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An active contour model based on fused texture features for image segmentation

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ABSTRACT

Texture image segmentation plays an important role in various computer vision tasks. In this paper, a convex texture image segmentation model is proposed. First, the texture features of Gabor and GLCM (gray level co-occurrence matrix) are extracted for original image. Then, the two kinds of texture features are fused together to effectively construct a discriminative feature space by concatenating with each other. In the image segmentation step, a convex energy function is defined by taking the non-convex vector-valued model of Active Contour without Edges (ACWE) into a global minimization framework (GMAC). The proposed global minimization energy function with fused textures (GMFT) can avoid the existence of local minima in the minimization of the vector-valued ACWE model. In addition, a fast dual formulation is adopted to achieve the efficient contour evolution. The experimental results on synthetic and natural animal images demonstrate that the proposed GMFT model obtains more satisfactory segmentation results compared to two state-of-the-art methods in terms of segmentation accuracy and efficiency.

1. Introduction

Image segmentation is one of the most extensively studied problems in computer vision tasks [1], which is crucial to image analysis, understanding, and interpretation. Texture image segmentation has been an important topic in image processing field for a long time [2], which aims at segmenting a texture image into several regions with different texture features. There is no known method that is able to consistently and accurately segment all kinds of texture images. Generally, the overall quality of texture segmentation is determined by both the performance of texture features and the segmentation approach [3].

There are numerous methods focusing on image segmentation [1,4–12], such as region-growing, split-and-merge, Bayesian, neural networks (NN) and active contour model (ACM), etc. Recently, ACM has been one of the most successful methods for image segmentation [13]. Compared with other methods, ACMs have many advantages [14]. First, ACMs can achieve sub-pixel accuracy of object boundaries. Second, various prior knowledge including shape, intensity distribution and texture features can be easily incorporated into ACMs for robust image segmentation. Third, the resultant contours are closed and quite regular, which are convenient for further applications, such as shape analysis, classification, and recognition. A review of major ACMs can be found in [15]. One of the most famous ACMs is the active contour without edges (ACWE) [16] which can be seen as a simplified Mumford–Shah (MS) function [17]. Due to the problem of intensity inhomogeneity, texture objects and low contrast in images, there are still some difficulties in practical applications. Recently, lots of researchers have made great improvements on ACM to overcome these difficulties, such as [18–27]. Wang [26] proposed an efficient ACM by using local features for image segmentation. Another main problem of ACMs is that the contour tends to be trapped into local minima during the process of evolution, which still exist in both [13,18]. Chan et al. [28] proposed a standard global minimization framework (GMAC) based on the non-compactly supported smooth approximation of the Heaviside function. Bresson [29] unifies three different models into GMAC and proposes a dual formulation for the minimization problem.

For the texture feature extraction, there are numerous methods which can be classified into four categories [30]: statistical, geometrical, model-based and signal processing methods. Most of literatures focused on the analysis of individual texture feature methods, while few papers consider the fusion of texture features. Classical methods for extracting texture features include GLCM, Gabor and MRF (Markov random field) [31–33], etc. Proper fusion

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of different texture features is expected to produce an improved texture features with better discriminative ability. The available examples often combine different texture features by the concatenation operation. Solberg and Jain [34] adopted a variety of texture features to perform a supervised classification of four satellite-based synthetic aperture radar (SAR) images and noted that a feature fusion improved the classification rate. In addition to the direct fusion, the optimization of multiple features is also proposed. Zhao et al. [35] recognize human face using neural networks based on multiple features. Shang et al. [36] proposed a fast independent component analysis (ICA) optimized radial basis probabilistic NN to recognize palmprint. Li et al. [37] proposed a locally linear discriminant embedding methods for recognizing human face. Clausi et al. [38] states that GLCM captures the higher frequency texture information, while Gabor captures the lower and mid-frequency texture information. GLCM and Gabor feature are fused together for unsupervised segmentation to deal with boundary confusion.

In this paper, a novel algorithm is proposed to solve the above problems. First, GLCM and Gabor features of the original texture images are extracted and fused together after principal component analysis (PCA) optimization. Second, the fused feature sets are incorporated in a modified convex vector-valued ACWE model. Compared with two state-of-the-art ACMs, the proposed global minimization energy function with fused textures (GMFT) has two main superiorities. First, it can successfully segment animal texture images by utilizing the fusion of GLCM and Gabor. Second, it can avoid the local minima in the process of contour evolution by defining a new convex energy function in the GMAC framework. In addition, a fast dual formulation is employed to make the computation more efficient.

The rest of the paper is organized as follows. Section 2 discusses the feature extraction techniques of GLCM and Gabor, and the feature fusion strategy. Section 3 presents a convex vector-valued ACWE model, a fast minimization method of dual formation and the flowchart of the proposed algorithm in detail. In Section 4, we validate our method by various experiments on synthetic and animal texture images. Conclusions are drawn in Section 5.

2. Texture feature extraction

This section discusses the texture feature extraction techniques of GLCM and Gabor, and the feature fusion strategy. GLCM and Gabor are two commonly used texture features, which belong to the statistical methods and signal processing methods, respectively.

2.1. GLCM feature

GLCM is a texture feature extraction method proposed by Haralick et al. [31]. The calculation of GLCM contains two steps. The first one is to compute a co-occurring probability matrix. The elements of the matrix are the conditional joint probabilities of all pair wise combinations of gray levels (i,j) in a given spatial window (the size is N). In the process of computing GLCM matrix, two parameters need to be determined: interpixel orientation (θ) and distance (δ).

$$P(i,j) = Pr(i,j|\delta,\theta,G,N) \tag{1}$$

Usually, a variety of orientations and inter-pixel distances are selected. Besides, the quantization of gray level G and the window size N should also be determined. Coarser quantization G can significantly accelerate calculations and reduce noise overcoming the high computational complexity of GLCM. However, abundant texture information is also lost [38]. The window size parameter N affects the ability of GLCM to capture texture features. Small windows can lead to poor local estimates while large windows increase the risk of misleading classification for the multiple texture features appearing in the window.

On the basis of co-occurring probability matrix, many texture statistics are defined. The second step is to apply the predefined statistics to extract corresponding texture features. A texture statistic can identify some structural aspect of the co-occurring probabilities which in turn reflect some qualitative characteristic of the local image texture, e.g., smoothness or roughness. Each window generates a feature vector which is associated with the center pixel of the window. As a result, all pixels in the image have a feature vector associated with it. 14 GLCM statistics are designed [31]. However, only six statistics of them are advocated [38] and will be used in our paper: *contrast (Con), dissimilarity (Dis), entropy (Ent), homogeneity (Hom), inverse difference (Inv), uniformity (Uni).*

2.2. Gabor feature

Gabor is a frequency transform method and has the ability to model the frequency and orientation sensitivity characteristic of the human visual system. It has been applied in various image processing tasks, such as texture feature extraction, face recognition, and so on. Clausi [38] describes the use of Gabor filters for texture segmentation. A Gabor function is a Gaussian modulated complex sinusoid function in spatial domain. The two-dimensional Gaussian function has an aspect ratio of σ_x/σ_y. The complex exponential has a spatial frequency of F and an orientation θ. The mathematical tractability of Gabor filter in the spatial-frequency domain is appealing since it can be simplified as a Gaussian function centered on the frequency of interest, e.g.

$$H(u,v) = \exp\left(-2\pi^2\left((u-F)^2\sigma_x^2 + v\sigma_y^2\right)\right) \tag{2}$$

Typically, a filter configuration is created by allowing for the complete coverage of spatial-frequency plane. The filters are set up in a pseudo wavelet format to match the filter's frequency with its spatial extent. Each pixel will have a response to each filter, so each pixel is represented by a feature vector dimensioned to the number of filters. Although there exist many techniques to extract features from Gabor filter outputs, there is experimental evidence by Clausi and Jernigan [39] to support using the magnitude of Gabor filter response.

2.3. Feature fusion strategy

The aforementioned GLCM and Gabor are sensitive to different kinds of texture features. The GLCM produce more consistent measurements at higher signal frequency texture features, while Gabor filters produce the lower and mid-frequency texture information. Sometimes, it is necessary to simultaneously use GLCM and Gabor rather than only one of them to achieve better segmentation results. Thus, the GLCM can be combined with Gabor by substituting or supplementing the high frequency band of Gabor features. The fused texture features is expected to possess both the advantages of GLCM and Gabor.

The fusion of GLCM and Gabor is composed of the following three steps. First, 24-dimensional (24-D) GLCM texture features of the original image are extracted. The 24-D GLCM feature maps are obtained by the combination of 4 different orientations (0°, 45°, 90°, and 135°) and 6 different texture statistics (*Con, Dis, Ent, Hom, Inv, Uni*). The other two parameters of window size and inter-pixel distance are fixed according to the characteristic of texture image. Second, 5-dimensional (5-D) Gabor texture features of the original image are extracted. The 5-D Gabor feature maps are obtained by the combination of five different orientations $(0, \pi/5, 2\pi/5, 3\pi/$