Postprint of Color Morphological Image Processing Method Based on Fuzzy Similarity

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Abstract

To extend traditional grayscale image mathematical morphology to color images, a color morphological image processing method that incorporates vector-space fuzzy similarity is proposed. Firstly, in RGB color space, a fuzzy similarity measure is defined utilizing the distance and angle between color vectors to characterize the degree of color similarity that aligns with human visual perception. Using the aforementioned similarity measure as a criterion, the supremum and infimum of any arbitrary set of colors in color space are defined. The fundamental operations of color morphology, including dilation, erosion, opening, and closing, are constructed by employing the supremum and infimum of the center pixel and the pixels within its structuring element. Furthermore, the proposed color morphological operations are applied to high-resolution remote sensing imagery, and their capabilities for deforming and smoothing ground object targets are validated through experimental comparisons, thereby demonstrating their practicality and effectiveness.

Full Text

Preamble

Title: Color Morphology Image Processing Method Based on Fuzzy Similarity

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Abstract: To extend mathematical morphology from grayscale to color images, this paper proposes a color mathematical morphology based on fuzzy similarity defined in the RGB color vector space. First, in RGB color space, a fuzzy similarity measure consistent with human visual perception is defined using the distance and angle between two color vectors to describe their similarity degree.

Based on this similarity measure, the supremum and infimum of any set of colors in the color space are defined. The basic operations of color mathematical morphology, including dilation, erosion, opening, and closing, are constructed using the supremum and infimum of the center pixel and its neighboring pixels within the structural element. Finally, the proposed color morphological operations are applied to high-resolution remote sensing images. Experimental comparisons verify their capability for object deformation and smoothing, demonstrating their practicality and effectiveness.

Keywords: color space; color morphology; fuzzy similarity measure; image processing

0 Introduction

In recent years, color images have been widely used in various fields of human production and life. Compared with binary and grayscale images, color images contain not only brightness information but also color information perceivable by humans, making color image processing an increasingly important research area. In image processing, mathematical morphology utilizes structural elements (such as circles, squares, line segments, etc.) as basic units to process image information for analyzing and identifying geometric features and structures of image targets. As a nonlinear image processing and analysis method, mathematical morphology has been successfully applied to binary and grayscale images, forming a complete morphological theory. Binary morphology treats binary images as sets and employs simple set operations (such as intersection, union, complement, and translation) to detect geometric structures embedded in images. Since these operations are set-based, binary morphology offers clear principles, simple computation, easy extension, and suitability for parallel processing, and has been widely used in image processing tasks such as denoising, boundary detection, skeletonization, and region segmentation. Grayscale morphology evolved from binary morphology by replacing intersection and union operations with the minimum and maximum gray values within the structural element.

However, extending grayscale morphology to color morphology faces significant challenges. The simplest approach treats an RGB color image as three independent monochrome images (red, green, and blue), processes each using grayscale morphology, and then combines the results back into an RGB color image. This approach has two major drawbacks: first, it alters the original colors, resulting in lost or distorted image information; second, it fails to consider the correlation between color components, treating the color image as merely three independent images rather than effectively utilizing color information. Another approach extends grayscale morphology to color morphology based on multivariate data ordering criteria, such as marginal ordering, conditional ordering, regional ordering, and reduced ordering, which rank colors within the structural element and define basic morphological operations using principles similar to minimum and maximum values in grayscale morphology. However, for rich and diverse color images, it is difficult to find a suitable and universal color vector ordering method, making this approach highly limited.

To overcome these limitations, this paper introduces the concept of fuzzy similarity measures in RGB color space to characterize the similarity between color vectors and defines basic color morphological operations accordingly. This color morphology can not only smooth color targets but also effectively handle detail features with inconsistent pixels in homogeneous regions, ultimately achieving the goals of color image analysis and processing.

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1 Color Morphology Method Based on Fuzzy Similarity

1.1 Fuzzy Similarity Measure

The RGB color space is the most fundamental and commonly used three-dimensional vector space for color representation. Let $V = \{v_i, i = 1, \dots, n\}$ be the set of all color vectors in RGB color space, where n is the total number of colors in the space, i is the color index, and $v_i = (v_{iR}, v_{iG}, v_{iB})$ is the color vector for color i, with v_{iR}, v_{iG}, and v_{iB} representing the red, green, and blue components of color vector i, respectively.

In this color space, given a pair of color vectors $v_i, v_i' \in V$, as shown in [Figure 1: see original paper], the fuzzy similarity measure is defined as:

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

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

$$d(v_i, v_i') = \sqrt{(v_{iR} - v_{iR}')^2 + (v_{iG} - v_{iG}')^2 + (v_{iB} - v_{iB}')^2}$$

$$\theta(v_i, v_i') = \arccos\left(\frac{v_{iR}v_{iR}' + v_{iG}v_{iG}' + v_{iB}v_{iB}'}{\sqrt{v_{iR}^2 + v_{iG}^2 + v_{iB}^2} \cdot \sqrt{v_{iR}'^2 + v_{iG}'^2 + v_{iB}'^2}}\right)$$

From Equation (1), we can see that the defined fuzzy similarity measure takes values in the interval $[0, 1]$. In RGB color space, when two color vectors are closer in distance and angle (i.e., smaller distance and smaller angle), the similarity measure value is larger, indicating higher similarity. Conversely, when the distance or angle between two color vectors is large, the similarity measure value is smaller, indicating lower similarity. When two color vectors coincide (i.e., are identical), both distance and angle are zero, and the similarity measure equals 1, representing the highest similarity. These characteristics align with actual visual perception. Additionally, due to individual differences in color perception—where the similarity between the same two color vectors may vary based on personal visual perception—this similarity has inherent fuzziness. Therefore, parameters k_1 and k_2 are introduced in Equation (1) to artificially adjust the similarity degree between two vectors, making it consistent with the fuzziness of human visual perception.

The fuzzy similarity measure defined in this paper not only characterizes the similarity between color vectors but also aligns with the uncertainty and fuzziness of human visual perception, providing the theoretical foundation for constructing color morphology.

1.2 Basic Operations of Color Morphology

Given a color image C, let $V_C = \{v_j, j = 1, \ldots, m\}$ be the set of all color vectors in C, where j is the pixel index and m is the number of pixels in color image C. Let V_j denote the set of color vectors within the structural element centered at pixel j, i.e., $V_j = \{v_{jp}, p = 1, \ldots, q\} \subset V_C$, where p is the pixel index in V_j and q is the number of color vectors in this set.

In the current structural element V_j, the set of least similar color vector pairs V_j^{ds} can be obtained by:

$$V_j^{ds} = \{(v_{jp}, v'_{jp}) \mid (v_{jp}, v'_{jp}) = \arg\min\{\mu(v_{jk}, v_{jl}) \mid v_{jk}, v_{jl} \in V_j\}\}$$

That is, V_j^{ds} is the set of all color vector pairs in $V_j \times V_j$ with the minimum fuzzy similarity measure. Then, a pair is randomly selected from V_j^{ds} as the least similar color vector pair, denoted as $(v_{jds1}, v_{jds2}) \in V_j^{ds}$. Based on their magnitudes, v_{jds1} and v_{jds2} are called the maximum color vector (the one with larger magnitude) v_{jmax} and the minimum color vector (the one with smaller magnitude) v_{jmin}, respectively.

As shown in [Figure 2: see original paper], assuming the color vector set V_j within the structural element centered at pixel j consists of 16 two-dimensional vectors (where vector length and relative direction serve as the basis for similarity judgment, and colors are assigned only for illustrative convenience), the least similar color vector pair obtained through fuzzy similarity measure calculation is (v_{jmax}, v_{jmin}). The vector represented in bold red is longer than the one in bold blue, so the bold red vector represents the maximum color vector v_{jmax}, while the bold blue vector represents the minimum color vector v_{jmin}.

Using the maximum and minimum color vectors (v_{jmax}, v_{jmin}) as cores, all color vectors in V_j are divided into two classes, denoted as CL_{jmax} and CL_{jmin}. For any color vector $v_{jp} \in V_j$, if the similarity measure between v_{jp} and v_{jmax} is greater than that between v_{jp} and v_{jmin}, then v_{jp} belongs to CL_{jmax}; otherwise, v_{jp} belongs to CL_{jmin}:

$$CL_{jmin} = \{v_{jp} \mid \mu(v_{jp}, v_{jmin}) \geq \mu(v_{jp}, v_{jmax}), v_{jp} \in V_j\}$$

$$CL_{jmax} = \{v_{jp} \mid \mu(v_{jp}, v_{jmax}) \geq \mu(v_{jp}, v_{jmin}), v_{jp} \in V_j\}$$

Based on the calculated similarity measures, we can determine that the other vectors shown in blue in [Figure 2: see original paper] have higher similarity with v_{jmin} than with v_{jmax}, thus belonging to CL_{jmin}. Similarly, the vectors shown in red have higher similarity with v_{jmax} than with v_{jmin}, thus belonging to CL_{jmax}. All blue vectors in CL_{jmin} exhibit good similarity, and all red vectors in CL_{jmax} exhibit good similarity.

The color vectors with highest similarity in CL_{jmin} and CL_{jmax}, denoted as v_{cljmin} and v_{cljmax}, can be expressed as:

$$v_{cljmin} = \arg \max_{v_{jp} \in CL_{jmin}} \sum_{v'_{jp} \in CL_{jmin}} \mu(v_{jp}, v'_{jp})$$

$$v_{cljmax} = \arg \max_{v_{jp} \in CL_{jmax}} \sum_{v'_{jp} \in CL_{jmax}} \mu(v_{jp}, v'_{jp})$$

Based on the highest similarity color vectors obtained from Equations (7) and (8), the infimum operation $\wedge$ and supremum operation $\vee$ in structural element V_j can be defined as:

$$\bigwedge V_j = v_{cljmin}$$

$$\bigvee V_j = v_{cljmax}$$

From Equations (9) and (10), we can see that the color vectors output by the infimum operation $\wedge$ and supremum operation $\vee$ are the highest similarity color vectors v_{cljmin} and v_{cljmax} in color vector classes CL_{jmin} and CL_{jmax}, respectively. These vectors maximize the sum of similarity measures with all other color vectors in their respective classes. Moreover, the color vectors output by supremum and infimum operations are both from the color vectors within the structural element of the given color image, meaning these operations do not generate new color vectors and thus effectively preserve the original image information.

The basic operations of the proposed color morphology are defined using the supremum and infimum of structural element V_j. For a given color image C, where all color vectors form set V_C, the dilation operation δ_C, erosion operation ε_C, closing operation χ_C, and opening operation $\circ_C$ are expressed as:

$$\delta_C(V_C) = \{\bigvee V_j \mid j = 1, 2, \dots, m\}$$

$$\varepsilon_C(V_C) = \{\bigwedge V_j \mid j = 1, 2, \dots, m\}$$

$$\chi_C(V_C) = \delta_C(\varepsilon_C(V_C))$$

$$\circ_C(V_C) = \varepsilon_C(\delta_C(V_C))$$

From these color morphological operations, we can see that the dilation operation on the color vector set V_C finds the supremum of the color vector subset within structural element V_j, while the erosion operation finds the infimum. Opening and closing operations are composites of dilation and erosion, differing only in the order of computing supremum and infimum. This approach not only effectively completes color image morphological processing but also largely preserves the basic characteristics of pixel color vectors in the original image. The algorithm flowchart for applying this method to practical color image processing is shown in [Figure 3: see original paper].

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2 Experimental Results and Analysis

2.1 Parameter Analysis of Fuzzy Similarity Measure

The fuzzy similarity measure is the foundation of the proposed color morphological operations, with parameters k_1 and k_2 introduced to control and adjust the similarity degree between two vectors. For the same pair of vectors, different values of k_1 and k_2 yield different similarity degrees, which aligns with the fuzziness of human visual perception.

To investigate the effect of parameter k_1 on the defined fuzzy similarity measure, we set $k_2 = 1$ in Equation (1) and vary k_1 through values of 0, 0.1, 0.25, 0.5, 0.75, and 1.0. The variation of the fuzzy similarity measure is shown in [Figure 4: see original paper]. In Figure 4: see original paper, with $k_1 = 0$, the similarity measure depends only on the angle between vectors, independent of distance, and decreases gradually as the relative angle increases. As shown in Figure 4: see original paper-(f), when k_1 takes values of 0.1, 0.25, 0.5, 0.75, and 1.0, the similarity measure is highly sensitive to k_1, decreasing rapidly as k_1 increases.

Similarly, to study the effect of parameter k_2, we set $k_1 = 1$ in Equation (1) and vary k_2 through values of 0, 0.6, 0.7, 0.8, 0.9, and 1.0. The influence on the similarity measure is shown in [Figure 5: see original paper]. Figure 5: see original paper shows that when $k_2 = 0$, the similarity measure depends only on distance, independent of angle, and decreases with increasing distance. As shown in Figure 5: see original paper-(f), the similarity measure between color vectors decreases gradually as k_2 increases.

To further analyze the combined effect of parameters k_1 and k_2, we assume $d = 1$ and $\theta = \pi/4$, and examine the variation of the fuzzy similarity measure between two vectors as shown in [Figure 6: see original paper]. The results clearly demonstrate that for the same pair of color vectors, different combinations of k_1 and k_2 produce different similarity measures. The parameters directly determine the similarity degree: as k_1 and k_2 increase, the similarity measure decreases and similarity declines, and vice versa. Parameter k_1 has a greater influence than k_2, with the similarity measure being more sensitive to changes in k_1. This aligns with the characteristic that color vector similarity varies with individuals and environments, satisfying the uncertainty and fuzziness introduced by human visual perception in color image processing.

2.2 Parameter Analysis in Structural Unit

The structural element is the basic unit and window for color morphological image processing. To further analyze the determination of the least similar color vector pair, maximum/minimum color vectors, highest similarity color vectors, and supremum/infimum, we consider a structural element V_j in color image C containing six color vectors: (255, 0, 0), (205, 0, 0), (205, 50, 0), (40, 255, 0), (40, 215, 0), and (80, 215, 0). Based on the previous analysis of parameters k_1 and k_2, we select $k_1 = 0.001$ and $k_2 = 0.8$ to compute the fuzzy similarity measures between these six color vectors using Equation (1). The results are shown in .

From , we can see that color vectors 1 (255, 0, 0) and 4 (40, 255, 0) have the smallest fuzzy similarity measure (0.3043). According to Equation (4), we obtain the set of least similar color vector pairs V_j^{ds}, which contains only the pair $\{$(255, 0, 0), (40, 255, 0)$\}$. Since color vector 4 (40, 255, 0) has a larger magnitude than color vector 1 (255, 0, 0), they are designated as the maximum and minimum color vectors, respectively. Comparing the similarity measures of vectors in V_j with the maximum (vector 4) and minimum (vector 1) color vectors, we find that vectors 2 and 3 have higher similarity with vector 1 than with vector 4, while vectors 5 and 6 have higher similarity with vector 4. Therefore, vectors 1, 2, and 3 belong to color vector class CL_{jmin}, while vectors 4, 5, and 6 belong to CL_{jmax}.

Using Equations (7) and (8), we compute that color vector 2 (205, 0, 0) has the maximum cumulative similarity sum (2.8851) with other vectors in CL_{jmin}, making it the highest similarity color vector v_{cljmin} in this class—the infimum of structural element V_j and the erosion output for the current structural element. Similarly, color vector 5 (40, 215, 0) is the highest similarity color vector

v_{cljmax} in CL_{jmax}—the supremum of V_j and the dilation output for the current structural element.

2.3 Basic Operations Experiment of Color Morphology

Based on the definitions and parameter analysis above, we select a 30×30 region centered at pixel (70, 55) from the color image "Peppers" as the test region for morphological operations. This region, shown in the blue box in Figure 7: see original paper, contains four typical target objects: red pepper, green pepper, yellow pepper, and black shadow. The extracted region is shown in Figure 7: see original paper and magnified 5× in Figure 7: see original paper. The parameters for computing the color fuzzy similarity measure are set to $k_1 = 0.001$ and $k_2 = 0.8$, and the structural element is a 3×3 pixel square. The results of color morphological operations—including erosion, dilation, opening, and closing—are shown in Figure 7: see original paper-(c4). To observe details clearly, the processed images are magnified 5× in Figure 7: see original paper-(d4).

Figure 7: see original paper and (d1) show that erosion operation expands the shadow area (background) while compressing other targets, fills small gaps, and makes the color and edges of each target smoother. Figure 7: see original paper and (d2) demonstrate that dilation produces the opposite effect: the shadow area is compressed while other targets are expanded (light colors extend, dark colors compress), and "spikes" in the original image are eliminated, again with smoother colors and edges. Opening and closing operations, shown in Figure 7: see original paper-(d3) and (c4)-(d4), exhibit similar characteristics. These experiments demonstrate that the proposed color morphological operations conform to the fundamental principles of morphology, effectively address the problem of inconsistent pixels in homogeneous regions, and enable applications such as color image segmentation, filtering, and target extraction.

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3 Color Morphology Processing of High-Resolution Remote Sensing Images

3.1 Parameter Impact Analysis on Remote Sensing Images

To further analyze the impact of fuzzy similarity measure parameters on actual color image processing results, we select a 150×150 pixel Ikonos high-resolution color remote sensing image, shown in [Figure 8: see original paper]. Three parameter sets for the fuzzy similarity measure are used: (a) $k_1 = 0.01$ and $k_2 = 0.2$, (b) $k_1 = 0.005$ and $k_2 = 0.5$, and (c) $k_1 = 0.001$ and $k_2 = 0.8$. The structural element is a 3×3 pixel square. The results of color morphological operations (erosion, dilation, opening, closing) are shown in [Figure 9: see original paper]-[Figure 12: see original paper].

The results demonstrate that parameters k_1 and k_2 significantly affect color morphological operations. For the same color image and morphological operation, different parameter values produce different results, satisfying the requirements of fuzziness and uncertainty in human visual perception. Comparing the morphological operation results, we observe that when $k_1 = 0.001$ and $k_2 = 0.8$ (Figure 9: see original paper–Figure 12: see original paper), all operations achieve optimal performance in terms of both smoothing targets and preserving original image edge characteristics. As k_1 decreases and k_2 increases, the results of all morphological operations improve noticeably, with parameter k_1 having a greater impact than k_2. Additionally, when k_1 decreases while k_2 increases, the similarity between images after dilation and erosion operations increases. Regardless of whether the operation causes target contraction or expansion, color targets and edges become smoother, achieving the desired goals of color image processing.

3.2 Comparative Experiments of Color Morphology

To compare the proposed color morphology with methods extended from grayscale morphology and region-based ordering morphology, we use the same Ikonos color remote sensing image from [Figure 8: see original paper] as the test image. The grayscale morphology extension method treats the color image as three monochrome images (red, green, blue), processes each with grayscale morphology, and combines the results. The region-based ordering morphology ranks vectors by gradient within the current region (3×3 pixels) and uses the vectors with minimum and maximum gradients as morphological outputs. For our proposed method, the fuzzy similarity measure parameters are set to $k_1 = 0.001$ and $k_2 = 0.8$, with a 3×3 pixel structural element. The results of erosion, dilation, opening, and closing operations are shown in [Figure 13: see original paper]–[Figure 16: see original paper], where (a) shows our color morphology results, (b) shows grayscale morphology extension results, and (c) shows region-based ordering morphology results.

Visual comparison reveals that our proposed color morphology processes color images more delicately. It smooths color target edges while preserving original image details without causing distortion (Figure 13: see original paper–Figure 16: see original paper). The grayscale morphology extension method loses some image details, produces unsmooth target edges, and causes image distortion (Figure 13: see original paper–Figure 16: see original paper). The region-based ordering morphology performs reasonably well for erosion (which uses the closest gradient vector) but poorly for operations involving dilation (Figure 13: see original paper–Figure 16: see original paper). These comparative experiments clearly demonstrate that our proposed color morphology not only effectively processes color images but also achieves superior results, providing a solid foundation for color image target extraction, filtering, and segmentation. Furthermore, this color morphology can produce more practical results by adjusting parameters k_1 and k_2 and varying window sizes, fully proving its effectiveness and practicality.

3.3 Performance Analysis of Color Morphology Operations

To evaluate the performance of our proposed color morphology operations, we conduct quantitative analysis of the impact on grayscale and color information after morphological operations. From the perspective of grayscale morphology theory, we convert the color images resulting from the three different morphological methods in [Figure 13: see original paper]-[Figure 16: see original paper] to their corresponding grayscale images and compute the average similarity measure with the original grayscale image. As shown in [Figure 17: see original paper], all morphological operations (erosion, dilation, opening, closing) alter the grayscale information of the original image. Our proposed color morphology and the grayscale morphology extension method show higher similarity and consistency with the original grayscale image, with our method producing more gradual changes—better preserving grayscale detail information. The region-based ordering morphology is less satisfactory in terms of grayscale value changes.

Additionally, from the perspective of color image similarity, we compute the average fuzzy similarity measure between the morphological operation results in [Figure 13: see original paper]-[Figure 16: see original paper] and the original image on a pixel-by-pixel basis (erosion-original, dilation-original, opening-original, closing-original) to evaluate their similarity to the original image. As shown in [Figure 18: see original paper], all morphological operations alter the original image, but our proposed color morphology maintains the highest similarity. This means that while achieving the same color image processing goals, our morphological operations introduce minimal changes to the original image' s detail features, significantly reducing color image distortion. This quantitative analysis aligns with visual observations from [Figure 13: see original paper]-[Figure 16: see original paper].

Through these quantitative comparisons, we can conclude that our proposed fuzzy similarity-based color morphology not only aligns with classical binary and grayscale morphology theory but also effectively preserves original image detail features, demonstrating excellent processing performance and establishing a foundation for its broader application.

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4 Conclusion

To develop color morphology, this paper introduces a fuzzy similarity measure in RGB color space based on color vector distance and angle, which characterizes color vector relationships according to human visual perception characteristics. Using this fuzzy similarity measure along with supremum and infimum concepts, we define color morphological operations for color images, including dilation, erosion, closing, and opening. Through experiments, we conduct in-depth analysis and research on the parameters and characteristics of the fuzzy similarity measure. Comparative experiments with other color morphology methods demonstrate that our proposed approach not only processes color images effectively but also achieves superior results, providing a solid foundation for color image target extraction, filtering, and segmentation. Moreover, this color morphology can produce more realistic results by adjusting parameters k_1 and k_2 and varying window sizes, fully proving its effectiveness and practicality.

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