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A Brief Survey of Color Image Preprocessing and Segmentation Techniques

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Abstract

Multichannel information processing from a diverse range of channel information is highly time- and space-complex owing to the variety and enormity of underlying data. Most of the classical approaches rely on filtering and statistical techniques. Methods in this direction involve Markov random models, vector directional filters and statistical mixture models like Gaussian and Dirichlet mixtures. The non-classical approaches comprising the *neuro-fuzzy-genetic* paradigm or its variants are bestowed with features for real time applications. This article presents a brief survey of the aforestated trends in color image enhancement and segmentation.

Keywords: Color image enhancement, Color image segmentation, Classical approaches, Non-classical approaches

1. Introduction

Multichannel information processing has assumed great importance of late due to the evolution of the fields of remote sensing, GIS, biomedical imaging, multispectral data management, to name a few. Retrieval and analysis of object specific features from such a diverse range of channel information are essentially complex tasks primarily due to the complexity of underlying data. Color image preprocessing and segmentation are classical examples of multichannel information processing. The primary challenges faced in the processing of color images are the variety and enormity of the color intensity gamut along with the processing of the spectral characteristics of the different color components therein. To be precise, the task of color image processing involves a vast amount of processing overhead since color intensity information is generally manifested in the form of admixtures of different color components. Moreover, the relative proportions of the component colors and their inter-correlations also exhibit nonlinear characteristics.

The main steps in digital image processing are (i) preprocessing, which is a data preparation step for contrast enhancement, noise reduction or filtering [1, 2], (ii) feature extraction, for retrieving non-redundant and significant information from an image. This operation is targeted at achieving time efficiency at the cost of data reduction [3, 4] followed by object detection, localization and recognition, which determine the position, location and orientation of objects [5]. A plethora of algorithms targeted at the aforementioned objectives, has been evolved from time to time. In general, the characteristics and efficiency of an algorithm is determined by the domain of input data to be processed. Typical input domains comprise pixels, local features, image edges, embedded objects, to name a few. The output domains invariably comprise homogeneous image segments, edges of detected/localized objects, regions/segments, and different objects differing in size, shape, color and textural information.

It may be mentioned that a good understanding of the different color models is also a prerequisite for the task of processing of color images. A score of articles enumerating the advantages and disadvantages of the existing color spaces is available in [6, 7]. Variants of the standard RGB color space have also been evolved to minimize the complexity and for the faithful representation of colors.

It is worth mentioning that the performance of any color image segmentation algorithm, whether classical or non-classical, can be judged by several unsupervised approaches [8]. Notable among them are the F measure by Liu and Yang [9], F' measure (which is a modified F measure) by Borsotti *et al.* [10], Q measure by Borsotti *et al.* [10] and image entropy based measure E by Zhang *et al.* [11]. These empirical goodness measures reflect the quality of segmentation. The lower are the values of these measures, the better is the quality of segmentation achieved. Interested readers may refer to [11] for details regarding these measures and their applications to color image segmentation.

2. Classical Approaches to Color Image Preprocessing and Segmentation

Out of the existing image enhancement procedures, filtering techniques [1, 12, 13, 14, 15, 16] have become very popular over the years for addressing the problem of noise removal and edge enhancement. Vector directional filters (VDF) [12] play very important roles in color image processing by considering them as vector-valued signals. Both directional and magnitude processing of the signal content are carried out by this class of filters independently [13, 14]. Tang *et al.* [15] proposed a multichannel edge enhancing filter (MEEF) based on the vector median for enhancing degraded edges in color images. In the proposed approach, an input multichannel signal is filtered with three sub-filters. The final output is determined by comparing the outputs of the sub-filters and their vector median. Plataniotis *et al.* [16] proposed an adaptive nearest neighbor multichannel filter to deal with the problem of noise attenuation for multichannel data. The filter utilizes adaptively determined data-dependent coefficients based on a novel distance measure involving both vector directional filtering with vector magnitude filtering. Other applications of multichannel filters for processing of color images can be found in the literature [17].

A completely different framework for chromatic filtering of color images was introduced by Lucchese *et al.* [18]. The approach is centered on encoding the chromatic and achromatic contents of a color image in different ways. The chromatic content is encoded in the *CIE* chromaticity coordinates. The achromatic content is encoded as a *CIE* tristimulus value. The colors in the chromatic part are added according to the well-known center of gravity law of additive color mixtures and filtered accordingly. The achromatic content is processed with traditional linear or nonlinear filtering schemes. A plethora of chromatic filters designed for the processing of noisy and noise-free color images exist in the literature [19, 20]. But most of these approaches suffer from the need of an *a priori* knowledge regarding the noise distribution in the input images.

As regards to the segmentation of color images, Makrogiannis *et al.* [21, 22] proposed a multiresolution image segmentation scheme based on a graph-theoretic approach. The technique employs a feature-based, inter-region dissimilarity relation between the adjacent regions of the images under consideration. Finally, the regions are grouped to achieve the desired segmented outputs. The grouping strategy however, is dependent on the chosen inter-region dissimilarity relation. Grady and Schwartz [23] treated image segmentation as a linear problem instead of the eigenvector approach to a graph-partitioning problem [24]. They achieved segmentation out of spectral partitions with a small isoperimetric constant. The choice of an isoperimetric indicator function obviates the requirements of any coordinate information about the graph. Hence, it results in partitions with optimal cardinalities. Comaniciu and Meer [25] employed the mean shift analysis (MS) algorithm in searching for the exact estimation of the color cluster centers in color space. Wenbing *et al.* [26] developed a robust real-time approach for color image segmentation using the MS segmentation and the normalized cut (Ncut) [24] partitioning methods. The method resorts to the Ncut method to optimize the images clustered by the MS algorithm. These methods however, suffer from the shortcomings in the heuristic choice of a threshold eigenvalue for attaining stable segments. Luo and Khoshgoftaar [27] applied the MS clustering method for designing an unsupervised multiscale color image segmentation algorithm. The resultant oversegmented images are then merged based upon a minimum description length criterion.

Markov random field (MRF) models have often been used for modeling and analysis of the spatial dependencies between multispectral image data [28, 29] supported by the Expectation Maximization (EM) algorithm [30]. However, the computational complexity of these methods prevents their use in real-time applications. Several alternatives to the MRF models have been proposed to cut down the time complexity [31, 32]. Celeux *et al.* [33] proposed an approximate to the MRF model-based image segmentation technique. An EM algorithm is used to estimate the different parameters in hidden Markov models for the purpose of reducing the dependence structure in the models. Diplaros *et al.* [34] resorted to a spatially constrained EM algorithm to estimate the model parameters. The estimation procedure uses a data-dependent penalty factor to maximize the likelihood of data sets thereby reducing the computational overhead.

Several statistical mixture models have been proposed to suitably estimate the structural distributions of image data. Examples include the Gaussian mixture [35] and the Dirichlet mixture models [36]. The Gaussian mixture is popular since it is isotropic and can represent data distributions by a mean vector and a covariance matrix. Penalver *et al.* [37] used it to find the maximum-likelihood solution to the segmentation problem by a single starting kernel. However, the Gaussian mixture fails to discover the true structure of non-Gaussian and asymmetric data distributions [38]. In these situations, the Dirichlet distribution, which is a multivariate generalization of the Beta distribution, can be a very good choice for modeling data. In [36] Bouguila *et al.* applied the Dirichlet mixture model for several image processing and segmentation tasks viz., histogram estimation, image database characterization, and human skin detection in multimedia databases.

3. Other Approaches to Color Image Preprocessing and Segmentation

Most of the classical approaches mentioned in Section 2, require some *a priori* knowledge regarding the image data to be processed either in the form of the underlying intensity distributions or about appropriate parameters to be operated upon. On the contrary, other approaches, which include *neuro-fuzzy-genetic* and *wavelet* based approaches, operate on the underlying data regardless of the distributions and operating parameters. This section provides a bird's eye view on these types of approaches.

3.1 Neural Network Based Approaches

The inherent parallelism of neural networks have been put to use in color image processing [39, 40, 41, 42]. Lee *et al.* [43] employed a CNN multilayer neural network structure for processing of color images following the *RGB* color model. In this approach, each primary color is assigned to a unique CNN layer for processing in parallel. Roska *et al.* [44] also applied a multilayer CNN structure for handling color images.

Uchiyama and Arbib [45] employed competitive learning (CL) for online color clustering based on the least sum of squares criterion. CL converges to a local optimum for color clustering. Scheunders [46] compared the performance of CL clustering with other clustering algorithms like CMA, GCMA, and HCL. The evaluations show that HCL and GCMA are insensitive to the initial conditions. The GCMA produces the most optimal results with a high computational cost, but HCL can reach the near-optimal results with a low computational cost. A two-stage clustering approach is proposed for fast clustering in [47], where CL identifies the local density centers of the clustering data.
Self organizing maps (SOM) [48, 49] are widely used in this domain since they can retrieve the dominant color content of images [50]. Jiang and Zhou [51] used an ensemble of multiple SOM networks for clustering based on color and spatial features of image pixels. The clustered outputs finally produce the desired segmentation. In [52], SOM generates the primitive clustering results based on a training set of five-dimensional vectors (R, G, B, and x, y). The image is segmented by merging the scattered blocks and eliminating isolated pixels. A parallel version of the multilayer self organizing neural network (PSONN) is efficient in extracting color objects from a noisy pure color image [53]. Bhattacharyya *et al.* employed the PSONN architecture for the segmentation of true color images using several multilevel activation functions [54] characterized by fixed and uniform thresholding parameters.

3.2 Fuzzy Based Approaches

Fuzzy set theory and fuzzy logic have often been applied to handle the vast amount of uncertainty manifested in the color image intensity gamut [55, 56, 57, 58, 59]. The fuzzy c-means (FCM) [60] algorithm is a novel approach that allows ambiguous boundaries between clusters. Huntsberger *et al.* [61] developed an iterative image segmentation algorithm using fuzzy logic. Huang and Wu [62] applied a HSV color space based fuzzy approach for recognizing color objects in a complex background under varying illumination conditions. The novelty of the proposed approach lies in its ability to tune the fuzzy rules dynamically based on the properties of image pixels. Estevez *et al.* [42] developed a fuzzy min-max neural network based color image segmentation technique (FMMIS) for detection of image artifacts. The proposed method finds the minimum bounded rectangle (MBR) for each object present in an image. The method grows boxes around starting seed pixels to delineate different object regions in the image.
Fuzzy labeled neural gas (FLNG) [63] is an interesting prototype based vector quantization neural gas algorithm oriented clustering scheme. It belongs to the class of gradient descent supervised learning schemes [64, 65]. FC-WINN [66] is a neuro-fuzzy system based on a new type of artificial neural networks, called Weighted Incremental Neural Networks (WINN), which were introduced by Hamid Muhammed in 2002. It operates in three steps. Firstly, the input data set is processed to get the corresponding weighted connected net. This reflects and preserves the topology of the input data set, whereby the dimensionality of the problem is reduced considerably. The second step clusters the resulting weighted connected net using a watershed-like procedure resulting in a one dimensional problem. A number of separated weighted connected sub-nets representing the obtained clusters with one sub-net for each cluster, is thus formed. Moreover, all the nodes in a sub-net possess the same label value. Finally, the clustering result is mapped onto the input data set using a nearest neighbor classifier, thereby classifying each input data sample as belonging to the nearest sub-net; i.e. the nearest cluster. Thus, this approach reduces the memory and computational load considerably in the case of large input data sets.

3.3 Genetic Algorithm Based Approaches

Genetic algorithms are used for the optimization of relevant parameters in the existing segmentation algorithms [67, 68]. Farmer and Shugars [67] categorized the applications of genetic algorithms for image segmentation into two major classes, viz., (i) application to segmentation parameter selection for improved segmented outputs and (ii) application to pixel-level segmentation involving region labeling. Since most of the existing image segmentation methods require utilization of optimized parameters, the first class of applications is used more often [69, 70, 71].

Bhanu *et al.* [69] used genetic algorithms for adapting four parameters of the Phoenix segmentation algorithm [72] for outdoor color imagery. Feitosa *et al.* [73] modified the region growing segmentation algorithm using a fitness function based on the similarity of resulting segments to a target segmentation provided by the user. Zingaretti *et al.* [74] applied genetic algorithms to unsupervised color image segmentation techniques, which resort to multi-pass thresholding during each pass of the algorithm. Pignalberi *et al.* [75] focused on range images, by segmenting outside surfaces of 3D objects. However, this method can also be applied to segmentation of 2D images as well.

In pixel-level segmentation, genetic algorithms find use in region labeling depending on the characteristics of constituent pixels [67]. Peng *et al.* [76] represented each pixel in an image by a chromosome, which labels a region. Ramos and Muge [71] applied genetic algorithms to find the optimal clusters in an image thereby obviating any user-intervention in the segmentation process. Chun and Yang [77] used a fuzzy fitness function to account for the associated uncertainty in their proposed genetic algorithm based segmentation technique.

Gong and Yang [78] represented the original and segmented images by means of quad-trees. They defined a two pass genetic algorithm based optimization system similar to the method by Zingaretti *et al.* [74]. In the first pass, genetic algorithms minimize an energy function. In the second pass, fine tuning of the segmentation method is carried out.

3.4 Wavelet Based Approaches

Multi-resolution analysis (MRA) is often used for signal representation and processing for its ability to represent signals at the split resolution and scale space. MRA is applied to divide a complicated signal into several simpler signals so that each divided part can be dealt with separately.

MRA is usually used for dimensionality reduction of images [79]. A wavelet transform is an efficient tool for data approximation, compression, and noise removal [80, 81]. Shi and Shibasaki [82] used wavelets for detection of edges. In [83], texture analysis is carried out using wavelet frame analysis. Other methods have been devised for color texture segmentation in the wavelet domain [84, 85]. Porter and Canagarajah [86] devised an automatic clustering technique using the approximating capabilities of wavelets.

Since, wavelets are efficient in replicating the spectral structures of input data, they have often been used for the extraction of image features [87, 88]. In [89], Karkanis *et al.* presented a wavelet based approach for the detection of tumors in colonoscopic video. The color features extracted from the video frames are referred to as color wavelet covariance (CWC). These CWCs are based on the covariances of second-order textural measures. A selection algorithm is then applied to select an optimum subset of CWCs. A linear discriminant analysis (LDA) procedure is also used for the characterization of the image regions in the video frames. In [90], a new color image segmentation method based on the low-level features like color, texture and spatial information, is proposed. The method uses wavelet frames for the purpose of translation invariant texture analysis. Other notable contributions as regards to color image segmentation based on wavelet analysis of images are available in [91, 92].

The different classical and non-classical approaches discussed in Sections 2 and 3 can be made more efficient if the image color content is quantized and the dimensionality of the feature space is reduced [93, 94, 95]. Dong and Xie [96] proposed a neural network based optimal color image segmentation method, which incorporates color reduction followed by color clustering. A SOM network is used to project the image colors (in a modified $L*u*v$ color space) into a reduced set of color prototypes. Finally, simulated annealing is used to find out the optimal clusters in the SOM-derived prototypes. In [97], color quantization is implemented by a one-dimensional SOM. The acceptable quantization is achieved by dynamically expanding or contracting the SOM.

Thresholding also plays a significant role in color image segmentation process. Interested readers may refer to [98, 99] for different thresholding techniques in vogue. Among the multilevel thresholding techniques, Papamarkos *et al.* [100] applied PCA and Kohonen's self organized feature map (SOFM) for thresholding of color images. Hosseini and Safabakhsh [101] used a growing time-adaptive SOM for automatic thresholding of color images. Other common thresholding techniques, which have assumed importance include applications of regions adjacency graph [102], moment-preserving thresholding techniques [103], minimum error thresholding [104], to name a few.

4. Discussions and Conclusion

A review of some of the popular algorithms for preprocessing/segmentation of color images is presented. Classical methods suitable for color image processing, ranging from filtering techniques to statistical models, are discussed. Recent techniques, which mainly use neural networks, fuzzy logic, genetic algorithms and wavelet decomposition procedures, are revisited. Representative examples of these approaches are highlighted. The review suggests that the performance of these methods depend among various factors on the data distribution, operating parameters and the operating environment. The article concludes with a note on the role of color quantization and thresholding in segmentation.

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