SHAPE AND DATA DRIVEN TEXTURE SEGMENTATION USING LOCAL BINARY PATTERNS

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ABSTRACT

We propose a shape and data driven texture segmentation method using local binary patterns (LBP) and active contours. In particular, we pass textured images through a new LBP-based filter, which produces non-textured images. In this "filtered" domain each textured region of the original image exhibits a characteristic intensity distribution. In this domain we pose the segmentation problem as an optimization problem in a Bayesian framework. The cost functional contains a data-driven term, as well as a term that brings in information about the shapes of the objects to be segmented. We solve the optimization problem using level set-based active contours. Our experimental results on synthetic and real textures demonstrate the effectiveness of our approach in segmenting challenging textures as well as its robustness to missing data and occlusions.

1. INTRODUCTION

Image segmentation has an important role in image processing. It is a fundamental step which can be defined as isolating homogeneous regions within an image or finding the boundaries between such regions. Image segmentation has been approached from a wide variety of perspectives but still it is a challenging problem. One of those perspectives involves active contours [1, 2, 5, 6, 7, 8], which we use in our work as well. In several cases of image segmentation problems; intensity values, color, mean or variance of image intensity distributions and edge information cannot play a discriminative role. In such scenarios, texture might be a good feature to handle the segmentation problem. There are many application areas of image processing in which texture plays an important role. Some important application areas are biomedical image analysis, industrial inspection, analysis of satellite imagery, content-based retrieval from image databases, document analysis, biometric person authentication, scene analysis for robot navigation, texture synthesis for computer graphics and animation, and image coding. The need to deal with textures makes the segmentation problem more challenging.

In recent years there has been increasing interest in incorporating shape information into segmentation problems. While that could in principle improve the segmentation process, effective and practical incorporation of such information still involves many challenges.

In this work, our aim is to combine existing successful active contour and shape based image segmentation methods in texture segmentation problems. Our first contribution is the development of an LBP based texture filter to reduce the texture segmentation problem to an intensity based image segmentation problem to enable the use of existing image segmentation techniques. Our second contribution is the use nonparametric density estimation based shape prior information in texture segmentation problems.

Local Binary Pattern (LBP) is a high discriminative powered texture analysis technique which is an ordered set of binary comparisons of pixel intensities between the center pixel and its neighboring pixels[4]. By using LBP we have developed a texture filter to remove the textural structures of the texture images. We pass the textured image through our filter to produce a "filtered image" where the regions can be discriminated according to structurally independent pixel values. Then we produce a data term for our energy equation which involves maximizing mutual information between the region labels and the image pixel intensities. Also we produce a nonparametric shape prior by estimating underlying shape distribution by using Parzen density estimator in space of shapes. Then we combine the data term and shape prior term within a Bayesian framework to form the energy functional which we minimize using active contours for segmentation. We show the effectiveness and robustness of our approach on synthetic and natural textured images in experimental results section.

2. SHAPE AND DATA DRIVEN TEXTURE SEGMENTATION USING LOCAL BINARY PATTERNS

2.1 LBP Based Texture Filtering

The local binary pattern (LBP) is a non-parametric operator which is used for describing the local spatial structure of an image. Local binary pattern has been first introduced in [4] as a high discriminative powered texture analysis technique. At a given pixel position, LBP is defined as an ordered set of

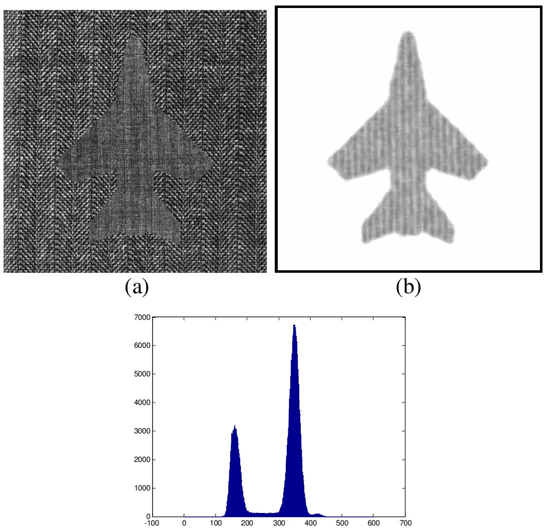
65	90	135
130	121	163
112	45	121

Thresholding according ----------→ to the center pixel value

	1st bit	2nd bit	3th bit	
	0	0	1	
8th bit	1		1	4th bit
	0	0	1	
	7th bit	6th bit	5th bit	

8-bit binary representation ----------→ $(00111001)_2$ ----------→ Decimal Representation 57

Figure 1- Graphical view of the LBP procedure. After the thresholding step, the top-left digit is assigned as the first digit and the 8-bit binary code is written in the clockwise order. For the last step the decimal value of the binary representation is found which is our decimal LBP code for the center pixel.



(a) (b) (c)

Figure 2- a) Textured Fighter Image b) Filtered Fighter Image c)Histogram of the filtered image

binary comparisons of pixel intensities between the center pixel and its neighboring pixels. LBP operator labels the pixels of an image by using the value of the center pixel as a threshold value at the 3 by 3 neighborhood of every pixel. If the neighboring pixel value is greater than or equal to the center pixel value this pixel takes the value 1 otherwise it takes 0. Then an 8-bit LBP code for a neighborhood is formed. The decimal value of this binary code gives the local structural information around the given pixel (Figure 1).The mathematical formulation of LBP for a pixel is as follows:

$$LBP(x) = \sum_{i=1}^{8} s(G(x_i) - G(x))2^{i-1} \qquad (1)$$

$$s(t) = \begin{cases} 1, t \geq 0 \\ 0, t < 0 \end{cases}, \qquad (2)$$

where x is the location of the center pixel. x_i is the location of the ith neighboring pixel and $G(.)$ is the pixel intensity value. By applying this procedure we form an LBP image which has pixel values ranging between 0 and 255. Every LBP value corresponds to a different pattern. When we take the histogram of the LBP image, it shows us, how often each of these 256 different patterns appears in a given texture. It is possible to decrease the number of patterns in the LBP histogram by using uniform patterns, but since we are not using uniform patterns in our work we refer the reader to [4] for details. There are different versions of the LBP representation, including 8-bit binary representation with 2 pixel radius, 16-bit binary representation with 2 pixel radius and 24-bit binary representation with 3 pixel radius of LBP. Figure 1 represents the 8-bit binary representation with 1 pixel radius, but in our work we use the 8-bit binary representation with 2 pixel radius. In 8-bit binary representation with 2 pixel radius the gray level values of which do not fall exactly in the center of pixels are estimated by interpolation.

Ideally texture filters are expected to produce filtering results with i.i.d. pixel intensities in each homogeneous region but practical texture filters cannot achieve that perfectly. Nevertheless the idea is to reduce the texture segmentation problem to a pixel intensity based image segmentation problem by using a texture filter. Based on this idea we propose an LBP based texture filter to remove the textural structures of textured images and produce separable regions by intensity distributions in the image. We train our texture filter by taking a texture patch from the region that we want to segment. Our training phase is actually to find out the structural information of the texture we want to segment by using a texture template. In training image for every pixel at location x and intensity value G(x) we generate the LBP value by equations (1) and (2) and produce a new image in the LBP domain. Then we calculate the histogram of the image in the LBP domain.

Note that since LBP values, which are discrete random variables, are produced from decimal values of 8 bit binary LBP code, it would be a wrong approach to treat an LBP histogram as a continuous histogram. LBP histograms represent the characteristic structure of textures by their bin numbers (they are associated with a probability mass function). For instance, in image domain when we produce the histogram of an image the closest values to bin number 116 are 115 and 117. On the other hand in the LBP domain histogram the bin number 116 is the decimal value of $(01110100)_2$. So, the decimal values of binary numbers with 1 bit difference from $(01110100)_2$ are the closest values for 116 in structural manner. (e.g.: 117, 118, 124, 244). Then we pass our test image (e.g. consider the image in Figure 2(a) for concreteness) through our filter and produce its representation in the LBP domain. In the LBP domain for every pixel in the test image we take a 17 by 17 window where the pixel is located at the center of this window. Then we compare this window's histogram with the training image's LBP histogram by using the L_1 distance metric. The formulation of the L1 distance between two histograms at an arbitrary location x is as follows:

$$\left\| H_{Train} - H_{test} \right\|_1 = \sum_{i=1}^{n} \left| H_{Train}[i] - H_{test}[i] \right| \qquad (3)$$

Where H_{Train} and H_{test} are the histograms of training and test images respectively. n is the number of histogram bins. Then we assign $L_1(H_{Train}, H_{test})$ distance value as pixel intensity value of our image in image domain.

$$G(x) = \|H_{Train} - H_{test}\|_1 \qquad (4)$$

We apply this procedure to every pixel in the test image in the LBP domain. If the texture in the window is similar to the texture in training image, then this pixel will have a low value. If the texture in the window is not similar to the texture in training image, then this pixel will have a high value. For the textured image in Figure 2(a) the resulting image with L_1 distance intensity values is in Figure 2(b).

By using window based comparison in LBP domain we take into account the structural information about all the pixels in window. For this reason the L_1 distance value which we assign as a pixel value is the result of strong information about the structure of the texture. This is the property that makes our filter robust. However, while the windowing process provides robustness; it also results in smoothing in forming the filtered images. Smoothness is a good effect for removing off the image from the textural structure but on the other hand it causes boundary effects. During the windowing process when the windows are shared by two different textured regions smoothing occurs at the boundaries.

Yet, contribution of the windowing process to robustness is more important compared to the boundary effect. Also, the boundary effect can be minimized by several approaches. For instance, at the boundaries using a smaller window size would be a good approach for boundary effect. The size of the windows can be decided according to the homogeneities inside the windows at the boundaries. The homogeneity criterion can be formed by calculating the entropies inside the windows.

2.2 Energy Functional

We pose segmentation as an optimization problem in filtered domain. We use the energy functional in equation (4) which combines a data term and a shape prior term under a Bayesian framework.

$$E(C) = -\log p(data \mid C) - \log p_C(C) \qquad (4)$$

We describe the selection of each of the two terms in this energy functional in the following two subsections.

2.2.1 Data Term

After filtering process, we reduced the texture segmentation problem to a pixel intensity based image segmentation problem, as we have eluded the textured image from the structural properties of the textures. In filtered image we produce our data term by using mutual information based data term in [2]. However, this data term is not the only choice we can use. Because, especially in uniform textured images like in Figure 2(a), the output images of our filter mostly consist of two easily separable regions by intensity distributions. For this reason using other data terms can be suitable for our approach. For instance separation of means approach or Chen and Vese's approach [1] can be used. However in difficult textures (like nonuniform textures) it is difficult to reach clear filtering results as in uniform textures. When texture filter produces noisy results at difficult textures using separation of means or other approaches does not give satisfactory results. We have used several data terms in our experiments and we have reached good segmentation results, but for generalizing we choose a nonparametric mutual information-based data term which can deal with variety of intensity distributions [2]. We cast the segmentation problem as maximization of mutual information between region labels and image pixel intensities. The mutual information based data term is as follows:

$$-|\Omega|\,\hat{I}(G(X); L_{\vec{C}}(X)) \qquad (5)$$

Where $\hat{I}(.)$ is the estimated mutual information between intensity values *G(x)* and binary label $(L_{\vec{C}}(X))$. $|\Omega|$ is the area of the image domain and *X* is the pixel index.

2.2.2 Shape Priors

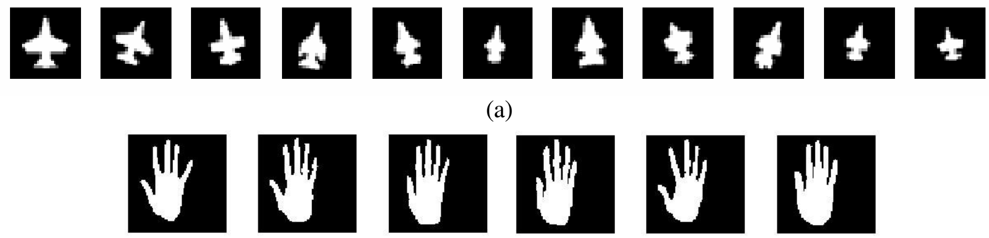
Shape prior information can aid the segmentation problems involving missing data, occlusions, or low quality images. For the shape term we use the nonparametric shape prior approach in [3]. We produce a shape prior distribution such that given an arbitrary shape; likelihood of this shape can be evaluated. We estimate the underlying shape distribution by using Parzen density estimator in space of shapes. Density estimates are expressed in terms of distances between shapes. The Parzen density estimate in shape space is as follows:

$$\hat{p}_{\tilde{C}}(\tilde{C}) = \frac{1}{n}\sum_{i=1}^{n} k(d_C(\tilde{C}, \tilde{C}_i), \sigma) \qquad (6)$$

Equation (6) is the Parzen density estimate in space of curves. *k()* *n* is the number of training shapes. $\tilde{C}$ is the aligned candidate curve and $\tilde{C}_i$ are the aligned training curves in the curve space. σ is the Gaussian kernel size. d_C is the respectively distance metric in space of curves. We have used two distance metrics which are template metric and L_2 distance between signed distance functions. Template metric can be expressed as L_1 distance between two binary maps I_1 and I_2 whose values are 1 inside the shape and 0 outside the shape, namely:

$$d_T(\tilde{C}, \tilde{C}_i) = \int_\Omega \|I_1(x) - I_2(x)\| dx \qquad (7)$$

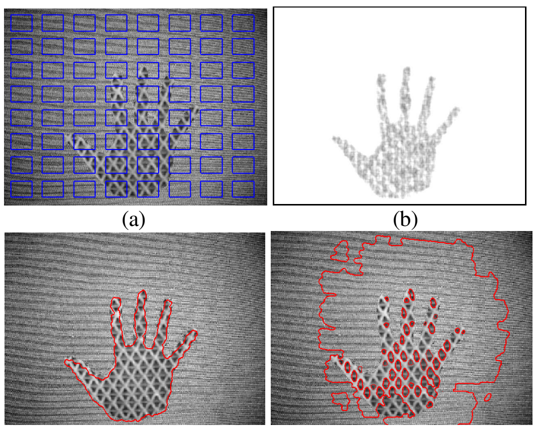
and L_2 distance is a norm of difference between two signed distance functions. For shape based texture segmentation we combine the nonparametric shape prior term in equation(6) and the mutual information based data term in equation (5) under a Bayesian framework in Equation (4). We solve this optimization problem through gradient descent using level sets. During each iteration of this process the evolving curve is aligned with the training shapes as well.



(a)

(b)

Figure 3- a) Jet fighter training shapes before alignment **b)** Hand training shapes after alignment



(a) (b)

(c) (d)

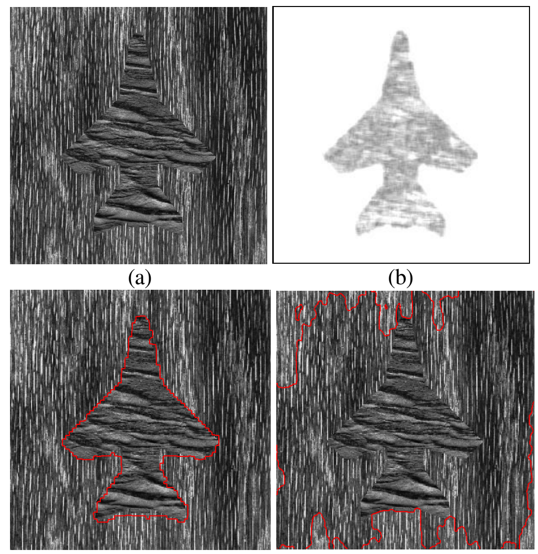
Figure 4- (a) Test image and the initial curve **(b)**Filtered image **(c)** Segmentation result **(d)** Segmentation result using [2] without our filtering process

3. EXPERIMENTAL RESULTS

(1)In our experiments we have used natural and synthetic textured images for different shapes. We have chosen the synthetic textured images from Brodatz database and we have made our experiments with hand and fighter shapes. We have tried to choose the test images to point the cases when other features are not able to discriminate regions. We have used eleven jet fighter and six hand shapes for training in our experiments. For our shape space we align the shapes to eliminate the variations in shapes due to pose differences. We align our shapes by using the technique in [6].The training jet fighter shapes before alignment process are in figure 3(a). Our aligned training shapes for jet fighter and hand are shown in figure 3(b)(c).

3.1 Segmentation Results for Uniform Textures:

[1]In figure 4(a) we have two textured regions which are taken from a jumper and from a doormat. These textures have low contrast between each other. Their first order pdfs are close and it is difficult to distinguish these regions by using other features than texture. By using texture as a feature with shape prior information about the hand, we have reached to satisfactory segmentation result in figure 4(c). When we apply the method in [2] without our filtering process the segmentation results are unsatisfactory in figure 4(d). Also for the synthetic textured test image in figure 5(a) we can see the robustness of our approach in figure 5(c). The regions in fig-ure 5(a) are not separable by using intensity distributions. Our texture filter provides output images with high contrast between regions which can be distinguished clearly. Then by the information provided from our mutual information based data term and with shape prior term we can reach good segmentation results as shown in figures 5(c). Since the filtering results of the images in figures 4(a) and 5(a) consist of two clearly separable regions, we have reached very close segmentation results by using separation of means based data term. When the outputs of the filter become noisy mutual information based data term provide more successful results.



(a) (b)

(c) (d)

Figure 5- (a) Textured image with fighter shaped region **(b)** Filtering result of (a) **(c)** Segmentation result of (a) **(d)** Segmentation result using [2] without our filtering process.

3.2 Segmentation Results for Nonuniform Textures:

For nonuniform textures we have used challenging test images which are structurally difficult to analyze. The difficulty with nonuniform textures is, it is probable that nonuniform textures include similar structures with other textures. For this reason texture analysis tools have some problems to clearly identify and discriminate nonuniform textures from other textures. Our texture filter produces some noisy results

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[1] Kindly view the experimental results on the screen or please take colored print out since the contours may not be visible in black and white print out.

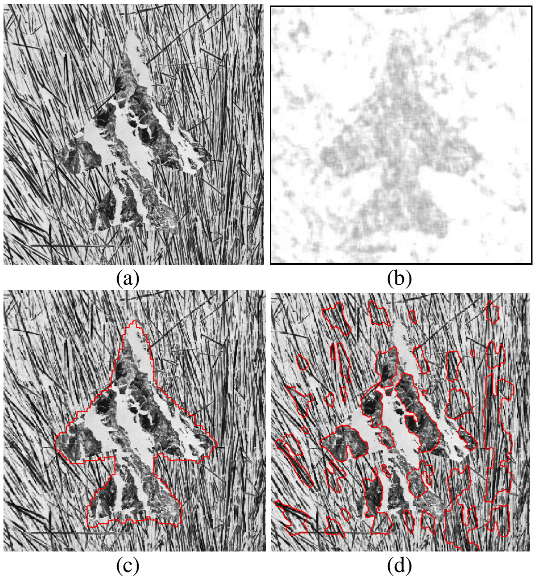

Figure 6-(a) Test image with nonuniform textured background and foreground **(b)** Filtering result **(c)** Segmentation result **(d)** Segmentation result using [2] without our filtering process

with nonuniform textures but we compensate this fact by our mutual information based data term and shape prior information in our energy equation.

In figure 6(a) we have used two challenging nonuniform textures in the foreground and in the background. Although our texture filter produces noisy filtering results we can reach satisfactory segmentation result as shown in figure 6(c).

3.3 Segmentation Results in Occluded Shapes:

We have occluded the head of the jet fighter in the textured image in figure 7(a). In our segmentation result in figure 7(b) our curve estimates the occluded parts of the fighters according to the information from data and the training shapes. Our algorithm does not have any prior information on the missing data of the shape in the image.

4. CONCLUSION

We have proposed a shape and data driven texture segmentation method using local binary patterns (LBP) and active contours method. We have passed textured images through an LBP-based texture filter to produce non-textured images. In this “filtered” domain we have posed the segmentation problem as an optimization problem in a Bayesian framework. For the cost functional we have used a mutual information based data-driven term, as well as a nonparametric shape prior term that brings in information about the shapes of the objects to be segmented. We have solved the optimization problem through gradient descent using level set-based active contours. Finally we have demonstrated the effectiveness and robustness of our approach to missing data and occlusions in our experiments on challenging textured images.

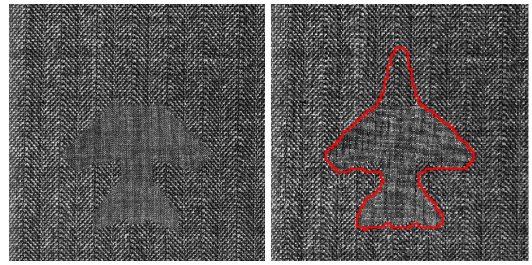

Figure 7- a) Occluded textured object b) Our Segmentation result

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