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A NOVEL APPROACH FOR EXTRACTION OF DOMINANT REPRESENTATION POINTS OF THE IMAGE

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Abstract

In the applications of computer vision, the image representation techniques are found to be prominent. Among various techniques, visual representation techniques are found to be better than the other techniques. In visual representation techniques, the representation points are to be identified efficiently. So, the present paper proposes a novel approach for representation of dominant points (NARDP). With these dominant points, the represented image will be efficiently described with various features. The proposed NARDP algorithm works on four different types of the images and the results show the efficacy of the proposed algorithm.

I. Introduction

The computer vision majorly focuses on the object recognition approaches. Among various approaches, the representation of shape of the image is found to be crucial for all the algorithms. The verge representation points [1] are found to be prominent for reconstruction of input image. These points are further used for representing the input image at multiple scales. The

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problems with the symmetric representation are resolved with the Overlapped Rectangle Image Representation [2]. This uses the encoding and decoding procedures. The scalable representation points [3] are found to be prominent for representing the input image at various transformations. The sparse and dense components [4] are found to be efficient for representation of the input image for getting good distortion performance. The curvilinear edges [5] are found to be efficient for representation of the image. These edges are further uses the triangulation and with optimization, the dominant representation points will be estimated.

The max pooling strategy [6] is used for the representing the input image. It internally uses the multi level sparse coding approach. The polygonal based shape representation [7] is found to handle various orientations of the input image efficiently and further it can be used for the matching algorithms [8]. The autoregressive models [9] are used to represent the input image with set of low resolution images. The linear conventional Quadtrees [10] are used for representing the grey level image with the non symmetry and anti packing object models. The present paper is organized into five sections. The section 1 discusses about the introduction. The methodology is discussed in section 2, the section 3discusses about the results and discussions and section 4 discusses about the conclusions.

II. Methodology

The present paper proposes a novel approach for representation of dominant points (NARDP) in the input image. The NARDP algorithm works with the grey level images. In the input image, the representation points are essential for recognition. So, to extract the dominant representation points, the proposed NARDP algorithms are majorly focuses on the extraction of corner points. Among various extracted representation points, the NARDP will extract the dominant points for the representation of the input image.

The representation of the input image is based on the contour or region approaches. The present paper uses contour based approach. The present NARDP approach initially estimates the contour of the input image. Then on the estimated contour, the representation points are identified based on its neighborhood size of $M \times N$ by using the following equation.

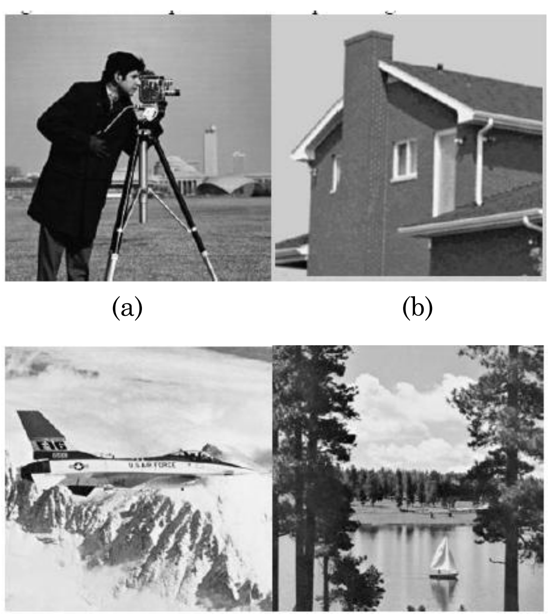
$$R(x,\ y) = \overset{x}{\underset{i=0}{\forall}}\ \overset{y}{\underset{j=0}{\forall}} \sum_{i=x}^{x+m} \sum_{j=y}^{y+n} I(i,\ j) + t \tag{1}$$

After extraction of representation points, the maximum Weightage points w.r.t. its histogram will be considered as the dominant representation points.

$$DRP = \max(R(x,\ y)) \tag{2}$$

III. Results and Discussions

The present paper proposes NARDP approach for the representation of the input image with dominant representation points. The Figure 1 represents the original images used for NARDP algorithm. The extracted dominant representation points for the input images are shown in Figure 2. The representation view of NARDP for the input images are shown in Figure 3. The histogram view of NARDP for the input images are shown in Figure 4. From the results, it is clear that the proposed NARDP algorithm is efficiently representing the dominant points of the input image.



(a) (b) (c) (d)

Figure 1. Input Images (a) Input Image 1 (b) Input Image 2 (c) Input Image 3 (d) Input Image 4.

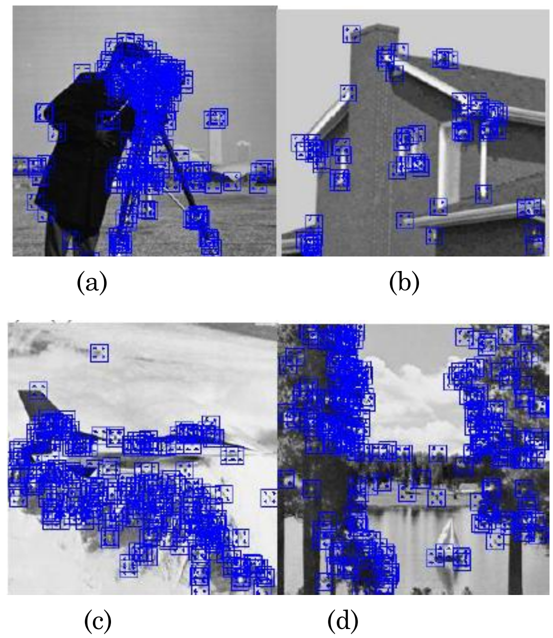


Figure 2. NARDP Extracted Dominant Representation Points of (a) Input Image1 (b) Input Image 2 (c) Input Image 3 (d) Input Image 4.

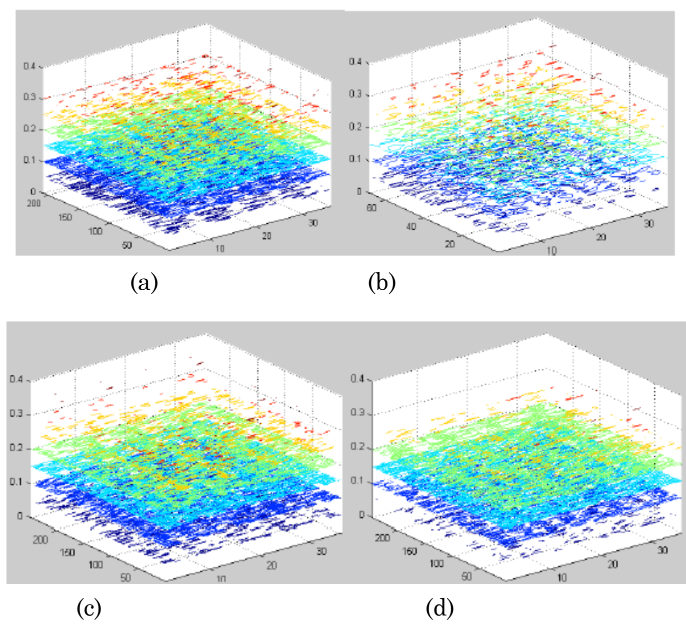
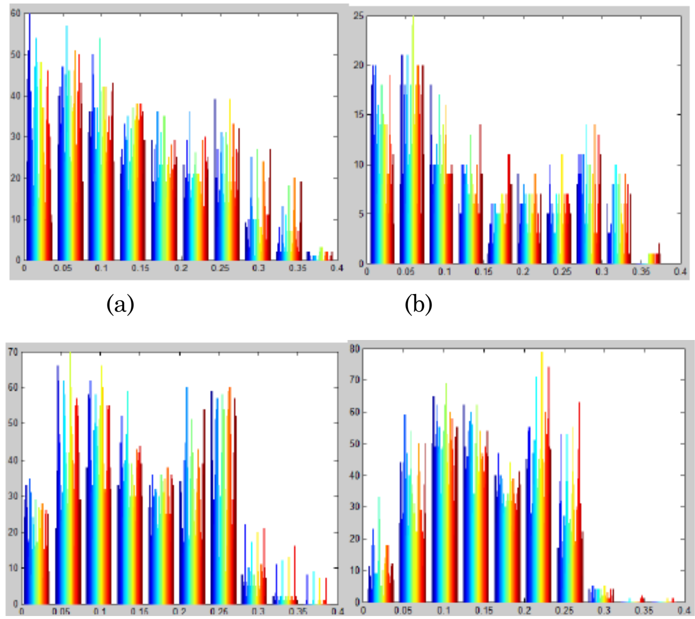


Figure 3. Representation View of NARDP for (a) Input Image 1 (b) Input Image 2 (c) Input Image 3 (d) Input Image 4.



(a) (b) (c) (d)

Figure 4. Histogram of NARDP Features for (a) Input Image1 (b) Input Image 2 (c) Input Image 3 (d) Input Image 4.

IV. Conclusions

The representation of the input image is essential for the object recognition. So, extraction of representation points is essential for the computer vision algorithms. The visual representation algorithms are found to be prominent for the computer vision algorithms. The present paper proposes NARDP algorithm for estimation of dominant representation algorithms for the input image. The NARDP algorithm is found to be efficient for various types of images.

References

[1] Sheng-Jyh Wang, Lun-Chia Kuo, Hsin-Haw Jong and Zong-Han Wu, Representing images using points on image surfaces, IEEE Transactions on Image Processing, doi: 10.1109/TIP.2005.851693. 14 (8) (2005), 1043-1056.

[2] W. Huang, C. Chen and M. Sarem, A New Lossless Gray Level Image Representation, 2008 IEEE International Symposium on Knowledge Acquisition and Modeling Workshop, Wuhan, doi: 10.1109/KAMW.2008.4810607. (2008), 781-785.

[3] A. Kingston, B. Parrein and F. Autrusseau, Redundant image representation via multi-

scale digital Radon projections, 2008 15th IEEE International Conference on Image Processing, San Diego, CA, doi: 10.1109/ICIP.2008.4712406. (2008), 2920-2923.

[4] B. Han, F. Wu and D. Wu, Image representation by compressed sensing, 2008 15th IEEE International Conference on Image Processing, San Diego, CA, doi: 10.1109/ICIP.2008.4712012. (2008), 1344-1347.

[5] H. Zhou, J. Zheng and L. Wei, Representing Images Using Curvilinear Feature Driven Subdivision Surfaces, IEEE Transactions on Image Processing, doi: 10.1109/TIP.2014.2327807. 23, 8 (2014), 3268-3280.

[6] K. Lu, J. Li, X. An and H. He, Hierarchical image representation via multi-level sparse coding, 2014 IEEE International Conference on Image Processing (ICIP), Paris, doi: 10.1109/ICIP.2014.7025993. (2014), 4902-4906.

[7] O. M. Soysal, B. Gunturk and K. L. Matthews, Image Retrieval using Canonical Cyclic String Representation of Polygons, 2006 International Conference on Image Processing, Atlanta, GA, doi: 10.1109/ICIP.2006.312565. (2006), 1493-1496.

[8] J. Tarquino, A. Rueda and E. Romero, A multiscale/sparse representation for Diffusion Weighted Imaging (DWI) super-resolution, 2014 IEEE 11th International Symposium on Biomedical Imaging (ISBI), Beijing, doi: 10.1109/ISBI.2014.6868037. (2014), 983-986.

[9] W. Dong, L. Zhang, R. Lukac and G. Shi, Sparse Representation Based Image Interpolation With Nonlocal Autoregressive Modeling, IEEE Transactions on Image Processing, April, doi: 10.1109/TIP.2012.2231086. 22, (4) 1 (2013), 382-1394.

[10] F. Xiao, J. Tian and G. Wang, An improved line-NAM model for gray images representation, 2017 4th International Conference on Systems and Informatics (ICSAI), Hangzhou, doi: 10.1109/ICSAI.2017.8248460. (2017), 1158-1162.