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An FPCA-Based Color Morphological Filter for Noise Removal

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Abstract. *Morphological filtering is a useful technique for the processing and analysis of binary and gray scale images. The extension of morphological techniques to color images is not a straightforward task because this extension stems from the multivariate ordering problem. Since multivariate ordering is ambiguous, existing approaches have used known vector ordering schemes for the color ordering purpose. In the last decade, many different color morphological operators have been introduced in the literature. Some of them have focused on noise suppression purposes. However, none has shown good performance, especially on edgy regions. In this paper, new color morphological operators, based on a fuzzy principle component analysis, are proposed for noise removal. These operators employ statistical information (obtained by applying a fuzzy clustering algorithm on the color space) to achieve the desired results for the denoising application. The performance of the proposed operators is compared with recent morphological operators, reported in the literature, for denoising purposes and the superiority of the proposed method is shown.*

Keywords: *Color morphological operators; Noise suppression; Ordering; FPCA.*

INTRODUCTION

Mathematical morphology is an important technique used in different image processing applications. It is a geometric approach that has been developed as a powerful tool for shape analysis in binary and gray scale images. Unfortunately, the extension of the concepts of binary and gray scale morphology to color images is not a straightforward task [1].

Axioms of morphology generalization have been discussed in [2]. These axioms have been reduced to three key ideas: An order relationship (for example, set inclusion for binary morphology), a supremum or an infimum pertaining to that order, and the possibility of admitting the infinity of operands. The first two of these axioms, the order relationship and the supremum (or infimum), are missing for color images because there is no unambiguous way to order two or more colors [2]. Thus, these fundamental concepts cannot be applied to color images. However, it is possible to extend some techniques to define morphological operators on color images [1].

Morphological operators are usually defined in terms of a geometric description. This type of description is based on small synthetic images called structuring elements. However, mathematical morphology can also be defined algebraically in terms of operators on complete lattices. The lattice description is more general than the geometric description [3]. This type of description has allowed morphological theorems and techniques to be applied to structures beyond binary and gray scale images.

Most of the existing research in the field of color morphology has focused on defining order relationships on a specified color space. Indeed, they map the input color image to the target color space and use an ordering scheme for finding the superimum and infimum to compute dilated and eroded images. In [4], color morphological operators have been applied to the HSV color space. A lexicographical ordering scheme has been used for finding the superimum and infimum. This approach has been extended in [5] by defining the soft ordering scheme using fuzzy rules. In [5], the authors have claimed that their method performs significantly better than other reported morphological

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operators for the purpose of noise suppression, but they have compared this method only with their previously reported method in [4]. The introduced methods in [4,5] have many shortcomings. First, they add (subtract) structuring element values with (from) corresponding image values during the dilation (erosion) operator. As a consequence of this process, new colors may appear in the obtained image (although the authors have claimed that their operators are vector preserving). Also, the ordering of hue components is not as straightforward [3] as they have claimed. It must be mentioned that previously introduced methods in [3,6,7] have considered some of the difficulties in hue component ordering.

In [8], the RGB color space is first linearly transformed to the target color space. Then, the transformed colors are ranked using a lexicographic ordering method. The performance of resulted morphological operators in the edge detection application has been shown. In [9], the performance of some previously introduced morphological operators (which had used reduced ordering) has been compared and these operators have been mapped to a generic programming framework. Some morphological techniques that have appeared in the literature were reviewed in [10] and a new technique, based on vector projections, was introduced in this paper. In [11], a reduced ordering approach, based on a new geometrical transformation, has been introduced and its experimental results for contrast enhancement and edge detection have been shown. In [12], the luminance component in the HLS color space has been used for the definition of basic morphological operators. Then, new composite morphological operators have been defined, based on the basic operators, and the application of the composite operators for noise suppression and multi-resolution edge detection has been experimented. In [13], the use of color morphological operators, defined on the HSI color space for brightness elimination application, has been discussed. The use of mathematical morphology in the $L^*a^*b^*$ color space has also been discussed in [14]. This method is based on using weighting functions to impose reduced ordering on the color space. Various color weighting functions have been considered and one, based on an electrostatic potential model, has been chosen in [14].

On the other hand, Köppen et al. have used a different approach for color ordering in their work. In [15-17], the important class of Pareto-Morphologies has been introduced and a new ranking scheme, based on fuzzy-subsethood, has been used for multivariate data ordering. Also, a few experimental results of applying Fuzzy Pareto Morphology (FPM) operators have been reported in [15-17].

Recently, in some studies, color statistical information has been used in color ordering schemes. In [18], morphological operations have been defined, based on the Mahalanobis distance of colors in the RGB color space. The covariance matrix has been computed for the whole color image (all colors appearing in the input image). In the dilated image, the color of each pixel is replaced by the color of one of its neighbors whose color has the longest distance from its color. In this approach, one covariance matrix has been considered for the whole color space, though the color space is composed of some clusters (each has its own covariance matrix). The performance of the resulted morphological operators has been evaluated subjectively. In [19], color vectors have been ordered using the first fuzzy principal component in the whole RGB space. The result of applying this morphological operator has been reported for the application of building extraction. In [20], a majority ordering method has been introduced for the color ordering purpose. This approach is based on counting the number of image pixels and ordering colors, accordingly. Thus, the dilation process decreases the number of pixels having the dominant color. As this method has used the number of color occurences for the color ordering purpose, it provides morphological operators for increasing or descreasing the dominant colors of images. Thus, the introduced dilation and erosion operators in [20] can be used for some specific applications.

Recently, a comparative review of the existing multivariate morphological framework has been provided in [21]. Additionally, the results of a brief series of illustrative application-oriented tests of some selected vector ordering schemes on color and multispectral remote sensing data have also been discussed in [21].

Although the most recent methods have used some statistical information [18-20], we can use more meaningful and useful statistical information for noise suppression purposes. Since color pixels of an image usually compose some clusters in the color space, defining one covariance matrix for the whole image, as in [18], or specifying one PCA vector in the color space, as in [19], may not provide the desired information. In this paper, we use the statistical information of different clusters in the color space. The Fuzzy Principle Component Analysis (FPCA) algorithm introduced in [22,23] is used for finding such information. Using this type of information, we have designed morphological filters for the purpose of noise suppression. In our proposed approach, we use the statistical information of clusters (obtained using the FPCA technique) instead of the global statistical information. This approach yields better results compared with existing morphological filtering techniques.

The rest of this paper is organized as follows:

First, an introduction to the color ordering concept is presented. Then, some color morphological operators are studied and their performances are compared. Following that the proposed morphological filtering approach is explained and the experimental results are presented. Finally, the paper is concluded.

COLOR ORDERING SCHEMES

The problem of ordering multivariate data is not limited to color ordering in the field of mathematical morphology. In several research fields, like multi-objective optimization, multi-sensorial fusion and etc., the need has arisen to rank multivariate data. Yet, unlike scalars, there is no unambiguous way of ordering vectors (multivariate data) [21]. Thus, many techniques have been used for finding the incomplete ordering (may be ambiguous) of multivariate data and much work has been done to define concepts such as median, range, and extremes for multivariate analysis [1].

Barnett [24] has investigated the possible use of incomplete ordering relations for multi-dimensional data and has proposed four possibilities: marginal ordering, reduced ordering, partial ordering and conditional ordering.

In the marginal ordering scheme, ranking takes place within one (or more) of the marginal sets of samples (i.e. scalar ranking is performed for each component). Thus, to order a collection of color vectors using marginal ordering the components in each spectral band are ordered independently. Morphological operations that are defined using marginal ordering are referred to as component-wise operations. Because the component images are filtered separately by using the marginal ordering, there is a possibility of altering the spectral composition of the image.

In the reduced ordering scheme, each multivariate observation is reduced to a single value by a transformation function of component values. Then, the multivariate samples are ranked according to this scalar value. In [25], Mardia further developed the sub-classification of reduced ordering schemes: Distance ordering and projection ordering. Distance ordering schemes refer to the use of any specific measure of distance and the projection ordering schemes perform the sample ordering using the first principal component (PCA1) or the next principal components.

In the partial ordering scheme, multivariate samples are grouped into some distinct subsets such that the members of each subset have the same ordering value. This ranking scheme is somewhat complex and is rarely used for color ordering purposes.

In the conditional ordering, multivariate vectors are conditionally ordered based on the value of different components. One type of conditional ordering scheme, lexicographic ordering, has been used in many studies [4,5,8,14] for color ordering purposes. In this scheme, first the most significant component is chosen and multivariate ordering is done according to its value. Then, for those vectors having the same ordering level, values of the second most significant component are compared. The procedure continues for other components in the same manner.

All the above mentioned approaches have been derived from distance-based color filtering methods (i.e. scalars defined by distances in the color space). Different approaches can be considered, such as: the mapping of initial data vectors (colors) into more "familiar" objects such as one-dimensional functions, smileys (Chernoff faces), or two-dimensional polygons [11].

COLOR MORPHOLOGICAL OPERATIONS

The two most widely used ordering schemes in defining color morphological operators are reduced ordering and lexicographic ordering. The latter scheme is generally based on the selection of a color space and choosing the order in which components must be ranked. Also, the ranking of a complex component such as hue itself must be noticed carefully [3,6,7]. In this section, we describe the morphological operations that are based on reduced ordering; the lexicographic ordering-based operations can also be defined by considering function $r : R_3 \to R$ such that it shows the rank of input colors in the lexicographic order.

If the structuring element is the set S and the scalar-valued function used for reduced ordering is $r : R_3 \to R$, the value of the vector dilation of f (by S) at point (x, y) is defined as:

$$\begin{aligned}
&(f \oplus_v S)(x,y) = a,\\
&a \in \{f(u,v) | (u,v) \in S_{(x,y)}\},\\
&r(a) \geq r(f(u,v)),\\
&\forall (u,v) \in S_{(x,y)}. \qquad (1)
\end{aligned}$$

Similarly, the value of the vector erosion of f (by S) at point (x, y) is defined as:

$$\begin{aligned}
&(f \Theta_v S)(x,y) = a,\\
&a \in \{f(u,v) | (u,v) \in S_{(x,y)}\},\\
&r(a) \leq r(f(u,v)),\\
&\forall (u,v) \in S_{(x,y)}. \qquad (2)
\end{aligned}$$

With these definitions, the output vector at each image point is one of the vectors in the original image. Thus, there is no possibility of creating new color vectors. Often, the metric used to perform reduced ordering is some type of distance metric [1]. The output of the vector filter will depend not only on the input image and the structuring element, but also on the scalar-valued function used to perform the reduced ordering. For many image processing applications, it might make sense to use a characteristic of the human visual system (such as luminance) as a metric for reduced ordering.

The selection of a scalar-valued function provides flexibility in incorporating spectral information into the multi-valued image representation. For example, certain linear combinations of tristimulus values can be used [9]. This can be written as:

$$\mathbf{v} \leq \mathbf{v}' \leftrightarrow f(\mathbf{v}) \leq f(\mathbf{v}'),$$

$$f(\mathbf{v}) = av_1 + bv_2 + cv_3. \tag{3}$$

For example, in the RGB color space, if we set $a = 0.299$, $b = 0.587$ and $c = 0.114$, the ranking function becomes the luminance component. The values of a, b and c parameters can also be selected in order to enhance or suppress specific colors. Any of these scalar-valued functions can be useful for a specific application such as object recognition, noise suppression and similar applications. Thus, the extension from gray scale to color morphology depends on the specific application.

We have investigated different choices for color morphological operators. First, we used the methods introduced in [4,5]. These methods are based on lexicographic ordering applied to the HSV color space. Neither of these methods results in a good performance for noise removal. Also, applying the dilation and erosion operators reported in [4,5] did not provide appropriate results. Then, we used a reduced ordering scheme that is based on a luminance component called Luminance Reduced Ordering (LRO). This method performed better comparing the methods mentioned in [4,5] for noise suppression purposes. In the next section, we use this ordering scheme.

PROPOSED MORPHOLOGICAL FILTERING METHOD

Morphological image processing has been successfully applied to a variety of image processing tasks. In this section, we focus on color morphology for the purpose of noise suppression. Filtering techniques are of great importance among image enhancement techniques. Many methods have been proposed in the literature for color impulsive noise elimination. The median filter, rank-order filter and, more recently, morphological filters are among these techniques. In [1,4,5,9,12,18,26], some color morphological filters have been introduced and applied to the denoising application. However, none of these color morphological filtering techniques have shown satisfactory results.

In this section, we design color morphological filters that are based on color statistical information. Among existing studies, the authors of [18,19] have used statistical information in their morphological filters. But, they have extracted global statistical information for the whole color space instead of considering the clusters in the color space. Thus, they have not used such meaningful information. Also, in the field of multivariate median filter design, some studies have used local statistics [27,28]. In [28], the Mahalanobis distance has been proposed as the local statistics-based distance metric. The vector median of a collection of vectors has been computed as the vector from the collection which has the minimum aggregate Mahalanobis distance from all other vectors in that collection [28]. This distance measure has been computed according to the local statistics inside the filter window.

In our proposed method, we have designed a color morphological filtering method that is based on the statistical information of clusters in the color space. It must be mentioned that the utilized ideas in this filtering method can also be employed to design new multivariate median filters.

Shortcoming of Color Morphological Filters for Denoising

By studying existing color morphology techniques, we came to the conclusion that all these techniques (independent of their used ordering scheme) show a shortcoming when being applied for the purpose of noise removal. The following examples explain this problem.

Example 1

For simplicity, we consider a gray scale image, shown in Figure 1a, and a one-dimensional 1×3 structuring element. The shaded cell in Figure 1a is a noisy point. We suppose $A < N < B$ in this figure. For noise removal, usually the opening operator followed by the closing operator is used as the morphology filtering method. The opening (closing) of an image is resulted from firstly applying the erosion (dilation) operator and then applying the dilation (erosion) operator on the eroded (dilated) image. Figure 1b shows the results of applying the opening operator on Figure 1a and Figure 1c has been obtained from applying the closing operator on Figure 1b. These figures are independent of the ordering scheme used

(a)

A	A	A	B	B	B
A	A	A	B	B	B
A	A	A	N	B	B
A	A	A	B	B	B
A	A	A	B	B	B

(b)

A	A	A	B	B	B
A	A	A	B	B	B
A	A	A	N	B	B
A	A	A	B	B	B
A	A	A	B	B	B

(c)

A	A	A	B	B	B
A	A	A	B	B	B
A	A	A	N	B	B
A	A	A	B	B	B
A	A	A	B	B	B

Figure 1. Applying the noise removal filter on a simple image. (a) Original image; (b) Result of applying opening on (a); (c) Result of applying closing on (b).

in morphological operators. According to the resulted image in Figure 1c, the opening followed by the closing operator cannot remove the noisy point at the edge location. Thus, on images having more than two levels of intensity, this problem may appear at edge locations. Furthermore, the noise removal operator may extend the noisy point located on more edgy regions, as explained in Example 2.

Example 2

Similar to the previous example, the noise removal technique is applied to the input image, shown in Figure 2a. This image has four levels of intensity ($A < N < B < C$). According to the resulted image in Figure 2c, the noise removal operator has extended the noisy point located on the edgy region.

As shown in Figure 2, the morphological noise removal operator (the opening followed by the closing operator) cannot remove the noise located at edge locations. Also, this filter may even extend noisy points. The existing color morphology filters, similar to the gray scale morphological filters, suffer from this problem. But, in color images, we can use color information to design better filters. In this paper, we use the FPCA method introduced in [22,23] as an appropriate clustering algorithm for analyzing the data points (corresponding to the pixels) in the color space of an image. Using this approach, we can find more reliable data points and the ordering is applied to the found data points.

Fuzzy PCA-Based Clustering Algorithm

Fuzzy objective function-based clustering methods are proved to be fast tools for classification and segmentation purposes [22]. Unfortunately, most of the available fuzzy clustering methods use spherical or ellipsoidal distance measures, which are proved to result in spurious clusters when working on color data. In [22], a FPCA clustering algorithm has been introduced and its convergence has been proved. Also, it has been proved that the Fuzzy C-Means (FCM) and the Fuzzy C-Variates (FCV) clustering methods are special cases of it. This clustering method is based on a likelihood measure, and has been proved to outperform Euclidean and Mahalanobis distance measures in color fields. Based on this color clustering method, a fuzzy segmentation approach has been introduced in [22] and the superiority of the FPCA method, compared to the FCM method (for the segmentation of color images), was shown.

It is proved that the Linear Partial Reconstruction Error (LPRE) used in [22,23] results in a proper likelihood measure for processing natural color images. In this methodology, the likelihood of vector $\vec{x}$ to cluster c_i is defined as $e_{c_i}(\vec{x}) = \|\vec{v}_i^t(\vec{x} - \vec{\eta}_i)\vec{v}_i - (\vec{x} - \vec{\eta}_i)\|$, where, $\vec{v}_i$ and η_i denote the direction of the first

(a)

A	A	B	C	C	C
A	A	B	C	C	C
A	A	B	N	C	C
A	A	B	C	C	C
A	A	B	C	C	C

(b)

A	A	B	C	C	C
A	A	B	C	C	C
A	A	N	N	C	C
A	A	B	C	C	C
A	A	B	C	C	C

(c)

A	A	B	C	C	C
A	A	B	C	C	C
A	A	N	N	C	C
A	A	B	C	C	C
A	A	B	C	C	C

Figure 2. Applying the noise removal filter on a gray scale image. (a) Original image; (b) Result of applying opening on (a); (c) Result of applying closing on (b).

principle component of cluster c_i and the mean vector c_i, respectively ($\|.\|$ shows the normalized L_1 norm) [22]. Based on this likelihood measure, the objective function, $J(X,\Phi) = \sum_{i=1}^{n} \sum_{j=1}^{C} p_{ij}^m D_{ij}$, which describes the best choice of clustering data points $X = \{\vec{x}_1, \cdots, \vec{x}_n\}$ into C clusters, is formed. Here, p_{ij} is the fuzzy membership of $\vec{x}_i$ to the jth cluster and D_{ij} is the distance between this point and the cluster. Then, the performance comparison of the LPRE with conventional Euclidean and Mahalanobis distances has proved its superiority, both in terms of the likelihood measurement and homogeneity decision [22].

Proposed Noise Suppression Method

In our proposed method, we have defined dilation and erosion operators, such that the corresponding supremun and infimum values are selected from the more reliable points. In the other words, these values are less likely to be noisy points. For this purpose, we use statistical information resulted from the FPCA algorithm. In other words, the center and the main direction (PCA1) of fuzzy clusters in the color space are used to suppress noisy points. Then, the ordering scheme is applied to the remaining points.

For reducing noise effects, the FPCA clustering algorithm is used as described below. This method specifies the existing clusters in the color space and computes the fuzzy membership of data points (colors) to different clusters. According to the resulted membership values, those points that have nearly the same membership to different clusters can be suppressed. Based on the FPCA clustering technique, we can define a measure of reliability for a specified color as:

$$K = \sum_{i=1}^{C} \left(\mu_i - \frac{1}{C}\right)^2, \tag{4}$$

in which, the value of μ_i is the membership of the desired color point to the ith cluster and C denotes the number of considered clusters in the image. The value of this measure is high for color points that are similar to the color content of the original image and is low for others. Thus, by employing this information, we can restrict the ordering scheme to those color points that are less likely to be noisy points. Then, we use the reduced ordering scheme, which is based on the luminance component, on reliable color points. Morphological filters can be constructed using an opening (erosion followed by dilation) operation followed by a closing (dilation followed by erosion) operation. These filters can attenuate or completely eliminate positive, negative, or both positive and negative impulsive noise, from an image.

EXPERIMENTAL RESULTS

The aim of noise filtering is the elimination (or at least reduction) of noise and its related effects from images while degrading the image content quality as little as possible [5]. In this section, we study the result of applying our proposed method and other morphological filters for the purpose of impulsive noise removal. In many practical situations, images are corrupted by impulsive noise of a short duration and high energy. Impulsive noise can appear during image capture, transmission or storage [29]. This type of noise occurs mostly over air transmissions, such as in standard broadcasting and satellite transmission. Common sources of impulsive noise include lightening, industrial machines, car starters, the faulty or dusty insulation of high-voltage power lines, and various unprotected electric switches [30]. Among color morphological filters, those filters introduced in [1,4,5,9,12,18,26,29] have been applied to the denoising application. Among these studies, [18,26] have reported quantitative results for the performance evaluation of their filtering methods. The results of applying the introduced method in [18] are only reported for some synthetic images. All other methods [1,4,5,9,12,26,29] have shown their results on one or two sample images. Also, only the test images of [1,4,5,26] are similar and the other studies have used their individual test images. In the following parts, we quantitatively compare our method with one of the most recent methods introduced by Louverdis et al. in [26].

A significant problem in the study of noise effects on color images is the lack of a multivariate impulsive noise model [5]. Some impulsive noise models have been recently introduced to assist in the development of color image filters. Here, we use the extended impulsive noise model introduced in [31,32], as follows:

$$o' = (o'_1, o'_2, o'_3)$$
$$= \begin{cases} (o_1, o_2, o_3) & \text{with probability } (1-p) \\ (v_1, o_2, o_3) & \text{with probability } p_1 p \\ (o_1, v_2, o_3) & \text{with probability } p_2 p \\ (o_1, o_2, v_3) & \text{with probability } p_3 p \\ (v_1, v_2, v_3) & \text{with probability } p_s p \end{cases} \tag{5}$$

where o is the original color point and o' is its noisy version. The $v_i \in \{0, 255\}$ ($i = 1, 2, 3$) parameters show the value of impulsive noise appearing in different components and p shows the degree of impulse contamination of the image, when:

$$p_s = 1 - p_1 - p_2 - p_3, \tag{6}$$

$$p_1 + p_2 + p_3 \leq 1. \tag{7}$$

In the following experiments, the values of p_1, p_2, p_3 and p_s are equally set to $p_1 = p_2 = p_3 = p_s = 0.25$. Several different objective measures can be utilized for the performance comparison of noise removal filters. These measures must show some degree of closeness between two images by exploiting the differences in statistical distributions of pixel values [5]. To measure the restoration quality, the commonly used Peak Signal-to-Noise Ratio (PSNR) is used. It is a good measure of impulsive noise suppression efficiency [30]. The PSNR is defined as:

$$\text{PSNR} = 20\log_{10}\left(\frac{255}{\sqrt{\text{MSE}}}\right), \tag{8}$$

where:

$$\text{MSE} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left\|o'_{i,j} - o_{i,j}\right\|^2}{3\text{ MN}}. \tag{9}$$

M and N denote the image dimensions and $o_{i,j}$ and $o'_{i,j}$ show the original and noisy image pixels located at (i,j), respectively.

To evaluate the detail preservation capability, the Mean Absolute Error (MAE) is used:

$$\text{MAE} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left\|o'_{i,j} - o_{i,j}\right\|_{L_1}}{3MN}. \tag{10}$$

Another objective similarity measure used for assessing the perceptual closeness between two color images is the Normalized Color Difference (NCD) [5,30]. The NCD uses the Euclidean distance between two color vectors in the desired color space. Since the RGB color space is not a perceptually uniform space, restoration errors are often analyzed using perceptually uniform color spaces. In this paper, we use the YCbCr color space and define the NCD measure as:

$$\Delta E = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\sqrt{(Y'_{i,j}-Y_{i,j})^2+(Cb'_{i,j}-Cb_{i,j})^2+(Cr'_{i,j}-Cr_{i,j})^2}}{MN}, \tag{11}$$

$$\text{NCD} = \frac{NM(\Delta E)}{\sum_{i=1}^{M}\sum_{j=1}^{N}\sqrt{(Y_{i,j})^2+(Cb_{i,j})^2+(Cr_{i,j})^2}}, \tag{12}$$

where Y represents the luminance component and Cb, Cr denote the chrominance components. Indeed, the original $o_{i,j}$ and the noisy $o'_{i,j}$ signals are transformed to the $YCbCr$ color space.

The noise attenuation properties of the proposed morphological filters are examined by applying them to several color images. Table 1 lists the results of applying the proposed method and the LRO-based method on the 512×512 'Lena' image. Also, the value of measures is reported when no filtering technique is applied. In this case, the original image has been contaminated by 10% impulsive noise. According to the above equations, MSE, MAE and NCD are measures of similarity between the filtered and the original image. The results of our proposed algorithm have been obtained for some different values of C (number of clusters). Also, the value of the similarity measures has been computed by averaging these values over five runs.

As mentioned above, the only method that has reported its objective results on a real (non-synthetic) image is the one introduced in [26]. In order to compare the results of our proposed operators with the soft operators introduced in [26], we have computed the reported measures in [26]. Table 2 lists the value of the similarity measures reported in [26] and the corresponding values of these measures for our proposed method. Values have been obtained from applying filters to the 512×512 'Lena' image contaminated with 4% impulsive noise. In order to compare our results with the reported results in [26], we have used the NMSE measure, defined in [26] as:

$$\text{NMSE} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left|f_{i,j} - g_{i,j}\right|^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left|f_{i,j}\right|^2}, \tag{13}$$

where $f_{i,j}$, $g_{i,j}$ are the original and noisy components of images at the (i,j) pixel. Also, the NCD measure in Table 2 is computed in the HSV color space. We present the results of our proposed method for three different values of C (the number of clusters).

The subjective results on some noisy images have been shown in Figures 3 and 4. In Figure 3, we

Table 1. Results of the proposed method and the LRO-based method on 512×512 Lena image contaminated with 10% impulsive noise.

	MSE	**PSNR**	**MAE**	**NCD**
NO Filtering	1003.8	18.11	6.473	0.036
LRO-Based Method	153.49	26.27	4.78	0.021
Proposed Method ($C = 4$)	86.90	28.80	4.38	0.019
Proposed Method ($C = 6$)	81.81	29.01	4.25	0.018
Proposed Method ($C = 8$)	87.96	28.71	4.30	0.019

Table 2. Reported similarity measures in [26] and the corresponding values for the proposed method on 512×512 Lena image contaminated with 4% impulsive noise.

	NMSE(H)	NMSE(S)	NMSE(V)	NCD
Soft Filtering [26] ($k = 1$)	0.1842	0.0279	0.0273	0.1461
Soft Filtering [26] ($k = 4$)	0.1582	0.0186	0.0045	0.1056
Proposed Method ($C = 4$)	0.1264	0.0040	0.0010	0.0858
Proposed Method ($C = 6$)	0.1262	0.0039	0.0009	0.0855
Proposed Method ($C = 8$)	0.1260	0.0039	0.0009	0.0851
LRO-Based Method	0.1295	0.0058	0.0010	0.0878

0	1	0
1	1	1
0	1	0

(e)

Figure 3. Results of noise suppression methods on 'peppers' image. (a) 'Peppers' corrupted by 10% impulsive noise. (b) Result of applying the improved version of [5]. (c) Result of applying the luminance ordering morphological filter. (d) Result of applying our proposed morphological filter. (e) Structuring element.

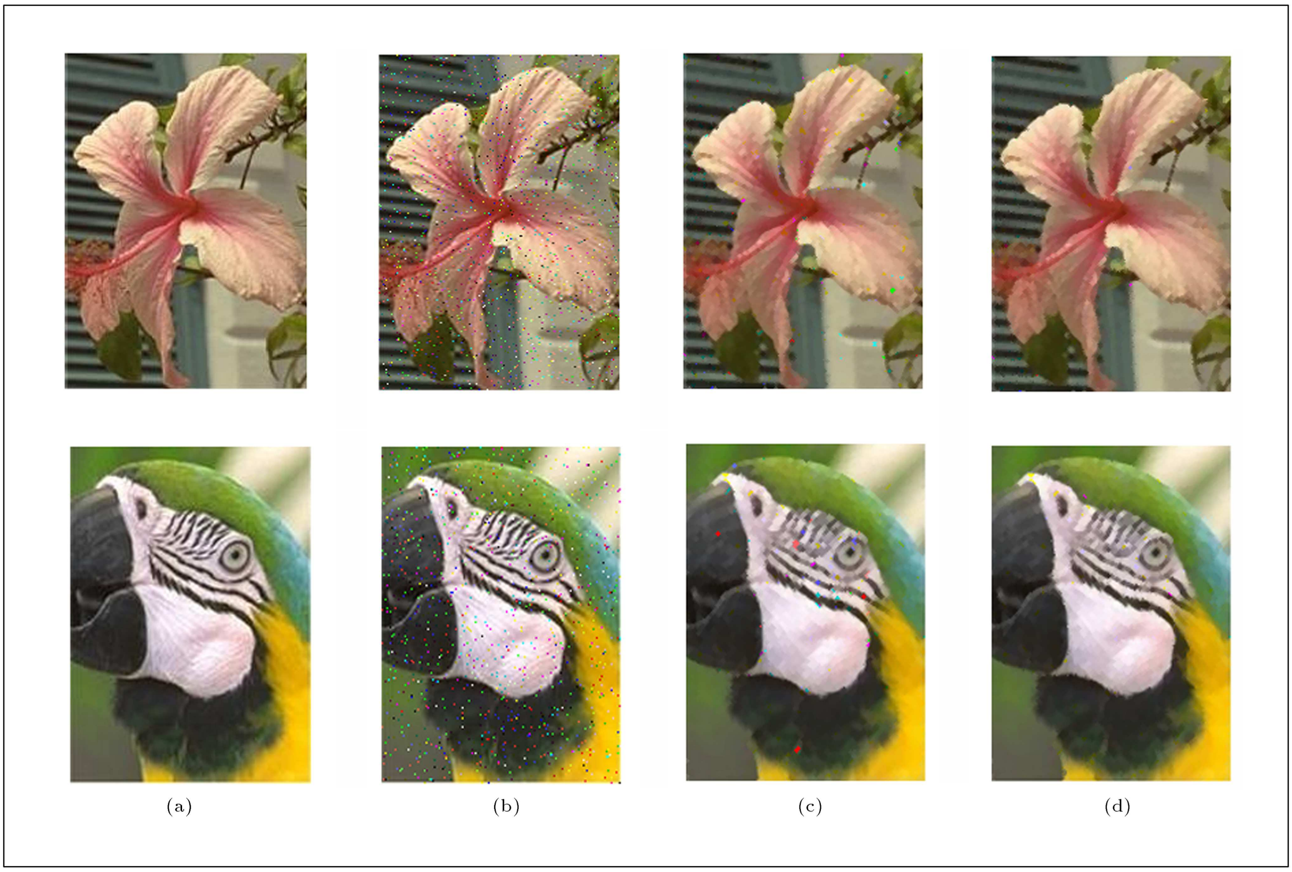

Figure 4. Illustrative examples of filtering efficiency. (a) Parts of color test images; 'Flower' and 'Parrot'. (b) Images contaminated by 5% impulsive noise. (c) Filtered results achieved by LRO-based operators. (d) Filtered results achieved by our proposed operators.

compare the results of our proposed filters with the results of the introduced method in [5] and also with LRO-based morphological filters. Since the introduced method in [5] does not provide a good performance for noise removal applications, we have improved it by ignoring the addition (subtraction) of the structuring element by (from) image components during the erosion (dilation) operation (at least the hue component must be preserved). The original image contaminated by 10% impulsive noise has been shown in Figure 3a. The results of applying the improved version of the introduced method in [5], the LRO-based operators and also our proposed filtering operators have been shown in Figures 3d, 3c and 3b, respectively. The LRO-based filtering operator provides better experimental results compared with the results of the introduced method in [5]. Figure 3c shows that most of the remaining noisy points, after applying LRO-based operators, are located on edgy regions. In the proposed method, three clusters have been considered for the FPCA clustering algorithm. The structuring element used in these methods has been shown in Figure 3e. A comparison between Figures 3c and 3d demonstrates the superior performance of our proposed operators in the removal of color impulsive noise. But, in future work, this new method can be improved by using both global (clusters) and local statistics. Indeed, we can also pre-filter those points whose colors have no coordination with the colors of neighboring points.

In Figure 4, the subjective results of applying LRO-based filter and our proposed filter have been shown on parts of the 'Flower' and 'Parrot' images. According to these figures, our proposed method outperforms the LRO-based method in all cases.

CONCLUSION

In this paper, we proposed new color morphology filters for the purpose of noise suppression. It was shown that the existing morphological-based noise suppression filters introduced for gray scale and color images cannot remove noise data located on edgy regions. In our proposed method, the statistical information of clusters is used to design more appropriate filters for the denoising application. The result of applying the proposed method was compared with that of other morphological filters reported in the literature and the superiority of our proposed method was shown by objective and subjective testing.

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