https://doi.org/10.2352/ISSN.2470-1173.2019.11.IPAS-277

The quaternion-based anisotropic gradient for the color images

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Abstract

Image gradient, as a preprocessing step is an essential tool in image processing in many research areas such as edge detection, segmentation, smoothing, inpainting, etc. In the present paper, we develop a new gradient by integrated the quaternion framework with LPA-ICI (local polynomial approximation – the intersection of confidence intervals) based on anisotropic gradient concepts for the color image processing applications. Computer simulations on the Berkeley Segmentation Dataset show that the new quaternion anisotropic gradient exhibits fewer color artifacts compared to state-of-the-art techniques including well-knowledge gradient operators.

Introduction

Image gradient, as a preprocessing step is an essential tool in image processing in many research areas such as edge detection, segmentation, smoothing, inpainting, etc. It is critical to receive useful gradient estimation on noisy color images while preserving the sharp edges. Color images may provide a vast amount of information about real-world objects. Efficient color image gradient calculation has become a very challenging task, and a has quickly lead to a broad interdisciplinary (computer vision, machine vision, computer graphics, and image processing) field of research. Usually, the anisotropic gradient used to analyze the gray-value images. The extension to color images is not straightforward. Conventionally color image processing methods are based on dealing out each color-components (red, green, and blue) separately, which fails to capture the inherent correlation between the components and results in color artifacts. As well, the noise that may exist in a color image may not be correlated across channels. So, a suitable for color images gradient need to be conducted. Recently, quaternion algebra has been using to represent a color image. In the present paper, we develop a new gradient by integrated the quaternion framework with LPA-ICI (local polynomial approximation – the intersection of confidence w intervals) based on anisotropic gradient concepts for the color image processing applications. Computer simulations on the Berkeley Segmentation Dataset show that the new quaternion anisotropic gradient exhibits fewer color artifacts compared to state-of-the-art techniques including well-knowledge gradient operators.

Related Work

Gradient calculation is one of the key procedures in many image processing (image segmentation, feature extraction), medical imaging and computer vision (object, segmentation, registration, and recognition) applications [1-4].

Edge detection is one of the fundamental tasks in image processing because it contains useful information about an image. In most cases detection algorithms based on the gradient calculations.

The derivative is one of the most popular edge detection approaches with next zero-crossings in the second derivative of the image function [5]. The first derivative is positive at the edge, negative at the non-edge, and zero in homogeneous areas.

The authors in [4] proposed to use 24 directional derivatives. They select the one with the largest magnitude as the gradient. D. Zenzo proposed to use the local contrast variations multichannel images [8]. Another method used a histogram representation of a neighborhood and edge [9]. A local vector statistic base on the differences between the average color vectors of the samples inside the windows proposed in [10]. In [11] Shiozaki proposed a method based on entropy calculation.

The algorithm "Brightness / Color / Texture Gradients" uses a combination of local brightness, color, and texture gradients to detect boundaries [12]. Each gradient is computed as the chi-squared difference in the distribution of some feature. Another algorithm "Brightness / Texture Gradients" base on a combination of local brightness and texture gradients. This approach uses a logistic to model the posterior probability of a boundary.

P. Dollar in [13] proposed boosted edge learning. This algorithm selects and combines many features across different scales using an extended version of the Probabilistic Boosting Tree classification.

In [14] proposed smooth gradient representations. This algorithm is base on a neuronal architecture, which clarifies how spatially accurate gradient representations can be obtained by relying on only high-resolution retinal responses.

Numerous gradient calculation method for grayscale images have been developed. The color images usually presented as 3D vector fields, that is difficult to processing for standard derivative approaches. Color as the human visual system plays a significant role in the perception of boundaries. Monochrome edge detection may not be enough for certain applications since no edges will be detected in gray-level images when neighboring objects have different hues but equal intensities [15]. Some of the color models (RGB, YUV, CMY and HIS) used for color edge detectors [1, 16]. The image data is transformed into luminance and two chrominance components, and an edge detector is used to find the edge map.

So, the weaknesses of traditional methods are:

- The derivative-based gradient cannot capture small neighborhood dominant features with large scale structures.
- Sensitive to a severe illumination (typically during non-monotonic lighting variations) changes and blurred/noisy images.
- Color image processing methods are based on dealing out each color-components (red, green, and blue) separately, which fails to capture the inherent correlation between the components and results in color artifacts.
- It is critical to receive useful gradient estimation on noisy color images while preserving the sharp edges.

The objective of this work is to develop a new quaternion-based anisotropic gradient for the color images (Fig. 1).

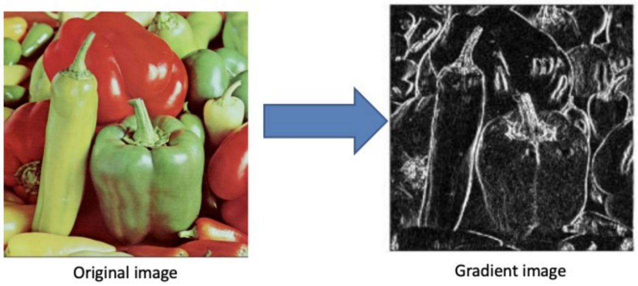

Figure 1. Image gradient

Proposed method

The main steps of the algorithm are shown in figure 2. The block diagram of the proposed gradient calculation algorithm is shown in figure 3.

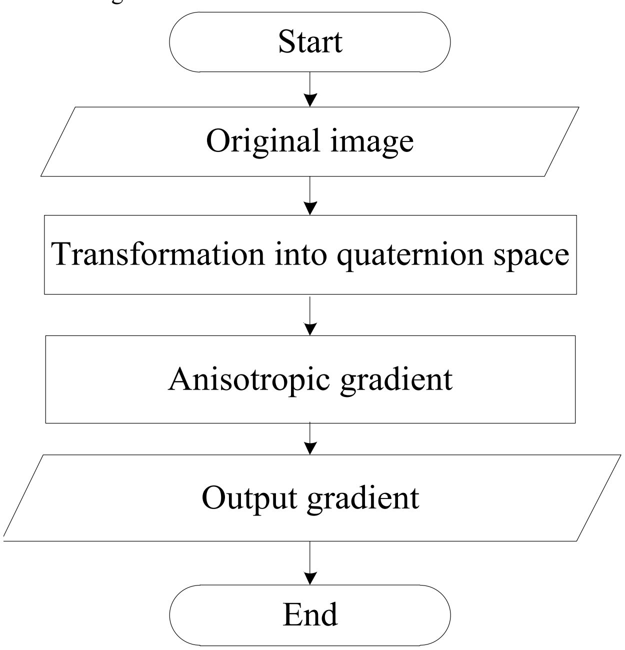

Fig. 2. The general flowchart of the proposed method

Algorithm 1 Gradient calculation

Input: Original image $I_{i,j}$

for all pixels
    calculation $Q = q_0 + q_1 i + q_2 j + q_3 k$
    for every direction from i =1 to 8 **step** 1
        building the neighborhood ω
        design a bank of linear filters of various bandwidth
        convolution with different derivative kernels
    end
end
gradient fusion

Output: Gradient image $\tilde{I}(i,j)$

Figure 3. The general flowchart of the proposed algorithm

Quaternion Framework

The color images of the *RGB* type store three colors in each pixel (red, green and blue). For segmentation tasks, the image is usually converted to grayscale, thereby losing important information about color, saturation, and other important information associated color. Components of a color image can be represented as a quaternion Q. It is usually described using the form, where the basic algebraic form for a quaternion $q \in \mathbb{H}$ is [17]:

$$Q = q_0 + q_1 i + q_2 j + q_3 k$$

where $q_0, q_1, q_2, q_3 \in \mathbb{R}$, the field of real numbers, and i, j, k are three imaginary numbers. $\mathbb{H}$ can be regarded as a 4-dimensional vector space over $\mathbb{R}$ with the natural definition of addition and scalar multiplication. Each pixel for the color image can be regarded as a pure quaternion with zero real part [18].

Figure 4 shows the color map of the RGB colors into the quaternion [19].

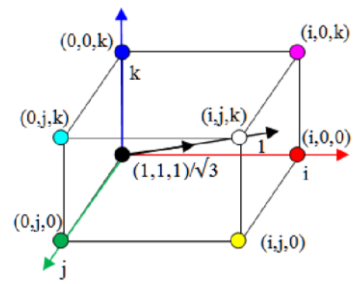

Figure 4. RBG color cube in the quaternion space

Anisotropic Gradient Calculation

As a method of noise reduction, adaptive filtering based on local polynomial estimates using the ICI rule (LPA-ICI) is used [20]. The LPA-ICI technique combines two independent ideas [21]:

- Local polynomial approximation (LPA) to design a bank of linear filters of various bandwidth that perform pixel-wise polynomial fit on a certain neighborhood.
- The intersection of confidence interval rule (ICI) is an adaptation algorithm, used to define the most suitable neighborhood where the polynomial assumptions fit better the observations.

We use the LPA-ICI method to build the ‘ideal’ neighborhood ω in the discrete image domain using LPA filters having directional supports for the image f (x, y) (Fig. 5).

The anisotropic gradient concept allows the existence of a few neighborhoods V_l at the pixel p with the corresponding a few possible different vectors $(\nabla f(p))_l$ such that

$$f(p+v) - f(p) - v^T (\nabla f(p))_l = o(|v|), v \in V_l.$$

The ICI adaptive anisotropic differentiation is aimed at estimating simultaneously both the gradients $(\nabla f(p))_l$ and the neighborhoods V_l. We propose to use the convolution quaternion metrology, which described in [17,19] for calculation convolution with different derivative kernels.

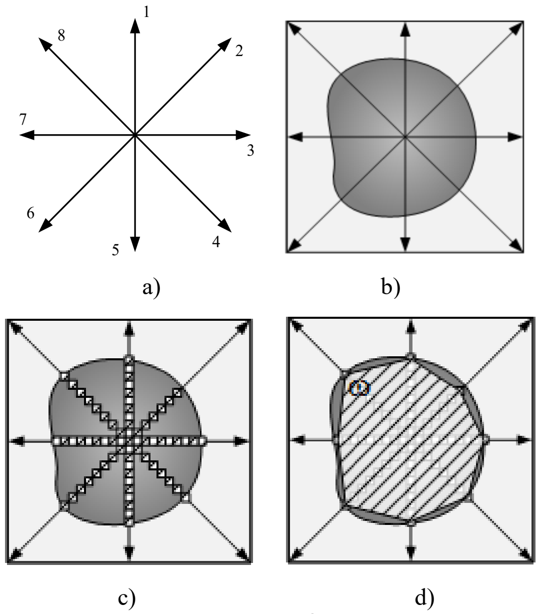

Figure 5. Building neighborhoods using LPA-ICI method

Figure 6 demonstrates the image gradient calculation results obtained by the proposed and the derivative-based algorithm respectively.


Standard magnitude gradient

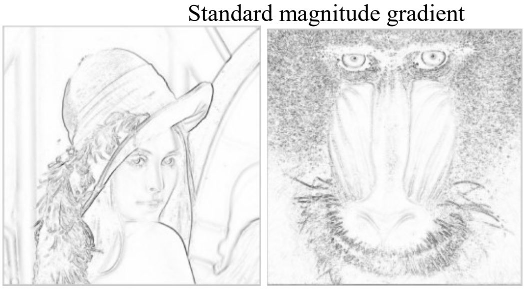
LPA-ICI anisotropic gradient

Figure 6. Gradient images

Experiments

We evaluate gradients algorithms on the Berkeley Segmentation Dataset and Benchmark (BSDS500) [22]. This dataset contains hand-labeled segmentations of dataset images from 30 human subjects. Half of the segmentations were obtained from presenting the subject with a color image; the other half from presenting a grayscale image. The public benchmark includes 300 images which are divided into a training set of 200 images and a test set of 100 images.

Figure 7 demonstrates the examples of the proposed gradient algorithm on different images from BSDS500.

We compare the image labeled by a human, the classical well-known algorithm Brightness/Color/Texture gradients and the proposed. Figures 8-10 demonstrate the image gradient calculation results obtained by various algorithms respectively (a – original image; b - the contour labeled by a human; c - the contour image by the Brightness / Color/Texture Gradients [9]; d – the contour image by the proposed method).

The examples demonstrate the effectiveness of the proposed gradient algorithm on different images with a qualitative opinion in a human observer study. The artifacts are nullified, and the fine details are brought out. It is evident that the proposed method detects proper edges at the proper location and no false edge is detected.


Figure 7. Gradient image

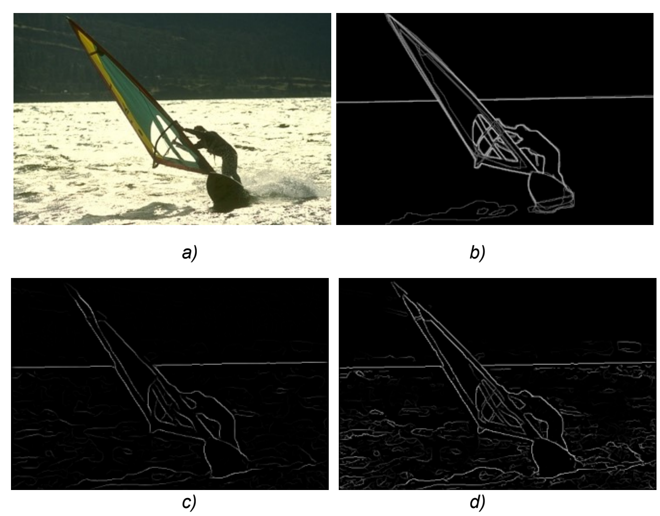

Figure 8. Examples of contour detection

We apply thresholding for the proposed gradient operator for color edge detection. For all gradient operators, the edge maps are obtained by adjusting the high and low thresholds until the best edge results are obtained. It is easy to observe from the figures that the proposed method produces more continuous and pleasing edges compared to other methods.

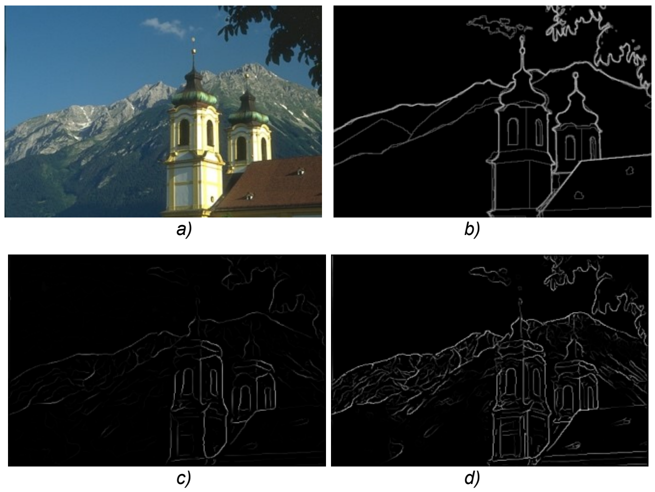

Figure 9. Examples of the contour detection

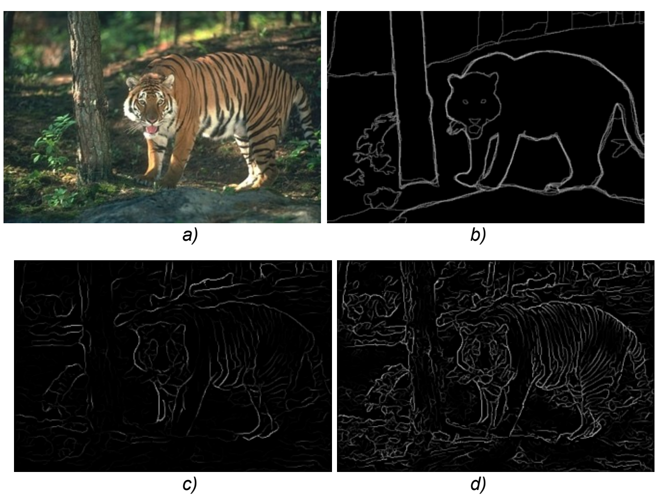

Figure 10. Examples of contour detection

Conclusions

We present a new quaternion-based anisotropic gradient. The basic idea is the anisotropic extension gradient to color images using the quaternion algebra. The quaternion framework is used to represent a color image to take into account all three channels simultaneously. The anisotropic gradient calculation is based on LPA-ICI (local polynomial approximation – the intersection of confidence intervals). Computer simulations on the Berkeley Segmentation Dataset show that the new quaternion anisotropic gradient exhibits fewer color artifacts compared to state-of-the-art techniques.

Acknowledgment

This work is supported by the Russian Science Foundation under grant №18-71-00137.

References

[1] K.N. Plataniotis and A.N. Venetsanopoulos. Color Image Processing and Applications. Springer-Verlag, Berlin, 2000.

[2] S.K. Naik and C.A. Murthy. Standardization of Edge Magnitude in Color Images. IEEE Trans. Image processing, vol. 15 (9): 2006.

[3] G. Robinson. Color edge detection. Opt. Eng., vol. 16 (5): pp. 479–484, 1977.

[4] K.N. Plataniotis, A.N. Venetsanopoulos. Color Edge Detection. In: Color Image Processing and Applications. Digital Signal Processing. Springer, Berlin, Heidelberg, 2000.

[5] D. Soumya, B.C. Bidyut. A Color Edge Detection Algorithm in RGB Color Space. International Conference on Advances in Recent Technologies in Communication and Computing, 2009.

[6] R. Nevatia. A color edge detector and its use in scene segmentation. IEEE Trans. Syst., Man, Cybern., vol. SMC-7 (11): pp. 820–826, 1977.

[7] G. Robinson. Color edge detection. Opt. Eng., vol. 16 (5): pp. 479–484, 1977.

[8] S. Di Zenzo. A note on the gradient of a multi-image. Comput. Vis. Graph. Image Process., vol. 33 (1): pp. 116– 125, 1986.

[9] M.A. Ruzon and C. Tomasi. Edge, junction, and corner detection using color distributions. IEEE PAMI, vol. 23 (11): pp. 1281–1295, 2001.

[10] L. Jin and D. Li. An efficient color-impulse detector and its application to color images. IEEE Signal Process. Lett., vol. 14 (6): pp. 397–400, 2007.

[11] A. Shiozaki. Edge extraction using entropy operator. Computer Vis.,Graph., Image Process., vol. 36 (1): pp. 1–9, 1986.

[12] C. Fowlkes, S. Belongie, F. Chung and J. Malik. Spectral Grouping Using the Nyström Method. IEEE PAMI, 2004.

[13] P. Dollar, Z. Tu, and S. Belongie. Supervised Learning of Edges and Object Boundaries. IEEE Computer Vision and Pattern Recognition (CVPR), 2006.

[14] M. Keil, Smooth gradient representations as a unifying account of Chevreul's illusion, Mach bands, and a variant of the Ehrenstein disk. Neural Computation, 18 (4): pp. 871-903, 2006.

[15] J. Scharcanski and A. N. Venetsanopoulos. Edge detection of color images using directional operators. IEEE Trans Circuits Syst Video Technol., vol. 7 (2): pp. 397–401, 1997.

[16] S.K. Naik and C.A. Murthy. Standardization of Edge Magnitude in Color Images. IEEE Trans. Image processing, vol. 15 (9), 2006.

[17] P. Denis, P. Carre, and C. Fernandez-Maloigne. Spatial and spectral quaternionic approaches for colour images. Comput. Vis. Image Und., vol. 107: pp. 74–87, 2007.

[18] A.M. Grigoryan and S.S. Agaian. Alpha-rooting method of color image enhancement by discrete quaternion Fourier

transform,” [9019-3], in Proc. SPIE 9019, Image Processing: Algorithms and Systems XII, 901904; 12 p., 2014.

[19] A. Grigoryan and Sos S. Agaian. Retooling of color imaging in the quaternion algebra. Applied Mathematics and Sciences: An International Journal (MathSJ), vol. 1 (3): 2014.

[20] V. Katkovnik, K. Egiazarian, J. Astola. Local Approximation Techniques in Signal and Image Processing, SPIE Press, Bellingham, WA, USA, 2006.

[21] A. Foi. Anisotropic Nonparametric Image Processing: Theory, Algorithms, and Applications. Ph.D. Thesis, Politecnico di Milano, Milano. Italy, 2005.

[22] Berkeley Segmentation Dataset, 2002. http://www.cs.berkeley.edu/projects/vision/bsds.

Authors Biography

Viacheslav Voronin was born in Rostov (Russian Federation) in 1985. He received his BS in radio engineering from the South-Russian State University of Economics and Service (2006), his MS in radio engineering from the South-Russian State University of Economics and Service (2008) and his Ph.D. in technics from Southern Federal University (2009). Voronin V. is a member of the Program Committee of conference SPIE. His research interests include image processing, inpainting, and computer vision.

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