IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 8, August 2016

Texture Segmentation using Threshold Entropy Filter

Harjot[1], Rupinder Kaur Wahla[2]

Research Scholar, Computer Science, RIMT, Gobindgarh, India[1]

Assistant Professor, Computer Science, RIMT, Gobindgarh, India[2]

Abstract: Texture segmentation has come a long way from manual segmentation to reasonable automated segmentation. Using just a few simple grouping cues, one can now produce rather impressive segmentation on a large set of Textures. In some cases from texture, meaningful objects have been identified based on variations of color depth beyond a threshold value. In some case boundary between two regions are measured by comparing intensity differences across the boundary and intensity differences between neighboring pixels within each region. But the works done so far will not be able to get meaningful texture segmentation in all cases, particularly when the threshold values change drastically within the same object or the object is a combination of various different parts with different features and colors. Although it is safe to draw the conclusion that very thorough, accurate and meaningful texture segmentation would be extremely difficult to achieve, the past and present directions and efforts of research on this problem seem to be appropriate and as such should be continued to achieve more accuracy as far as possible.

Keywords: Texture, Pixel, Segmentation, Discrete Wavelet Transform.

I. INTRODUCTION

Segmentation [1] is the fundamental process which partitions a data space into meaningful salient regions. Image segmentation essentially affects the overall performance of any automated image analysis system thus its quality is of the utmost importance. Image regions, homogeneous with respect to some usually textural or colour measure, which result from a segmentation algorithm are analysed in subsequent interpretation steps. Texture based image segmentation is area of intense research activity in the past thirty years and many algorithms were published in consequence of all this effort, starting from simple thresholding methods up to the most sophisticated random field type methods. Image textures [2] can be artificially created (as shown in figure 1) or found in natural scenes captured in an image (as shown in figure 2). Image textures are one way that can be used to help in segmentation or classification of images. For more accurate segmentation the most useful features are spatial frequency and an average grey level.

Figure 1 Artificial texture example

Figure 2 Natural texture examples

II. LITERATURE REVIEW

M. Pietikainen, T. Ojala, Z. Xu in the paper "Rotation-Invariant texture classification using feature distributions, Pattern Recognition" [3] presented some features based on center-symmetric auto-correlation, local binary pattern, and gray-level difference to describe texture images. Most of these features are locally invariant to rotation including linear symmetric auto-correlation measures (SAC), rank order versions (SRAC), related covariance measures (SCOV), rotation invariant local binary pattern (LBPROT) features and gray-level difference (DIFF4). A feature distribution method is proposed based on the G statistics to test those features for rotation invariant texture analysis.

Since a single feature does not contain enough information to describe a texture, the experiment is carried out with various pairs of center-symmetric features and local binary pattern features. Results show that the use of joint distributions of such a pair of features outperforms a single feature and the feature pair of LBPROT=SCOV provides the best results. In the second case, a comparative study is presented, the performance of their method is compared with the well-known circular symmetric autoregressive model (CSAR) feature. It is shown that this approach can give better results than CSAR features.

M.K. Tsatsanis and G.B. Giannakis in the paper "Object and texture classification using high order statistics" [4] have demonstrated in their experiment that using the high-order statistics can give a promising result, however B. Julesz, T. Caelli in the paper "On the limits of fourier decompositions in visual texture perception" [5] has suggested that there may be little useful information in high-order statistics for texture discrimination. Whether

DOI 10.17148/IJARCCE.2016.58124

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 8, August 2016

high-order statistics can provide a very powerful tool for texture discrimination needs further study.

F. Cohen et al. in the paper "Classification of rotated and scaled texture images using Gaussian Markov random field models" [6] model texture as Gaussian Markov random fields and use the maximum likelihood to estimate coefficients and rotation angles. The problem of this method is that the likelihood function is highly nonlinear and local maxima may exist. In addition the algorithm must be realized by using an iterative method that is computationally intensive.

J. L. Chen, A. Kundu in the paper "Unsupervised texture segmentation using multichannel decomposition and hidden Markov models" [7] address rotation invariance by using multichannel subband decomposition and hidden Markov model (HMM). They obtain the rotation invariant texture features using HMM in two stages. In the first stage, the quadrature mirror 0lter (QMF) bank is used to decompose the texture image into subbands. In the second stage, the sequence of subbands is modeled as HMM which is used to exploit the dependence of these subbands and is capable of capturing the trend of changes caused by the rotation. Two sets of statistic features are extracted from each subband. The first consists of the third- and fourth-order central moments normalized with respect to the second-order central moments.

The second is composed of normalized entropy and energy. When texture samples are rotated, feature vectors derived from the original texture and its rotated version through the QMF bank are obviously different. Some problems have to be considered in their method. Variations of these feature vectors will increase as the number of texture samples of the same class grows. Although Chen and Kundu have reported that the HMM classifier can handle the variations, however when the number of texture classes increases, the performance of the HMM classifier may deteriorate due to the increasing variations. If these variations can be handled before using the HMM, the HMM classifier may produce better results.

Fang Liu, R.W. Picard in the paper "Periodicity, directionality, and randomness: wold features for perceptional pattern recognition" [8] proposed a new Wold based model to extract Wold texture features. These features which preserve the perceptual property of the Wold component are extracted without having to decompose each original texture.

Y. Wu, Y. Yoshida in the paper "An efficient method for rotation and scaling invariant texture classification" [9] described a new method of using the Wold model for invariant texture analysis. In their method, texture images are decomposed into a deterministic field and an indeterminstic field. The SDF of the former is a sum of 1- or 2-D delta functions. The 2-D autocorrelation function (ACF) is used to model the indeterministic component. The parameters of ACF are extracted by using the least squares method. These parameters combined with the positions of the 2-D delta functions and the directions of the 1-D delta functions are used to produce rotation invariant texture features. Eighteen Brodatz texture classes are selected and tested in the experiment. The experiment is performed in two cases. In the first case, texture images undergo only rotations (12 samples per class). The correct classification rate is 99.1% in the 0rst case. In the second case, texture samples are both scaled and rotated (30 samples per class). And the correct classification rate of 91.3% is obtained.

III. OBJECTIVES

- Design of texture differentiation filter in the picture.
- Enhancement of filter design using entropy enhancement in pixels of picture.
- Compare performance of system with base model.

IV. RESULTS

Figure 3 shows the original image and differentiated binary image of texture 1. In this we consider the upper part of the image as texture 1.

Figure 3. Original image and Texture 1 binary image

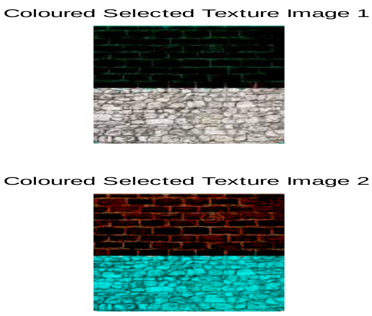

Figure 4. Coloured selected texture image 1 and 2.

Figure 4. Shows the coloured selected texture image 1 and 2

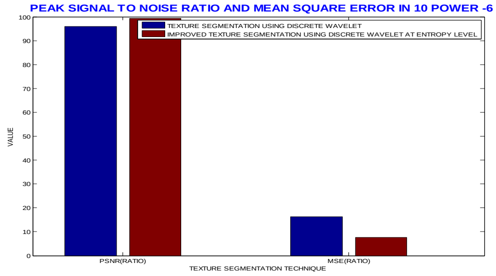

Figure 5. PSNR and MSE of proposed method and texture segmentation using discrete wavelet technique

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 8, August 2016

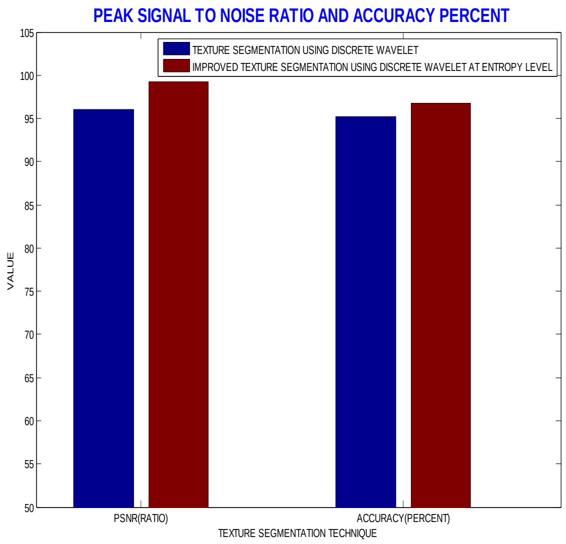

Figure 6. PSNR and Accuracy percent of proposed method and texture segmentation using discrete wavelet technique

Above results shows the comparison bar graph of proposed method and texture segmentation using discrete wavelet technique.

V. CONCLUSION

In this paper we have used the improved texture segmentation using discrete wavelet transform at entropy level on image and show the comparison between our proposed method and texture segmentation using discrete wavelet transform technique. Results shows that PSNR and Accuracy of improved texture segmentation using discrete wavelet transform at entropy level is higher than PSNR and accuracy of texture segmentation using discrete wavelet transform and MSE of improved texture segmentation using discrete wavelet transform at entropy level is less than MSE of texture segmentation using discrete wavelet transform. Our results indicate that the improved texture segmentation using discrete wavelet transform at entropy level is better than simple texture segmentation using discrete wavelet transform.

REFERENCES

1. Michal Haindl and Stanislav Mikes(2008), "Unsupervised Texture Segmentation", Pattern Recognition Techniques, Technology and Applications, pp. 626,I-Tech, Vienna, Austria.
2. https://en.wikipedia.org/wiki/Image_texture
3. M. Pietikainen, T. Ojala, Z. Xu, Rotation-Invariant texture classification using feature distributions, Pattern Recognition, 33 (2000) 43–52.
4. M.K. Tsatsanis, G.B. Giannakis, Object and texture classification using high order statistics, IEEE Trans. PAMI 14 (7) (1992) 733–750.
5. B. Julesz, T. Caelli, On the limits of fourier decompositions in visual texture perception, Perception 8, (1979) 69–73.
6. F. Cohen et al., Classification of rotated and scaled texture images using Gaussian Markov random field models, IEEE Trans. PAMI 13 (2) (1992) 192–202.
7. J.-L. Chen, A. Kundu, Unsupervised texture segmentation using multichannel decomposition and hidden Markov models, IEEE Trans. Image Process. 4 (5) (1995) 603–619.
8. Fang Liu, R.W. Picard, Periodicity, directionality, and randomness: wold features for perceptional pattern recognition, Proceedings of the International Conference on Pattern Recognition, Vol. 11, Jerusalem, October 1994, pp. 184–185.
9. Y. Wu, Y. Yoshida, An e.cient method for rotation and scaling invariant texture classi0cation, Proceedings of ICASSP, Vol. 4, 1995 pp. 2519–2522. (1996) 722–733.