IMAGE SEGMENTATION USING COLOR AND TEXTURE FEATURES

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ABSTRACT

This paper describes a new color image segmentation method based on low-level features including color, texture and spatial information. The mean-shift algorithm with color and spatial information in color image segmentation is in general successful, however, in some cases, the color and spatial information are not sufficient for superior segmentation. The proposed method addresses this problem and employs texture as an additional feature. The method uses wavelet frames that provide translation invariant texture analysis. The method integrates additional texture feature to the color and spatial space of standard mean shift segmentation algorithm. The new algorithm with high dimensional extended feature space provides better results than standard mean shift segmentation algorithm as shown in experimental results.

1. INTRODUCTION

Image segmentation is an important step for many image processing and computer vision algorithms. The interest is motivated by applications over a wide spectrum of topics. For example, analyzing different regions of an aerial photo is useful for understanding plant/land distribution. Extracting an object of interest from background of an image is important for building intelligent machines for factory automation systems. Segmenting and counting blood cells from cell images can help hematologists to improve diagnosis of diseases. Scene segmentation is also helpful to retrieve images from large image databases for content-based image retrieval systems [1], [2]. Most of the methods require using image features that characterize the regions to be segmented. Particularly, texture and color have been independently and extensively used in the area [3, 4, 5, and 6]. However, the methods combining multiple features in a probabilistic framework remain limited and active. Some of the recent work includes [7-13].

This paper considers the segmentation problem of image regions based on color, texture and spatial information in a nonparametric framework. The proposed method uses discrete Wavelet frames (DWF) [3] to characterize textured regions in images. DWF decomposition of a textured region provides a translation invariant texture description which results in better estimation and more detailed texture characterization at region boundaries. Color and spatial feature space of mean shift algorithm [6] is then extended using these texture characteristics to create higher dimensional feature space for improved segmentation.

The rest of the paper is organized as follows. In section 2, the brief description of texture characterization using wavelet frames are presented. Subsequently in section 3, building the higher dimensional feature space using spatial, color and texture information and the mean shift filtering based on this feature space is described. The experimental results are given in section 4. Finally the section 5 concludes the paper.

2. WAVELET FRAMES FOR TEXTURE CHARACTERIZATION

In this paper, the discrete wavelet frame (DWF) decomposition, a variation of the discrete wavelet transform, is used for texture characterization. Unlike other decompositions, DWF is computationally inexpensive for the evaluation of low-frequency components. Dissimilar to other wavelet-based approaches, the output of the filter banks is not sub-sampled in DWF decomposition between levels. This provides translation invariant texture description of input signal. This property yields a better estimation of texture statistics and more detailed characterization at region boundaries. DWF decomposition can be calculated by successive 1-D processing along the rows and columns of the image. A block diagram of one-level DWF decomposition of an image signal is presented in Figure 1 where L and H correspond to low-pass and high-pass filters respectively.

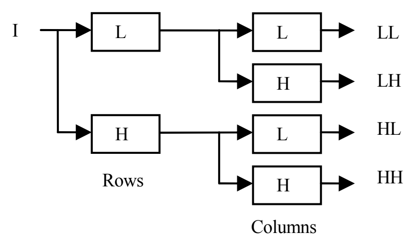


Figure 1. Illustration of discrete wavelet frame decomposition with lowpass (L) and highpass (H) filters. The input image is decomposed into four subbands.

A texture is characterized by a set of median values of energy estimated in a local window at the output of the corresponding filter bank. The energy in a local window can be calculated using coefficients of DWF decompositions (LL,

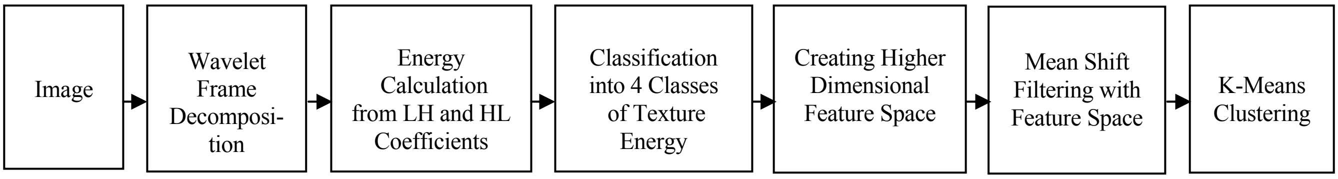
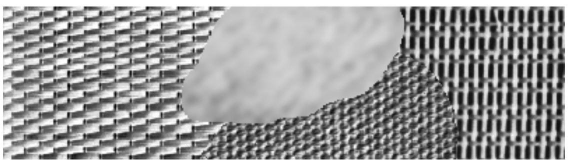
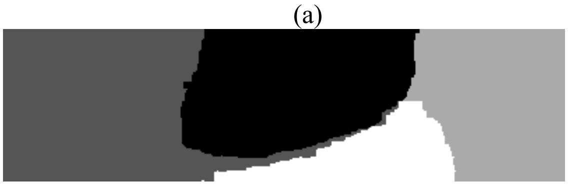


Figure 2. Overview of the proposed approach.

LH, HL, and HH) where the energy is defined as the square of the coefficients. The advantage of using median filter is that it preserves the energy associated with texture between regions. The subbands at the output of filter bank in Figure 1correspond to approximate, horizontal, vertical and diago nal components of the input image signal. Due to the fact that most of the texture information are contained in LH and HL subbands, we used only these decomposition coefficients to obtain texture features. A pixel in textured region can be classified into one of four texture categories based on texture orientation [7]. These are *vertical, horizontal, smooth* (not enough energy in any orientation), and *complex* (no dominant orientation). Texture feature extraction consists of two steps. First, the energy of LH and HL subbands are classified into two categories (0 and 1) using K-means clustering algorithm. Second, a further classification is made using combination of two categories in each subband LH and HL. A pixel is classified as *smooth* if its category is 0 in both LH and HL subbands. A pixel is classified *vertical* if its category is 0 in LH, and 1 in HL subbands. Similarly, a pixel is classified *horizontal* if its category is 1 in LH, and 0 in HL subbands. Finally, a pixel is classified as *complex* if its category is 1 in both LH and HL subbands. For example, an input image with different textures as well as the classification results are illustrated in Figure 3. In Figure 3(a), four regions with different Brodatz textures are shown. In Figure 3(b), the regions are classified based on their energy and orientation. The regions having different texture classes (smooth, horizontal, vertical and complex) are represented as different colors *black, dark gray, gray* and *white* respectively. The goal is to characterize image pixels using these texture features and use them to extent the mean shift feature space to obtain better segmentation.



(a)



(b)

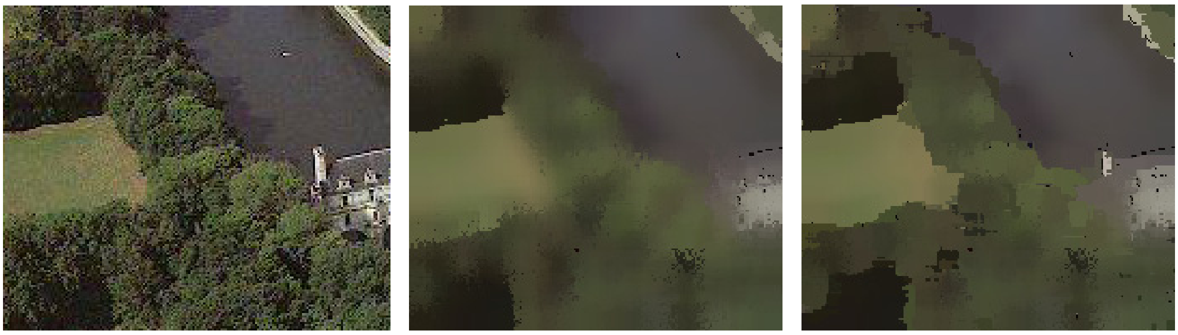
Figure 3. Illustration of classifying different textured regions. (a) A textured image containing vertical, horizontal, smooth and complex textures. (b) Classification result using DWF decomposition with median energy in a 15x15 local window.

The details of extending mean shift feature space is given in the following section.

3. MEAN SHIFT FILTERING IN HIGHER DIMENSIONAL SPACE AND SEGMENTATION

The mean shift image segmentation algorithm [6] considers a joint domain representation that includes spatial and range domains. An image is represented as a two dimensional lattice where the space of the lattice is known as spatial domain, and the gray-level or color information is represented in the range domain. Every pixel in the image can be considered as a p-dimensional vectors where $p=1$ in gray-level case and $p=3$ for color images. The dimension of joint domain representation becomes $d=p+2$. Using this representation, the mean shift filtering is performed to smooth the image and to preserve the region boundaries based on color and spatial information. However, in cases where colors in region boundaries are similar, this representation will not be sufficient and additional features are needed. In this paper, we addressed this problem and thus we extended the mean shift feature space by integrating texture feature to improve the segmentation. The block diagram of proposed method is shown in Figure 2. The steps can be explained as follows:

1. Use Wavelet transformation to decompose the image into subbands (LL, LH, HL, and HH). The DWF decompositions are the same as these subbands except that there is no subsampling. Most of the texture information are in the LH and HL subbands.
2. Calculate the median energy using coefficients of LH and HL subbands in a local window. The size of the window should be large enough to capture the local texture characteristics. The energy is defined as the square of the coefficients, and used for texture characterization.
3. Use K-means clustering algorithm to classify the energy values in two classes for each subband. There will be four texture classes based on energy: smooth (not enough energy in any orientation), vertical (dominant energy in vertical orientation), horizontal (dominant energy in horizontal orientation), and complex (no dominant orientation).
4. Generate the feature vector such that every pixel in the image has p-dimensional feature vector which includes spatial (x,y), color (gray-level or L*u*v values) and texture (smooth, vertical, horizontal or complex) information.



(a) (b) (c)

Figure 4. The comparison of filtering results. (a) Original image. (b) Mean shift filtering result. (c) Texture supported filtering result. Note that the region boundaries are well-separated.

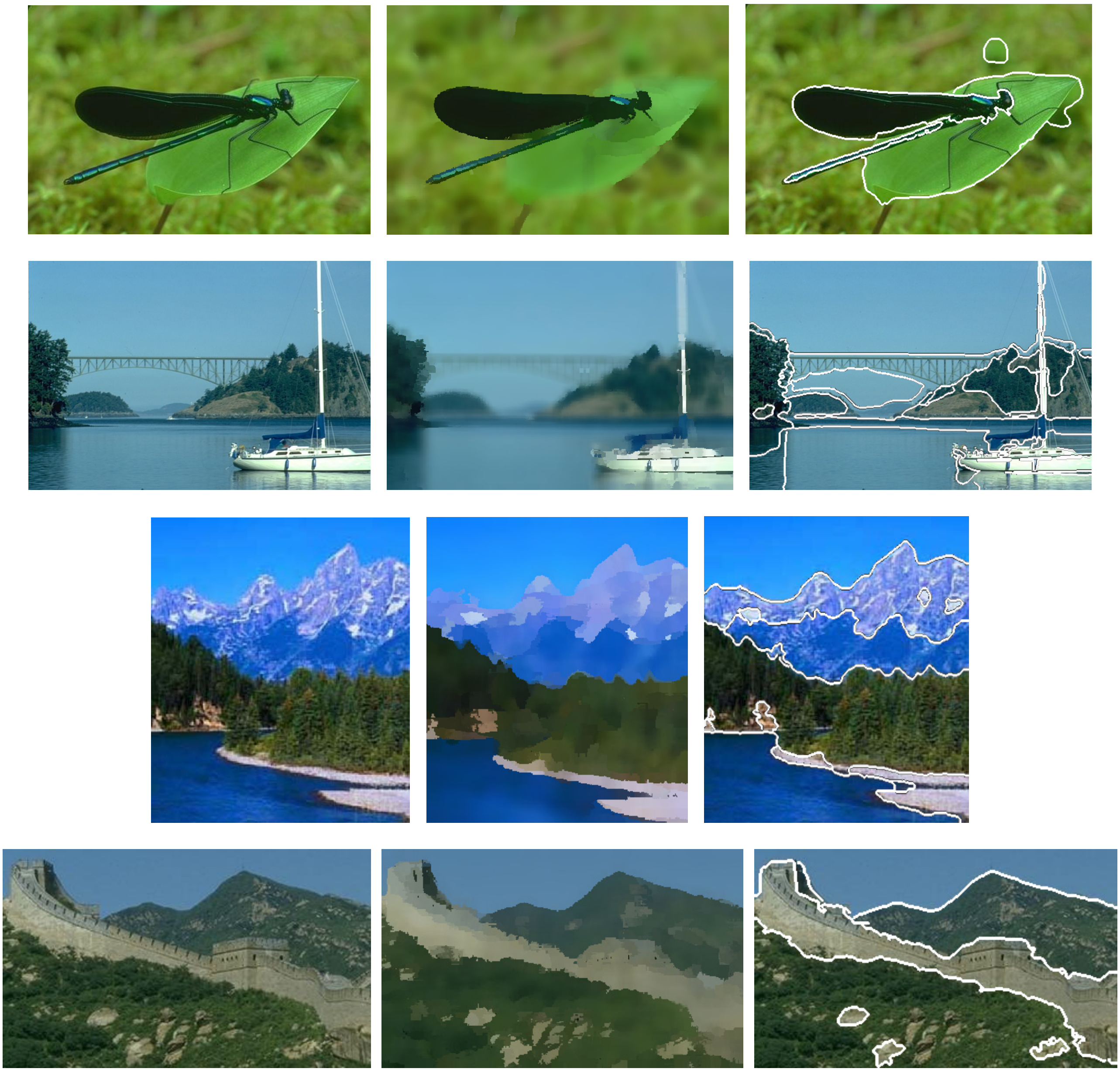


Figure 5. Image segmentation results using proposed approach. Left images: Original images. Middle Images: Filtered images. Right Images: Edges are superimposed on original images.

5. Filter the image using mean shift algorithm in higher dimensional feature space which includes spatial, color and texture information. The filtering operation can be controlled by setting the spatial window radius (h_s) and color range (h_r). The filter output (convergence point in mean shift algorithm)is determined by color as well as texture information unlike in standard mean shift filtering. This provides better discrimination between regions where colors are similar but texture is different.
6. The output image can be segmented using K-means clustering algorithm.

The results will be given in the following section.

4. RESULTS

The objective of the proposed algorithm is to achieve robust and accurate segmentation in images. To demonstrate the performance of the algorithm, we experimented with a number of natural images. To illustrate the accuracy of the proposed algorithm, an image with trees, grass, river and a house is used as shown in Figure 4(a). The standard (spatial and color-based) mean shift filtering result is shown in Figure 4(b) as a comparison. The filtering result using proposed algorithm is also shown in Figure 4(c). It can be easily seen in Figure 4(b) that the transition region between trees and grass is smoothed and blurred which negatively affect robust segmentation of regions. More improved and separated regions can be obtained using proposed algorithm as shown in Figure 4(c). The accuracy of the filtering output can be adjusted by changing the size of the texture window, color range and spatial window. The integration of texture information to the mean shift feature space provided more improved results particularly between regions due to the fact that the proposed approach contributes better estimation and more detailed texture characterization at region boundaries. More results are shown in Figure 5. The original images are shown on the left, filtered images are shown in the middle and the segmented images are shown on the right columns. The regions smaller than a threshold were removed for better visualization.

5. CONCLUSIONS

In this paper we presented a new approach for image segmentation based on low-level features including color, texture and spatial information. The proposed approach is based on extending feature space for filtering in mean shift algorithm. The proposed method uses discrete Wavelet frames (DWF) to characterize textured regions in images. DWF decomposition of a textured region provides a translation invariant texture description which results in better estimation and more detailed texture characterization at region boundaries. The performance of the proposed approach has been demonstrated using natural images where color and texture information are available. The filtering with extended feature space provided satisfactory results particularly between regions. The results indicate that the proposed approach is more robust and accurate than standard mean shift filtering.

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