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► To cite this version:

Huazhong Shu, Limin M. Luo, Jean-Louis Coatrieux. A look at Moment-based approaches in imaging part 4: Some applications.. IEEE Engineering in Medicine and Biology Magazine, 2008, 27 (5), pp.116-8. 10.1109/MEMB.2008.927990 . inserm-00337827

HAL Id: inserm-00337827

<https://inserm.hal.science/inserm-00337827>

Submitted on 12 Nov 2008

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Moment-based Approaches in Image.Part 4:

some applications

Huazhong Shu, Limin Luo, Jean Louis Coatrieux

This last paper of this series provides a survey of the topics the moments have addressed in image processing at large. Our introductive papers dealt with the theoretical expressions of orthogonal and non-orthogonal basis functions [1], with important properties like geometric invariance, robustness to noise or blurring [2] and the computational accuracy and complexity [3]. Here, most of the steps going from image reconstruction, segmentation, motion tracking to pattern recognition are examined through moment-based techniques. Though they have not an equal importance in this wide spectrum of applications, they can offer sound solutions. Rather than entering into methodological details and examples, this paper is intended to identify the main contributions brought by moments.

Featuring Image analysis

The multiple applications of digital images lead to segment the field into many areas, each having their own journals and conferences. This diversity makes more difficult to have a full view on the on-going research and may hide the general interest of a given method. It must be first pointed out that the physical process underlying the image formation is of major importance for the all subsequent processing. If not properly dealt with, most of the information later extracted can be biased. The reconstruction problem, so important in medical imaging, can be dealt with purely mathematical views but the capability to model and control the acquisition device should open new pathways. Conversely, the search for generic algorithms, a major trend in image analysis, is attractive: the efficiency of such approach has been demonstrated through many examples. Assumptions are always required however and they must be adapted to the situations under study. Thus, a full apprehension of the field has to take into account the 4-tuple, “observations (or data), objects (properties), goals (analysis objectives), methods (algorithms)”.

Multidimensional observations are more and more available in medicine (volume (3-D) images, 2-D+t and 3-D+t image sequences, with scalar or vectorial descriptions). The spatial and temporal sampling is here critical according to the task to be carried out. The huge data sets they provide (hundreds of slices or 2-D projections) call for challenging time computations. The objects of interest are varying in shape among individuals and with disorders, may change and deform over time, have poor contrast. Moreover, they are not reducible to simple geometric patterns. These difficulties may be compensated by introducing some, but limited, interactive pointing or delineation. The ultimate goal (omitting the image formation) is to provide the user with relevant features for clinical decision and therapeutic

guidance. It includes parameters for quantifying the lesion extent and discriminating them, locating the abnormal patterns in anatomical space, or characterizing the behavior in space and time. The methods that may bring answers to these issues are many. The classical paradigms like low vs high level, data-driven vs model-driven, salient feature and primitive grouping, edge and region cooperation, local vs global analysis, image understanding through semantic labeling and spatial relation modeling, etc. are still of value in most of the problems to solve. Non-stationary noise and artifacts, low contrast, object occlusions and deformations, variability in observation conditions, etc. lead to recurrent challenges in computer vision when robustness, accuracy, completeness must be achieved under real-time constraints.

The main applications

Reconstruction

This issue has received much attention in the medical imaging literature. A number of imaging modalities are concerned from X-ray computerized tomography and emission tomography up to acoustic and optical techniques. They all bring different insights in the human body either morphological or functional. Recent works deal with reconstruction from only limited range projections with the aim to estimate the projections at unknown views such as the moment-based approaches reported by Salzman [4] and Goncharev [5]. Milanfar et al. [6] presented a variational framework for the tomographic reconstruction of an image from the maximum likelihood estimates of its orthogonal moments. Basu and Bresler [7, 8] investigated the problem of recovering the view angles from the projection data by means of moment method. Rouze et al. [9] derived a relation between Zernike moments and the Radon transform, and then applied it to reconstruction. By establishing a relationship between the image geometric moments and projection moments, Wang and Sze [10] presented an approach to reconstruct the CT images from limited range projections. Shu et al. [11] extended Wang's method using the orthogonal Legendre moments to improve the quality of the reconstructed image. The advantage of Shu's method is that the orthogonal moments have simple inverse transform, thus, the image can be more easily obtained from the orthogonal moments. Moreover, the geometric moments, especially at high order, are sensitive to noise and digitization error. However, both methods were based on the use of continuous moments. When applied to 2-D digital images, the double integrals are usually approximated by discrete summations that lead to numerical errors in the computed moments. The discrete orthogonal moments, in particular Tchebichef moments, do not require any discrete approximation for numerical implementation and moreover the discrete orthogonal Tchebichef polynomials are the simplest among all the discrete orthogonal polynomials with a definition domain ideally suited for square images [12]. However, the traditional Radon transform is no longer applicable, and a discrete version of Radon transform is required. Beylkin [13] described a discrete Radon transform (DRT) to map a set of sampled image points onto a set of discrete projections. The algebraic mapping for this transformation can be computed exactly, since no interpolation of the data is required. Matus and Flusser [14] developed a group theoretic and Fourier based

approach to the DRT. Svalbe [15] and Kingston [16] derived improved versions of DRT to handle both continuous projections and discrete projections in Fourier and Radon space. The advantage of the techniques reported in [15] and [16] is that they require a straightforward 1-D linear interpolation, a simple sorting of projection samples and no pre-processing of the projection data. The purely mathematical views provided by moments for the reconstruction problem have a drawback: the difficulties they have to deal with the physical characteristics inherent to any image capture.

Pattern Recognition

This topic represents certainly the major applications of moments and a survey of the all literature is out of reach in a short paper. The classical views regarding pattern recognition rely on the ability to extract the objects of interest, on the choice of their representation and the final decision step, e.g. allocation to classes. These classes may be formed beforehand through a learning phase. Many techniques are available to manage that either by contour-based or region-based features with local or global descriptions. They can operate in the image or in the transform domains. They include kernel methods (like Support Vector Machine), neural networks, rigid or elastic matching, string coding and matching, etc. They all require a distance measure to estimate the similarity between two shapes. The flexibility of moments in dealing with binary or grey level images, polygonal and region representations on one hand and, in the other hand, the invariance properties discussed in [2] make them particularly attractive for a number of applications. They offer compact and robust descriptions and bring statistical cues on pixel (or voxel) value distributions: in some cases (the low orders) they have physical interpretations.

Invariance properties are central for pattern recognition as discussed in [2] [17]. Many attempts have been reported using moments for aircraft recognition [18], identification of building and bridge [19], partially occluded object localization [20], flower shape analysis [21], image retrieval [22], character recognition [23-27]. Bailey and Srinath [28] investigated invariant character recognition using Legendre, Zernike and pseudo-Zernike moments with different classifiers. Khotanzad and Hong [29] has shown that a neural network classifier using Zernike moments has a strong class separability power. The evolution towards images with higher dimensions (3-D and n-D) has also motivated a lot of theoretical works [30-36].

Beyond shape features, texture patterns are also of interest in order to recognize objects. Less moment-based works have been devoted to texture analysis [37, 38]. The attempts made for tissue characterization did not however show a significant breakthrough: this can be due to the texture complexity, resulting from mixture of structural tissue properties, partial volume effects, noise and reconstruction artefacts.

Miscellaneous

We briefly review here some additional topics where the moments have been called for but with limited impact. As pointed out above, nearly every system is initialized by detection and segmentation tasks. Despite the recent achievements provided by deformable models, level set and graph-cut methods, these problems remain open in

medical applications and require some user interaction. Edge *detection* is mainly carried out by derivative operators while integrative schemes may offer a sound alternative as shown in 2-D with geometric moments [39] or Zernike moments [40]. Geometric and Legendre moments have also been proposed for 3-D surface detection assuming a local planar patch [41] or a parabolic model [42]. Image *registration* or alignment is another active area. Most approaches rely on establishing the feature correspondence between a reference image and the target image, a task that can be dealt with moments [43-50]. *Motion estimation* is another major area in image analysis [51]. Optical flow methods based on differential-geometric descriptors and matching techniques (or correlation) have been widely explored. Joint motion-tracking approaches combining different types of information (boundary-region) and different sources (gradient, intensity, motion) in scenes with multiple objects should provide new perspectives. Moments have not received much attention in this area and the few attempts made were essentially focused on optical flow methods using Zernike moments [52, 53].

Conclusion

Moment-based methods are still marginal in image processing and it is our hope that this series will motivate new research on this topic and open new applications especially in medical imaging. These techniques cover, as we pointed out, a wide spectrum of applications and deserve to be confronted to other attractive and competitive methods. They should also be combined in order to take advantage of their basic features, in particular the invariance properties and the continuously improvements in computational complexity.

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References

1. H.Z. Shu, L.M. Luo, J.L. Coatrieux, Moment-based approaches in image, Part 1: basic features, *IEEE Eng. Med. Biol. Mag.*, vol. 26, no.5, pp. 70-75, 2007.
2. H.Z. Shu, L.M. Luo, J.L. Coatrieux, Moment-based approaches in image, Part 2: invariance, *IEEE Eng. Med. Biol. Mag.*, vol. 27, no. 1, pp. 81-83, 2008.
3. H.Z. Shu, L.M. Luo, J.L. Coatrieux, Moment-based approaches in image, Part 3: computational considerations, *IEEE Eng. Med. Biol. Mag.*, vol. 27, no. 3, pp. 89-91, 2008.
4. D. Salzman, A method of general moments for orienting 2D projections of unknown 3D objects, *Comput. Vis. Graph. Image Process.*, vol. 50, no. 2, pp. 129-156, 1990.
5. A.B. Goncharev, Methods of integral geometry and recovering a function with compact support from its projections in unknown directions, *Acta Appl. Math.*, vol. 11, no. 3, pp. 213-222, 1988.
6. P.M. Milanfar, W.C. Karl, A.S. Willsky, A moment-based variational approach to tomographic reconstruction, *IEEE Trans. Image Process.*, vol. 5, no. 3, pp. 459-470, 1996.
7. S. Basu and Y. Bresler, Uniqueness of tomography with unknown view angles, *IEEE Trans. Image Process.*, vol. 9, no. 6, pp. 1094-1106, 2000.
8. S. Basu and Y. Bresler, Feasibility of tomography with unknown view angles, *IEEE Trans. Image Process.*, vol. 9, no. 6, pp. 1107-1122, 2000.
9. N.C. Rouze, V.C. Soon, G.D. Hutchins, On the connection between the Zernike moments and Radon transform of an image, *Pattern Recognit. Lett.*, vol. 27, no. 6, pp. 636-642, 2006.
10. T.J. Wang and T.W. Sze, The image moment method for the limited range CT image reconstruction and pattern recognition, *Pattern Recognit.*, vol. 34, no. 11, pp. 2145-2154, 2001.
11. H.Z. Shu, J. Zhou, G.N. Han, L.M. Luo, J.L. Coatrieux, Image reconstruction from limited range projections using orthogonal moments, *Pattern Recognit.*, vol. 40, no. 2, pp. 670-680, 2007.
12. X.B. Dai, H.Z. Shu, L.M. Luo, G.N. Han, J.L. Coatrieux, Reconstruction of tomographic image from limited range projections using discrete Radon transform and Tchebichef moments, Submitted to *IEEE Trans. Image Process.*.
13. G. Beylkin, Discrete Radon transform, *IEEE Trans. Acoustics Speech Signal Process.*, vol. 35, no. 2, pp. 162-172, 1987.
14. F. Matus and J. Flusser, Image representation via a finite radon transform, *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 15, no. 10, pp. 996-1106, 1993.
15. I. Svalbe and Dimitri van der Spek, Reconstruction of tomographic images using analog projections and the digital radon transform, *Linear Algebra and Its Applications*, vol. 339, no. 1, pp.125-145, 2001.
16. A. Kingston and I. Svalbe, Mapping between digital and continuous projections via the discrete radon transform in Fourier space, DICTA'03, Sydney, pp.1-10, Dec. 2003.

17. M. Hu, Visual pattern recognition by moment invariant, *IRE Trans. Inform. Theory*, vol. 8, no. 2, pp. 179-187, 1962.
18. S.A. Dudani, S.K. Breeding, R. McGhee, Aircraft identification by moment invariants, *IEEE Trans. Comput.*, vol. 26, no. 1, pp. 39-45, 1977.
19. J.F. Gilmore and W.W. Boyd, Building and bredge classification by invariant moments, *Proc. SPIE*, vol. 292, pp. 256-263, 1981.
20. A. Sluzek, Using moment invariants to recognize and locate partially occluded 2D objects, *Pattern Recognit. Lett.*, vol. 7, no. 4, pp. 253-257, 1988.
21. Z.J. Miao, Zernike moment-based image shape analysis and its application, *Pattern Recognit. Lett.*, vol. 21, no. 2, pp. 169-177, 2000.
22. W.Y. Kim and Y.S. Kim, A region-based shape descriptor using Zernike moments, *Signal Processing: Image Communication*, vol. 16, no. 1-2, pp. 95-102, 2000.
23. M. Fang and G. Hausler, Class of transforms invariant under shift, rotation, and scaling, *Appl. Opt.*, vol. 29, no. 5, pp. 704-708, 1990.
24. T.H. Reiss, The revised fundamental theorem of moment invariants, *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 13, no. 8, pp. 830-834, 1991.
25. L. Shen and Y. Sheng, Noncentral image moments for invariant pattern recognition, *Opt. Eng.*, vol. 34, no. 11, pp. 3181-3186, 1995.
26. M. Gruhen and K.Y. Hsu, Moment-based image normalization with high noise tolerance, *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 19, no. 2, pp. 136-139, 1997.
27. C. Kan and M.D. Srinath, Invariant character recognition with Zernike and orthogonal Fourier-Mellin moments, *Pattern Recognit.*, vol. 35, no. 1, pp. 143-154, 2002.
28. R.R. Bailey and M.D. Srinath, Orthogonal moment features for use with parametric and non-parametric classifiers, *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 18, no. 4, pp. 389-399, 1996.
29. A. Khotanzad and Y.H. Hong, Classification of invariant image representations using a neural network, *IEEE Trans. Acoust. Speech Signal Process.*, vol. 38, no. 6, pp. 1028-1038, 1990.
30. F.A. Sadjadi and E.L. Hall, Three-dimensional moment invariants, *IEEE Trans Pattern Anal. Machine Intell.*, vol. 2, no. 2, pp. 127-136, 1980.
31. C.H. Lo and H.S. Don, 3-D moment forms: their construction and application to object identification and positioning, *IEEE Trans Pattern Anal. Machine Intell.*, vol. 11, no. 10, pp. 1053-1064, 1989.
32. N. Canterakis, 3D Zernike moments and Zernike affine invariants for 3D image analysis and recognition, *Proc of 11th Scandinavian Conference on Image Analysis*, pp. 85-93, 1999.
33. M. Novotni and R. Klein, Shape retrieval using 3D Zernike descriptors, *Comput. Aided Design*, vol. 36, no. 11, pp. 1047-1062, 2004.
34. A.G. Mamistvalov, N-dimensional moment invariants and conceptual mathematical theory of recognition n-dimensional solids, *IEEE Trans Pattern Anal. Machine Intell.*, vol. 20, no. 8, pp. 819-831, 1998.
35. J. Flusser, J. Boldys, B. Zivova, Moment forms invariant to rotation and blur in

- arbitrary number of dimensions, *IEEE Trans Pattern Anal. Machine Intell.*, vol. 25, no. 2, pp. 234-246, 2003.
36. D. Xu and H. Li, Geometric moment invariants, *Pattern Recognit.*, vol. 41, no. 1, pp. 240-249, 2008.
 37. M. Tuceryan, Moment based texture segmentation, *Pattern Recognit. Lett.*, vol. 15, no. 7, pp. 659-667, 1994.
 38. J. Wang and G. Healey, Using Zernike moments for the illumination and geometry invariant classification of multispectral texture, *IEEE Trans. Image Process.*, vol. 7, no. 2, pp. 196-203, 1998.
 39. L.M. Luo, X.H. Xie, X.D. Bao, A modified moment-based edge operator for rectangular pixel image, *IEEE Trans. Circ. Sys. Video Tech.*, vol. 4, no. 6, pp. 552-554, 1994.
 40. S. Ghosal and R. Mehrotra, Orthogonal moment operators for subpixel edge detection, *Pattern Recognit.*, vol. 26, no. 2, pp. 295-306, 1993.
 41. L. M. Luo, C. Hamitouche, J. L. Dillenseger, J. L. Coatrieux, A moment-based three-dimensional edge operator, *IEEE Trans. Biomed. Eng.*, vol. 40, no. 7, pp. 693-703, 1993.
 42. H. Zhang, H.Z. Shu, L.M. Luo, J.L. Dillenseger, A Legendre orthogonal moment based 3D edge operator, *Science in China Ser. G*, vol. 48, no. 1, pp. 1-13, 2005.
 43. R.Y. Wong and E.L. Hall, Scene matching with invariant moments, *Comput. Vis. Graph. Image Process.*, vol. 8, no. 1, pp. 16-24, 1978.
 44. X.H. Yang, W. Birkfellner and P. Niederer, A similarity based on Tchebichef moments for 2D/3D medical image registration, *International Congress Series*, vol. 1268, pp. 153-158, 2004.
 45. J. Liu and T.X. Zhang, Matching and normalization of affine deformed image from regular moments, *Pattern Recognit. Lett.*, vol. 25, no. 14, pp. 1619-1631, 2004.
 46. J. Heikkila, Pattern matching with affine moment descriptors, *Pattern Recognit.*, vol. 37, no. 9, pp. 1825-1834, 2004.
 47. Z. Yang and F.S. Cohen, Cross-weighted moments and affine invariants for image registration and matching, *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 21, no. 8, pp. 804-814, 1999.
 48. I. Rothe, H. Susse, K. Voss, The method of normalization to determine invariants, *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 18, no. 4, pp. 366-376, 1996.
 49. L. Dong, A.L. Boyer, A portal image alignment and patient setup verification procedure using moments and correlation techniques, *Phys. Med. Biol.*, vol. 41, no. 4, pp. 697-723, 1996.
 50. H.Z. Shu, Y. Ge, L.M. Luo, J.W. Wang, W.X. Yu, X.D. Bao, An orthogonal moment-based method for automatic verification of radiation field shape, *Phys. Med. Biol.*, vol. 45, no. 10, pp. 2897-2911, 2000.
 51. J.L. Coatrieux, Shape and function from motion in biomedical imaging: part 3, *IEEE Eng. Med. Biol. Mag.*, vol. 26, no. 3, pp. 81-83, 2007.
 52. S. Ghosal and R. Mehrotra. Robust optical flow estimation using semi-invariant local features, *Pattern Recognit.*, vol. 30, no. 2, pp. 229-237, 1997.

53. J. Gu, L.M. Luo, H.Z. Shu, A local optimization algorithm for computing 2D optical flow field of heart echocardiograph image using Zernike moments, *Acta Electronic Sinica*, vol. 29, no. 3, pp. 350-353, 2001.