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Color texture segmentation based on image pixel classification

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ABSTRACT

Image segmentation partitions an image into nonoverlapping regions, which ideally should be meaningful for a certain purpose. Thus, image segmentation plays an important role in many multimedia applications. In recent years, many image segmentation algorithms have been developed, but they are often very complex and some undesired results occur frequently. By combination of Fuzzy Support Vector Machine (FSVM) and Fuzzy C-Means (FCM), a color texture segmentation based on image pixel classification is proposed in this paper. Specifically, we first extract the pixel-level color feature and texture feature of the image via the local spatial similarity measure model and localized Fourier transform, which is used as input of FSVM model (classifier). We then train the FSVM model (classifier) by using FCM with the extracted pixel-level features. Color image segmentation can be then performed through the trained FSVM model (classifier). Compared with three other segmentation algorithms, the results show that the proposed algorithm is more effective in color image segmentation.

1. Introduction

The main objective of image segmentation is to divide an image into regions that can be considered homogeneous with respect to a given criterion such as color or texture. Image segmentation is one of the most widely studied problems in image analysis and computer vision and, it is a significant step towards image understanding. In the past three decades, a variety of image segmentation methods have been developed in the image processing and computer vision communities. Although seemingly very different, they all share the same property: to divide the image into regions with similar attributes (Unnikrishnan et al., 2007; Rigau et al., 2009; Francisco and Allan 2009). The existing image segmentation work can be roughly divided into *Thresholding* (Aroraa et al., 2008; Horng 2011; Hammouche et al., 2008), *Template matching* (Zeng et al., 2004; Chen et al., 2008), *Edge detection* (Li et al., 2007; Horng, 2011; Christoudias et al., 2002), *Clustering* (Chatzis and Varvarigou, 2008; Comaniciu and Meer, 2002; Wang and Bu, 2010), *Region growing* (Yu and Clausi, 2008; Kang et al., 2012; Panagiotakis et al., 2011), *and Graph-based methods* (Wenbing et al., 2007; Boykov et al., 2001; Salah et al., 2011).

Thresholding (Rigau et al., 2009; Aroraa et al., 2008; Horng 2011; Hammouche et al., 2008) is a basic technique of image segmentation with a significant degree of popularity, especially in applications where speed is an important factor. The thresholding algorithm provides a number of threshold levels, which determine the region in which each pixel belongs depending on its intensity value. In order to find these thresholds, almost all methods analyze the histogram of the image. In most cases, the optimal thresholds are found by either minimizing or maximizing an objective function, which depends on the positions of the thresholds. Thresholding is best suited for bimodal distribution, such as solid objects resting upon a contrasted background. However, traditional histogram-based thresholding algorithms cannot separate those areas which have the same gray level but do not belong to the same part. In addition, they cannot process images whose histograms are nearly unimodal, especially when the target region is much smaller than the background area. Template matching method becomes time consuming when the image becomes more complex or larger in size (Zeng et al., 2004; Guan-Yu Chen et al., 2008). Edge-based segmentation methods perform segmentation, on the basis of the information conveyed by the edges that exist in an image (Li et al., 2007; Horng 2011; Christoudias et al., 2002). Supplementary processing steps must follow to combine edges into edge chains (borders) in order to form coherent objects in the image. The edge-based methods are insensitive to image nonstationarity and are efficient in describing local behaviors, but are ineffective in producing results globally meaningful. Cluster analysis is a methodology developed for capturing local substructures in multivariate data by applying an affinity criterion to group data points. Many authors have proposed image segmentation schemes based on fuzzy set theory (Chatzis and Varvarigou. 2008). During the last decades, fuzzy clustering methodologies, especially the fuzzy c-means algorithm (FCM), have been widely applied as the effective means to conduct image segmentation (Comaniciu and Meer 2002; Wang and Bu, 2010). Their success chiefly is attributed

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to their fuzzy nature, which appears to allow the clustering procedure to retain more information from the original image than the crisp or hard clustering methodologies. Although the FCM algorithm usually performs well with noise-free images, it obtains a rather poor result when having to deal with images corrupted by noise, outliers, and other imaging artifacts, as is often the case with real-world images. Region-based segmentation methods perform segmentation by dividing an image into zones of maximum homogeneity (Li et al., 2007; Yu and Clausi 2008; Kang et al., 2012; Panagiotakis et al., 2011). The criteria for homogeneity can be based on gray-level, color, texture, and shape information. Several criteria can then be employed to force region growing in order to form consistent objects in the image. It is very important to note that region-based methods may produce different segmentation results, and therefore a combination of the segmentation results is often used as the objective is to form the most accurate segmentation map. The region splitting and merging category provides the possibility of incorporating a variety of regional features but often has difficulty in determining suitable merging and stopping criteria for a result that is neither oversegmented nor undersegmented. Graph-based approaches can be regarded as image perceptual grouping and organization methods based on the fusion of the feature and spatial information. In such approaches, visual group is based on several key factors such as similarity, proximity, and continuation. The common theme underlying these approaches is the formation of a weighted graph, where each vertex corresponds to n image pixel or a region, and the weight of each edge connecting two pixels or two regions represents the likelihood that they belong to the same segment. The weights are usually related to the color and texture features, as well as the spatial characteristic of the corresponding pixels or regions. A graph is partitioned into multiple components that minimize some cost function of the vertices in the components and/or the boundaries between those components. So far, several graph cut-based methods have been developed for image segmentations (Wenbing et al., 2007; Boykov et al., 2001; Salah et al., 2011). But generally, graph-based segmentation approaches suffer from high computational complexity.

More recently, intelligent approaches, such as neural network and support vector machine (SVM) (Sowmya and Sheela Rani 2011), have already been utilized successfully in image segmentation. Sowmya and Sheela Rani (2011) explained the task of segmenting any given color image using fuzzy clustering algorithms and competitive neural network. Lian and Wu (2011) presented a new approach based on adaptive probabilistic neural network (APNN) and level set method for brain segmentation with magnetic resonance imaging (MRI). The APNN is employed to classify the input MR image, and to extract the initial contours. Based on the extracted contours as the initial zero level set contours, the modified level set evolution is performed to accomplish the segmentation. Quan and Wen (2008) proposed an effective multiscale method for the segmentation of the synthetic aperture radar (SAR) images via probabilistic neural network. By combining the probabilistic neural network (PNN) with the multiscale autoregressive (MAR) model, a classifier, which inherits the excellent strongpoint from both of them, is designed. Yu and Chang (2004) presented an effective and efficient method for solving scenery image segmentation by applying the SVMs methodology. Cyganek (2008) proposed an efficient color segmentation method which is based on the SVM classifier operating in a one-class mode, and the method has been developed especially for the road signs recognition system. Wang et al. (2011) presented a color image segmentation algorithm by integrating the support vector machine (SVM) and fuzzy c-means. Both local spatial similarity measure model based color features and Steerable filter based texture features are extracted from the image. Before feeding to SVM algorithm for image segmentation, fuzzy c-means based algorithm is employed for clustering color and texture features. Yu et al. (2011) proposed a modified SVM based on the properties of support vectors and a pruning strategy to preserve support vectors, while eliminating redundant training vectors at the same time. Bertelli et al. (2011) proposed a supervised segmentation approach that tightly integrates object-level top down information with low-level image cues. The information from the two levels is fused under a kernelized structural SVM learning framework.

In this paper, we propose a color texture segmentation based on image pixel classification. We first extract the pixel-level color feature and texture feature of the image via the local spatial similarity measure model and localized Fourier transform, which is used as input of FSVM model (classifier). We then train the FSVM model (classifier) by using FCM with the extracted pixel-level features. Color image segmentation can be then performed through the trained FSVM model (classifier). Compared with three other segmentation algorithms, the results show that the proposed algorithm is more effective in color image segmentation.

The rest of this paper is organized as follows. Section 2 presents the basic theory about FSVM and FCM. In Section 3, the pixel-level color feature and texture feature extraction are described. Section 4 contains the description of our color image segmentation. Simulation results in Section 5 will show the performance of our scheme. Finally, Section 6 concludes this presentation.

2. The fuzzy C-means clustering and fuzzy support vector machine classification

2.1. The fuzzy C-means (FCM)

Clustering analysis is a branch of unsupervised pattern recognition. The fuzzy cluster analysis attracts more and more attention recently with introducing the fuzzy set theory. Clustering algorithms are used to find groups in unlabeled data, based on a similarity measure between the data patterns (elements). This means that similar patterns are placed together in the same cluster. The main difference between fuzzy clustering and other clustering techniques is that it generates fuzzy partitions of the data instead of hard partitions. Therefore, data patterns may belong to several clusters, having in each cluster different membership values.

The FCM algorithm assigns pixels to each category by using fuzzy memberships (Chen and Zhang 2004). Let $I=f(i,j),0\le i\le M,0\le j<N$ denote an image with $M\times N$ pixels to be partitioned into c clusters, where $f(i,j)$ represents multispectral (features) data. The algorithm is an iterative optimization that minimizes the cost function defined as follows:

$$J(U,V)=\sum_{i,j}\sum_{k=0}^{c-1}(\mu_k(i,j))^m(d_k(i,j))^2 \tag{1}$$

where $U=[\mu_k(i,j)]$ is the fuzzy clustering matrix, $V=v_0,v_1,v_2,\cdots,v_{c-1}$ is the set of clustering centers, $u_k(i,j)$ represents the membership of pixel $f(i,j)$ in the k^{th} cluster, m is the weighting exponent and a constant, which controls the fuzziness of the resulting portions, and $m=2$ is used in this study. $d_k(i,j)$ is the distance between pixel $f(i,j)$ and the kth cluster which is defined as

$$(d_k(i,j))^2=\|f(i,j)-v_k\|^2=(f(i,j)-v_k)^T(f(i,j)-v_k) \tag{2}$$

where $f(i,j)\in I$, T denotes matrix transposition, $\|\bullet\|$ is a norm metric, denotes Euclidean distance.

The cost function is minimized when pixels close to the centroid of their clusters are assigned high membership values, and low membership values are assigned to pixels with data far from the centroid. The membership function represents the probability