Advances in Computer Science and Information Technology (ACSIT)
p-ISSN: 2393-9907; e-ISSN: 2393-9915; Volume 6, Issue 1; January-March, 2019, pp. 55-59

http://www.krishisanskriti.org/Publication.html

Comparative Analysis by Moments on Fingerprint Recognition

Harinder Kaur[1] and Gaganpreet Kaur[2]

[1]Dept. of Mathematics,
Sri Guru Granth Sahib World University
Fatehgarh Sahib (Punjab) India
[2]Computer Science and Engineering Dept.
Sri Guru Granth Sahib World University
Fatehgarh Sahib (Punjab) India
E-mail: [1]h.kaur1989@gmail, [2]gagan1492003@yahoo.com

Abstract—*Moments play an impotent role in image analysis and invariant pattern recognition. They have two types orthogonal moments and non-orthogonal moments. Orthogonal moments perform better than non-orthogonal moments; they have properties such as robustness to image noise and geometrical invariant properties such as scale, rotation and translation. The popular continuous orthogonal moments are Zernike moments, Pseudo Zernike moments, Orthogonal Fourier Mellin moments, Chebyshev Harmonic moments, Radial Harmonic Fourier moments and Discrete Orthogonal moments are Tchebichef moments, Krawtchouk moments etc. They have the ability to characterize digital information with minimum redundant information and therefore have been used in various areas such as face recognition, fingerprint recognition and image reconstruction etc. This paper presents comparative analysis of continuous and discrete moments in the field of fingerprint recognition.*

1. INTRODUCTION

Fingerprints recognition refers to the automated method of verifying a match between two fingerprints of the same person. Fingerprints include patterns such as ridges and minutiae points. A ridge is a curved line in finger image and minutiae are the major features of a fingerprint. A fingerprint recognition system can be used for both verification and identification. The steps for fingerprint recognition include image acquisition, pre-processing, feature extraction and matching as shown in figure 1. A fingerprint sensor is used to capture a digital image of fingerprint pattern. Pre-processing includes image enhancement, image binarization and image segmentation. Moments are used for feature extraction. They have imagerepresentation capability. In this paper we will analyze the performance of moments on image analysis and compare their results.

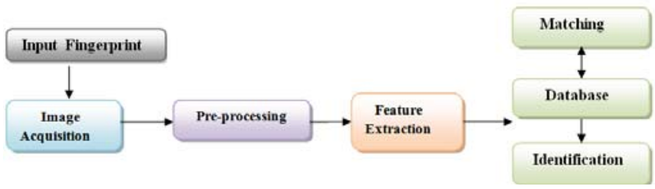

Figure 1: Steps for fingerprint recognition

Moments gives information about geometrical features of the image. Non orthogonal moments are decomposed into complex moments, geometric moments and rotational moments. Orthogonal Moments are divided into two categories discrete and continuous moments, they have interesting features for image applications. Orthogonal moments specify independent features of the image; therefore, their information redundancy is minimum. Orthogonal moments have many applications in pattern recognition and image analysis because they have ability to represent image features. Continuous orthogonal moments are Zernike moments (ZMs), Legendre moments(LMs), Pseudo Zernike moments (PZMs), Radial Harmonic Fourier moments (RHFMs), Chebyshev's Harmonic Fourier moments (CHFMs) and Orthogonal Fourier Mellin moments (OFMMs). The discrete orthogonal moments are Tchebichef moments,Racah moments, Krawtchouk moments and Dual Hahn moments have also been introduced. Orthogonal Rotation Invariant Moments (ORIMs) are wide variety of applications and imaging science is one of the significant application areas. ORIMs have invariant to rotation property. They can be made invariant to translation and scale [1, 2]. Jacobi-Fourier moments (JFMs) are a generic class of ORIMs investigated by Ping *et al.* [3]. Hoang and Tabbone [4] introduced a wide range of ORIMs. Teague [5] presented orthogonal Zernike moments and Legendre moments which are less sensitive to noise and has rotation invariance property. ZMs are very useful in fingerprint recognition and image processing. Bhatia and Wolf [6] introduced pseudo Zernike moments. ZMs and PZMs have similar characteristics of their minimum information redundancy and noise sensitivity. Sheng and Shen [7] presented Orthogonal Fourier Mellin moments. In terms of noise sensitivity for small size of images, OFMMs perform better than ZMs and PZMs. Because the repetition parameter *q* in ZMs and PZMs polynomials is not independent. Orthogonal radial moments are computationally complex and numerically unstable at higher order of moments. Radial Harmonic Fourier moments (RHFMs) [8] are introduced to minimize these problems, which are also orthogonal. These moments face the problem of numerical instability in computing higher order moments. Because many factorial terms are involved for calculating the moments. Chebyshev-Fourier moments are special cases of JFMs. CHFMs are introduced by Ping *et al.* [9]. They have observed that it possess better reconstruction capability and noise sensitivity as compared to OFMMs. The computations of CHFMs involve factorial terms, which are computation intensive. Upneja and Singh [10] have proposed fast computation of JFMs of which CHFMs are a special case. Discretization error is the main problem with continuous momentsintroduced by Yap et al. [11]. Discrete orthogonal moments are introduced to minimize these problems. Zhu et al. [12, 13] have shown that Dual Hahn and Recah discrete orthogonal moments are more superior than continuous moments in terms of robustness to noise. Mukundan [14] introduced another set of discrete orthogonal moments is known as Tchebichef moments. TMs do not include any numerical approximation. So this property makes TMs superior. The new set of discrete orthogonal moments is known as Krawtchouk moments [15, 16]. The Krawtchouk moments can be used to extract local features of the image but other moments capture only global features of the image. Hmimid et al. [17] investigated Charlier moments. Charlier invariants moments are used in pattern recognition.

2. FEATURE EXTRACTION

Feature extraction means calculate features to define the behaviour of the image and useful in classifying and recognition of images. Orthogonal radial moments are used for feature extraction. These moments are selected as feature extractor due to its properties like geometrical invariant properties, orthogonal properties and robustness to image noise.

3. ORTHOGONAL RADIAL MOMENTS

Orthogonal Radial moments are commonly used in pattern recognition. They are able to characterize digital information with minimum redundant information. Orthogonal radial moments have invariant properties, therefore, they are useful in feature extraction. Feature extraction is useful for achieving high recognition.Invariant means an image feature remains unchanged if that image undergoes the geometrical changes such as scale, rotation, translation and reflection. Orthogonal radial moments are specify independent features of the image; therefore, their information redundancy is minimum. There are various efficient moments which are used in feature extraction. Moments can be classified into various sections which are shown in figure 2.

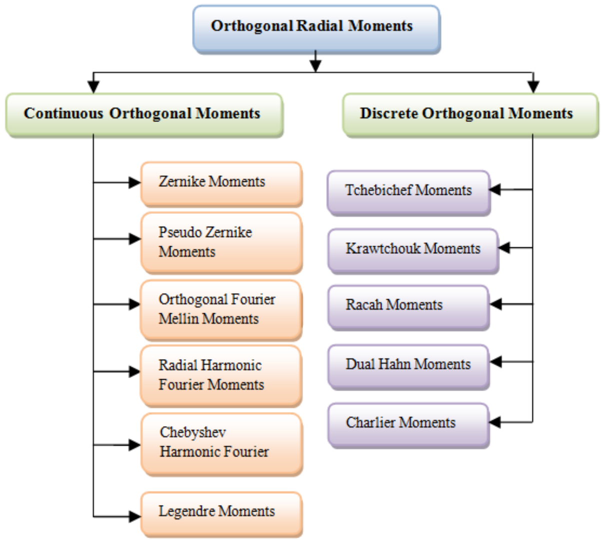

Figure 2: Classification of various moments

4. FINGERPRINT RECOGNITION TECHNIQUES

There are various prominent fingerprint recognition techniques which are used in fingerprint matching and can be divided into three types such as minutiae based technique, correlation-based techniques and pattern-based techniques.

4.1 Minutiae based matching

In this technique, extract the minutiae of template and input image are from the same finger. Fingerprint verification is obtained by using minutiae matching (point wise matching) instead of pixel-wise matching. This technique includes two stages alignment stage and match stage. Firstly match the ridges of two minutiae points and in the alignment stage, two minutiae are aligned for matching. The minutiae-based technique includes finding the alignment between the two images. It gives results in maximum no. of minutiae pairing.

Wahid, Tasweer and muhammed has applied Minutiae based technique for fingerprint verification. Fast Fourier transform is used to enhance the image and converted into binary image. In next step minutiae of images are extracted. Then match the two minutiae points.

Sahuet al. introduced minutiae based technique with low FRR rate. In this paper image enhancement, feature extraction and minutiae matching is included. Hough transform is applied for robustness and distortion of fingerprint image.

Jiang et al. presented Local and Global structures of minutiae for fingerprint matching. The local structure of minutiae defines the rotation and translation invariant features of image.

Global structure describes the uniqueness of fingerprint image. The minutiae matching through local structure are less reliable. So to improve the reliability, global structure is used.

4.2 Pattern based matching

The performance of pattern-based matching technique is better. Ridges and valleys are used for fingerprint verification. Pattern-based technique compared basic fingerprint patterns (arch, whorl, and loop) between input and enrolled images.

Jin et al. presented a hybrid method to improve the fingerprint recognition rate by using pattern based matching techniques. This technique is used for feature extraction. To find the similarity between two objects Euclidean distance is used. After improvement of matching score 98.75% is obtained. The performance of hybrid method for both low and high quality images is able to achieve 100% recognition rate.

Patel et al. In this paper effective fingerprint matching based on pattern based technique is discussed. The quality of input image doesn't matter is the main advantages of this paper. In pre-processing, first the image is converted into gray scale image then it converted to binary image. In post processing, all the features of image are extracted.

4.3 Correlation based matching

The correlation-based technique is used to compare the grey level images and find a correlation between input and enrolled images for each corresponding pixels. It is based on the local features of the image. In global features of the image, results obtained from different impressions of the same finger are inaccurate.

Lindoso et al. introduced correlation based fingerprint matching with orientation field alignment. In this paper, alignment step is introduced to reduce the amount of correlation. The pre-processing includes steps: Normalization, Low frequency filter, Orientation field frequency map, Gabor filtering, Equallization. Fingerprint matching has three steps: image alignment, selection of correlation regions, correlation based matching. For correlation local regions are used. The orientation field is used to select local region of correlation. This paper presented that the Fingerprint matching accuracy are improved.

Bazen et al. presented a correlation based fingerprint verification system. For bad quality images correlation based fingerprint verification system is used because no minutiae can be extracted reliably from them. In this paper, instead of using minutiae locations they use directly gray level information from input image. Because it includes much richer information then minutiae locations. As compared to other approaches it does not require pre-processing. It is capable to dealing with non-uniform shape distortions problems.

Sandbhor et al. In this paper correlation based fingerprint recognition technique is discussed. It uses pixel values of image and gray scale information. Correlation based fingerprint recognition technique chooses template, pixel values of template which is correlates with pixel values of database image and see the maximum value which is greater than threshold value. This technique is less time consuming.

5. COMPARATIVE ANALYSIS

In this section, we did comparative analysis of various continuous and discrete moments**.** Table (I) details the moments and their performance metrics.

TABLE 1: Comparative analysis of moments on fingerprint recognition

Moments	Reference	Highlights	Results
Zernike moments	Qader et al.[20]	Region of interest, Euclidean distance, ZMI feature extractor	ZM is able to match the fingerprint image with recognition rate 92.89%
Pseudo Zernike moments	Deepika et al. [21]	ROI extraction, Wavelet transform, Bayes net classifier	At lower order moments, PZMs gives accuracy of the system is 96.89%.
Orthogonal Fourier mellin moments	Sheng et al.[7]	Noisy image reconstruction error, Signal to noise ratio	Orthogonal Fourier mellin moments perform better than Zernike moments for small size of images.
Radial Harmonic Fourier moments	Kejia et al.[24]	Feature extraction, normalization	The accuracy of the system was found to be 99.57% in real world datasets and 99.49% in artificial datasets.
Chebyshev Harmonic Fourier moments	Ping et al.[9]	Noisy image reconstruction error, Signal to noise ratio	The performance of CHFMs in describing images in comparison with performance of the OFMMs is investigated. Both have almost the same performance
Legendre moments	Saradha et al.[25]	Linear discriminate analysis, nearest neighbour, Euclidean distance	A good recognition percentage 98.25% is achieved with feature representation using Legendre moments. It is found superior to Hu's moments.
Racah moments	Zhu et al.[12]	Racah polynomials, weighted racah polynomials, recurrence relation	The results show the behaviour of the racah moments over the other transforms in terms of compression capability is superior.

Krawtchouk moments	Yap et al.[15]	Krawtchouk polynomial, Weighted Krawtchouk polynomials, recurrence relation	In both noisy and noise free conditions, Krawtchouk moments have better performance than Hu's moments.
Tchebichef moments	Mukundan et al.[14]	Tchebichef polynomials, orthogonal moments	The Tchebichef moments have superior feature representation capability as comparative with Zernike and Legendre moments.
Dual Hahn moments	Zhou et al.[26]	Hahn polynomials, mean square error	Comparative analysis of Chebyshev moments, Krawtchouk moments and Hahn moments shows that the Dual Hahn moment is superior then others in terms of reconstruction methods.
Charlier moments	Hmimid et al.[19]	Mean square error, Euclidean distance,Charlier discrete orthogonal polynomials	Under noisy conditions, The Charlier moments are more robust to image transformations.

6. CONCLUSION

Fingerprint recognition is a modern imaging technology. In this survey paper, we have explained discrete orthogonal moments and continuous orthogonal moments along with their performance analysis. These moments are invariants to scale, rotation and translation; therefore, they are used for feature extractor. ZMs and PZMs have ability to match the fingerprint image with high accuracy. For small size of mages OFMMs perform better than ZMs and PZMs. CHFMs and OFMMs have same performance in describing the image. LMs are found superior to Hu's moments. The results show that behaviour of RAMs in terms of compression capability is good. The feature representation capabilities of TMs are superior to ZMs and LMs. Both in noisy and noise free conditions, KMs are used. The DHMs based reconstruction method is superior to CHFMs and KMs. CMs gives good recognition accuracy. Prominent fingerprint recognition techniques which are used for the fingerprint matching have been discussed in this paper.

REFERENCES

[1]M. K. Hu, "Visual pattern recognition by moment invariants," IRE Transaction Information Theory, vol. 8, pp. 179-187, 1962.

[2]C. H. Teh and R. T. Chin, "On image analysis by the methods of moments," IEEE Transactions on Pattern Analysis Machine Intelligence, vol. 10, no. 4, pp. 496-513, 1988.

[3]Z. Ping, H. Ren, J. Zou, Y. Sheng, and W. Bo, "Generic orthogonal moments: Jacobi-Fourier moments for invariant image description," Pattern Recognition, vol. 40, no. 4, pp. 1245-1254, 2007.

[4]T. V. Hoang and S. Tabbone, "Errata and comments on 'Generic orthogonal moments: Jacobi-Fourier moments for invariant image description'," Pattern Recognition, vol. 46, no. 11, pp. 3148-3155, 2013.

[5] M. R. Teague, "Image analysis via the general theory of moments," Journal of the Optical Society of America, vol. 70, no. 8, pp. 920-930, 1980.

[6] A. B. Bhatia and E. Wolf, "On the circle polynomials of Zernike and related orthogonal sets," Mathematical Proceedings of the Cambridge Philosophical Society, vol. 50, no. 01, pp. 40-48, 1954.

[7]Y. Sheng and L. Shen, "Orthogonal Fourier Mellin moments for invariant pattern recognition," J. Opt. Soc. Am. A, vol. 11, no. 6, pp. 1748-1757, 1994.

[8]H.Ren, A.Liu, J.Zou, D.Bai, and Z.Ping, "Character Reconstruction with Radial Harmonic Fourier Moments," in 4th International Conference on Fuzzy Systems and Knoweldge Discovery (FSKD07) (Haikou, 2007), Vol. 3, pp. 307-310.

[9]Z. Ping, R. Wu, and Y. Sheng, "Image description with Chebyshev-Fourier moments," J. Opt. Soc. Am. A, vol. 19, no. 9, pp. 1748-1754, 2002.

[10]R. Upneja and C. Singh, "Fast computation of Jacobi-Fourier moments for invariant image recognition," Pattern Recognition, vol.48, no.5, pp.1836-1843, 2015.

[11] P.T. Yap, R. Paramesran and S.H. Ong, "Image Analysis by Krawtchouk Moments,"IEEE Transactions on Image Processing, vol12, no. 11, pp. 1367-1377, 2003.

[12]H. Q. Zhu, H. Z. Shu, J. Liang, L. M. Luo, and J. L. Coatrieux, ''Image analysis by discrete orthogonal Racah moments,'' Sign. Luo al Processing, vol. 87, no. 4, pp. 687–708, 2007.

[13] H. Q. Zhu, H. Z. Shu, J. Liang, L. M, and J. L. Coatrieux, ''Image analysis by discrete orthogonal dual-Hahn moments,'' Pattern Recognition Letters, vol. 28, no. 13, pp. 1688–1704, 2007.

[14]R. Mukundan, S. H. Ong, and P. A. Lee, "Image analysis by Tchebichef moments," IEEE Transactions on Image Processing, vol. 10, no. 9, pp. 1357–1364, 2001.

[15]P. T. Yap, P. Raveendran, and S. H. Ong, "Krawtchouk moments as a new set of moments for image reconstruction," in Processing IJCNN'02, vol.1, pp. 908–912, 2002.

[16]R.mukundan, S. H. Ong, and P. A. Lee, "Image analysis by Krawtchouk moments," IEEE Transactions Image Processing, vol.10, no.9, pp.1357-1364, 2001.

[17]C. H. Teh and R. T. Chin, "On image analysis by the method of moments," IEEE Transactions on Pattern Analysis Machine Intelligence, vol. 10, no. 4, pp. 496–513, 1988.

[18]R. Mukundan and K. R. Ramakrishnan, "Fast computation of Legendre and Zernike moments," Pattern Recognition, vol. 28, no. 9, pp. 1433–1442, 1995.

[19]A.Hmimid, M.Sayyouri and Hassan, "Image Classification Using Novel Set of Charlier Moment Invariants," Wseas Transactions on Signal Processing, vol.10, pp.156-167, 2014.

[20]H.A.Qader, A.R.Ramli and S.A.Haddad, "Fingerprint Recognition using Zernike Moments," The International Arab

Journal of Information Technology, vol 4, no. 4,pp. 372-376, 2007.
[21]C.L.Deepika, A.Kandaswamy, C.Vimal and B.Sathish, "Invariant Feature Extraction from Fingerprint Biometric Using Pseudo Zernike Moments," International Journal of Computer Communication and Information System, vol. 2, no. 1, pp. 104-108, 2010.
[22]M. Sayyouri, A. Hmimd and H. Qjidaa, "A fast computation of Charlier moments for binary and gray-scale images," Information Science and Technology Colloquium (CIST), Fez, Morocco, pp.101-105, 2012.
[23]M. Sayyouri, A. Hmimd and H. Qjidaa, "Image analysis using separable discretemoments of Charlier-Tchebichef,"International Journal of Circuits, Systems and Signal Processing, vol 8, pp.91-100, 2014.
[24]W.Kejia, Z.Honggang, P.Ziliang and Haiying, "Chinese Chess Character Recognition with Radial Harmonic Fourier Moments," International Conference on Document Analysis and Recognition, pp. 1369-1373, 2011.
[25]S.Annadurai and A.Saradha, "Face Recognition Using Legendre Moments," Proceedings of the Fourth Indian Conference on Computer Vision, Graphics & Image Processing, 2004.
[26]J.Zhou, H.Shu and H.Zhu, "Image Analysis by Discrete Orthogonal Hahn Moments," pp. 524-531, 2005.
[27]X.Jiang and W.Yau. "Fingerprint minutiae matching based on the local and global structures," In Pattern recognition, 2000. Proceedings 15th International Conference on, volume 2, pages 1038-1041, IEEE, 2000.
[28]D.Sahu and R.Shrivas, "Minutaie based fingerprint matching for identification and verification," International Journal of Science and Research, vol. 5, no. 3, 2016.
[29]H. Patel and P. Asrodia, "Fingerprint matching using two methods," International Journal of Engineering and Applications, vol. 2, no. 3, pp. 857-860, 2012.
[30]A.Lindoso, L.Entrena and J.L.Jimenez, "Correlation Based Fingerprint Matching with Orientation Field Alignment,"International Conference on Biometrics, vol. 4642, pp. 713-721, 2007.
[31]A.Sandbhor, K.Deshpande and S.S.Jahagirdar, "Cross-correlation Based Algorithm for Fingerprint Recognition using MATLAB," International Conference of Engineering and Technical Research, vol. 2, no. 3, pp. 116-118, 2014.
[32]A.M.Bazen, B.J.V.D Zwaag and S.H.Gerez, "A Correlation Based Fingerprint Verfication System," Workshop on Circuits, Systems and Signal processing, 2014.