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Abstract
Image segmentation is a classical problem in the area of image processing, motion estimation, and so on. Although there exist a lot of clustering based approaches to perform image segmentation, few of them study how to obtain more accurate image segmentation results by designing a suitable clustering method. In this paper, we select an appropriate distance measure in the composite feature space of color and texture. Then the distance measure is incorporated in a clustering method that utilizes the spatial information of each feature vector. Finally, the proposed scheme performs morphology filtering to obtain the final segmented regions. Experimental results show that proposed scheme can constantly achieve higher segmentation accuracy compared to some state-of-art image segmentation algorithms and has the desired ability for the segmentation of color image in a variety of vision tasks.

Keywords: Texture image segmentation, Clustering, Distance measure

1. Introduction

Image segmentation is a hot topic in many areas [1]-[4], such as medical analysis, image processing, pattern recognition, and so on, due to its broad applications. It partitions the image into different meaningful regions with homogeneous characteristics using discontinuities or similarities of image components, the subsequent processes rely heavily on its performance. In most cases, the segmentation of color image demonstrates to be more useful than the segmentation of monochrome image, because color image expresses much more image features than monochrome image. In fact, each pixel is characterized by a great number of combination of R, G, B chromatic component-24. However, more complicated segmentation techniques are required to deal with rich chromatic information in the segmentation of color images.

In general, the image segmentation algorithms can be categorized into two types:
(1) Supervised learning based image segmentation algorithms [1]-[2], which separate the image based on the sample of object colors using prior knowledge. The algorithms which belong to the category first design a classifier (such as one based on SVM, decision tree, naive Bayes or the k-nearest neighbor approach, and so on) based on a set of given image pixels with known class membership. Then, the obtained classifier is applied to new image pixels and the labels of these image pixels are predicted. For example, Taur et al. [1] proposed an image segmentation algorithm based on a multi-resolution based signature subspace classifier (MSSC), and achieved better performance on psoriasis images, when comparing with the LS-SVM approach. The supervised segmentation is commonly used in the applications where the sample of object colors can be acquires in advance, e.g., object tracking, face/gesture recognition, and image retrieval etc.

(2) Unsupervised learning based image segmentation algorithms [3]-[4], which attempt to construct the “natural grouping” of the image without using any prior knowledge. The algorithms in this category often consist of two steps. A clustering algorithm, such as K-means, hierarchical clustering, self organizing map (SOM), normalized cut algorithm, and so on. In this paper, we focus on the second category. The unsupervised segmentation is widely used in the applications where the image features are unknown, such as nature scene understanding, satellite image analysis etc.
Recently, S. Makrogiannis [3] has designed a new image segmentation approach that incorporates the cluster analysis information into a spatial grouping scheme to produce good segmentation results by the graph cut algorithm. W. Tao [4] made use of the advantages of the Mean Shift approach and the Normalized Cut approach to design a hybrid image segmentation algorithm, achieving good results for color images.

Traditional clustering algorithms usually combine the color feature and the texture feature for color-texture image segmentation, with normalization in color space and texture space respectively. Although it can balance the importance of the color and the texture, the weights for color and texture are difficult to determine. Furthermore, in these algorithms, the Euclidean distance measure is then used for matching feature vectors. Since the color-texture composite feature vector space is not actually a Euclidean space, the Euclidean distance measure applied to this space will not produce an accurate clustering. In order to combine the color feature and the texture feature more effectively, it is necessary to present a new feature clustering algorithm incorporating a true distance measure in the color-texture composite feature space. In addition, the spatial information is incorporated in the proposed clustering method naturally to separate regions far away from each other.

The remainder of the paper is organized as follows. Section 2.1 describes how to extract color and texture feature. Section 2.2 presents a true distance measure and then the clustering method is elaborated. Experimental results are shown in Section 3, and finally Section 4 concludes the paper.

2. Proposed algorithm

The framework is simple: extraction color and texture feature respectively, and then use a new clustering method to cluster these color-texture feature vectors. The image pixels corresponding to a feature cluster are within the same segmented region. Morphology filtering is then used to eliminate the small isolated regions, and the image segmentation task is completed. A general clustering-based image segmenter is illustrated in Figure 1. This is a completely data-driven scheme in that no a priori information related to the intensity image and region field is provided. First, the feature vectors are extracted from the input image for each image subunit and presented in an appropriate form. For example, it can be intensity (of multispectral band data or a color image), range data, or any other features characterising an image. Then the feature vectors are passed to the cluster estimator to find the number of true clusters. Finally the true cluster number is fed to the clustering segmenter which partitions the input feature vectors into subsets and labels the corresponding image subunits.

![Figure 1. Structure of clustering based segmenter](image-url)

2.1. Feature extraction

Gray images are normalized to have intensities with mean zero and unit standard deviation. Color images are first normalized to have R, G, and B components as in Gray World [7]: \( R^* = \frac{R - \mu}{\mu_r}, \ G^* = \frac{G - \mu}{\mu_g}, \ B^* = \frac{B - \mu}{\mu_b} \), where \( \mu = (\mu_r + \mu_g + \mu_b)/3 \), and \( \mu_r, \mu_g \) and \( \mu_b \) are the mean of each component. The color feature is then extracted from the CIE L*a*b* color space for each pixel with the normalized R, G and B
values. We adopt the CIE L*a*b* color feature here since this color space is one of the most widely adopted color models for describing colors visible to the human. Color and color contrast are important features for humans to identify the objects in an image, and our approach is based on this observation. A 3-dimensional color feature vector is obtained for each pixel of the image.

The Gabor filter [5] [6] is widely applied to extract the local feature in texture-image segmentation, since the filter not only can achieve the required selectivity in the preferred orientation and the preferred spatial frequency, but also possesses optimal joint localization properties in both spatial and frequency domains. In order to completely segment a texture image, a number of different Gabor filters are used in what is called the multichannel image filtering. Selecting the filter bands for efficient discrimination of all the textures in an image is one of the major issues in texture segmentation based on Gabor filters.

Gabor filters are of Gaussian nature, having a center frequency one orientation and two parameters of spatial expansion. By varying these parameters the filter can be tuned to filter any elliptical area in the frequency domain. A two dimensional Gabor function \( g(x, y) \) can be expressed as:

\[
g(x, y) = \frac{1}{(2\pi\sigma_x\sigma_y)} \exp\left\{ -\frac{1}{2} \left( \frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right) \right\} + 2\pi j \sigma_x \pi \sigma_y
\]

where \( \sigma_x = 1/2\pi\sigma_x \) and \( \sigma_y = 1/2\pi\sigma_y \), respectively.

Consider \( g(x, y) \) as the mother Gabor wavelet, and then we can get a class of self-similar Gabor wavelets by some dilations and rotations:

\[
g_{mn}(x, y) = a^{-m}g(x', y')
\]

\[
x' = a^m(x\cos\theta + y\sin\theta), \quad y' = a^m(-x\sin\theta + y\cos\theta)
\]

where \( a > 1 \), \( m \) and \( n \) are integers, \( \theta = n\pi / K \) and \( K \) is the total number of orientations.

Let \( U_L \) and \( U_H \) denote the lower and upper center frequencies of interest, and \( S \) be the number of scales, then the filter parameters \( \sigma_u \) and \( \sigma_v \) can be computed as follows:

\[
a = (U_H/U_L)^{1/(S-1)}, \quad \sigma_u = (a - 1)U_H^k\left( (a + 1)\sqrt{2\ln 2} \right)
\]

\[
\sigma_v = \tan\left( \frac{\pi}{2k} \right) U_H^2 \left( \frac{2\sigma_u}{\sigma_v} \right) \left( \frac{2(2\ln 2)^2\sigma_v^2}{U_H^2} \right)^{-1/2}
\]

where \( m = 0,1,...,S-1 \). Here, we set \( K = 8 \), and \( S = 4 \). In order to eliminate the effect of correlation to the absolute intensity values \( G(0,0) \) is set to be 0.

After we get the Gabor filters with different parameters, the Gabor feature image \( GFI(x, y) \) is obtained by convolving the input image \( I(x, y) \) with the Gabor function \( g_{mn}(x, y) \) as follows:

\[
GFI(u, v) = \iint \int I(x, y)g_{mn}^*(u-x, v-y)dxdy
\]

where \((x, y) \in S\), and \( S \) denotes the set of points in the image domain. By the Gabor filter convolution, we obtain a 24-dimensional texture feature vector for each image pixel.

### 2.2 Clustering algorithm

Data clustering is concerned with the partitioning of a data set into several groups such that the similarity within a group is larger than that among groups. It involves two main parts: one is the distance measure and the other is the clustering criterion.
2.2.1 Similarity Measure

To compute the distance between two feature vectors in the color-texture composite space, we use the Mallows distance [8]. Suppose random variable \( X \in \mathbb{R}^k \) follow the distribution \( \gamma_1 \) and \( Y \in \mathbb{R}^k \) follow the distribution \( \gamma_2 \). Let \( \mathcal{Y}(\gamma_1, \gamma_2) \) be the set of joint distributions over \( X \) and \( Y \) with marginal distributions of \( X \) and \( Y \) constrained to \( \gamma_1 \) and \( \gamma_2 \), respectively. Specifically, if \( \zeta \in \mathcal{Y}(\gamma_1, \gamma_2) \), then \( \zeta \) has sample space \( \mathbb{R}^k \times \mathbb{R}^k \) and its marginals \( \zeta_X = \gamma_1 \) and \( \zeta_Y = \gamma_2 \). The Mallows distance is defined as the minimum expected distance between two discrete distributions \( X \) and \( Y \) optimized over all joint distributions \( \zeta \in \mathcal{Y}(\gamma_1, \gamma_2) \).

\[
D(\gamma_1, \gamma_2) = \min_{\zeta \in \mathcal{Y}(\gamma_1, \gamma_2)} \left( \mathbb{E} \|X - Y\| \right)^{1/p}
\]

where \( \|\cdot\| \) denotes the L_p distance between two vectors. In this algorithm, we use the L_2 distance. The Mallows distance is proved to be a true metric [9].

2.2.2 K-medoid Clustering

In this paper, we adopt the k-medoid clustering method [10]. The most popular and efficient clustering algorithm is k-means clustering which is numerical, unsupervised, non-deterministic and iterative. However, it requires a well defined vector space and has many weaknesses: (1) The number of clusters, \( K \), must be determined before the algorithm is implemented. This procedure is time-consuming and is too subjective for different users; (2) The algorithm is sensitive to initial conditions (i.e. different initial conditions may produce different results of cluster). Furthermore, the algorithm may be trapped in the local optimum. As a result, the trapped clusters or centers could represent wrong groups of data. (3) Data which are isolated far away from the centers may pull the centers away from their optimum location. This could lead to poor representation of data. At the same time, the color-texture composite space is not a Euclidean space; hence the k-means clustering technique cannot be applied. Observe that k-medoid clustering can be used over any feature space endowed with a metric. The aim is to cluster together features using the similarity function (8) and spatial information about the region. The similarity function for the clustering algorithm is finally defined as

\[
D(\gamma_1, \gamma_2) = D_0(\gamma_1, \gamma_2) \cdot \Gamma(\gamma_1, \gamma_2)
\]

for \( \Gamma(\gamma_1, \gamma_2) = \min d(\gamma_1, \gamma_2) + 1 \), where \( d \) is the Chebyshev distance over the positions of the corresponding pixel:

\[
d(\gamma_1, \gamma_2) = \max \left( |v - y|, |x - z| \right)
\]

Observe that the similarity measure \( d(\gamma_1, \gamma_2) \) weights (8) using the actual spatial distance between the two feature vectors \( \gamma_1 \) and \( \gamma_2 \).

2.3 Morphology filtering

Our noise filtering algorithm is motivated by the observed properties of the noise and outliers, which are essentially a set of discontinuous and distributed pixels with small areas. The filtering algorithm considers the segmented regions one by one, and applies morphological operations [11,12] to eliminate all connected components whose areas are smaller than a threshold, which is set at 1% of the total image area.

3. Experimental results and analysis

The proposed system is a general-purposed tool for the segmentation of color images. Extensive experiments have been conducted to evaluate the performance of the system. Our
database consists of 2000 images, part of which come from the COREL and Berkeley image libraries, and others are manually collected from the web. The segmentation results derived from the proposed clustering algorithm is compared with the k-means clustering algorithm based on normalization of color and texture respectively, as well as some classical or state-of-art algorithms [11-17]. According to the database, the proposed method shows obviously better segmentation results consistently according to human perception. Due to the space limitation, only results of several test images are shown.

Figure 2 illustrates an example of the proposed method compared with the traditional k-means based image segmentation method. Different regions of segmented image are marked with distinct colors. Evident from Figure 1, the proposed segmentation scheme is much better than the traditional k-means based image segmentation method, because we have carefully select the distance measure and designed a novel clustering algorithm. The proposed algorithm can separate the mushroom completely from the background in the right image of Figure 1, while k-means only identifies part of the mushroom, including much noise.

![Figure 2](image)

**Figure 2.** Comparison with original k-means-based method. (mushroom from COREL)
(a) Original image; (b) K-means result; (c) Result of the proposed algorithm

We randomly select 3 images from the Berkeley image database to illustrate the performance of three approaches. Figure 3 compares the segmented results by different approaches. Results show that for these test images, the proposed method can produce much better results than state-of-art methods [11,12], which produce over-segmentation results. From the figures, we can notice that the final segmented regions are very close to ground truth segmentation, except for some disconnected small regions.

![Figure 3](image)

**Figure 3.** Comparison with Edge flow and Perceptual color image segmentation. (images from The Berkeley Segmentation Dataset and Benchmark) (a) Original image; (b) Edge flow; (c) Perceptual color; (d) Proposed method
4. Conclusions

In this paper, we investigate the problem of image segmentation based on cluster ensemble. In the third step, ISOPF partitions the common regions into the core regions and the non-core regions. Finally, the segmented results of the original image are obtained by merging the non-core regions to the closest core regions. In the future, we will improve the cluster ensemble approach and explore the application in the image processing area further.

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6. References

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