

Principal Color and its Application to Color Image Segmentation

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Color image segmentation is a primitive operation in many image processing and computer vision applications. Accordingly, there exist numerous segmentation approaches in the literature, which might be misleading for a researcher who is looking for a practical algorithm. While many researchers are still using the tools which belong to the old color space paradigm, there is evidence in the research established in the eighties that a proper descriptor of color vectors should act locally in the color domain. In this paper, these results are used to propose a new color image segmentation method. The proposed method searches for the principal colors, defined as the intersections of the cylindrical representations of homogeneous blocks of the given image. As such, rather than using the noisy individual pixels, which may contain many outliers, the proposed method uses the linear representation of homogeneous blocks of the image. The paper includes comprehensive mathematical discussion of the proposed method and experimental results to show the efficiency of the proposed algorithm.

INTRODUCTION

In 1988, Klinker, Shafer and Kanade presented a novel approach to measure the highlights in color images [1]. In that work, they developed a proper model for the reflected light from an arbitrary point of a dielectric object. In 1990, they applied their approach to color image understanding [2]. However, more than a decade passed until the idea was successfully incorporated into a practical algorithm. In 2003, without paying too much attention to the theoretical aspects, Cheng and Hsia used the Principal Component Analysis (PCA) for color image processing [3]. Then, in 2004, Nikolaev and Nikolayev started the work again from the theory and proved that the PCA is a proper tool for color image processing [4]. The next necessary step was introduced in 1991, when Turk and Pentland proposed their eigenface method [5], in a completely different context. There, they developed a novel idea, which connected together the eigenproblems in the color domain and the spatial domain. Although there is a rich theoretical background for the linear local models of color, it is quite common to see research procedures that are based

on the old color space paradigm, even published in 2005. For a more comprehensive discussion of this topic refer to [6].

In different works, the authors of this paper have applied the PCA and, then, the fuzzy PCA (FPCA) to many different color image processing tasks. The essential idea of those works, which was borrowed from the above-mentioned literature, is that homogeneous swatches in color images of nature produce thin cylinders in the RGB space. In this framework, fuzzy clustering is a proper tool for finding these structures [7]. This theory opens plenty of opportunity for efficient color image processing tasks. Interested readers can refer to [8,9] for two applications of this theory. Also, see [6] for more examples.

In the PCA framework, each color swatch is represented by a line, which passes through its expectation vector and is parallel to its principal direction. Although it is proved that the lines representing similar materials lie on a unique plane [1], the theory neglects the (possibly virtual) intersection of these lines. A virtual intersection of a set of lines is a point very close to the place that almost all of them pass. In this paper, it is empirically shown that the lines representing similar materials do intersect and shown that this intersection leads to a new technique for color image segmentation. This intersection point is called the principal color of the underlying material.

A review of the color image processing literature

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shows the huge amount of research dedicated to basic primitive methods, such as color image segmentation. This results in a vast variety of approaches with different motivations and tools. The reader is referred to [10,11] and the references therein for more details. Although there are many available segmentation algorithms, no numerical criterion is standardized to give a reasonable comparison between the results of different approaches. In fact, the only globally accepted and referred to factors are the elapsed time and the visual properness of the results. Furthermore, the utilization of many techniques includes many parameters that must be tuned by an expert. Failure to do the required tuning may result in total or partial collapse of the method (see [12] as an example). In this paper, the performance of the proposed method is compared with that of an available approach, which is based on the same theory [7] and it is shown that the new method outperforms the previous one. For comparison of that method with available literature, refer to [7].

The rest of this paper is organized as follows. First, the concept of principal colors is introduced and experimental cues for their existence are given. Then, the proposed method is described to use principal colors to perform color image segmentation. After that, the experimental results and discussions are held and, finally, the paper is concluded.

METHOD

Here, an investigation is proposed, through which the existence of the principal colors could be empirically perceived. It is emphasized that this empirical result has to be confirmed by theoretical investigation. The authors believe that the increasing number of research projects devoted to processing color images will pave the way to the formal approval of this theory, something which is outside the scope of this paper.

Figure 1 shows three sets of color swatches representing skin, sky and leaf materials. Each set contains 30 images; each a 64×64 JPEG file with quality of 100. The skin samples are extracted from erotic images downloaded from free resources on the Internet. The sky and leaf samples are captured by a Cannon A60 digital camera at different times of the day and in different locations. For each category, the

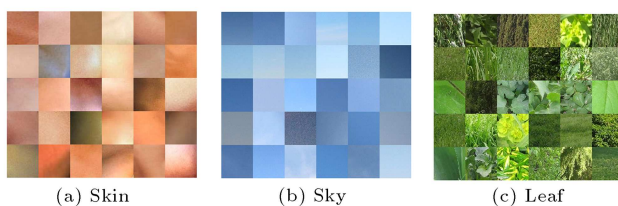


Figure 1. Randomly selected samples representing three different materials.

lines representing each single swatch are drawn in a common *RGB* space. Figure 2 shows these three sets of lines. Note that, for each material, all the lines pass through a small region in the color space. This (virtual) intersection of the lines is called, the principal color of that material. Figure 3 shows the principal colors of skin, sky and leaf extracted by the proposed

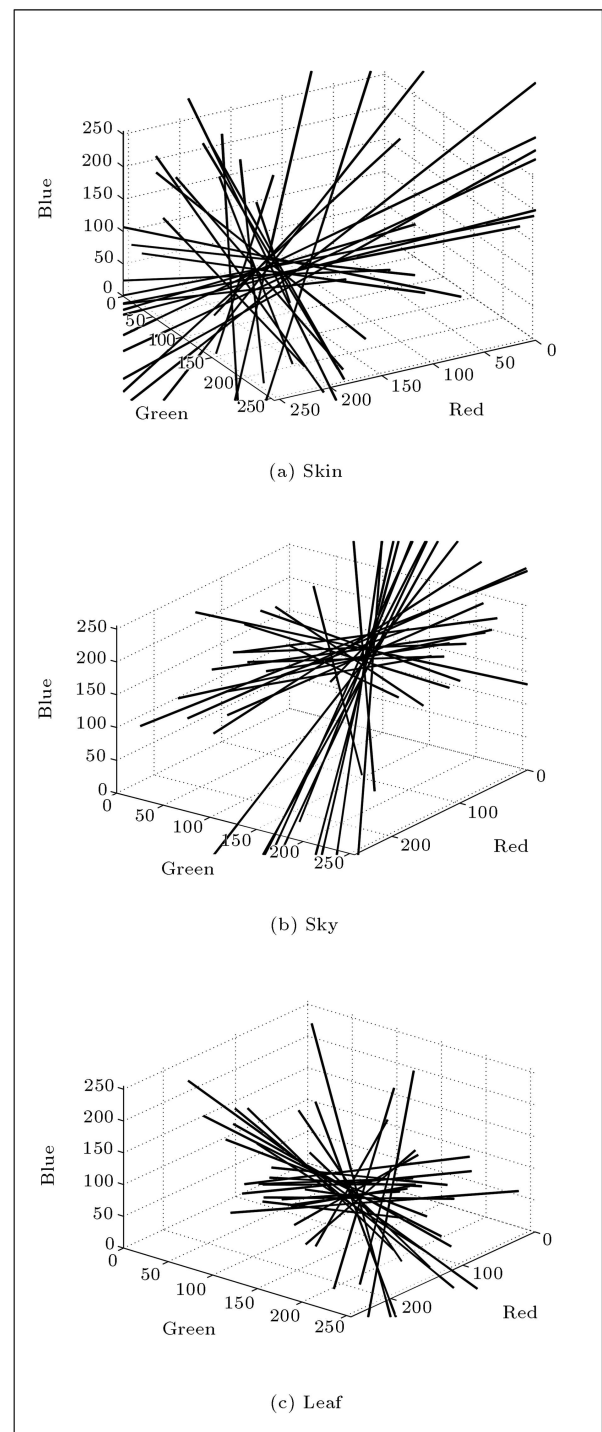


Figure 2. Linear representation of the samples shown in Figure 1.

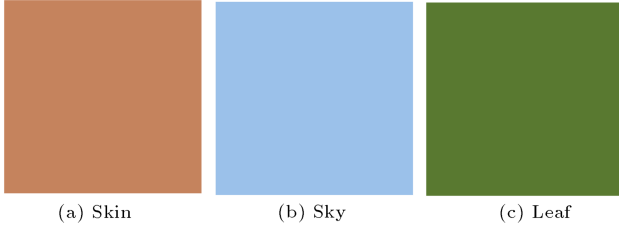


Figure 3. Principal color of the samples shown in Figure 1 extracted by the proposed method.

method. The following sections give the mathematical details about the process, which finds this point, and develops the idea further to include a set of fuzzy (or weighted) lines. Then, principal color theory will be incorporated with the general clustering algorithm described, previously, to propose a new color image segmentation method.

Finding the Closest Point to a Set of Lines

Assume that n lines of l_1, \dots, l_n in \mathbb{R}^m are given. Also, assume that l_i is indicated by the two vectors, $\vec{\eta}_i$ and \vec{v}_i . As such, $\vec{\eta}_i$ is a vector starting from the origin (with its head on l_i) and \vec{v}_i is the direction of l_i , satisfying $\|\vec{v}_i\| = 1$. Hence, the points on l_i occupy the set $\mathbf{L}_i \subset \mathbb{R}^m$, which is defined as:

$$\mathbf{L}_i = \{\vec{\eta}_i + \lambda \vec{v}_i | \lambda \in \mathbb{R}\}. \quad (1)$$

It is assumed that $\vec{\eta}_i$ is perpendicular to \vec{v}_i ($\vec{\eta}_i^T \vec{v}_i = 0$). If this condition is not met, $\vec{\eta}_i$ is replaced with,

$$\vec{\eta}_i^* = \vec{\eta}_i - (\vec{v}_i^T \vec{\eta}_i) \vec{v}_i. \quad (2)$$

The closest point to the n lines, l_1, \dots, l_n , is the point $\vec{x} \in \mathbb{R}^m$, which minimizes the following objective function,

$$\Delta = \sum_{i=1}^n d(\vec{x}, l_i)^2, \quad (3)$$

where, $d(\vec{x}, l_i)$ is the distance from point \vec{x} to line l_i . Linear algebra shows that:

$$d(\vec{x}, l_i)^2 = \|(\vec{x} - \vec{\eta}_i) - [\vec{v}_i^T (\vec{x} - \vec{\eta}_i)] \vec{v}_i\|^2, \quad (4)$$

which is simplified to,

$$d(\vec{x}, l_i)^2 = (\vec{x} - \vec{\eta}_i)^T [\mathbf{I} - \vec{v}_i \vec{v}_i^T] (\vec{x} - \vec{\eta}_i). \quad (5)$$

Substituting Equation 5 in Equation 3 gives:

$$\Delta = \sum_{i=1}^n (\vec{x} - \vec{\eta}_i)^T [\mathbf{I} - \vec{v}_i \vec{v}_i^T] (\vec{x} - \vec{\eta}_i). \quad (6)$$

From calculus, one knows that [13],

$$\frac{\partial (\vec{x}^T \mathbf{A} \vec{x})}{\partial \vec{x}} = \mathbf{A} \vec{x} + \mathbf{A}^T \vec{x}. \quad (7)$$

Hence,

$$\frac{\partial \Delta}{\partial \vec{x}} = 2 \sum_{i=1}^n [\mathbf{I} - \vec{v}_i \vec{v}_i^T] (\vec{x} - \vec{\eta}_i). \quad (8)$$

Setting $\frac{\partial \Delta}{\partial \vec{x}} = 0$ gives:

$$\left[\mathbf{I} - \frac{1}{n} \sum_{i=1}^n \vec{v}_i \vec{v}_i^T \right] \vec{x} = \frac{1}{n} \sum_{i=1}^n \vec{\eta}_i. \quad (9)$$

Now, it will be proven that the $n \times n$ matrix on the left hand side of Equation 9, which is called \mathbf{U} , is always non-singular, given that not all \vec{v}_i s are parallel.

A theory in linear algebra states that, “if $\mathbf{I} + \mathbf{E}$ is singular then $\|\mathbf{E}\| \geq 1$, where $\|\cdot\|$ is a subordinate matrix norm” [14]. First, this theorem will be proven. Assume that $\mathbf{I} + \mathbf{E}$ is singular. Hence, there exists a non-zero vector, \vec{x} , satisfying $(\mathbf{I} + \mathbf{E})\vec{x} = \vec{0}$. Thus, $\vec{x} = -\mathbf{E}\vec{x}$ or equivalently:

$$\|\mathbf{E}\| \geq \frac{\|\mathbf{E}\vec{x}\|}{\|\vec{x}\|} = 1. \quad (10)$$

Thus, to prove that \mathbf{U} in Equation 9 is non-singular, it suffices to show that:

$$\left\| \sum_{i=1}^n \vec{v}_i \vec{v}_i^T \right\| < n. \quad (11)$$

Equation 11 is proven by showing that, for any vector, \vec{y} , satisfying $\|\vec{y}\| = 1$, one has:

$$\left\| \sum_{i=1}^n \vec{v}_i \vec{v}_i^T \vec{y} \right\| < n. \quad (12)$$

First, it is known that, for any two arbitrary $m \times 1$ vectors, \vec{u} and \vec{v} ,

$$|\vec{u}^T \vec{v}| \leq \sqrt{\|\vec{u}\|^2 \|\vec{v}\|^2}. \quad (13)$$

Note that equality occurs for $\vec{u} \parallel \vec{v}$. Thus, in the case discussed here, one has $|\vec{v}_i^T \vec{y}| \leq 1$, which results in:

$$\left\| \sum_{i=1}^n \vec{v}_i \vec{v}_i^T \vec{y} \right\| \leq \sum_{i=1}^n |\vec{v}_i^T \vec{y}| \|\vec{v}_i\| \leq \sum_{i=1}^n \|\vec{v}_i\| = n. \quad (14)$$

Here, equality only happens if all \vec{v}_i s are parallel. Thus, ignoring this very especial case, Equation 12 is proved, proving that the solution to Equation 9 exists and is as follows:

$$\vec{x} = \left[n\mathbf{I} - \sum_{i=1}^n \vec{v}_i \vec{v}_i^T \right]^{-1} \sum_{i=1}^n \vec{\eta}_i. \quad (15)$$

Here, \vec{x} is the closest point to the n lines l_1, \dots, l_n .

Finding the Closest Point to a Set of Fuzzy Lines

Assume that, one is looking for the closest point to the set of n lines, l_1, \dots, l_n , in \mathbb{R}^m . Also, assume that the importance of l_i is $p_i \geq 0$. This means that, when composing the objective function, one will weigh the satisfaction of l_i by p_i . Hence, as p_i grows, the importance of l_i in decisions grows linearly and vice versa. As such, one is looking for $\vec{x} \in \mathbb{R}^m$, which minimizes, as follows:

$$\tilde{\Delta} = \sum_{i=1}^n p_i d(\vec{x}, l_i)^2. \quad (16)$$

Note that, by setting $\forall i, p_i = 1$ converts Equation 16 into Equation 3. An analysis similar to the one performed in the previous section, reveals that \vec{x} is computed as follows:

$$\vec{x} = \left[\sum_{i=1}^n p_i I - \sum_{i=1}^n p_i \vec{v}_i \vec{v}_i^T \right]^{-1} \sum_{i=1}^n p_i \vec{\eta}_i. \quad (17)$$

Again, note that by assuming $\forall i, p_i = 1$ converts Equation 17 into Equation 15 as expected.

General Clustering Algorithm

Assume that the fuzzy set of n vectors, $\vec{x}_1, \dots, \vec{x}_n$ in \mathbb{R}^m , is given as $\tilde{\mathbf{X}} = \{(\vec{x}_i; p_i) \mid i = 1, \dots, n\}$. Also, assume that a human observer has a perception of homogeneity for the subspaces of this space. For example, for $m = 3$, every human being is able to think and argue about the homogeneity of a set of color vectors. Also, when considering lines in \mathbb{R}^3 , which are members of \mathbb{R}^6 , the meaning of homogeneity used here is the existence of a point that is very close to almost all of them. On many occasions, a homogeneous set may be parameterizable. For example, research shows that a homogeneous set of color vectors occupies a thin cylinder, which will be described by two vectors. Similarly, a set of (virtually) intersecting lines may be parameterized by a single point. Thus, It is assumed that there is a function, Υ , that extracts this parameterization for the homogeneous fuzzy set, $\tilde{\mathbf{X}}$. As an example, if a homogeneous set in \mathbb{R}^m is defined as a sphere, the Υ function will be a fuzzy expectation operator. Also, for the cylindrical homogeneity, Υ will be the FPCA [7]. Having defined the description of a homogeneous set as ϕ , there might exist a function, Ψ , which measures the distance from an arbitrary element to ϕ . For the spherical example, the Ψ function is the Euclidean distance. Also, the Ψ function of the cylindrical homogeneity is the Linear Partial Reconstruction Error (LPRE) distance proposed in [6].

Having proper dual functions, Υ and Ψ , and a fuzzy set, $\tilde{\mathbf{X}}$, an important problem is how to separate $\tilde{\mathbf{X}}$ into c homogenous clusters, where c is known. This problem is called the general clustering problem [7]. The special cases of this problem are the Fuzzy C-Means (FCM) [15] (in which the clusters are spherical) and Fuzzy C-Varieties (FCV) [16] (in which the clusters are subspaces). Other examples are Gath-Geva [17], fuzzy ellipotypes [18], Gustafson-Kessel [19] and FPCA-based Clustering (FPCAC) [7] algorithms. Figure 4 shows the pseudo-code of an iterative solution to the general clustering problem. The interested reader is referred to [8] for related mathematics and proof of the convergence.

As shown in Figure 4, the algorithm, first, randomly initializes the clusters. Then, it iterates between computing the distance of each member to each cluster and, then, renewing each cluster, according to the membership value of the realizations to it. The algorithm contains an important parameter of fuzziness [20], m , which is always more than unity. The general clustering algorithm enables the clustering of any kind of data, given that a proper distance function and its dual are available. In the following section, a distance function will be given, which searches a set of lines for lines passing through or getting very close to a common point. The distance function is, then, integrated into a novel color image segmentation procedure.

- **Aim:** Clustering data according to the given model.
- **Inputs:**
 - Appropriate distance function (Ψ and its dual Υ).
 - Set of realizations ($\mathbf{X} = \{\vec{x}_1, \dots, \vec{x}_n\}$).
 - Number of clusters (c).
 - Fuzziness (m).
 - Halting threshold (δ).
- **Outputs:**
 - Fuzzy membership values (p_{ij}).
 - c cluster descriptors (ϕ_1, \dots, ϕ_c).
- **Method:**
 - 1 $k = 0$ and randomize ϕ_1, \dots, ϕ_c .
 - 2 $k = k + 1$.
 - 3 $D_{ij} = \Psi(\vec{x}_i, \phi_j)$.
 - 4 $p_{ij} = D_{ij}^{-1/(m-1)} / \sum_{k=1}^c D_{ik}^{-1/(m-1)}$.
 - 5 $F_{kij} = p_{ij}$.
 - 6 $\phi_j = \Upsilon\{(\vec{x}_1; p_{1j}^m), \dots, (\vec{x}_n; p_{nj}^m)\}$.
 - 7 if $k = 1$, then goto 2.
 - 8 $\delta_k^2 = \min_{1 \leq p \leq l-1} E_{i,j} \{(F_{pij} - F_{kij})^2\}$.
 - 9 if $\delta_k > \delta$, then goto 2, else return.

Figure 4. Pseudo-code of the general clustering algorithm [7].

Color Image Segmentation Using Principal Colors

Assume that the $H \times W$ color image I is given. Also, assume that the integer, c , is given as the number of homogeneous segments that I should be split into. For now, assume that both H and W are divisible by 2^n , where n is an integer larger than 2. It is clear that, by using zero-padding or resampling, the same operation is applicable to any image. It is proposed to cut I into $2^{-2n}WH$ non-overlapping rectangular blocks of $2^n \times 2^n$ pixels.

In [6], the authors proposed a novel homogeneity criterion for color swatches. In that work, the LPRE criterion was compared to the Euclidean and Mahalanobis distances and its superiority was proven. As such, the non-homogeneity of the swatch, \mathbf{i} , is defined as [6],

$$\tau(\mathbf{i})^2 = E_{\bar{\mathbf{c}} \in \mathbf{i}} \left\{ \left\| (\bar{\mathbf{c}} - \bar{\eta}_i) - \bar{\mathbf{v}}_i^T (\bar{\mathbf{c}} - \bar{\eta}_i) \bar{\mathbf{v}}_i \right\|^2 \right\}. \quad (18)$$

Here, $\bar{\eta}_i$ is the expectation vector of \mathbf{i} and $\bar{\mathbf{v}}_i$ is the principal direction of \mathbf{i} . Also, $\|\bar{\mathbf{x}}\|$ is the Euclidean length of the vector, $\bar{\mathbf{x}}$. $\tau(\mathbf{i}) < \theta$ is used to decide whether a swatch is homogeneous or not, where θ is a constant threshold. Experiments show that $\theta = 10$ is a proper choice [6].

In the proposed segmentation method, from the $2^{-2n}WH$ blocks, those which are not homogeneous are deleted. For the remaining blocks, the PCA representations are saved, as the m lines of l_1, \dots, l_m , all in \mathbb{R}^3 . Now, the problem is to find c proper intersections of these lines. Using the notations of the general clustering algorithm (see previous section), each realization is a line in \mathbb{R}^3 and the cluster model is a 3-D point. As such, the distance between the line, l , (denoted by $\bar{\eta}$ and $\bar{\mathbf{v}}$) and the point, $\bar{\mathbf{x}}$, is defined as follows:

$$\Psi(l, \bar{\mathbf{x}}) = \left\| (\bar{\mathbf{x}} - \bar{\eta}) - \bar{\mathbf{v}}^T (\bar{\mathbf{x}} - \bar{\eta}) \bar{\mathbf{v}} \right\|^2. \quad (19)$$

In this framework, the dual function, Υ , is given by Equation 17. Here, the fuzzy set is $\bar{\mathbf{L}} = \{(l_i; p_i) \mid i = 1 \dots, m\}$, where l_i is represented by $\bar{\eta}_i$ and $\bar{\mathbf{v}}_i$.

The general clustering algorithm results in a set of c points in \mathbb{R}^3 , where each point is the principal color of the respective cluster. Note that, at the beginning of this process, the non-homogeneous blocks were removed. That was done because the principal direction of those blocks is not meaningful. Therefore, at this point, the process should assign each block to a cluster, even those that are not homogeneous enough. Also, note that the result of the general clustering algorithm is a set of fuzzy membership values for each block and each cluster. Thus, using a maximum-likelihood operator, each block is deterministically

assigned to one of the clusters. By finding the distance of each omitted block from all clusters, the process assigns them to one of the computed clusters. The next step is to interpolate the assignment for all pixels. As each block is a $2^n \times 2^n$ swatch, performing bilinear double-sampling on the resulting index map, for n times, yields the desired segmentation. In practice, blocks of size $2^{n_1} \times 2^{n_1}$ are used to find the clusters and, then, $2^{n_2} \times 2^{n_2}$ blocks are examined to compute the index-map.

EXPERIMENTAL RESULTS

The proposed algorithm is developed in MATLAB 6.5, on a PIV 2600 MHz personal computer, with 256 MB of RAM. All sample images used in this paper are 512×512 color images in JPEG format with a quality of 100 (see Figure 5).

Figure 6 shows the results of three independent runs of the proposed method on the image Peppers. Here, $m = 2$, $c = 2$, $n_1 = 4$ and $n_2 = 3$ are

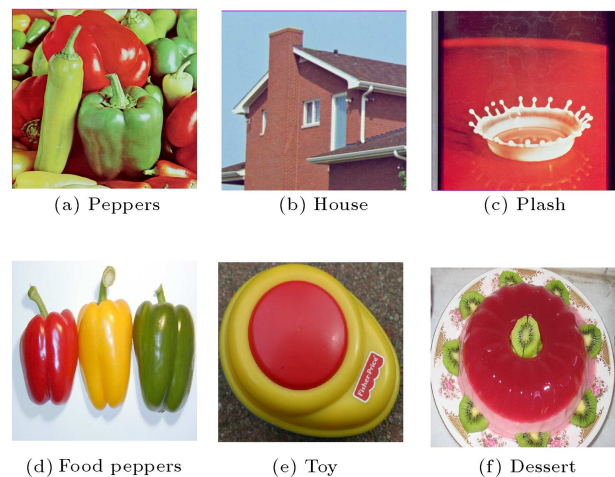


Figure 5. Some sample images; a,b,c) Courtesy of USC-SIPI, signal and image processing institute at the University of Southern California; d) Courtesy of freeimages.co.uk; e) Courtesy of computational vision at caltech, <http://www.vision.caltech.edu>.

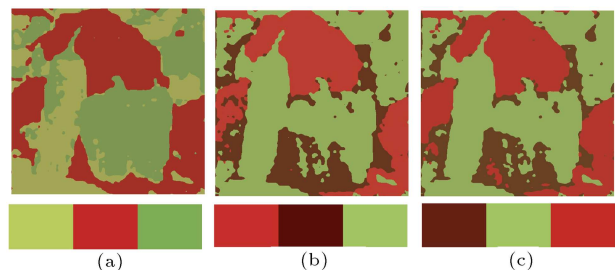


Figure 6. Results of three independent runs of the proposed method on the image Peppers. Top: Results of segmentation. Bottom: Principal colors.

used. This figure shows that, while the proposed method always results acceptably, its output is never identical in different runs, even with the identical values of the parameters, similar to the entire category of fuzzy clustering algorithms [21]. It should be emphasized, though, that in contrast with the conventional pixel-based fuzzy clustering approaches, in which local minimum is a common unsolved problem [21], the proposed method shows less tendency of falling into local minima. A local minimum in a fuzzy clustering algorithm can be identified by a solution that does not satisfy the merits which the problem defines, but still cannot be improved by the local approach utilized in a general clustering algorithm [21]. It is argued that the relative immunity of the proposed method against being trapped in local minima is the result of two innovations in it. First, rather than working on the original realizations, which are noisy and may contain many outliers, the proposed method works on more robust statistical parameters of the blocks of the image. Secondly, the proposed distance function models the physical phenomenon more appropriately, compared to the pixel-level operators used before. It is worth emphasizing that the proposed method is more repeatable, compared to the FPCAC [7], which uses a similar distance measure at the pixels level. In the experiments shown in Figure 6, the algorithm has converged in 9, 6 and 5 iterations, elapsing 16 sec, 14 sec and 14 sec, respectively.

Figure 7 shows the results of the proposed method applied on the image House, while different values of m are used. Here, with $c = 3$ and $m \in \{1\frac{1}{3}, 1\frac{2}{3}, 2\}$, the algorithm has converged in 4, 10 and 9 iterations, elapsing 13 sec, 16 sec and 16 sec, respectively. More experiments show that the actual value of m has a minimal effect on the results of the proposed method. Hence, the value of $m = 2$ is used as the default value. Similarly, the values of n_1 and n_2 only affect the spatial precision of the results and the elapsed time. As a compromise, $n_1 = 4$ and $n_2 = 3$ are always selected.

In a proper segmentation process, it is expected that increasing c should result in an increasingly better

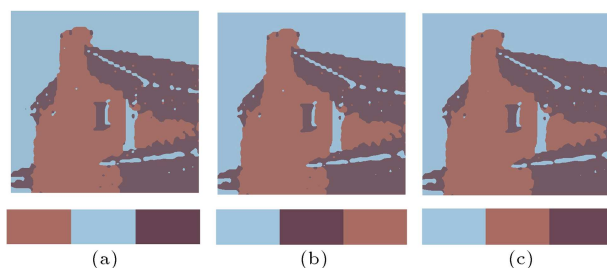


Figure 7. Effects of m on the results of the proposed method on the image House. Top: Results of segmentation. Bottom: Principal colors.

depiction of different regions in the image. Using values of $c = 2$, $c = 3$ and $c = 4$, this aspect of the proposed method is investigated in Figure 8. As expected, increasing the number of clusters results in more detailed segmentation results. In these experiments, the algorithm has converged in 9, 5 and 8 iterations, elapsing 12 sec, 14 sec and 18 sec, respectively. It should be emphasized that the elapsed time of the proposed algorithm depends almost linearly on the number of clusters.

Figure 9 compares the performance of the proposed method with the FPCAC [7]. This comparison is important, because both methods search for cylindrical structures in the color space. Note that, while the FPCAC works on individual pixels, the proposed method utilizes more robust statistically computed features. In this experiment, the FPCAC is utilized with its own default value of $m = 1.05$ [7]. Table 1 lists the elapsed time and the number of iterations of each method when working on each image. Also, the value of $c = 4$ is used for both methods in all cases.

As mentioned previously, there is no standard

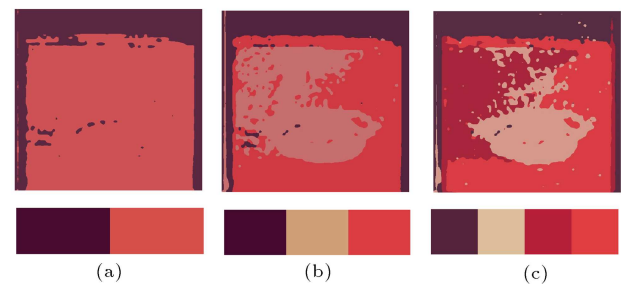


Figure 8. Effects of c on the results of the proposed method on the image Splash. Top: Results of segmentation. Bottom: Principal colors.

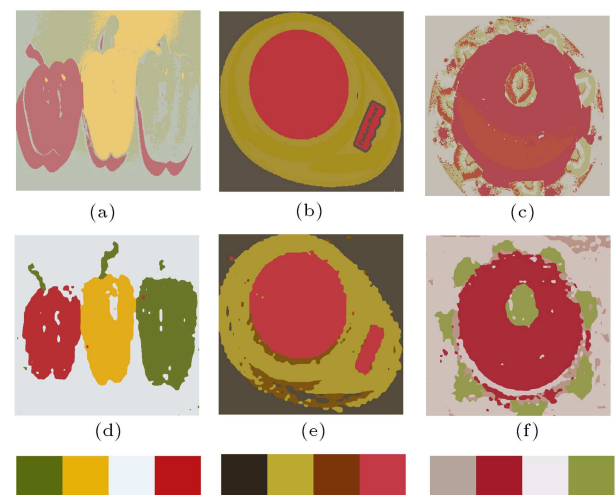


Figure 9. Comparison of the proposed method with the FPCAC [7]; (a), (b) and (c) Results of the FPCAC; (d), (e) and (f) Results of the proposed method.

Table 1. Performance comparison of the proposed method and the FPCAC [7]. t : Elapsed time and i : Number of iterations before convergence.

Image	Proposed Method		FPCAC [7]	
	t (s)	i	t (s)	i
Figure 5d	20	10	26	40
Figure 5e	18	6	8	19
Figure 5f	21	11	24	38

method for comparing the performance of different segmentation methods. Thus, here, the results of the proposed method and the FPCAC are compared, as shown in Figure 9, based on a heuristic approach. Comparing Figure 9a with Figure 9d, a very common problem of many segmentation methods can be seen. This way, in Figure 9a, FPCAC has mistakenly included parts of the gray background in the yellow pepper. Also, the shadow of the red pepper and other parts of the background are included in the red and green peppers, respectively. However, looking at Figure 9d, a proper segmentation can be seen of the image into four distinguished parts of red, yellow, and green peppers, and the background by the proposed method. Figures 9b and 9e show an example where the two methods perform similarly, except for the fact that FPCAC has resulted in an over-segmentation. This way, as seen in Figures 9b, FPCAC has segmented the text on the object into two different classes (because of being pixel-based). The proposed method, on the other hand, has given a smoother segmentation result. This effect is also visible in Figure 9c, where FPCAC has, again, resulted in many tiny segments. In contrast, the proposed method has again produced a smooth segmentation result. It is worth mentioning that the proposed method is also faster than the FPCAC. The reader is referred to [6] for more examples.

In analyzing the performance of the proposed method, it is worth mentioning that as the proposed algorithm is primarily concerned with spectral accuracy, some details in the spatial domain might be ignored. For example, looking at Figure 9e, it is observed that the proposed method has ignored details in the text on the object. This is a direct result of looking at the image at lower resolutions, as is done when using n_1 and n_2 . While this is useful in applications, which look for the general geometry of the objects, in other applications, which demand more precision (including coding), a pixel-based approach would yield results that are more detailed. Thus, it is argued that the proposed method produces the desired results when one aims at finding homogeneous regions in an image with more emphasis on color information rather than on spatial details.

CONCLUSIONS

In this paper, a new color image segmentation method is proposed, which utilizes the general clustering algorithm with an innovative distance function. The mathematics of the proposed method is discussed comprehensively and experimental results are presented. Comparison of the performance of the proposed method with an available clustering method, which searches for similar cylindrical structures in the pixel domain, shows that the proposed method is more stable and faster. It is argued that this is mainly because of applying the clustering task on a more robust statistical feature. It is also observed that the proposed method decreases the probability of local minimum entrapment. The repeatability of the proposed segmentation method is also more than the available methods. Furthermore, while the proposed method gives more perceptually satisfactory segmentation results, it demands less processing resources.

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