Texture Segmentation: Different Methods

Vaijinath V. Bhosle, Vrushsen P. Pawar

Abstract—Image Segmentation is an important pixel base measurement of image processing, which often has a large impact on quantitative image analysis results. The texture is most important attribute in many image analysis or computer vision applications. The procedures developed for texture problem can be subdivided into four categories: structural approach, statistical approach, model based approach and filter based approach. Different definitions of texture are described, but more importance is given to filter based methods. Such as Fourier transform, Gabor, Thresholding, Histogram and wavelet transforms. These filters are used to VisTex images and Brodatz Textures Database. The main objective of this paper is to study different methods for texture segmentation.

Keywords-Texture segmentation, Gabor Filter, Thresholding, VisTex, Brodatz.

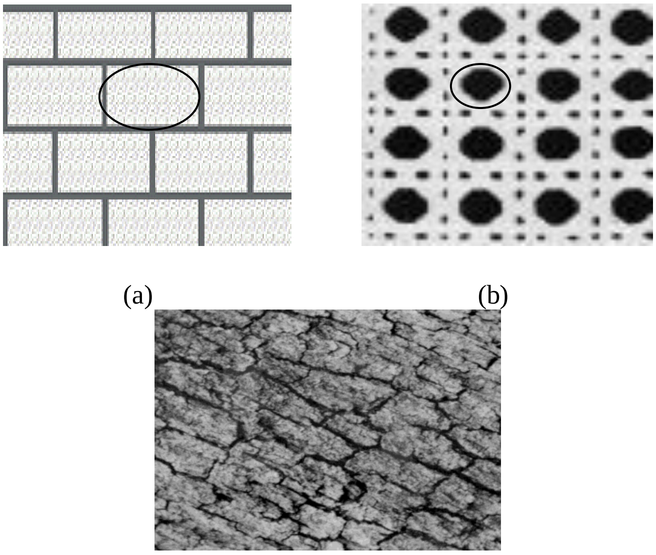
I. INTRODUCTION

Segmentation is a commonly used term for identifying differences between particularly interesting and uninteresting objects as well as distinguishing foreground from background content. Partitioning an image into a small number of homogeneous regions highlights important features, allowing a user to analyze the image more easily. Image segmentation methods can be subdivided into region based vs. edge-based methods. In order to identify possibilities for acquisition of scene information by digital images an analysis of the principle features of these images is required. In this regard, textures are the only possibility to derive information from imagery, besides the grey or color values and structural features and texture-based segmentation seems to be an adequate approach, because of the panchromatic images. For this reason, texture analysis methods were used since the beginning of digital image processing. There are continuous suggestions for new algorithmic approaches to texture-based scene analyses. Thereby, also Laws-Energy and Fourier approaches are analyzed besides first and higher order statistics. Single texture features are unsuitable for texture segmentation, caused by different viewing and illumination conditions as well as shadows, etc. Since single statistical texture features don't permit image segmentation examinations were carried out using couples of texture features [1]. Many recent publications reported good improvements in object learning, there is still the VisTex and Brodatz that their learning databases have been manually and carefully constructed [2].

II. TEXTURE

The regular repetition of an element or pattern on a surface it is called as texture. It is used to identify different textured and nontextured regions in an image. To classify/segment different texture regions in an image. To extract boundaries between major texture regions.

Texture is a difficult concept to represent. The identification of specific textures in an image is achieved primarily by modeling texture as a two-dimensional gray level variation. The relative brightness of pairs of pixels is computed such that degree of contrast, regularity, coarseness and directionality.



(a) (b)

(c)

Fig 1: Different Texture Images (a, b, c)

There is some example of texture if we extract region or boundary. Then we use different method or filter.

A. Algorithm

Step1 : Read Image from database x=image.
Step2 : If image in color then convert into grayscales.
Step3 : Apply any one filter on image.
Step4 : If extract region then
Step5 : Display the Segmented Image.
else
Step6 : Repeat step 3.
Step7 : Stored in database.

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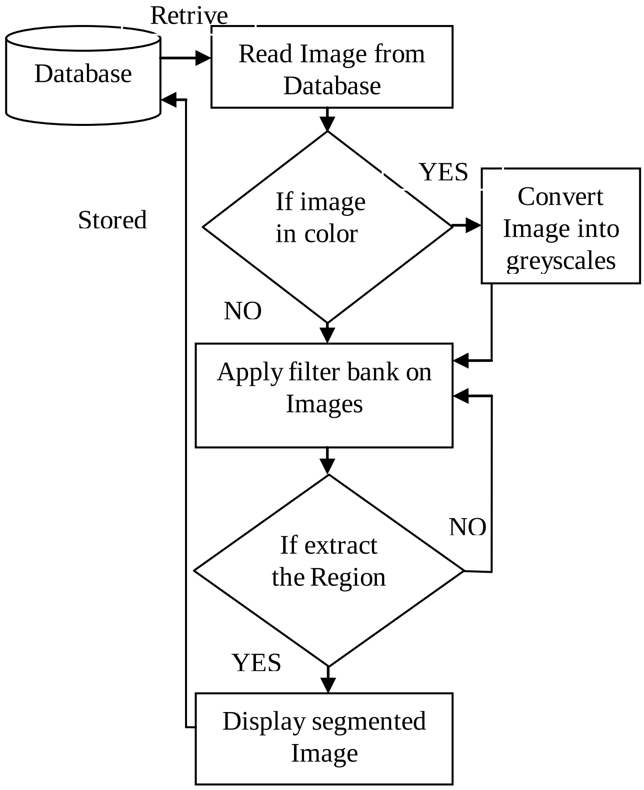
B. Flow-chart of a typical method of Texture Segmentation



C. Motivation for the Texture Segmentation

There are two main goals in this work. The first is to develop segmentation algorithms for images of VisTex and Brodatz, in which color and texture typically do not exhibit uniform statistical characteristics. The second is to incorporate knowledge of human perception in the design of underlying feature extraction algorithms.

Segmentation of images of VisTex and Brodatz is particularly difficult because, unlike artificial images that are composed of more or less pure textures, the texture properties are not well defined. The texture characteristics of perceptually distinct regions are not uniform due to effects of lighting, perspective, scale changes, etc. Fig. 4 shows two manually segmented images. These are some images in this images extract region from images.

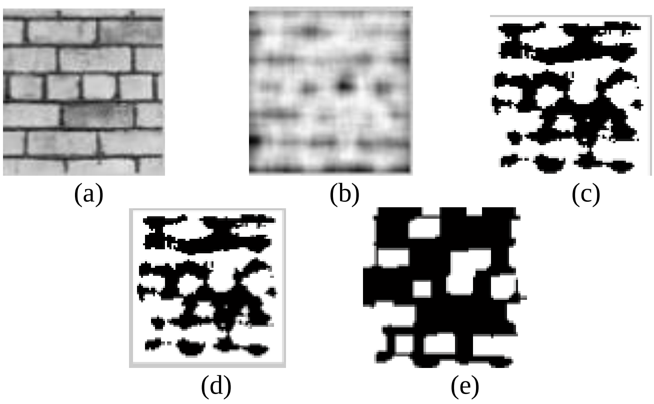


Fig 2: (a) original image, (b) entropy filtered image, (c) black and white image of energy filtered, (d) morphological closed image of the complentary entropy filtered image, (e) complementary image morphologically opened.

D. There are four major issues in texture analysis

1. Feature extraction: to compute a characteristic of a digital image able to numerically describe its texture properties;
2. Texture discrimination: to partition a textured image into regions, each corresponding to a perceptually homogeneous texture (leads to image segmentation);
3. Texture classification: to determine to which of a finite number of physically defined classes (such as normal and abnormal tissue) a homogeneous texture region belongs;
4. Shape from texture: to reconstruct 3D surface geometry from texture information.

III. METHODS USED FOR TEXTURE EGMENTATION

A. Gabor Filter

In image processing, a Gabor filter, named after Dennis Gabor, is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave.

A two dimensional Gabor function g(x, y) is defined as:

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

Gabor filter is a linear filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function. Gabor filters can be applied to many image-processing applications, such as texture segmentation, document analysis, edge detection, retina identification and image representation an advantage of these filters is that they satisfy the minimum space-bandwidth product per the uncertainty principle [3]. Hence, they provide simultaneous optimal resolution in both the space and spatial-frequency domains. Gabor filters are used to solve problems involving complicated images comprised of textured regions. The problem of segmenting textured images is considered in this paper [4].

This work presents evaluation of Gabor filter's parameters for various noisy and filtered images using Gabor filters. A lot of combinations of these noisy and filtered images have been obtained to find the best values as per the analysis of those two images of the quality metrics, SNR, Correlation and SSIM. It provides better result as compares to other filter [5, 6].

B. Edge Detection

Edges contain some of the most useful information in an image. We may use edges to measure the size of objects in an image; to isolate particular objects from their background; to recognize or classify objects.

There are a large number of edges finding algorithms in existence, and we shall look at some of the more straightforward of them.

Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have therefore been used as the base of another segmentation technique.

The edges identified by edge detection are often disconnected. To segment an object from an image however, one needs closed region boundaries. The desired edges are the boundaries between such objects. Segmentation methods can also be applied to edges obtained from edge detectors.

The different edge detection methods used are Sobel, Prewitt, Roberts, Canny, LoG, EM algorithm, OSTU algorithm and Genetic Algorithm or FPGA method is also used for edge detection. It consists of five functional blocks: 1.Interface, 2. Interlacer, 3. Memory, 4. Operator and 5. Control unit [7]. These kernels can then be combined together to find the absolute magnitude of the gradient at each point. The gradient magnitude is given by:

$$|G| = \sqrt{G_x^2 + G_y^2}$$

An Edge in an image is a significant local change in the image intensity, usually associated with a discontinuity in either the image intensity or the first derivative of the image intensity. The three steps in Edge detection process is [8] a) Filtering b) Enhancement and c) Detection.

Filtering: Images are corrupted by noise such as salt and pepper noise, impulse noise and Gaussian noise. As there is a trade-off between edge strength and noise reduction, filtering is done.

Enhancement: It emphasizes pixels where there is a significant change in local intensity values and is usually performed by computing the gradient magnitude.

Detection: Many points in an image have a nonzero value for the gradient, and not all of these points are edges for a particular application. Thresholding is used for the detection of edge points.

C. Content-Based Image Retrieval

Content-based image retrieval (CBIR), also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR) is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases. Content-based image retrieval is opposed to concept-based approaches.

Content-based means that the search analyzes the contents of the image rather than the metadata such as keywords, tags, or descriptions associated with the image. The term "content" in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself. CBIR is desirable because most web-based image search engines rely purely on metadata and this produces a lot of garbage in the results.

There is a growing interest in CBIR because of the limitations inherent in metadata-based systems, as well as the large range of possible uses for efficient image retrieval. Textual information about images can be easily searched using existing technology, but this requires humans to manually describe each image in the database. This is impractical for very large databases or for images that are generated automatically. It is also possible to miss images that use different synonyms in their descriptions.

Texture is one of the important features used in CBIR systems. The methods of characterizing texture fall into two major categories: Statistical and Structural. An experimental comparison of a number of different texture features for content-based image retrieval is presented by the author. The primary goal is to determine which texture feature or combination of texture features is most efficient in representing the spatial distribution of images. Author as analyze and evaluate both Statistical and Structural texture features [9]. author performs Combination of all features 78% result of texture segmentation.

The algorithm is based on a modified discrete wavelet frames and the mean shift algorithm. The proposed technique is tested on a range of textured images including composite texture images, synthetic texture images, real scene images as well as our main source of images, the museum images of various kinds. An extension to the automatic texture segmentation, a texture identifier is also introduced for integration into a retrieval system, providing an excellent approach to content-based image retrieval using texture features.[10].

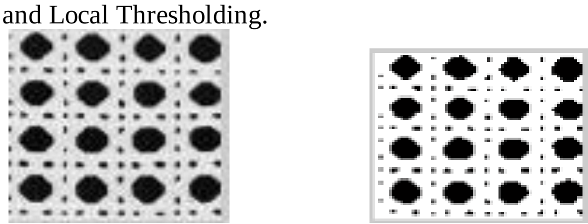
D. Thresholding

The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. The key of this method is to select the threshold value (or values when multiple-levels are selected). Several popular methods are used in industry including the maximum entropy method, Otsu's method (maximum variance), and k-means clustering. Recently, methods have been developed for thresholding computed tomography (CT) images [11].

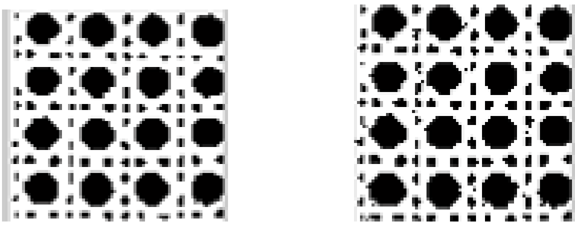
The object and background pixels have intensity levels grouped into two dominant modes. One obvious way to extract the object from the background is to select a threshold T that separates these modes. Then any point (x, y) for which $f(x,y) \geq T$ is called an object point; otherwise, the point is called a background point. In other words, the thresholded image g(x,y) is defined as

$$g(x,y) = \begin{cases} 1 & \text{If } f(x,y) \geq T \\ 0 & \text{If } f(x,y) < T \end{cases}$$

Pixels labeled 1 correspond to object, whereas pixels labeled 0 correspond to the background. When T is constant, this approach is called global thresholding. There are two types of thresholding method that is Global Thresholding and Local Thresholding.



(a) (b)



(c) (d)

Fig 3: (a) Original, (b) Threshold tool 0.35, (c) Threshold tool 0.75, (d) Threshold tool 0.80.

In above figure apply thresholding method and extract background of image using different tools. Fig 3.(a) is original image, Fig 3.(b) is after applying threshold tool 0.35 there is some noises in image. Fig 3.(c) after applying threshold tool 0.75 there is also some noises. Fig 3.(d) after applying threshold tool 0.80 there is no any noises in last image.

E. Markov Random Fields

A Markov random field (MRF) is a probabilistic process in which all interactions is local the probability that a cell is in a given state is entirely determined by probabilities for states of neighbouring cells (Blake 1987). Direct interaction occurs only between immediate neighbours. However, global effects can still occur as a result of propagation. The link between the image energy and probability is that

$$p \alpha \exp(-E / T)$$

Where T is a constant. The lower the energy of a particular image (that was generated by a particular MRF), the more likely it is to occur. There is a potential advantage in hidden Markov models (HMM) over other texture discrimination methods is that an HMM attempts to discern an underlying fundamental structure of an image that may not be directly observable. Experiments of texture discrimination using identified HMM parameters are described in (Povlow 1995), showing better performance than the autocorrelation method which required much larger neighbourhood, on both synthetic and real-world textures.[12, 13, 14].

F. Supervised Segmentation

Segmentation of objects of interest is a challenging yet important step towards the analysis of digital images. The speed, automation, accuracy and robustness of the segmentation methods often have a large impact on the performance of the application at hand, e.g. computer aided diagnosis. Fully automatic methods sometimes fail, producing incorrect results and requiring the intervention of a human operator [15].

G. Unsupervised Segmentation

Author presents a fully unsupervised texture segmentation algorithm by using modified discrete wavelet frames decomposition and a mean shift algorithm. By fully unsupervised, we mean the algorithm does not require any knowledge of the type of texture present nor the number of textures in the image to be segmented. The basic idea of the proposed method is to use the modified discrete wavelet frames to extract useful information from the image. Then, starting from the lowest level, the mean shift algorithm is used together with the fuzzy c-means clustering to divide the data into an appropriate number of clusters. The data clustering process is then refined at every level by taking into account the data at that particular level. The final crispy segmentation is obtained at the root level. This approach is applied to segment a variety of composite texture images into homogeneous texture areas and very good segmentation results are reported [16]. This leads to an average correct classification up to 96%. The experimentation gets repeated for different tolerance levels both for Brodatz , and the Vistex images [17]. The method performed very well in experiments. It is not sensitive to the selection of parameter values, does not require any prior knowledge about the number of textures or regions in the image, and seems to provide significantly better results than existing unsupervised texture segmentation approaches [18].

Table 1: Percentage of correctly detected number of textures using unsupervised method.

Number of textures in an image	Number of images tested	Images with correctly detected number of textures	Number of textures detected for the wrong detection case			
			2	3	4	5
2	16	15		1		
3	12	11				1
4	13	12				1
5	9	7			2	
Total	50	45 (90%)		1	2	2

H. Clustering Methods

Image after running k-means with k = 16. Note that a common technique to improve performance for large images is to down sample the image, compute the clusters, and then reassign the values to the larger image if necessary.

The K-means algorithm is an iterative technique that is used to partition an image into K clusters. The basic algorithm is:

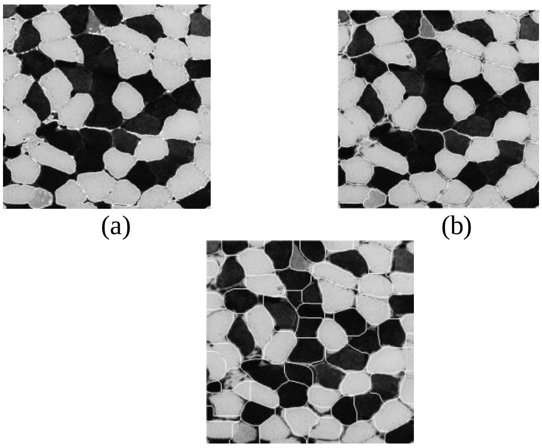
Pick K cluster centers, either randomly or based on some heuristic Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center

Re-compute the cluster centers by averaging all of the pixels in the cluster Repeat steps 2 and 3 until convergence is attained (e.g. no pixels change clusters)

In this case, distance is the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel color, intensity, texture, and location, or a weighted combination of these factors. K can be selected manually, randomly, or by a heuristic. This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K.[19]

I. Region-Based

Segmentation algorithms operate iteratively by grouping together pixels which are neighbors and have similar values and splitting groups of pixels which are dissimilar in value. Fig 4.(c) shows the boundaries produced by one such algorithm, based on the concept of watersheds [20].



(a) (b)

(c)

Fig 4 :- Boundaries produced by three segmentations of the muscle fibres image: (a) by thresholding, (b) connected regions after thresholding the output of Prewitt's edge filter and removing small regions, (c) result produced by watershed algorithm on output from a ariance filter with Gaussian weights (¾2 = 96).

J. Histogram-Based Methods

Histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image.

A refinement of this technique is to recursively apply the histogram-seeking method to clusters in the image in order to divide them into smaller clusters. This is repeated with smaller and smaller clusters until no more clusters are formed.

One disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image.

Histogram-based approaches can also be quickly adapted to occur over multiple frames, while maintaining their single pass efficiency. The histogram can be done in multiple fashions when multiple frames are considered. The same approach that is taken with one frame can be applied to multiple, and after the results are merged, peaks and valleys that were previously difficult to identify are more likely to be distinguishable. The histogram can also be applied on a per pixel basis where the information result are used to determine the most frequent color for the pixel location. This approach segments based on active objects and a static environment, resulting in a different type of segmentation useful in Video tracking.

They have presented a new segmentation method for images consisting of texture, as well as nontexture regions using local spectral histograms. By decomposing the algorithm into three stages, we derive probability models and couple feature extraction with segmentation through iterative updating. These lead to more accurate region boundaries, which are further localized through a localization stage. Comparisons with other methods show that our method gives more accurate segmentation. They introduce 95% Segmentation result using Intensity filter or also they use different filter for the segmentation [21].

Table 2: Texture Segmentation Accuracy by using different combination of the Eight Filters.

Filter(s)	Accuracy (%)	
	Without localization	With localization
Intensity filter	95.2	99.2
Two gradient filters	82.4	97.8
Intensity + two gradient filters	94.4	98.9
Two LOG filters	91.4	98.0
Three Gabor filters	88.9	99.3
Two LOG + three Gabor filters	93.2	98.7
Intensity + two LOG filters	94.3	99.2
Two gradient + three Gabor filters	90.9	98.7

IV. RESULTS OF DIFFERENT METHODS

A detailed comparison with some of the other recently proposed multiresolution texture image features are made in this section. All the methods are applied on VisTex database. Table 3 provides a summary of the experimental results using different methods. It shows the retrieval accuracy of the different texture features for each of the 116 texture classes in the database. The discrete wavelet frames decomposition, a mean shift algorithm, Hidden Markov model and Intensity filter give the best performance at close to 96% and 95.14 retrieval. This is closely followed by the Histogram features at 93.7%.

Table 3: Texture Segmentation Accuracy by using different by using different methods.

Sr No	Methods	Image Size	Accuracy (%)
1	Discrete wavelet frames decomposition and a mean shift algorithm	30 x 30	96
2	Discrete wavelet frames decomposition and a mean shift algorithm	256 x 256	*90*
3	Hidden Markov model	512 x 512	95.14
4	Intensity filter	43 x 43	93.7

V. CONCLUSION

The purpose of this paper is to study of different methods for texture segmentation based on Gabor filter, edge detection, content-based image retrieval, thresholding, Markov random fields, supervised segmentation, unsupervised segmentation, clustering methods, region-based and histogram-based methods. All these techniques are backbone for texture segmentation also planned to design a novel approach for region detection and segmentation for the texture. We found some drawbacks to extract region of interest from images, in future we will try to overcome from existing problems using new method. From the above methods we found that Hidden Markov model, discrete wavelet frames decomposition and a mean shift algorithm and Intensity filter methods give better accuracy to texture segmentation.

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