Research on Vector Similarity-Based Multivariate Filtering Methods: Postprint

Authors: He Xiaojun, Xu Aigong, Li Yu

Date: 2018-08-13T00:00:00+00:00

Abstract

To circumvent the sorting dilemma encountered in color image filtering, a multivariate filtering approach tailored for color images is proposed based on an investigation of vector similarity. First, within the RGB color space, a similarity measure is defined utilizing both the distance and angular relationships between color vectors to characterize color similarity that aligns with human visual perception. Second, guided by this color similarity criterion, a color multivariate filtering method is designed and constructed, with a comprehensive analysis and investigation conducted on how its associated parameters affect filtering performance. Finally, to validate the efficacy of the proposed method, it is applied to the filtering of both standard color images and color remote sensing imagery. Experimental results demonstrate that the proposed method not only effectively resolves the sorting problem inherent in traditional filtering approaches, but also mitigates issues such as image blurring and edge degradation resulting from filtering. Furthermore, comparative experiments between the proposed multivariate filtering and conventional methods reveal that it can effectively suppress multiple types of noise while preserving original image information, yielding clear and faithful image content. The visual quality surpasses that of traditional methods, with substantial improvements observed in objective evaluation metrics.

Full Text

Preamble

Title: Research on Multivariate Filtering Method Based on Vector Similarity

Authors: He Xiaojun[1], Xu Aigong[2], Li Yu[2]
[1]College of Innovation & Practice, [2]School of Geomatics, Liaoning Technical University, Fuxin, Liaoning 123000, China

Abstract: To avoid the sorting challenge inherent in color image filtering, this paper proposes a multivariate filtering method for color images based on vector similarity. First, in RGB color space, similarity measures between color vectors are defined using both distance and angle to characterize color similarity consistent with human visual perception. Second, a color multivariate filtering method is designed and constructed based on this color similarity criterion, with in-depth analysis of how related parameters affect filtering performance. Finally, to verify the effectiveness of the proposed method, it is applied to standard color images and color remote sensing image filtering. Experimental results demonstrate that the proposed method not only effectively solves the sorting problem of traditional filtering methods but also overcomes issues such as image blurring and unclear edges caused by filtering. Additionally, comparative experiments with traditional methods show that it can effectively remove various types of noise while better preserving original image information, resulting in clear and faithful image information with superior visual effects and significantly improved objective evaluation metrics.

Keywords: vector similarity; similarity measure; vector filtering; multivariate filtering

Introduction

Noise is generated during image acquisition, transmission, and processing, directly affecting image quality and the accuracy of processing results. Due to different generation mechanisms, common image noise includes Gaussian noise, salt-and-pepper noise, and various other types. Image filtering is an image processing technique aimed at image fidelity, which recovers original image information from noise-contaminated images while preserving target edges and detail information. Therefore, it holds significant practical importance in image processing.

From the perspective of image representation, image filtering can be divided into grayscale image filtering and color image filtering. Grayscale image filtering uses grayscale values as the sole basis and is relatively easy to implement. Unlike grayscale images, color images are multivariate, involving multiple color channels with strong correlations between them. Consequently, grayscale image filtering methods cannot be directly applied to color images, making color image filtering more complex and difficult. For color images, noise not only causes color distortion and reduced clarity but also directly impacts image processing and applications.

Common filtering methods for noise include scalar and vector filtering approaches. Scalar filtering applies filtering to the three color channels of a color image separately, then synthesizes the results to obtain the filtered color image. This method fails to consider the organic relationship among the three color components in color images, potentially producing colors not present in the original image, causing further distortion and even local color inconsistencies that destroy hue and edge detail information. Vector filtering treats color pixels as vectors in color space, fully considering the relationships among color channel components, and demonstrates better robustness in noise elimination, hue preservation, and edge/detail protection. Therefore, vector filtering methods for color images are more reasonable and effective than scalar methods.

Vector median filtering (VMF), vector direction filtering (VDF), and vector direction distance filtering (DDF) have received widespread attention, but these methods employ maximum quantity smoothing during filtering, often causing image distortion by damaging edge and detail information. In addition to these vector filtering methods, Lukac et al. proposed selection-weighted vector median filtering; Wu Kun et al. introduced quaternion theory into color image filtering; and Sun Jianzhao et al. utilized fuzzy neural networks for image noise filtering. Although these improved methods enhance performance in certain aspects, they all have limitations due to the special representation form and sorting issues of color images.

When implementing vector filtering, the m color vectors in the filtering window Wi centered at pixel i are sorted according to certain rules to form an ascending sequence:

$$z_{(1)} \leq z_{(2)} \leq ... \leq z_{(j)} \leq ... \leq z_{(m)}$$

where $z_{(j)}$ represents the j-th order statistic. The smallest vector $z_{(1)}$ and the largest vector $z_{(m)}$ then become the minimum and maximum filtering outputs for that window, respectively. Different vector ordering criteria produce different filtering outputs in practical applications, typically forming nonlinear filtering methods such as VMF, VDF, and DDF.

When using inter-vector distance as the ordering criterion, the cumulative sum of distances Δ_j from each vector z_j in the window to all vectors can be expressed as:

$$\Delta_j = \sum_{k \in J} d(z_j, z_k)$$

The resulting ordering sequence is:

$$\Delta_{(1)} \leq \Delta_{(2)} \leq ... \leq \Delta_{(j)} \leq ... \leq \Delta_{(m)}$$

The vector $z_{(1)}$ corresponding to the smallest cumulative distance sum in the sequence is the vector in the current filtering window with the minimum total distance to all other vectors. Using this as the filter output constitutes the

Vector Median Filter (VMF), which outputs an existing pixel from the window and effectively removes noise pixels that differ significantly in vector distance.

Similarly, when using the angle between two vectors for ordering, the cumulative sum of angles Θ_j from each vector z_j to all vectors can be expressed as:

$$\Theta_j = \sum_{k \in J} \theta(z_j, z_k)$$

The resulting ordering sequence is:

$$\Theta_{(1)} \leq \Theta_{(2)} \leq \ldots \leq \Theta_{(j)} \leq \ldots \leq \Theta_{(m)}$$

The vector $z_{(1)}$ corresponding to the smallest cumulative angle sum is the vector in the current filtering window with the minimum total angular difference to all other vectors. Using this as the filter output constitutes the Vector Direction Filter (VDF), which effectively removes noise pixels with significantly different hues.

For more comprehensive consideration of vector correlation characteristics, both vector distance and relative direction can be used simultaneously as ordering criteria. The product B_j of the cumulative distance and angle sums for each vector z_j to all vectors is expressed as:

$$B_j = \sum_{k \in J} d(z_j, z_k) \cdot \sum_{k \in J} \theta(z_j, z_k)$$

The resulting ordering sequence is:

$$B_{(1)} \leq B_{(2)} \leq \ldots \leq B_{(j)} \leq \ldots \leq B_{(m)}$$

The vector $z_{(1)}$ corresponding to the smallest product of distance and angle cumulative sums constitutes the Directional Distance Filter (DDF), which can remove both noise pixels with large vector distance differences and those with large hue differences.

The output pixels of these filtering methods are all existing pixels from the window, introducing no new colors. However, since all pixels are smoothed equally, even those not contaminated by noise are altered, causing damage to contours, edges, and details in color images. This creates a contradiction between noise suppression and detail preservation, and all methods require extensive vector sorting with computational complexity growing geometrically with window size, making them difficult to satisfy some practical application requirements. Moreover, finding a suitable and universal color vector ordering rule is challenging, so these methods have limitations in noise removal, image restoration, and preservation of original image details.

To avoid the sorting dilemma in color image filtering, this paper proposes a multivariate filtering method for color images based on color space vector similarity. This method not only eliminates filtering problems caused by sorting but also effectively removes image noise while preserving original image detail features without causing distortion through the creation of new colors. Compared with traditional filtering methods, its performance shows significant improvement.

---

1 Theoretical Foundation

1.1 Typical Vector Filtering

Given a color image $z = \{z_i(x_i, y_i), (x_i, y_i) \in P, i \in I\}$ defined on image domain P, where $I = \{1, 2, \dots, n\}$, (x_i, y_i) are the planar coordinates of pixel i, i is the pixel index, n is the number of pixels, P is the image domain, and $z_i = (z_i^R, z_i^G, z_i^B)$ is the color vector corresponding to pixel i in RGB space, with z_i^R, z_i^G, z_i^B representing the red, green, and blue components of color vector z_i, respectively.

The color vector set in the filtering window centered at pixel i is $W_i = (z_i, z_i') = \{z_j, j \in J\}$, where $i \in I$, $i' \in N_i$, N_i is the set of neighboring pixels of pixel i, j is the pixel index in the filtering window, $J = \{1, 2, \dots, m\}$, and m is the number of vectors in the filtering window. Color image vector filtering processes each pixel' s filtering window sequentially according to certain rules to achieve filtering output, thereby transforming color image filtering into a color space vector filtering problem.

1.2 Vector Similarity Measure

Generally, pixels in homogeneous regions of color images unaffected by noise exhibit high similarity, while their similarity decreases when affected by noise. This paper exploits this characteristic by introducing the concept of similarity measure to characterize the degree of similarity between color vectors, using it as the foundation for color image multivariate filtering and effectively avoiding the color vector sorting problem.

Similarity measure is an important metric for studying and analyzing relationships between targets, with wide applications in image processing, information retrieval, pattern recognition, data mining, multivariate data analysis, and image retrieval.

For the filtering window color vector set $W_i = \{z_j, j \in J\}$ constructed for any pixel i, given a color vector pair $z_j, z_k \in W_i$, $j, k \in J$, their vector similarity measure is defined as:

$$\mu(z_j, z_k) = \exp\left(-k_1 \cdot d(z_j, z_k)\right) \cdot \cos^{k_2}\left(\theta(z_j, z_k)\right)$$

where $k_1 \in [0, \infty)$ and $k_2 \in [0, 1]$ are parameters controlling the similarity degree, and $d(z_j, z_k)$ and $\theta(z_j, z_k) \in [0, \pi/2)$ represent the distance and angle between two color vectors, respectively, expressed as:

$$d(z_j, z_k) = \left(\sum_{q=1}^{3} |z_j^q - z_k^q|^p \right)^{1/p}$$

$$\cos\left(\theta(z_j, z_k)\right) = \frac{\sum_{q=1}^{3} z_j^q z_k^q}{\left(\sum_{q=1}^{3} |z_j^q|^p\right)^{1/p} \left(\sum_{q=1}^{3} |z_k^q|^p\right)^{1/p}}$$

where p is the vector norm, here taken as $p = 2$, meaning $d(z_j, z_k)$ is the Euclidean distance between vectors. From equation (8), the defined vector similarity measure ranges in $[0, 1]$. Thus, when two pixel colors are visually similar, their corresponding color vectors in RGB space are closer in distance and angle, resulting in a larger similarity measure value indicating higher similarity. Conversely, when two pixel colors differ significantly visually, their vector distance or angle is larger, yielding a smaller similarity measure value indicating lower similarity. When the colors are identical, the two color vectors coincide (becoming the same vector) with zero distance and angle, giving a similarity measure of 1, representing the highest similarity degree. This aligns well with actual human visual perception of color images.

Human color perception exhibits variability, and similarity differs based on visual perception. Additionally, edge and detail information in color images has certain uncertainties, making it difficult to precisely distinguish these edge detail pixels from noise. Therefore, parameters k_1 and k_2 are introduced in equation (8) to artificially adjust the similarity degree between two vectors by changing their values. For the same pair of vectors, different parameter selections for k_1 and k_2 yield different similarity measure values. For instance, if $d(z_j, z_k) = 1$ and $\theta(z_j, z_k) = \pi/4$, the variation in similarity measure between the two vectors is shown in [Figure 1: see original paper]. The figure clearly demonstrates that for the same pair of color vectors, different values of parameters k_1 and k_2 produce different fuzzy similarity measures from equation (8), consistent with the fuzziness and uncertainty of human visual perception. Experimental analysis shows that different combinations of parameters k_1 and k_2 directly determine the similarity degree between two vectors. As k_1 and k_2 increase, the similarity measure between vectors decreases and similarity reduces; conversely, similarity increases. Parameter k_1 has a greater influence on the similarity measure than k_2, with the similarity measure being more sensitive to changes in k_1. This similarity measure definition effectively characterizes the similarity relationship between two vectors, laying the foundation for color image multivariate filtering.

2 Algorithm Description

Multivariate filtering of color image z processes each pixel i' s corresponding filtering window W_i sequentially to achieve filtered vector output v_i, i.e., $v_i = \mathcal{L}(W_i)$, where the vector corresponding to the current pixel i in the window is designated as z_1. The specific implementation process is as follows:

First, calculate the similarity measures between vectors using equations (8)-(10) to form a $W_i \times W_i$ similarity relationship matrix R_i:

$$R_i = [\mu(z_j, z_k)], \quad j, k \in J, i \in I$$

The similarity relationship matrix R_i obtained from equation (11) satisfies the following two conditions:

a) Reflexivity: $\mu(z_j, z_j) = 1, \quad j \in J$

b) Symmetry: $\mu(z_j, z_k) = \mu(z_k, z_j), \quad j, k \in J$

The average similarity measure for $z_j \in W_i$ can then be expressed as:

$$A_j = \frac{1}{m} \sum_{k=1}^{m} \mu(z_j, z_k), \quad j, k \in J$$

In equation (12), the average similarity measure A_j represents the mean similarity measure between vector z_j and all vectors in W_i. The vector set U_i composed of vectors corresponding to the maximum value among these average similarity measures can be expressed as:

$$U_i = \{z_t | A_t = \max\{A_j\}, z_j \in W_i\}$$

From equation (13), we obtain the vector with the maximum average similarity measure in W_i, i.e., the most "central" vector in the current window. This yields a similarity cluster and corresponding similarity measures for the most "central" vector z_t. According to actual filtering requirements, if a threshold $\alpha(0 \leq \alpha \leq 1)$ is given, then vectors in this similarity cluster with similarity measures greater than the given threshold α constitute a cut set $W_i^\alpha \subseteq W_i$, called the α-cut set:

$$W_i^\alpha = \{z_j | \mu(z_t, z_j) \geq \alpha, z_j \in W_i\}$$

The multivariate filtering output based on vector similarity in the current filtering window W_i is then:

$$v_i = \begin{cases} z_1, & z_1 \in W_i^\alpha \\ z_t, & z_1 \notin W_i^\alpha \end{cases}$$

From equation (15), when the current vector is in W_i^α, the filtering window output v_i is the original current vector z_1; when the current vector z_1 is not in W_i^α, the output v_i is the most "central" vector z_t in the current filtering window. Both the current vector and the most "central" vector are original image pixel vectors from the current filtering window.

Thus, for a given color image $z = \{z_i, i \in I\}$, the filtered color image $V = \{v_i, i \in I\}$ is formed through the above operation $\mathcal{L}$, where $I = \{1, 2, \dots, n\}$. This processing not only better preserves original image detail features but also avoids filtering problems caused by vector sorting, significantly improving algorithm efficiency and performance.

---

3 Experimental Results and Analysis

3.1 Acquisition of Relevant Quantities in Multivariate Filtering Window

The filtering window is the basic unit and region for multivariate filtering. To further analyze the acquisition and determination of various quantities within it, assume that in color image z, a 3$×$3 pixel filtering window W_i is constructed centered at a certain pixel i, with its corresponding vector set $W_i = \{z_j, j \in J\}$, $J = \{1, 2, \dots, 9\}$. The nine color vectors are: $z_1 = (35, 47, 49)$, $z_2 = (232, 236, 236)$, $z_3 = (85, 97, 99)$, $z_4 = (29, 34, 13)$, $z_5 = (143, 145, 147)$, $z_6 = (9, 23, 45)$, $z_7 = (143, 137, 146)$, $z_8 = (56, 59, 70)$, and $z_9 = (12, 18, 41)$, where the vector corresponding to the current filtering pixel i is z_1.

To simplify experimental complexity, parameters $k_1 = 0.001$ and $k_2 = 0.2$ are selected. Using equations (8)-(12), the similarity measures between vectors are calculated to form a $W_i \times W_i$ similarity relationship matrix R_i and average similarity measures A_j. The results are shown in . From the table, the maximum average similarity measure A_j is 0.9124, with its corresponding vector set $U_i = \{z_8\}$, meaning z_8 is the most "central" vector in the current window. The similarity measures corresponding to this vector' s similarity cluster are: $\{0.9683, 0.7409, 0.9455, 0.9553, 0.8653, 0.9343, 0.8698, 1.000, 0.9326\}$. When the filtering threshold $\alpha = 0.9$, the α-cut set $W_i^\alpha = \{z_1, z_3, z_4, z_6, z_8, z_9\}$. Since the current filtering vector z_1 is in the α-cut set, the filtering window output v_i is the original vector z_1, fully demonstrating that this filtering method preserves the original features of the window and pixel as much as possible within the allowable range. When the filtering threshold $\alpha = 0.97$, the α-cut set $W_i^\alpha = \{z_8\}$. At this point, the current filtering vector z_1 is not included in the α-cut set, so the filtering output v_i is the most "central" vector z_8 in this filtering window, indicating that this method can find an optimal vector as output within the allowable range, which remains an original image vector.

3.2 Multivariate Filtering Experiments

To intuitively evaluate the performance of this multivariate filtering method, the classic 150$\times150pixelcolorimage'Pepper'anda150\times$150 pixel Ikonos high-resolution remote sensing image with 1m resolution were selected as test images, as shown in Figure 2: see original paper(a2). Salt-and-pepper noise with intensity 0.08 was added to create noisy images, as shown in Figure 2: see original paper(b2). For calculating vector similarity measures in equation (8), parameters $k_1 = 0.001$ and $k_2 = 0.2$ were selected, with a 3$\times$3 pixel rectangular filtering window and threshold $\alpha = 0.97$. The output images after multivariate filtering are shown in Figure 2: see original paper(c2). Visual comparison between the original images (Figure 2: see original paper(a2)) and filtered images (Figure 2: see original paper(c2)) demonstrates that this multivariate filtering method achieves excellent filtering effects, effectively removing noise while largely preserving edge and detail information of the actual images without causing image information blurring or distortion, laying a foundation for further application of color images.

3.3 Analysis and Evaluation of Parameter Influence on Filtering Performance

Evaluation of filtering method effectiveness and performance is conducted through both subjective and objective aspects. Subjective evaluation assesses image quality based on human perception, as performed in the above experiments. However, this approach is highly subjective and influenced by different observers, image types, and environments, introducing certain uncertainties. Therefore, objective evaluation, which quantifies metrics for filtered image assessment, is primarily used in practical image filtering quality evaluation. Generally, different objective evaluation standards are applied based on different image quality characteristics. However, evaluating performance is complex in practice because it is difficult to assess both noise elimination capability and preservation of unaffected pixels.

The normalized mean square error (NMSE) is adopted as the most widely used standard for performance evaluation of the multivariate filtering method. If z_i represents the vector corresponding to pixel i in the original color image and v_i represents its estimated value (the specific value after filtering), NMSE can be expressed as:

$$\text{NMSE} = \frac{\sum_{q=1}^{3} \sum_{i=1}^{n} ||z_i^q - v_i^q||^2}{\sum_{q=1}^{3} \sum_{i=1}^{n} ||z_i^q||^2}$$

To analyze the influence of parameters on filtering performance, a 150$\times$150 pixel 'Pepper' image was selected as the test image (Figure 2: see original paper). The image was contaminated with Gaussian noise, salt-and-pepper noise, and combinations thereof. The noise types and related parameters are listed in .

Table 2 Noise Types | Noise Mode | Noise Type | |———|———| | Mode 1 | Gaussian (variance 0.005) | | Mode 2 | Gaussian (variance 0.005) + Salt-and-pepper (intensity 0.02) | | Mode 3 | Salt-and-pepper (intensity 0.02) | | Mode 4 | Salt-and-pepper (intensity 0.02) + Gaussian (variance 0.005) |

The original test images contaminated with the above noise types are shown in [Figure 3: see original paper], where figures (a)-(d) correspond to the noise images generated by the four noise modes in .

First, the influence of parameter k_1 on filtering effect and performance under different noise interferences is evaluated. Assuming $k_2 = 0.2$ and threshold $\alpha = 0.5$, while k_1 varies from 0 to 10, the NMSE evaluation curves for multivariate filtering performance are shown in Figure 4: see original paper-(d). The results show that when $k_1 = 0.001$, the multivariate filtering method achieves the best filtering effect for noise mode 1 (Figure 4: see original paper); when $k_1 = 0.02$, it achieves the best filtering effect for noise modes 2-4 (Figure 4: see original paper-(d)). Overall, the filtering performance for noise mode 3 (salt-and-pepper noise) is particularly notable.

Similarly, when evaluating the influence of parameter k_2 on filtering performance, with $k_1 = 0.001$, threshold $\alpha = 0.5$, and parameter $k_2 \in [0, 1]$, the NMSE variation curves are shown in [Figure 5: see original paper]. The variation demonstrates that when $k_2 = 0.2$, the filtering effect and performance reach optimum for all noise modes.

The threshold α is used to adjust the probability of preserving original pixels during filtering. When $k_1 = 0.001$, $k_2 = 0.02$, and threshold α varies from 0 to 1, the NMSE curves are shown in [Figure 6: see original paper]. The variation indicates that when $\alpha < 0.6$, the best filtering effect is achieved for all noise modes.

Based on the above experiments and analysis, parameters k_1, k_2, and threshold α all directly affect multivariate filtering performance and should generally be determined according to specific conditions in practice.

3.4 Performance Comparison Experiments

The proposed multivariate filtering method is compared with typical filtering methods including VMF, VDF, and DDF to further study and analyze its performance. Based on previous experimental analysis, the parameters for the proposed multivariate filtering method are set as $k_1 = 0.001$, $k_2 = 0.2$, $\alpha = 0.5$, with a 3$×$3 pixel filtering window for all methods. The four test noisy images are shown in [Figure 3: see original paper].

The filtering results for VMF, VDF, DDF, and the proposed method for noise mode 1 are shown in Figure 7: see original paper-(a4), respectively; results for noise modes 2, 3, and 4 are shown in Figure 7: see original paper-(d1-d4). Visual comparison shows that the proposed method (Figure 7: see original paper-(d4)) achieves excellent filtering effects and performance, better preserving original image detail features while smoothing image edges.

While visual assessment can sometimes be difficult, NMSE is again used for evaluation and analysis. The NMSE performance curves are shown in [Figure 8: see original paper], where figure (a) shows NMSE evaluation for the four filtering methods against noise mode 1 (corresponding to Figure 7: see original paper-(a4)), and figures (b)-(d) show NMSE evaluation curves for noise modes 2, 3, and 4 (corresponding to Figure 7: see original paper-(d1-d4)). The NMSE curves clearly demonstrate that the proposed multivariate filtering method shows significant improvement in objective evaluation metrics compared with traditional VMF, VDF, and DDF methods, achieving better filtering effects and performance for all four noise types.

---

4 Conclusion

To address color image filtering problems, this paper defines a similarity measure using both distance and angle in RGB color space to characterize vector similarity relationships consistent with human visual perception. Based on this foundation and criterion, a multivariate filtering method for color images is constructed and proposed. This method not only avoids the vector sorting dilemma during filtering but also effectively removes image noise while preserving original image detail features without causing distortion through new color generation. Compared with traditional filtering methods, its performance shows substantial improvement.

The method demonstrates a good compromise between preserving original pixels and removing noise pixels, effectively maintaining image edge and detail characteristics. Experiments show it achieves excellent filtering effects, particularly when parameters $k_1 = 0.001$, $k_2 = 0.2$, and threshold $\alpha < 0.6$. Comparative experiments with common filtering methods using objective evaluation metric NMSE demonstrate that the proposed method can effectively remove various noise types while better preserving original image information, with superior visual effects and evaluation metrics compared to traditional methods, offering certain promotion and practical value.

References

[1] Tan Zhiguo, Ou Jianping, Zhang Jun, et al. A laminar denoising algorithm for depth image [J]. Acta Optica Sinica, 2017, 37 (5): 94-100.

[2] Yang Hao, Chen Leiting, Qiu Hang. Regularization filtering algorithm based on local characteristics [J]. Application Research of Computers, 2017, 34 (9): 2817-2821.

[3] Wang Yu, Yan Mo. Color image segmentation by global similarity measure [J]. Journal of Signal Processing, 2016, 32 (8): 951-959.

[4] Feng Pingxing. Adaptive filtering algorithm for blind signal processing [J]. Application Research of Computers, 2018, 35 (4): 1092-1095.

[5] Xiao Hongguang, Wen Jun, Chen Lifu, et al. New road extraction algorithm of high resolution SAR image [J]. Computer Engineering and Applications, 2016, 52 (15): 198-202, 207.

[6] Ma Lianghui, Li Dongxing, Zhang Huaqiang, et al. An algorithm of suppressing image noise based on the integration of wavelet threshold function and improved median filter [J]. Optical Technique, 2017, 43 (1): 38-42.

[7] Xie Wei, You Min, Zhou Yuqin. Guided image filter and application based on adaptive fractional-order differential [J]. Application Research of Computers, 2017, 34 (01): 283-286, 301.

[8] Zheng Dan, Ma Shangchang, Zhao Jing. Research on image enhancement method based on spatial filtering [J]. Microcomputer & Its Applications, 2017, 36 (4): 40-42, 46.

[9] Lukac R, Plataniotis K N, Smolka B, et al. Generalized selection weighted vector filters [J]. EURASIP Journal on Advances in Signal Processing, 2004, 2014 (1): 1870-1885.

[10] Wu Kun, Li Guiju, Han Guangliang, et al. Color image detail enhancement based on quaternion guided filter [J]. Journal of Computer-Aided Design & Computer Graphics, 2017, 29 (3): 419-427.

[11] Sun Jianzhao, Chang Qing. Research on image noise filtering algorithm [J]. Control Engineering of China, 2016, 23 (06): 848-851.

[12] Melo R O, Costa C F F, Costa M G F. Leak detection of natural gas with base on the components of color spaces RGB and HSI using novelty filter [J]. IEEE Latin America Transactions, 2014, 12 (8): 1560-1565.

[13] Sghaier M O, Foucher S, Lepage R. River extraction from high-resolution images combining structural feature and mathematical morphology [J]. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2017, 10 (3): 1025-1038.

[14] Shih H C, Liu E R. Automatic reference color selection using adaptive mathematical morphology and application in image segmentation [J]. IEEE Trans on Image Processing, 2016, 25 (10): 4665-4676.

[15] Liu Hui, Zhang Yunsheng, Zhang Yinhui, et al. Vector morphology image processing based on difference formula in uniform space [J]. Journal of Image and Graphics, 2011, 16 (12): 2145-2151.

[16] Li Shuqing, Li Ruihua, Wang Xiao. Research on split methods of ocean oil spill in SAR image [J]. Engineering of Surveying and Mapping, 2017, 26 (2):

37-41.

[17] Fang Zhiwen, Cao Zhiguo, Xiao Yang. Object proposal algorithm for the depth image [J]. Journal of Signal Processing, 2016, 32 (02): 193-202.

[18] Wang Yang, Lu Huanzhang, Sun Guangfu. Similarity measure between shapes based on spatial fuzzy representation [J]. Systems Engineering and Electronics, 2005, 27 (2): 340-342.

[19] An Jing. Image enhancement algorithm and the application based on mathematical morphology [D]. Lanzhou: Northwest Normal University, 2016.

[20] Yu Haiyan, Niu Qingli. Effective application of computer technology in image contour extraction [J]. Modern Electronics Technique, 2016, 39 (10): 34-36.

[21] Zheng Yahui. New grayscale morphology operator based on the hypergraph and the mathematical morphology [D]. Xi' an: Xidian University, 2016.

[22] Zhen Yong, Liu Wei, Chen Jianhong, et al. Geometric structure feature extraction of ship target in high-resolution SAR image [J]. Journal of Signal Processing, 2016, 32 (4): 424-429.

[23] Tang Hongzhong, Huang Huixian, Guo Xuefeng, et al. New method of morphological color image processing [J]. Journal of Computer Applications, 2010, 30 (8): 2101-2104.

[24] Wang Yu, Li Yu, Zhao Quanhua. Segmentation of the color remote sensing image with unknown number of classes based on the regular tessellation and RJMCMC [J]. Chinese Journal of Scientific Instrument, 2015, 36 (6): 1388-1396.

[25] Zhao Quanhua, Zhao Xuemei, Li Yu. A fuzzy ISODATA approach combing HMRF model for high resolution remote sensing image segmentation [J]. Journal of Signal Processing, 2016, 32 (2): 157-166.

[26] Xu Zeshui. On similarity measures of interval-valued intuitionist fuzzy sets and their application to pattern recognitions [J]. Journal of Southeast University, 2007, 23 (3): 139-143.

[27] Wang Shuqing, Yao Wei, Chen Jin, et al. Image edge detection based on hitogram equalisation and morphology processing [J]. Computer Applications and Software, 2016, 33 (3): 193-196.

[28] Yu Yanfei, Zheng Quan, Wang Song, et al. Image noise detection technology base on spatial domain [J]. Journal of Computer Applications, 2012, 32 (6): 1552-1556.

Note: Figure translations are in progress. See original paper for figures.