



Pixel classification based color image segmentation using quaternion exponent moments



Xiang-Yang Wang^{*}, Zhi-Fang Wu, Liang Chen, Hong-Liang Zheng, Hong-Ying Yang^{*}

School of Computer and Information Technology, Liaoning Normal University, Dalian 116029, PR China

ARTICLE INFO

Article history:

Received 30 December 2014

Received in revised form 8 October 2015

Accepted 22 October 2015

Available online 6 November 2015

Keywords:

Color image segmentation

Quaternion exponent moments

Twin support vector machines

Arimoto entropy

ABSTRACT

Image segmentation remains an important, but hard-to-solve, problem since it appears to be application dependent with usually no a priori information available regarding the image structure. In recent years, many image segmentation algorithms have been developed, but they are often very complex and some undesired results occur frequently. In this paper, we propose a pixel classification based color image segmentation using quaternion exponent moments. Firstly, the pixel-level image feature is extracted based on quaternion exponent moments (QEMs), which can capture effectively the image pixel content by considering the correlation between different color channels. Then, the pixel-level image feature is used as input of twin support vector machines (TSVM) classifier, and the TSVM model is trained by selecting the training samples with Arimoto entropy thresholding. Finally, the color image is segmented with the trained TSVM model. The proposed scheme has the following advantages: (1) the effective QEMs is introduced to describe color image pixel content, which considers the correlation between different color channels, (2) the excellent TSVM classifier is utilized, which has lower computation time and higher classification accuracy. Experimental results show that our proposed method has very promising segmentation performance compared with the state-of-the-art segmentation approaches recently proposed in the literature.

© 2015 Elsevier Ltd. All rights reserved.

1. Introduction

IMAGE segmentation is one of the most widely studied problems in image analysis and computer vision, because it simplifies the understanding of an image from thousands of pixels to a few regions. The goal of image segmentation is thus to partition the image domain Ω into homogeneous regions corresponding to individual objects or, equivalently, to find the contours C that define the boundaries of these objects. Image segmentation is currently being used in many of the state-of-the-art image and computer vision applications, such as object localization or recognition, data compression, tracking, or image retrieval (Estellers, Zosso, Bresson, & Thiran, 2014). Over the past 30 years, researchers have made great efforts in developing image segmentation algorithms, and quite a number of very inspiring and pioneering image segmentation approaches have been developed (Weinland, Ronfard, & Boyer, 2011). They can be roughly divided into five major categories (Chauhan, Silakari, &

Dixit, 2014; Unnikrishnan, Pantofaru, & Hebert, 2007; Weinland et al., 2011): Histogram thresholding-based methods, Clustering-based methods, Edge detection-based methods, Region-based methods, and Graph-based methods.

Histogram thresholding-based methods: Typically, a histogram-based image segmentation comprises three stages: recognizing the modes of the histogram, finding the valleys between the identified modes, and finally apply thresholds to the image based upon the valleys. Some works published in this field cover the peaks detection on the histogram curve based upon homogeneity criteria, recursive thresholding techniques based upon discriminant analysis, maximum correlation criterion for multilevel thresholding, entropy-based, using fuzzy sets, among several others (Chauhan et al., 2014; Weinland et al., 2011). Boulmerka, Allili, and Ait-Aoudia (2014) presented a new approach to multi-class thresholding-based segmentation. It considerably improves existing thresholding methods by efficiently modeling non-Gaussian and multi-modal class-conditional distributions using mixtures of generalized Gaussian distributions (MoGG). Dirami, Hammouche, and Diaf (2013) presented a fast and efficient method for segmenting complex images. This method is based on the determination of the number and the values of the thresholds required for the segmentation by introducing a new multilevel thresholding technique

^{*} Corresponding authors.

E-mail addresses: wxy37@126.com (X.-Y. Wang), yhy_65@126.com (H.-Y. Yang).

using a multiphase level set technique. Histogram thresholding-based methods are popular due to their simplicity, robustness, and accuracy. However, they cannot separate those areas which have the same gray level but do not belong to the same part. In addition, Histogram thresholding-based methods cannot process images whose histograms are nearly unimodal, especially when the target region is much smaller than the background area.

Clustering-based methods: Because of its simplicity and efficiency, clustering approaches were one of the most common techniques used for the segmentation of natural images. After the selection and the extraction of the image features, the feature samples, handled as vectors, are grouped together in compact but well-separated clusters corresponding to each class of the image. The set of connected pixels belonging to each estimated class thus defined the different regions of the scene (Chauhan et al., 2014; Comaniciu & Meer, 2002). Gong, Liang, and Shi (2013) presented an improved fuzzy C-means (FCM) algorithm for image segmentation by introducing a tradeoff weighted fuzzy factor and a kernel metric. The tradeoff weighted fuzzy factor depends on the space distance of all neighboring pixels and their gray-level difference simultaneously. The kernel parameter is adaptively determined by using a fast bandwidth selection rule based on the distance variance of all data points in the collection. Zhao, Fan, and Liu (2014) proposed an optimal-selection-based suppressed fuzzy c-means clustering algorithm with self-tuning non local spatial information for image segmentation. Firstly, an optimal-selection-based suppressed strategy is presented to modify the membership degree values for data points. Secondly, a novel gray level histogram is constructed by using the self-tuning non local spatial information for each pixel, and then fuzzy c-means clustering algorithm with the optimal-selection-based suppressed strategy is executed on this histogram. Balla-Arabé, Gao, and Wang (2013) designed an energy functional based on the fuzzy c-means objective function which incorporates the bias field that accounts for the intensity inhomogeneity of the real-world image. These clustering-based methods require a priori information, in particular the need for a previous definition of the number. Over-segmentation is the problem that must be settled and feature extraction is an important factor for clustering.

Edge detection-based methods: The edge detection method is one of the widely used approaches to the problem of image segmentation. Edge detection methods locate the pixels in the image that correspond to the edges of the objects seen in the image. The result is a binary image with the detected edge pixels (Chauhan et al., 2014; Christoudias, Georgescu, & Meer, 2002). Karasulu and Korukoglu (2011) treated the problem of image segmentation as a p-median problem, and used the simulated annealing to solve p-median problem as a probabilistic metaheuristic. In the scheme, the optimal threshold can be obtained for bi-level segmentation of grayscale images using the entropy-based simulated annealing (ESA) method. In Ma and Lu (2013), a new method based on learned bone-structure edge detectors and a coarse-to-fine deformable surface model was proposed to segment and identify vertebrae in 3D CT thoracic images. One approach to image segmentation defines a function of image partitions whose maxima correspond to perceptually salient segments. Wang and Oliensis (2010) extended previous approaches by adding a term to the objective function that seeks a sharp change in fitness with respect to the entire contour's position, generalizing from edge detection's search for sharp changes in local image brightness. The main disadvantages of the edge detection technique are that it does not work well (producing missing edges or extra edges) when images have many edges and noises, and it cannot easily identify a closed curve or boundary.

Region-based methods: Region-based approaches group the image pixels into clusters, maintaining connectivity among the

pixels of the same cluster. Examples include region growing algorithms, split and merge procedures, and watershed transformations (Chauhan et al., 2014). In region-based image segmentation, the intensity inside the region is assumed to be approximately constant, to vary only slowly or to be generated by a suitable probability model. Ge, Xiao, and Zhang (2012) proposed a new region-based active contour model for image segmentation. In particular, this model utilizes an improved region fitting term to partition the regions of interests in images depending on the local statistics regarding the intensity and the magnitude of gradient in the neighborhood of a contour. Zhao, Wang, Wang, and Shih (2014) proposed a new retinal vessel segmentation method based on level set and region growing. Firstly, a retinal vessel image is preprocessed by the contrast-limited adaptive histogram equalization and a 2D Gabor wavelet to enhance the vessels. Then, an anisotropic diffusion filter is used to smooth the image and preserve vessel boundaries. Finally, the region growing method and a region-based active contour model with level set implementation are applied to extract retinal vessels, and their results are combined to achieve the final segmentation. Ren and Shakhnarovich (2013) proposed a hierarchical segmentation algorithm that starts with a very fine over segmentation and gradually merges regions using a cascade of boundary classifiers. This approach allows the weights of region and boundary features to adapt to the segmentation scale at which they are applied. The effectiveness of region-based approaches depends on the application area and the input image. If the image is sufficiently simple, simple local techniques can be effective. However, on difficult scenes, even the most sophisticated techniques may not produce a satisfactory segmentation. Over-stringent criteria usually create fragmentation, and lenient ones overlook blurred boundaries and over-merge.

Graph-based methods: Graph-based approaches consider the image as a weighted graph, where nodes represent pixels and the weight of each edge connecting two nodes represents the similarity between them. They then formulate image segmentation as a problem of partitioning this graph into components, minimizing a cost function. It has been proposed to solve this problem using different similarity measures, different cost functions, and different optimization methods (Boykov, Veksler, & Zabih, 2001; Chauhan et al., 2014). Liu, Shi, and Shen (2012) firstly exploited the saliency map based graph cut to obtain an initial segmentation result, and then refined further the segmentation by utilizing the information of minimum cut generated using the kernel density estimation (KDE) model based graph cut. Peng, Zhang, and Zhang (2013) conducted a systematic survey of graph theoretical methods for image segmentation. They categorized these methods into five classes under a uniform notation, and also carried the quantitative evaluation. Chen, Udupa, and Alavi (2013) proposed a novel synergistic combination of the image based graph-cut (GC) method with the model based ASM method to arrive at the GC-ASM method for medical image segmentation. A multi-object GC cost function is proposed which effectively integrates the ASM shape information into the GC framework. Panagiotakis, Papadakis, and Grinias (2013) proposed a framework for interactive image segmentation. First, they partition the image into contiguous and perceptually similar regions (superpixels). Then, they construct a weighted graph that represents the superpixels and the connections between them. Finally, they use a Markov Random Field (MRF) model to get the image segmentation by minimizing a min-max Bayesian criterion. Generally, the graph-based segmentation approaches suffer from the high computational complexity.

These algorithms have been proven to be successful in many applications, but none of them are generally applicable to all images and different algorithms are usually not equally suitable for a particular application. In view of the problems mentioned above, plenty of approaches and their corresponding improvements have

Download English Version:

<https://daneshyari.com/en/article/405441>

Download Persian Version:

<https://daneshyari.com/article/405441>

[Daneshyari.com](https://daneshyari.com)