Color Image Segmentation: A State-of-the-Art Survey

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Abstract

Segmentation is the low-level operation concerned with partitioning images by determining disjoint and homogeneous regions or, equivalently, by finding edges or boundaries. The homogeneous regions, or the edges, are supposed to correspond to actual objects, or parts of them, within the images. Thus, in a large number of applications in image processing and computer vision, segmentation plays a fundamental role as the first step before applying to images higher-level operations such as recognition, semantic interpretation, and representation. Until very recently, attention has been focused on segmentation of gray-level images since these have been the only kind of visual information that acquisition devices were able to take and computer resources to handle. Nowadays, color imagery has definitely supplanted monochromatic information and computation power is no longer a limitation in processing large volumes of data. The attention has accordingly been focused in recent years on algorithms for segmentation of color images and various techniques, ofted borrowed from the background of gray-level image segmentation, have been proposed. This paper provides a review of methods advanced in the past few years for segmentation of color images.

1 Introduction

Segmentation is the process of partitioning an image into disjoint and homogeneous regions. This task can be equivalently achieved by finding the boundaries between the regions; these two strategies have been proven to be equivalent indeed. The desirable characteristics that a good image segmentation should exhibit have been clearly stated by Haralick and Shapiro in [1] with reference to gray-level images. "Regions of an image segmentation should be uniform and homogeneous with respect to some characteristics such as gray tone or texture. Region interiors should be simple and without many small holes. Adjacent regions of a segmentation should have significantly different values with respect to the characteristic on which they are uniform. Boundaries of each segment should be simple, not ragged, and must be spatially accurate." A more formal definition of segmentation, accounting for the principal requirements listed above, can be given in the following way [2, 4, 5]: Let $\boldsymbol{\mathcal{I}}$ denote an image and let $\mathcal{H}$ define a certain homogeneity predicate; then the segmentation of $\boldsymbol{\mathcal{I}}$ is a partition $\mathcal{P}$ of $\boldsymbol{\mathcal{I}}$ into a set of N regions $\boldsymbol{\mathcal{R}}_n$, $n = 1, \ldots, N$, such that: 1) $\bigcup_{n=1}^{N} \boldsymbol{\mathcal{R}}_n = \boldsymbol{\mathcal{I}}$ with $\boldsymbol{\mathcal{R}}_n \cap \boldsymbol{\mathcal{R}}_m \neq \emptyset$, $n \neq m$; 2) $\mathcal{H}(\boldsymbol{\mathcal{R}}_n) = \text{true}\ \forall\, n$; 3) $\mathcal{H}(\boldsymbol{\mathcal{R}}_n \cup \boldsymbol{\mathcal{R}}_m) = \text{false}\ \forall\, \boldsymbol{\mathcal{R}}_n$ and $\boldsymbol{\mathcal{R}}_m$ adjacent. Condition 1) states that the partition has to cover the whole image; condition 2) states that each region has to be homogeneous with respect to the predicate $\mathcal{H}$; and condition 3) states that the two adjacent region cannot be merged into a single region that satisfies the predicate $\mathcal{H}$.

Segmentation is an extremely important operation in several applications of image processing and computer vision, since it represents the very first step of low-level processing of imagery. As mentioned above, the essential goal of segmentation is to decompose an image into parts which should be meaningful for certain applications [1]. In this paper, we are concerned with color image segmentation which is becoming increasingly important in many applications. For instance, in *digital libraries* large collections of images and videos need to be catalogued, ordered, and stored in order to efficiently browse and retrieve visual information [6, 7]. Color and texture are the two most important low-level attributes used for *content based retrieval* of information in images and videos. Because of the complexity of the problem, segmentation with respect to both color and texture is often used for indexing and managing the data [8]. Another example is in the transmission of information over the Internet. At the present, huge streams of multimedia data circulate over the Internet where the limited bandwidth available creates the need for data compression. Current technology provides coding schemes which try to reduce visual artifacts by imitating the functions of the human visual system [7, 9]. They seek a semantic representation of the scene by subdividing it into regions which are psycho-visually meaningful. Such a partitioning is obtained through segmentation. Compression is then achieved by allocating more bits to areas visually more important and fewer bits to areas with less important details. A further example is in the latest wireless communication systems which allow the transmission of both speech and images. *Hand-held wireless sets* are now available which may also display color imagery with a limited resolution. Compression issues arise as in the above example with the further constraint of a limited availability of bits for displaying. In this application, segmentation is then important not only for compression but also for color quantization.

Until a few years ago, segmentation techniques were proposed mainly for gray-level images on which rather comprehensive surveys can be found in [1]-[4]. The reason is that, although color information permits a more complete representation of images and a more reliable segmentation of them, processing color images requires computation times considerably larger than those needed for gray-level images. This is no longer a major problem with an increasing speed and decreasing costs of computation; besides, relatively inexpensive color camera are nowadays largely available. Accordingly, there has been a remarkable growth of algorithms for segmentation of color images in this last decade [10, 11]. Most of the times, these are kind of "dimensional extensions" of techniques devised for gray-level images; thus they exploit the well-established background laid down in that field. In other cases, they are *ad hoc* techniques tailored on the particular nature of color information and on the physics of the interaction of light with colored materials.

In this paper, we present a brief survey of color image segmentation techniques and propose a classification scheme for them. Basically, we divide the segmentation algorithms into: 1) feature-space based techniques; 2) image-domain based techniques; and 3) physics based techniques. Each category is then further subdivided; as far as the first two categories are concerned, the further subdivision is suggested by the analogous classification schemes proposed for gray-level images [2]-[4]. Such a classification is not always straighforward since some techniques resort to more than one strategy to achieve segmentation and thus cannot be sharply categorized. The techniques of the third category instead adopt specific models of the interaction of light with colored materials of various nature and therefore they have no counterpart in the field of gray-level image segmentation.

This paper is organized as follows. Section 2 provides a brief summary of the color representations most widely adopted for segmentation. Section 3 presents the feature based techniques; Section 4 reports on image-domain based techniques. The algorithms based on physical models describing the interaction of light with color are discussed in Section 5. Section 6 finally draws the conclusions.

2 Color Representation

Several color representations are currently in use in color image processing. The most common is the RGB space where colors are represented by their red, green, and blue components in an orthogonal Cartesian space. This is in agreement with the *tristimulus theory of color* [12, 13] according to which the human visual system acquires color imagery by means of three band pass filters (three different kinds of photoreceptors in the *retina* called *cones* [12, 13]) whose spectral responses are tuned to the waveleghts of red, green, and blue. However, the RGB space does not lend itself to mimic the higher level processes which allow the perception of color of the human visual system; in this sense, color is better represented in terms of hue, saturation, and intensity [15, 16]. An example of such a kind of representation is the HSI space which can be obtained from RGB coordinates in various ways, *e.g.*, by defining hue $H \doteq \arctan\left(\sqrt{3}(G-B), 2R-G-B\right)$, saturation $S \doteq 1 - \min\left(R,G,B\right)/I$, and intensity $I \doteq \left(R+G+B\right)/3$, and by arranging them in a cylindrical coordinate system. The HSV space provides a description of color analogous to that of the HSI space: the hue H and the saturation S are similarly defined while the value V is defined as $V \doteq \max(R,G,B)$.

Both RGB and HSI (or HSV) spaces though are not perceptually uniform; this means that differences among colors perceived by the human eye as being of the same entity are not mirrored by similar distances between the points representing those colors in such spaces. This problem has been considerably reduced with the introduction of the *uniform color spaces*, the most widely used of which are the CIE $L^*u^*v^*$ and the CIE $L^*a^*b^*$ color spaces. The structure of the CIE spaces is such that a good metric for assessing perceptual differences among colors is given, respectively, by the simple Euclidean distances $||(L^*,u^*,v^*)|| = \sqrt{(L^*)^2+(u^*)^2+(v^*)^2}$ and $||(L^*,a^*,b^*)|| = \sqrt{(L^*)^2+(a^*)^2+(b^*)^2}$ [12, 13, 14].

Sometimes, color information can be more usefully represented and analyzed in 2D spaces rather than in 3D ones; in fact, important attributes are related to the *chromaticity coordinates* defined as the ratios of the tristimulus values (in RGB or XYZ coordinates) to their respective sums. This normalization allows one to use only two coordinates such as, for instance, $x \doteq X/(X+Y+Z)$ and $y \doteq Y/(X+Y+Z)$. The problem of perceptual uniformity arises of course also for these 2D chromaticity plots; a uniform chromaticity space ofted adopted in the $u'v'$ diagram obtained from the xy one through a projective transformation [12, 13, 14].

The literature of color measure offers a number of different spaces and metrics and it would be almost impossible to mention all of them here. Among the metrics proposed to improve segmentation results, the *total color difference measure* suggested by Valavanis *et al.* [17] is worth reporting. Such measure accounts for chrominance and luminance differences, both expressed in terms of Mac Adam's *just noticeable differences* (JND's) [12, 13, 14] and proves to achieve robustness in determining object boundaries over a wide range of luminance changes.

A comparison of color transformations for image segmentation is reported by Lee *et al.* in [18]; they propose a statistical model for the color variations of pixels within uniform color regions of an image and experimentally show that the best transformation, in terms of decorrelation of color coordinates, is provided by the variable *Karhunen-Loève transformation* (KLT) and by its modifications.

3 Feature-Space Based Techniques

If we assume that color is a constant property of the surface of each object within an image and we map each pixel of the color image into a certain color space, it is very likely that different objects present in the image will manifest themselves as clusters or clouds of points. The spreading of these points within each cluster is mainly determined by color variations due to shading effects and to the noise of the acquisition device. On the other hand, if instead of mapping pixels into color spaces, we build some *ad hoc* histograms upon color features, such as hue, for instance, it is likely that the objects will appear as peaks within these histograms.

Therefore, the problem of segmenting the objects of an image can be viewed as that of finding some clusters, according to the first strategy mentioned above, or as that of finding the peaks of some opportune histograms, according to the second strategy. These two approaches share a common property: they work in a certain feature space, which may be one of the color spaces described in Section 2 or a space induced by other color attributes, and they generally neglect the spatial relationships among colors. For this reason, we have decided to group them under the common denomination of *feature-space based techniques*; they will be however separately considered in the following sections.

3.1 Clustering

Clustering can be broadly defined as a nonsupervised classification of objects in which one has to generate classes or partitions without any *a priori* knowledge [19]. Analogously to the definition of segmentation given in Section 1, the problem of clustering can be analytically stated as follows: Let us suppose that we have M patterns $\boldsymbol{x}_1, \ldots, \boldsymbol{x}_M$ within a certain pattern space $\boldsymbol{\mathcal{S}}$; in our case, the space $\boldsymbol{\mathcal{S}}$ is a preselected color space while the patterns $\boldsymbol{x}_m$ are the representations of the image pixels within $\boldsymbol{\mathcal{S}}$. The process of clustering consists in determining the regions $\boldsymbol{\mathcal{S}}_1, \ldots, \boldsymbol{\mathcal{S}}_K$ such that every $\boldsymbol{x}_m$, $m = 1, \ldots, M$, belongs to one of these regions and no $\boldsymbol{x}_m$ belongs to two regions at the same time, *i.e.*, $\bigcup_{k=1}^{K} \boldsymbol{\mathcal{S}}_k = \boldsymbol{\mathcal{S}}$ and $\boldsymbol{\mathcal{S}}_i \bigcap \boldsymbol{\mathcal{S}}_j = \emptyset \ \forall\, i \neq j$. The classification of patterns into classes follows the general common sense principle that objects within each class should show a high degree of similarity while across different classes they should exhibit very low affinity.

A great many techniques have been proposed in the literature of cluster analysis [20, 19]. A classical technique for color image segmentation is the *k-means* (or *c-means*) *algorithm* [21], widely adopted also for vector quantization and data compression. Park *et. al* [22] apply this algorithm to a pattern space represented by RGB coordinates while Weeks and Hague [23] apply it to the HSI space. The k-means algorithm has been mostly used however in its fuzzy version (*fuzzy k-means algorithm*) [24]-[29]; a comparison between k-means and fuzzy k-means clustering is reported in [30]. The *possibilistic approach* to clustering of [31] is closely related to these fuzzy techniques.

ISODATA (Iterative Self-Organizing Data Analysis Technique) [19] is another algorithm often used for color space clustering [32, 33, 34]. Comaniciu and Meer [35] resort instead to the *mean shift algorithm* which is a non-parametric procedure for estimating density gradients of pattern distributions. *Competitive learning* based on the least-squares criterion is employed in [36, 37], whereas the theory of *connected components* [38] is adopted by Wang *et al.* in [39].

An original technique, proposed by Yung and Lai [40], adopts the *constrained gravitational clustering*: two points $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ within the RGB pattern space are modeled as two particles p_i and p_j respectively having masses m_i and m_j, and interacting according to the gravitational law $\boldsymbol{F} = -Gm_i m_j(\boldsymbol{x}_i - \boldsymbol{x}_j)/|\boldsymbol{x}_i - \boldsymbol{x}_j|^3$, where G is the gravitational constant. The net force on each particle determines the collapse of the points into clusters whose number is governed by a certain *force effective function*.

The RGB space is represented with a tree data strucure by Uchimura in [41] and clustering is achieved by a simplification of the tree. Kehtarnavaz *et al.* choose a 2D color space called *geodesic chromaticity* in which they introduce a *multi-scale clustering*; this algorithm determines the prominent color clusters through their *lifetime* [43].

Shi and Malik [44] and Shi *et al.* [45] tackle image segmentation via clustering as a graph partitioning problem. They represent the set of points in an arbitrary feature space as a *weighted undirected graph* $\mathcal{G} = (\boldsymbol{V}, \boldsymbol{E})$ [19], where the nodes are the points in the chosen feature space and edges are established between each pair of nodes. The weight $w(\boldsymbol{i}, \boldsymbol{j})$ of each edge is a function of the similarity between nodes $\boldsymbol{i}$ and $\boldsymbol{j}$. The goal is to partition the set of vertices $\boldsymbol{V}$ into disjoint sets $\boldsymbol{V}_1, \ldots, \boldsymbol{V}_M$ such that a predefined similarity measure is high for vertices within the same set and low across different sets. The partitioning of a graph $\mathcal{G} = (\boldsymbol{V}, \boldsymbol{E})$ into two disjoint sets $\boldsymbol{V}_1$ and $\boldsymbol{V}_2$, such that $\boldsymbol{V}_1 \cup \boldsymbol{V}_2 = \boldsymbol{V}$ and $\boldsymbol{V}_1 \cap \boldsymbol{V}_2 = \emptyset$, is obtained by removing all the edges connecting the two sets. The dissimilarity of the two sets can be measured as the total weight of the removed egdes which is called *cut* and is given by $cut(\boldsymbol{V}_1, \boldsymbol{V}_2) = \sum_{\boldsymbol{v}_1 \in \boldsymbol{V}_1, \boldsymbol{v}_2 \in \boldsymbol{V}_2} w(\boldsymbol{v}_1, \boldsymbol{v}_2)$. The optimal bi-partitioning of the graph is the one that minimizes the *cut* value. Wu and Lehay [46] originally devised an algorithm for segmentation based on such a *minimum cut*. In [44] and [45] the authors further develop this idea and report an interesting technique for finding a normalized version of the minimum cut. Moreover, Shah [47] formulates the analytic analog counterpart of the graph-theoretic formulation given above.

Usually, clustering is performed in 3D feature spaces. Lucchese and Mitra [48] instead present a technique which first finds clusters in the $u'v'$ chromaticity plane and then associates them with proper luminance values, respectively, with a 2D and a 1D k-means algorithm.

3.2 Adaptive k-means clustering

A special classification has to be devoted to a class of segmentation algorithms that combine the idea of k-means clustering with the desirable properties of local adaptivity to the color regions and of spatial continuity. In this sense, this class of algorithms might be regarded as lying in between the feature-space based techniques discussed here and the image-domain based techniques to be considered next. The traditional clustering techniques mentioned in the previous section assign pixels to clusters only on the basis of their color; each cluster is then characterized by a constant color value and no spatial constraints are imposed.

In [49] Pappas introduces a generalization of the k-means clustering algorithm which is adaptive and includes spatial constraints; this algorithm considers the segmentation of gray-level images as a *maximum a posteriori probability (MAP)* estimation problem. The extension of this technique to color images is proposed by Chang *et al.* in [50] and can be summarized as follows: Let us denote a given color image by $\boldsymbol{\mathcal{I}}$ and its segmentation by $\boldsymbol{\mathcal{S}}$. The estimated segmentation $\hat{\boldsymbol{\mathcal{S}}}$ is defined as the one that maximizes the posterior probability of the segmentation $\boldsymbol{\mathcal{S}}$ given the observed data $\boldsymbol{\mathcal{I}}$. By using the *Bayes rule*, it is $\hat{\boldsymbol{\mathcal{S}}} = \arg\max_{\boldsymbol{\mathcal{S}}} p(\boldsymbol{\mathcal{S}}|\boldsymbol{\mathcal{I}}) = \arg\max_{\boldsymbol{\mathcal{S}}} p(\boldsymbol{\mathcal{I}}|\boldsymbol{\mathcal{S}})p(\boldsymbol{\mathcal{S}})$, where $p(\boldsymbol{\mathcal{I}}|\boldsymbol{\mathcal{S}})$ represents the conditional probability of the image given the segmentation. A *Gibbs Random Field (GRF)* [52] is used as an image prior to model and enforce spatial homogeneity constraints. The conditional probability $p(\boldsymbol{\mathcal{I}}|\boldsymbol{\mathcal{S}})$ is modeled as a multivariate Gaussian with space-varying mean function. The algorithm alternates between the MAP estimation and the determination of the local class means. Initially, the means are constant in each region and equal to the k-means cluster centers. With an iterative procedure, the algorithm then updates the means by averaging them over a sliding window whose size progressively decreases. Therefore, the algorithm starts with global estimates and progressivley adapts to the local characteristics of each region.

Saber *et al.* [53] extend the algorithm of [50] to synergically combine color image segmentation and edge linking; in particular, they apply a split-and-merge strategy (see Section 4.1) to the regions of the segmented map so as to enforce consistency with the edge returned by color edge detector (see Section 4.3). Luo *et al.* in [54] modify the algorithm of [50] to incorporate a color space called Lst (instead of the RGB) and a certain color difference that can be defined within this space; they claim that with these provisions their algorithm can return segmentations physically more coherent. The same authors in [55] extend the algorithm of [50] by introducing in it derivative priors and by combining both region based and edge based statistical forces in segmentation.

3.3 Histogram thresholding

Histogram thresholding is among the most popular techniques for segmenting gray-level images and several strategies have been proposed to implement it [1]-[5]. In fact, peaks and valleys of the 1D brightness histogram can be easily identified, respectively, with objects and backgrounds of gray-level images. In the case of color images, things are a little more complicated since one has to identify different parts of a scene by combining peaks and valleys of three histograms or by partitioning 3D histograms. A common problem with the histogram based techniques is that often, because of noise, the profiles of the histograms are rather jagged giving rise to spurious peaks and thus to segmentation ambiguities; to prevent this from happening, some smoothing provisions are usually adopted.

Celenk and Uijt de Haag [56] indipendently threshold three histograms based on RGB coordinates by maximizing within-group variance and combine the three results with a predicate logic function. Shafarenko *et al.* [57] use a *watershed algorithm* [58] to segment either the 2D or the 3D color histogram of a color image; the histograms are built from $L^*u^*v^*$ coordinates and "coarsened" through convolution with a spherical window to avoid oversegmentation.

Tseng *et al.* [59] use only hue information and suggest a circular histogram thresholding of such attribute. The histogram smoothing is achieved by means of a *scale-space filter* [43]. The approaches of [60]-[63] have in common the partition of a cylindrical color space representing hue, saturation, and intensity into chromatic and achromatic regions. The former is segmented by using the hue histogram and the latter is segmented by using the intensity histogram. A scale-space filtering is adopted in [62]. In [64] a fast segmentation algorithm is suggested which resorts to a pre-clustered chromaticity plane after quantization of the HSV space represented in orthogonal Cartesian coordinates.

Sobottka and Pitas [65] single out faces from color images by defining appropriate domains corresponding to skin-like regions within the HSV space; by disregarding the value V (luminance), robustness can obtained against changes in illumination and shadows. The problem of segmenting faces within video sequences is dealt with also by Chai and Ngan in [66]; they adopt the YC_rC_b color space and its associate chromaticity diagram. Within this diagram it is possible to define a skin-color reference map which allows faces of various complexions to be robustly separated from the rest of the scene.

Guo *et al.* [67] suggest an *entropy based thresholding* which assumes that samples or patterns in the $L^*u^*v^*$ feature space are generated by two distinct sources called *modes* and *valleys*; first they classify patterns in either categories by using entropy thresholding and then they determine the number of modes in the feature space with a *modified Akaike's information criterion*.

Saber *et al.* [68] model the distribution of the chrominance components of the ojects in a scene as *Gaussian PDF's* allowing this way an adaptive setting of the object-class thresholds. Liu *et al.* [69] devise an adaptive threshold function for both RGB and HSI spaces by using *B-splines*; they can separate cell nuclei by means of this thresholding function which is obtained in a preliminary *learning phase*. Lucchese and Mitra in [70] suggest smoothing the hue histogram in $L^*u^*v^*$ coordinates by working with the low-low band of the wavelet transform of the image to be segmented; in [71] instead they find representative colors by determining first the main hue families, through histogram thresholding, and then the main clusters on planes at constant hue, by means of k-means clustering.

4 Image-Domain Based Techniques

Almost all the segmentation algorithms of the previous section exclusively operate in some feature spaces. Thus, the regions (segments) they return are expected to be homogeneous with respect to the characteristics represented in these spaces; however, there is no guarantee at all that these regions also show spatial compactness, which is a second desirable property in segmentation applications beside homogeneity. In fact, cluster analysis and histogram thresholding account in no way for the spatial locations of pixels; the description they provide is global and it does not exploit the important fact that points of a same object are usually spatially close due to *surface coherence* [5]. On the other hand, if pixels are clustered exclusively on the basis of their spatial relationships, the end result is likely to be with regions spatially well connected but with no guarantee that these regions are also homogeneous in a certain feature space.

In the literature of segmentation of gray-level images, a great many techniques have been suggested that try to satisfy both feature-space homogeneity and spatial compactness at the same time [1, 2]. The latter is ensured either by subdividing and merging or by progressively growing image regions, while the former is adopted as a criterion to direct these two processes [1, 2, 3, 5]. According to the strategy preferred for spatial grouping, these algorithms are usually divided into split-and-merge and region growing techniques; this distinction may also be extended to the corresponding algorithms for color image segmentation which will be analyzed in the following sections.

In the class of image-domain based techniques we have considered also a family of algorithms which exploit spatial information in neural network classifiers and the group of algorithms that partition images by finding the edges between homogeneously colored regions.

4.1 Split-and-merge techniques

A common characteristic of these methods is that they start with an initial inhomogeneous partition of the image (usually the initial segment is the image itself) and they keep performing splitting until homogeneous partitions are obtained. A common data structure used to implement this procedure is the *quadtree representation* [5, 19] which is a multiresolution scheme. After the splitting phase, there usually exist many small and fragmented regions which have to be somehow connected. The merging phase accomplishes this task by associating neighboring regions and guaranteeing that homogeneity requirements are met until maximally connected segments can be produced. The *region adjacency graph* (*RAG*) is the data structure commonly adopted in the merging phase [5, 19]. In many algorithms, smoothness and continuity of color regions are enforced with the adoption of a *Markov Random Field* (*MRF*) [51, 52] which basically is a stochastic process characterized by the following property: the conditional probability of a particular pixel taking in a certain value is only a function of the neighboring pixels, not of the entire image. Besides, the *Hammersley-Clifford theorem* establishes the equivalence between MRF's and *Gibbs distributions* [52].

Panjwani and Healey [72] model color texture in *RGB* components by means of a *Gaussian Markov Random Field* (*GMRF*) which embeds the spatial interaction within each of the three color planes as well as the interaction between different color planes. In the splitting phase, the image is recursively partitioned into square regions until each of them contains a single texture described by a color GMRF model. This phase is followed by an agglomerative clustering phase which consists of a conservative merging and of a stepwise optimal merging process.

Liu and Yang [73] define instead an MRF on the quadtree structure representing a color image and use the above mentioned equivalence with a Gibbs distribution. With a *relaxation process* [3] they control both splitting and merging of blocks in order to minimize the energy in the Gibbs distribution; this is shown to converge to a *MAP estimate* of the segmentation.

Numerous variations in the split-and-merge strategies have been investigated. In [74] a k-means algorithm is used for both classifying the pixels in the splitting phase and grouping pattern classes in the merging phase. In [75] the splitting is initially performed by segmenting the luminance and then refined by checking the chrominance homogeneity of the obtained regions; the merging is based on an *ad hoc* cost function. In [76] the splitting is operated with the *watershed transform* [58] of the gradient image of the luminance component simplified by a *morphological gray-scale opening* [5, 15, 16]; the merging step is realized with a *Kohonen's self-organizing map* (*SOM*) [19]. Shafarenko *et al.* [77] apply instead the watershed transform to the $L^*u^*v^*$ gradient of images and merge the patches of the watershed mosaic according to their color contrast until a termination criterion is met. A similar splitting approach is adopted in [78] whereas the merging phase is performed by iteratively processing the RAG constructed upon the resulting oversegmented regions. Also Round *et al.* [79] employ a split-and-merge strategy for segementation of skin cancers; the splitting phase is based on a quad-tree representation of the image and the following conservative merging is performed with a RAG.

Barni *et al.* [80] implicitly implement a split-and-merge strategy with a fuzzy expert system.

Gevers *et al.* [81, 82] believe that split-and-merge algorithms based on a quadtree structure are not able to adjust their tessellation to the underlying structure of the image data because of the rigid rectilinear nature of the quadtree structure; therefore, they suggest replacing it with an *incremental Delaunay triangulation* [19]. A further alternative possibility is to use *Voronoi diagrams* [19] as proposed by Schettini *et al.* [83] and by Itoh and Matsuda [84].

Broadly speaking, we can fit within the class of split-and-merge techniques also some algorithms based upon differential equations and pyramidal data structures. At first glance, they do not appear to belong to this category since the strategies they adopt to achieve segmentation are rather different from those reviewed so far; but a more careful look into them will bring to light an underlying split-and-merge idea.

Pollak *et al.* [85] and Gao *et al.* [86] apply *stabilized inverse diffusion equations (SIDE's)* [87] to segmentation of vector-valued images. The finest possible segmentation is initially assumed: each pixel represents a separate region. During an evolution process, two neighboring regions are merged whenever a certain color difference equals zero. The "color" $\boldsymbol{u}_i$ of the i-th region evolves according to $\dot{\boldsymbol{u}}_i = (1/m_i)\sum_{j\in A_i}(\dot{\boldsymbol{u}}_j - \dot{\boldsymbol{u}}_i)/\parallel \dot{\boldsymbol{u}}_j - \dot{\boldsymbol{u}}_i \parallel F(\parallel \dot{\boldsymbol{u}}_j - \dot{\boldsymbol{u}}_i \parallel)p_{ij}$, where m_i is the area of the i-th region (*i.e.*, the number of pixels), A_i denotes the set of indices of all neighbors of region i, p_{ij} is the length of the boundary between regions i and j, and $F(\,.\,)$ is a function with suitably defined properties.

The usefulness of pyramidal representation of images for segmentation was pointed out by Burt *et. al* [88] about two decades ago and ever since a number of methods to segment images by working with pyramids have appeared. It is well-known that pyramids are data structures in which images can be represented at different resolutions (fine-to-coarse) by means of tapering layers recursively obtained by averaging and downsampling their respective underlying layers [5] (the finest layer at the bottom of a pyramid is the image itself). Thus, *father-son relationships* can be naturally introduced between adjacent layers of pyramids; segmentation can be achieved with a *pyramid-linking process* [88] based on a tree data structure where the values of the fathers at a certain high layer are propagated down to the sons of the lowest level. The construction of a pyramid can be regarded as a splitting phase while the subsequent linking process can be seen as a merging phase. Recently, Lozano and Laget [89] have suggested *fractional pyramids* for segmentation of color images and Ziliani and Jensen [90] have proposed a modified version of the linking approach of [88].

4.2 Region growing techniques

An homogeneous region of an image may be obtained through a growth process which, starting from a preselected seed, progressively agglomerates points around it satisfying a certain homogeneity criterion; the growth process stops when no more points can be added to the region. The region growing techniques are mainly aimed at processing single regions; nevertheless, by combining different and subsequent growth processes, one may agglomerate in regions all the points of an image, obtaining this way its segmentation. After a region growing procedure, there might exist some very small regions or there could be two or more neighboring regions grown at different times exhibiting similar attributes. A common post-processing provision consists therefore in a merging phase that eliminates such instances by generating broader regions.

The region growing can be considered a sequential clustering or classification process [3]; thus the dependence of the results on the order according to which the image points are processed has to be accounted for. The main advantage offered by this kind of techniques is that the regions obtained are certainly spatially connected and rather compact. As for the clustering techniques of Section 3.1, where a similar problem arises in the feature space, also for the region growing techniques one is faced with the problem of choosing suitable seed points and an adequate homogeneity criterion.

As far as gray-level image segmentation is concerned, several region growing strategies can be found in the literature [1, 2, 3]. For color images some new interesting strategies for region growing based segmentation have been recently advanced.

Tremeau and Borel [91] suggest several different homogeneity criteria operating in RGB coordinates. In a first phase, they generate a certain number of connected regions with a growing process and, in a second phase, they merge all the regions having similar color distributions; after the second phase, the regions have therefore homogeneous colors but they may be disconnected. Kanai [92] develops a segmentation algorithm which resorts to both color and intensity information. The markers (seeds) are extracted from intensity via *morphological open-close operations* and from color through quantization of the HSV space; *joint markers* are defined as the sets comprising both kinds of markers. A region growing process based on a watershed algorithm starts from these *joint markers*. A region merging process eventually reduces the number of segmented regions.

In [93], the inital seeds are generated by retaining the significant local minima of the magnitude of the color image gradient; however, with this algorithm the two following situations might arise: 1) there is more than one seed per region; 2) small objects do not have any seed. The authors devise a procedure for obtaining markers having a ono-to-one correspondence with the image regions. The region growing is performed with a watershed-like algorithm proposed by the authors and working on the original color image instead of on a gradient image.

Deng *et al.* [94] determine a limited number of color classes within an image through *color quantization* and propose a criterion for "good" segmentation based on them. The application of this criterion within local windows and at multiple scales generates *J-images* in which high and low values respectively correspond to possible region boundaries and to region centers. A region growing method is adopted where the seeds are the valleys of the *J-images*; the resulting oversegmentation is finally removed with a merging phase.

Rehrmann and Priese [95] suggest using a special hexagonal topology in a hierarchical region growing algorithm which results indipendent of the starting point and of the order of processing. Ikonomakis *et al.* [96] develop an algorithm to segment both gray-scale and videophone-type color images; the procedure is a standard region growing process followed by region merging. Color homogeneity is tested with measurements in the HSI space.

If one define a cluster as a "collection of touching pixels that have almost the same color while the change in color is gradual," the fuzzy nature of the segmentation problem can be emphasized. Moghaddamzadeh and Bourbakis [97, 98] have adopted this outlook of the problem and advanced two algorithms working in RGB coordinates to implement a region growing strategy for both fine and coarse segmentation of color images. A fuzzy approach for region growing segmentation is adopted also in [99] whose algorithm is based upon several linguistic rules defining relationships among hue, chroma, and intensity. Colantoni and Laget [100] compare the results of four different algorithms obtained by the various combinations of region growing and watershed transform in a presegmentation step and in the actual segmentation algorithm. Images are represented in $L^*a^*b^*$ coordinates and handled by means of RAG's and *contour graphs*.

4.3 Edge based techniques

Segmentation can also be obtained by detecting the edges among regions. This approach has been extensively investigated for gray-level images [2, 3, 4]. Algorithms have also been proposed for the detection of discontinuities within color images. It is well-known that edges can be found in gray-level images by using functions approximating gradients or Laplacians of images, which are of course scalar functions. Gradient functions for color images may be basically defined in two ways: 1) by embedding in a single measure the variations of all three color channels or 2) by computing the gradients of the single channels and by combining them according to certain criteria.

The first approach requires some basic concepts of differential geometry [101]. Let $\boldsymbol{\Psi}(\boldsymbol{x}) : \mathbb{R}^2 \to \mathbb{R}^3$ be a color image with components $\Psi_n(\boldsymbol{x}) : \mathbb{R}^2 \to \mathbb{R}$. A simple differential distance for the manifold $\boldsymbol{\Psi}(\boldsymbol{x})$ is given by $d\boldsymbol{\Psi} = (\partial\boldsymbol{\Psi}/\partial x)dx + (\partial\boldsymbol{\Psi}/\partial y)dy$ whose squared norm can be expressed in matrix form as $d\boldsymbol{\Psi}^2 = d\boldsymbol{x}^T G d\boldsymbol{x}$, where G is a 2×2 matrix containing the partial derivatives of $\boldsymbol{\Psi}(\boldsymbol{x})$. This quadratic form is called *first fundamental form*: its extrema are obtained in the directions of the eigenvectors of the matrix G and the eigenvalues yield the values attained therein. In summary, the eigenvectors provide the direction of maximal and minimal change at a certain point of the image while the eigenvalues provide the corresponding rates of change. Upon this metric for vector-valued funtions are based the chromatic edge detectors of [102] and [103], both operating in RGB coordinates.

Examples of the second approach are given instead by [104] and [105]. Carron and Lambert [104] propose three different combinations of gradients of hue, saturation, and intensity computed in HSI coordinates. Tao and Huang [105] find clusters in the RGB space and compute egdes as the transitions from one cluster to another; the gradient information in each color channel is computed through a *Sobel operator* [5].

A truly original algorithm for boundary detection is proposed by Ma and Manjunath [106]: they use a kind of *predictive coding model* to identify the direction of change in color and texture at any point and at a given scale; this give rise to an *egde flow* which, through propagation, converges to the image boundaries. Perez and Koch [107] gather several arguments in favor of hue as the most important color attribute for segmentation; in particular, they demonstrate that, if the *integrated white condition* holds, hue is invariant to certain kinds of highlights, shading, and shadows. Egde detection is achieved by finding the zero crossings of the convolution of the *hue image* with a suitable Laplacian function. *Neural networks* in the form of Kohonen's SOM's [19] are used for contour segmentation in [108] and [109].

Within the context of the edge based techniques we can fit also the framework for object segmentation based on *color snakes*. Snakes or *active contours* were originally proposed by Kass and Witkin [110] and have received considerable attention since then. The classical snakes approach consists in deforming an initial contour towards the boundary of an object to be detected; the deformation is obtained by minimizing a global energy designed in such a way that its local minimum is attained in correspondence of the boundary of the object.

The formulation of active contours for vector-valued images (and therefore for color images) is due to Sapiro [111, 112]: he starts from the fundamental concepts of differential geometry reported above in this section and defines *color snakes* by means of a new Riemannian metric which captures the information from all image components. Gevers *et al.* propose instead *color invariant snakes* [113] that use color-invariant gradient information to drive the deformation process; in this way, the snakes return region boundaries rather insensitive to disturbances due to shadowing, shadows and highlights. A notable contribution to curve evolution applied to segmentation of color images is also due to Shah [114].

Sapiro [111, 112] shows the close relationships existing beween the active contours for color images and other algorithms based on *partial differential equations (PDE's)*, *anisotropic diffusion*, and *variational approaches* to image segmentation [43]. In this regard, a very interesting overview of variational methods for image segmentation is due to Morel and Solimini [115]. In particular, they show that the *Mumford-Shah variational model* [116] usefully represents a general model for image segmentation. Such model regards the segmentation problem as a joint smoothing and edge detection problem where one seeks to segment an image $\mathcal{I}(\boldsymbol{x})$ by simultaneously finding a piecewise smoothed image $\mathcal{S}(\boldsymbol{x})$ and a set of edges $\mathcal{E}$. The best segmentation is then obtained by minimizing the functional $J(\mathcal{S},\mathcal{E}) = \int_{\Omega\setminus\mathcal{E}}(|\nabla\mathcal{S}(\boldsymbol{x})|^2 + (\mathcal{S}(\boldsymbol{x}) - \mathcal{I}(\boldsymbol{x}))^2)d\boldsymbol{x} + length(\mathcal{E})$. The first term enforces the constraint that $\mathcal{S}(\boldsymbol{x})$ should be smooth outside the edges, the second the constraint that the piecewise smooth image $\mathcal{S}(\boldsymbol{x})$ should actually approximate the image $\mathcal{I}(\boldsymbol{x})$, and the third the constraint that the discontinuity set $\mathcal{E}$ should have minimal length.

4.4 Neural-network based classification techniques

A class *per se* is constituted by segmentation techniques adopting classification techniques based on *neural networks*. It is well-known that neural networks are structures made up of large numbers of elementary processors (cells) massively interconnected which perform simple functions [16, 19]. Their design try to imitate the information processing of biological neural cells. Despite the complexity that in some cases they require to be implemented, they offer two important properties in pattern recognition tasks: high degree of parallelism, which allows for very fast computational times and makes them suitable for real time applications, and good robustness to disturbances, which allows for reliable estimates. Another interesting feature is that, in the case of image segmentation, neural networks permit accounting for spatial information; on the other hand, one has to know beforehand the final number of segments within an image and to run a preliminary *learning phase* during which the network is trained to recognize patterns. Usually the number of classes is derived with some *a priori* knowledge on the problem or in a preprocessing stage.

A number of algorithms have been proposed for segmenting gray-level images with neural networks [4]. We discuss next some of the neural-network based techniques offered for color image segmentation.

Campadelli *et al.* [117] present two segmentation algorithms based on the idea of [118] of regarding the segmentation problem as the problem of minimizing a suitable energy function for a *Hopfield network* [19]. The first algorithm consists of three different networks, each dedicated to a color feature; their results are finally combined. The second algorithm consists instead of a single network which classifies the image pixels into classes obtained with a preliminary histogram analysis in color space. A similar approach based on the minimization of an energy function associated with a Hopfield neural network is undertaken in [119], where a preclassification algorithm spots out some *regions of interests (ROI's)* in a biomedical *RGB* image, and in [120], where an active-region segmentation algorithm is presented.

Okii *et al.* [121] present an algorithm for segmentation of medical stained images, where three are the possible classes, nuclear cell, interstitium, and background represented by three different colors. They suggest a three-layered neural network having the values R, G, B, R^2, G^2, B^2 of each pixel as the input layer and the three desired classes as the output layer. In this regard, we point out that the adoption of three layers is very common in neural networks since this structure is capable of implementing arbitrarily complex decision surfaces composed of intersecting hyperplanes in the pattern space [16, 19]. Classical is also the *learning phase* adopted in [121] which is obtained with a *back-propagation algorithm* [16, 19]. Similarly, Funakubo [122] uses two three-layered neural networks with learning through back-propagation to separate cells from background in medical images.

The aim of [123] and [124] is slightly different from the usual one of segmentation and it consists in determining the colors of inks used to generate a multicolored picture created by printing dots of cyan, magenta, yellow, and black. Nine possible combinations arise which constitute the output of a hierarchical modular neural network composed of three modules: 1) a binary decision tree whose nodes are neurons, 2) a counterpropagation network represented by a *Grossberg classifier* [19], and 3) a fuzzy post-processing unit.

Other examples of neural networks used for color segmentation are [125], where a neural network is trained to identify the color of a desired object for automated tracking purposes, and [126], where a *neural gas network* is employed.

5 Physics Based Techniques

All the algorithms examined so far are certainly prone to segmentation errors if the objects portrayed in the color images are affected by highlights, shadowing, and shadows. These phenomena cause the appearance of color of uniformly colored surfaces to change more or less drastically, whence those algorithms are very likely to return oversegmented regions. The only way to overcome this drawback is to analyze how light interact with colored materials and to introduce models of this physical interaction in the segmentation algorithms. This motivates the name of *physics based techniques* given to them. The mathematical tools they use do not significantly differ from those adopted by the algorithms of the previous section; the major difference with respect to those is the underlying physical model accounting for the reflections properties of colored matter.

Colored materials may be divided into three main categories: *optically inhomogeneous dielectrics*, *optically homogeneous dielectrics*, and *metals*. A milestone in the field of physics based segmentation was laid by Shafer in [127] where he introduces the *dichromatic reflection model* for inhomogeneous dielectrics. This model is defined by $\mathcal{L}(\lambda, g) = \mathcal{L}_s(\lambda, g) + \mathcal{L}_b(\lambda, g) = m_s(g)c_s(\lambda) + m_b(g)c_b(\lambda)$ and states that the total radiance $\mathcal{L}(\lambda, g)$ of the light reflected by an inhomogoneous dielectric is given by the sum of two indipendent parts: the radiance $\mathcal{L}_s(\lambda, g)$ of the light reflected by the object's surface and the radiance $\mathcal{L}_b(\lambda, g)$ of the light reflected from the underlying object's bulk. Symbol g denotes dependence on geometric parameters while λ is the wavelength. Moreover, the dichromatic reflection model states that each of the previous components can be split into a pure geometric coefficient $m(g)$ independent of wavelength and into a relative spectral power distribution $c(\lambda)$ that depends on wavelength but not on geometry. Shafer proves that in a color space such as the RGB the dichromatic reflection model simply reads $\mathcal{C}_{\mathcal{L}} = m_s\mathcal{C}_s + m_b\mathcal{C}_b$, where $\mathcal{C}_{\mathcal{L}}$ is the color (pixel value) measured, m_s and m_b are the magnitudes of reflection at the considered point, and $\mathcal{C}_s$ and $\mathcal{C}_b$ are the colors of interface and body reflection of the material. This model may effectively explain some particular shapes of clusters in the color space. Based upon this model, Klinker *et al.* [128] set up an algorithm (using either a split or a region-growing strategy) which makes some optical hypotheses relating objects' colors, shading, and highlights and try to justify with them the cluster shapes. The main limitation of this technique is that it can be applied only to inhomogeneous dielectrics.

Simplicity and effectiveness of representation have made the dichromatic reflection model very popular and many physics based techniques for segmentation resort to it [129]-[132]. Tsang and Tsang [133], for instance, use the dichromatic reflection model in the HSV space to detect edges. A very major contribution related with the model proposed by Shafer is represented by the work of Bajcsy *et al.* [134]. They propose a color reflection model based on the dichromatic model for dielectric materials and on a particular color space, called $\boldsymbol{S}$ space, built upon three orthogonal basis functions. In this space, brightness, hue, and saturation may be defined to analyze color variations of objects. They prove that it is possible to separate specular and diffuse interface reflections, and some inter-reflections from body reflections since they produce clusters with very peculiar shapes in the $\boldsymbol{S}$ space. The algorithm suggested in [134] allows segmentation of uniformly colored dielectric surfaces under singly colored scene illumination.

Healey [135] proposes a *unichromatic reflection model* for metals by supporting it with extensive experimental results. Such a model may be expressed as $R(r, \lambda) = m_s(g)c_s(\lambda)$, where symbols g and λ are as above; it states that metals give rise to a reflectance function $R(r, \lambda)$ which stems only from their surfaces and which, analogously to the dichromatic reflection model, can be separated into a geometric factor $m_s(g)$ and into a purely spectral component $c_s(\lambda)$. This independence of wavelength and geometry in the reflectance function hints that geometric effects in a scene can be factored out of color pixel values in an image (*normalized colors*). In [135] and [136] Healey comes up with two segmentation algorithms based on such a normalization of color which can cope with inhomogeneous dielectrics and metals at the same time.

The methods discussed above are able to work with one or two classes of materials (inhomogeneous dielectrics and metals) in the presence of a single illumination source. A more general and more complicated algorithm which also accounts for multiple illuminations is presented by Maxwell and Shafer in [137]. They introduce a general framework for segmentation of complex scenes which formulates multiple physical hypotheses about image formation. These hypotheses define broad classes for shape, illumination, and material properties of simple image regions obtained through an initial rough segmentation. A ranked set of possible segmentations is generated by analyzing, merging, and filtering the hypotheses; the pruning of such set finally yields a restricted number of plausible segmentations (interpretations) of the scene.

6 Concluding Remarks

In this paper we have presented an overview of algorithms for color image segmentation and we have proposed a classification scheme which highlights the main families of techniques available. A universal algorithm for segmenting images certainly does not exist and, on the contrary, most techniques are tailored on particular applications and may work only under certain hypotheses.

Some authors [73, 138] have proposed heuristic measures for quantitative evaluation of segmentation results. Hovever, the goodness of a segmentation result depends on so many factors such as homogeneity, spatial compactness, continuity, correspondence with psycho-visual perception [4], *etc.*, that a single measure is unlikely to capture all of them in a meaningful way. Such goodness should be evaluated by the usefulness that segmentation can provide in the particular application one is interested in. For instance, some authors [139, 140] have compared various techniques in order to determine the best segmentation strategy for the particular problem at hand.

Finally, we observe that, in this paper, we have decided to report on segmentation techniques exclusively based on color information, with a few exceptions where also texture information was taken into account. We would like to point out though that the literature numbers a great variety of methods which achieve image segmentation by combining both color and texture information. The reader is referred to [141]-[150] and references therein.

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