
[9] J. Wang, G. Wiederhold, O. Firschein, and X. Sha, "Content-Based Image Indexing and Searching Using Daubechies' Wavelets," Int. J. Digital Libraries, vol. 1, no. 4, pp. 311-328, 1998.
[10] J. Li, J. Wang, and G. Wiederhold, "Integrated Region Matching for Image Retrieval," In Proceedings of the 2000 ACM Multimedia Conference, Los Angeles, October 2000, pp. 147-156.
[11] J .Z. Wang, J. Li, G. Wiederhold, "SIMPLICITY: Semantics-sensitive Integrated Matching for Picture Libraries," In Proceedings of IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 23, No. 9, 2001, pp. 947-963.
[12] Y. Liu, D. Zhang, G. Lu, W.-Y. Ma, "A Survey of Content-Based Image Retrieval with High-Level Semantics, "Pattern Recognition, Vol. 40, No.1, January 2007, pp.262-282.
[13] Shan Li, Moon-Chuen Lee, and Chi-Man Pun, "Complex Zernike Moments Features for Shape-Based Image Retrieval" IEEE Transactions on Systems, Man, And Cybernetics, Vol. 39, No. 1, January 2009.
[14] A. Natsev, R. Rastogi, and K. Shim, "WALRUS: A Similarity Retrieval Algorithm for Image Databases," IEEE Trans. On Knowledge and Data Engineering, vol.16, pp. 301-318, Mar. 2004. In A. Cohen, C. Rabut, and L. L Schumaker, editors, Curve and Surface Fitting, Saint-Malo, Vanderbilt University Press.
[15] Anjali Goyal Ekta Walia, "Variants of dense descriptors and Zernike moments as features for accurate shape-based image retrieval," SIViP (2014) 8:1273–1289.
[16] A. Anbarasa Pandian and R. Balasubramanian, " Fusion of Contourlet Transform and Zernike Moments using Content based Image Retrieval for MRI Brain Tumor Images", Indian Journal of Science and Technology, Vol 9(29), August 2016.
[17] Sudarvizhi D, "Feature Based Image Retrieval System using Zernike Moments and Daubechies Wavelet Transform", IEEE International Conference On Recent Trends In Information Technology 978-1-4673-9802-2/16/© 2016 IEEE.
[18] Do, M.N and Vetterli, M, "The Contourlet Transform: An Efficient Directional Multiresolution Image Representation," IEEE Transactions On image Processing, Vol. 14, No. 12, 2005.
[19] Candes, E.J and Donoho, D.L, "Curvelets a Surprisingly Effective non-adaptive Representation for Objects with Edges", In A. Cohen, C. Rabut, and L. L Schumaker, editors, Curve and Surface Fitting, Saint-Malo, Vanderbilt University Press.
[20] http://www.cs.columbia.eduiCAVE/software/softlib/coil-100.php.
[21] Georgia Tech (GT) Face Database Available at. ftp://ftp.ee.gatech.edu./pub/users/hayesfacedb