



iJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 6 Issue: V Month of publication: May 2018

DOI: <http://doi.org/10.22214/ijraset.2018.5426>

www.ijraset.com

Call: ☎ 08813907089

E-mail ID: ijraset@gmail.com

A Study on Texture Image Segmentation

Ritty Jacob¹

¹Computer Science Department, VJCET, Vazhakulam, Kerala

Abstract: This paper provides a study on image segmentation using a compound image descriptor that encompasses both colour and texture information in an adaptive fashion. The image segmentation method extracts the texture information using low-level image descriptors (such as the Local Binary Patterns (LBP)) and colour information by using colour space partitioning. The use of the colour and texture information is inappropriate for natural images as they are generally heterogeneous with respect to colour and texture characteristics. Thus, the main problem is to use the colour and texture information in a joint descriptor that can adapt to the local properties of the image under analysis. This paper provides a study towards existing approaches to colour and texture analysis

Keywords: Texture analysis, Segmentation, Feature Extraction, pixel, intensity

I. INTRODUCTION

Image Segmentation is one of the most important tasks in image analysis and computer vision [1] [2] [3] [4] and can be addressed as a clustering problem. The segmentation of the image presented to an image analysis system is dependent on the scene to be sensed, the imaging geometry, configuration and sensor used to transducer the scene into a digital image and ultimately the desired output of the system. In image analysis, image segmentation is the first step in the workflow.

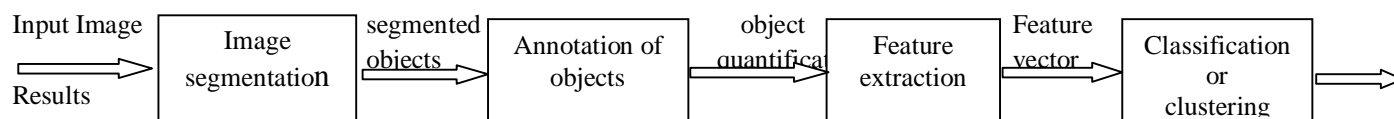


Fig. 1 A sample line graph using colors which contrast well both on screen and on a black-and-white photocopy

Image segmentation is defined as an exhaustive partitioning of an input image into regions, each of which is considered to be homogeneous with respect to some image property of interest (eg: intensity, colour or texture). Segmentation algorithms for images generally are based on one of the two basic categories dealing with properties of intensity values: a) Discontinuity and Similarity. In the first category, the boundaries of regions are sufficiently different from each other and from the background to allow boundary detection based on local discontinuities in intensity. Edge based segmentation is one of the approach used in this category. Region based segmentations are based on partitioning an image into regions that are similar according to a set of predefined criteria.

The aim of segmentation algorithm is to partition the input image into a number of disjoint regions with similar properties. Texture and colour [1][3][5][6] are two of such properties. Many images contain areas that are clearly differentiated by texture that could be used as a means of achieving segmentation.

For example in the kidney the parts like cortex and medulla can be differentiated from each other by the density and location of structures such as glomerulus. Texture is characterized not only by the pattern in a neighbourhood that surrounds the pixel. Texture features and analysis method can be loosely divided into statistical and structural methods where the following approaches can be applied. Hurst coefficient, grey level co-occurrence matrices, the power spectrum method of Fourier texture descriptor, Gabor filter filters and Markov random fields etc. are some of these approaches.

II. TEXTURE ANALYSIS

Texture is an important property of digital images, although image texture does not have a formal definition it can be regarded as a function of the variation of pixel intensities which form repeated patterns[6][7]. This can be of four categories:

- 1) statistical
- 2) model based
- 3) signal processing and
- 4) structural [2][5][6][8]

Among these major importance lies on statistical and signal processing categories.

A. Statistical

These categories analyse the spatial distribution of pixels using features extracted from first and second order histogram [6] [8]. For example gray level differences [9] and co-occurrence matrices [7]. These methods used more often for texture classification rather than texture based segmentation. Many other methods are also there [10].

B. Signal Processing

It is a recent approach. In these methods the image is typically filtered with a bank of filters of differing scales and orientations in order to capture frequency changes. eg. Gabor filters.

III.COLOUR ANALYSIS

Colour is another important characteristic of digital images. It is used in applications like object recognition [11], skin detection [12], image retrieval etc. Algorithms used for colour analysis can be divided into the following three categories:

- 1) *Pixel Based Colour Segmentation*: This segmentation is based on the following assumption. Colour is a constant in the image to be analysed and the segmentation task can be viewed as the process of grouping the pixels in different clusters that satisfy a colour uniformity criteria. It can be further divided into: a) Histogram thresholding and b) Colour clustering technique.
- 2) *Area Based Segmentation*: It is defined by the region growing and split & merge schemes. The main advantage with this scheme is that the spatial coherence between adjacent pixels is enforced during segmentation.
- 3) *Physics Based segmentation*: This scheme is required a significant amount of a-priori knowledge about illumination model.

A. Colour-Texture Analysis

The Colour-Texture segmentation technique is known as CTex. In these technique colour and texture information are combined adaptively in a composite image descriptor. Here the texture information is extracted using LBP method and colour information by using an Expectation-Maximization (EM) space. Colour and texture features are evaluated in flexible split & merge framework.

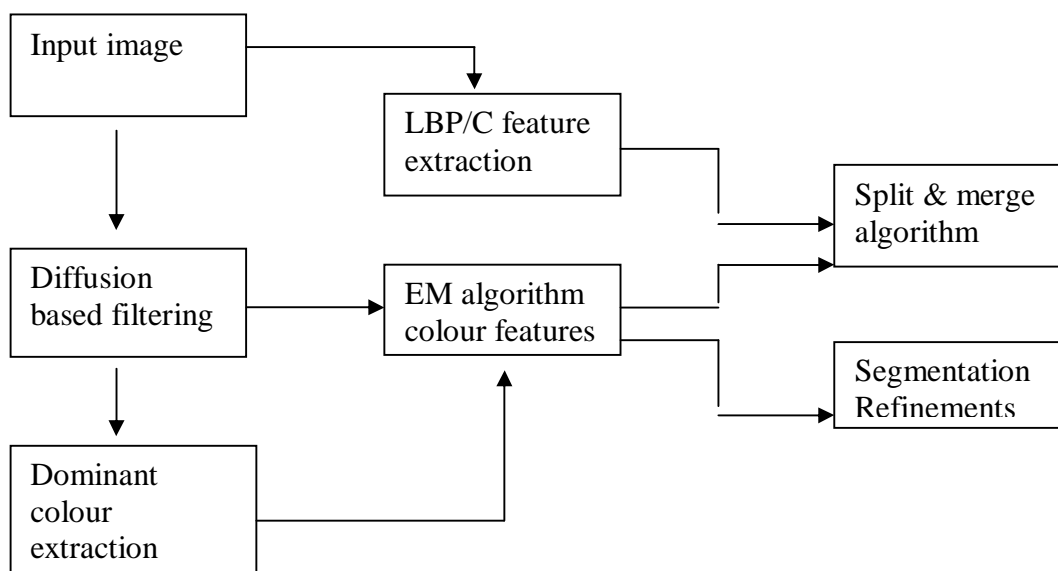


Fig. 2 Overview of CTex colour-texture segmentation

B. Extraction of Colour Texture Features

It follows Local Binary Patterns(LBP) concept .It decompose the texture into small texture units and texture features are defined by the histogram of LBP values calculated for each pixel in the region under analysis.LBP texture unit is obtained by applying a simple threshold operation with respect to central pixel of 3×3 neighbourhood.

$$T = t(th(g_0 - g_c), \dots, th(g_{a-1} - g_c))$$

$$th(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (1)$$

where,

T – is a texture unit
 g_c - grey value of central pixel
 g_a – pixels adjacent to central pixel
 th – threshold operation

LBP value for the tested pixel is:

$$LBP = \sum_{i=1}^P th(g_i - g_c)$$

where,

$th(g_i - g_c)$. is the value of thresholding operation in equation(1)

C. Diffusion Based Filtering

In order to improve the local colour homogeneity and eliminate the spurious regions caused by image noise, apply diffusion based filtering. This is mainly used to smooth the input image. The filtering strategy mainly follows anisotropic diffusion where smoothing is performed at intra regions and suppressed at region boundaries.

This non-linear smoothing can be defined in terms of the derivative of the flux function and is given by:

$$f_t = \text{div}(D(|\Delta f|)\Delta f)$$

where,

f – Input data
 D – Diffusion function
 t – Iteration step

This smoothing can be implemented using an iterative discrete formulation and is given by:

$$I_{x,y}^{t+1} = I_{x,y}^t + \lambda \sum_{j=1}^4 [D(\Delta_j I) \Delta_j]$$

$$D(\Delta I) = e^{-(\Delta I / k)^2} \xi(0,1]$$

Where,

$\Delta_j I$ – gradient operator defined in a 4 connected neighbourhood
 λ – contrast operator that is set in range $0 < \lambda < 0.16$
 k – diffusion parameter that controls smoothing level.

In cases where gradient has high values, $D(\Delta I) \rightarrow 0$ and the smoothing is halted.

D. Expectation – Maximization(EM) Algorithm

The key component of colour feature extraction is EM algorithm. This algorithm is implemented using an iterative framework that tries to calculate the maximum likelihood between input data and a number of Gaussian distributions. The main advantage of this method is the ability to better handle the uncertainties during the mixture assignment process. Assume we try to approximate data using M mixtures, the mixture density estimator can be calculated using:

$$P(x/\varphi) = \sum_{i=1}^M \alpha_i P_i(x/\varphi_i)$$

where,

$x = [x_1, x_2, \dots, x_k]$ is a k-dimensional vector
 α_i = mixing parameter for each GMM
 $\varphi_i = \{ \sigma_i, m_i \}$
 σ_i & m_i are the standard deviation & mean of the mixture.
 Function P_i is the Gaussian distribution

Algorithm mainly consists of two steps: 1) expectation step & 2) maximization step. The Expectation step(E-step) is represented by the expected log-likelihood function for complete data as:

$$Q(\varphi, \varphi(t)) = E [\log P(X, Y/\varphi) / X, \varphi(t)]$$

Where,

$\varphi(t)$ – current parameters

φ – new parameters that optimize the increase of Q

The Maximization Step(M-step) is applied to maximize the result obtained from E-step:

$$\varphi(t+1) = \arg \max_{\varphi} Q(\varphi / \varphi(t)) \text{ and}$$

$$Q(\varphi(t+1), \varphi(t)) \geq Q(\varphi, \varphi(t))$$

The E & M steps are applied iteratively until the increase of the log-likelihood function is smaller than a threshold value. The EM algorithm is a powerful space partitioning technique. Its major weakness is its sensitivity to the starting condition. Another disadvantage is the fact that, when executed with the same input data the space partitioning algorithm may produce different results. A large number of algorithms have been developed to address the initialization of space partitioning techniques.

IV. CONCLUSIONS

The aim of image segmentation algorithms is to partition the input image into a number of disjoint regions with similar properties. Texture and colour are two such image properties that have received significant interest from research community^{1,3,5,6}, with prior research generally focusing on examining colour and texture features as separate entities rather than a unified image descriptor. This is motivated by the fact that although innately related, the inclusion of colour and texture features in a coherent image segmentation framework has proven to be more difficult than initially anticipated. Many images contain areas that are clearly differentiated by texture that could be used as a means of achieving segmentation. Texture is characterized not only by the grey value at a given pixel, but also by the pattern in a neighbourhood that surrounds the pixel. This paper enlightens into the different texture image segmentation schemes.

REFERENCES

- [1] K.S. Fu and J.K. Mui, "A survey on image segmentation", Pattern Recognition, 13, p.3-16 (1981).
- [2] R.M. Haralick and L.G. Shapiro, "Computer and Robot Vision", Addison-Wesley Publishing Company (1993).
- [3] L. Lucchese and S.K. Mitra, Color "image segmentation: A state-of-the-art survey", in Proc. of the Indian National Science Academy, vol.67A, no. 2, p.207-221, New Delhi, India (2001).
- [4] Y.J. Zhang, "A survey on evaluation methods for image segmentation", Pattern Recognition, 29(8), p. 1335-1346 (1996).1999.
- [5] R. Chellappa, R.L. Kashyap and B.S. Manjunath, "Model based texture segmentation and classification", in The Handbook of Pattern Recognition and Computer Vision, C.H. Chen, L.F. Pau and P.S.P Wang (Editors) World Scientific Publishing (1998). 1999.
- [6] M. Tuceryan and A.K. Jain, "Texture analysis", in The Handbook of Pattern Recognition and Computer Vision, C.H. Chen, L.F. Pau and P.S.P Wang (eds.) World Scientific Publishing (1998).1997.
- [7] R.M. Haralick, "Statistical and structural approaches to texture", in Proc of IEEE, 67, p. 786-804 (1979).
- [8] A. Materka and M. Strzelecki, "Texture analysis methods – A review", Technical Report, University of Lodz, Cost B11 Report (1998).
- [9] J.S. Wezcka, C.R. Dyer, A. Rosenfeld, "A comparative study of texture measures for terrain classification", IEEE Transactions on Systems, Man and Cybernetics, 6(4), p. 269-285 (1976).
- [10] V.A. Kovalev and M. Petrou, "Multidimensional co-occurrence matrices for object recognition and matching. CVGIP: Graphical Model and Image Processing", 58(3), p. 187-197 (1996).
- [11] B. Schiele and J.L. Crowley, "Object recognition using multidimensional receptive field histograms", in Proc of the 4th European Conference on Computer Vision (ECCV 96), Cambridge, UK (1996).
- [12] M.J. Jones and J.M. Rehg, "Statistical color models with application to skin detection", International Journal of Computer Vision, 46(1), p. 81-96 (2002).



10.22214/IJRASET



45.98



IMPACT FACTOR:
7.129



IMPACT FACTOR:
7.429



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089  (24*7 Support on Whatsapp)