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Qualitative Analysis of Computer Synthesized Texture Images & its Classification

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Abstract – **Texture synthesis is vital for various applications in vision, image processing and computer graphics. An alternative way to create texture is texture synthesis. It is tough to develop an algorithm which can produce high quality results and is efficient. Here an efficient algorithm is proposed for texture synthesis. The new algorithm is easy for use and it needs only a sample texture for input. It gives us freedom to apply texture synthesis in the field where it was not practically possible earlier. A MRF (Markov Random Field) model is assumed and the conditional distribution of a pixel with all its neighbors synthesized is estimated by querying the sample image and finding all similar neighborhoods.**

***Index Terms*—Texture Synthesis, GMM, NP Sampling**

I. INTRODUCTION

Texture is a universal visual experience which can describe a large range of surface charecteristics namely terrain,plants,minerals,fur & skin. Textures are commonly employed when provision of synthetic images are to be made as in computer graphics world , major goal is to reproduce the visual realism of real world. Scanned photographs or hand-drawn pictures can provide us with required textures. Though hand-drawn pictures can look elegant but it can not be made photo-realistic. Many scanned images used directly for texture mapping are of faulty size and lead to visible repetitions or seams.

Textures can be created by an alternative way of texture synthesis. Texture synthesis have likely broad applications such as occlusion fill-in, image de-noisingand compression. A new algorithm for texture synythesis is to be generated which is general, user-friendly, able to produce high quality textures and efficient is our goal. Also texture synthesis horizon can be extend by searching different new applications based on our algorithm.

Image texture can be defined as a rich source of visual information about the nature and is easily perceived by humans as there is no perfect definition image texture. In general, textures are little bit complex visual patterns which are composed of sub-patterns having characteristics like slope, brightness, size, colour, etc. Texture synthesis problem can be formulated as given below: lets define some visual pattern as texture on an infinite 2-D plane which has a stationary distribution at some point. Now a finite sample is taken from some texture i.e. image, further goal is to synthesize other different samples from the same texture.

The normal assumption is taken as the sample is large enough that it captures the stationarity of the texture and rough scale of the texels is known. Classification of textures can be done as either regular or stochastic. Fact is, almost all real world textures lie in between these two types and single model can capture it. In literature several techniques of image segmentation exist (which includes watershed transformation, data clustering, graph cuts, edge based, mean shift and histogram thresholding). When needed different techniques are merged for obtaining better results. Watershed transformation and mean shift being unsupervised segmentation method produces large number of small regions and thus some region merging algorithm is applied to entertain this effect.

In data clustering the spatial structure and the edge information is not well looked after and also it is biased towards ellipsoidal clusters. In edge detection based methods it is not necessary that boundaries are closed and due to that results may vary where regions are fused together. For monochrome images Histogram thesholding works effectively but for color images the situation is different where multi-thresholding becomes challenging for RGB histograms.

II. LITERATURE SURVEY

To capture texture statistics many of the previous work in texture segmentation have employed filter banks consisting both isotropic and anisotropic filters. Gabor-filter responses have been used by researchers to discriminate between different kinds of textures . Gabor filters are very well known example of a very large class of oriented multiscale filters [10, 9]. For discriminating between specific textures, this approach gives importance to the extraction of appropriate features, which is generally a non-trivial task. On the other hand the proposed method does not depends on using specific descriptors which works for some kinds of textures, but relies on an approach which tries to capture the core properties adequately from large range of textures.

Bigun *et al.* [6] uses the second-order moment matrix e.g., for analyzing flow-like patterns and for detecting local orientation. Rousson *et al.* [7] instead of using Gaussian blurring, refined this strategy by using vector-valued anisotropic diffusion on the available feature space using the structure tensor components. Doretto *et al.* [8] used a Gauss-Markov process for dynamic texture segmentation approach to model the relations among pixels within regions and over time. But for image intensities, the approach assumes a Gaussian process that cannot be easily taken into account for subtle or complex texture geometries [8, 7, 10]. Rousson *et al.* [7] proposed method which generalizes the strategy to the high order image statistics by using nonparametric statistics for the image-intensity histogram in the available feature space to counter this restriction.

In images nonparametric Markov sampling is used first by Popat *et al.* [12]. For learning neighborhood relationships this method takes a supervised approach. They uses the estimation of cluster based non-parametric density to capture the higher order nonlinear image statistics and then their technique is applied for texture classification.

Simoncelli and Portilla [11] have done the latest work in texture synthesis which is based on the first and second order properties of joint wavelet coefficients and also provides effective results. Both repeated textures and stochastic textures are quite well captured by the method but still on some highly structured patterns it fails to provide high frequency information.

III. OUR APPROACH

In our algorithm, texture is developed pixel by pixel, outwards from an initial seed. High frequency of information is extracted by our model as we choose a single pixel *p*. In a square window around *p* every pixels which are synthesized previously are used as context. Probability tables for the distribution of *p* are needed to proceed with the synthesis process. For text content , these tables are of convenient size while in our texture setting establishing them easily is unimaginable.

We choose not to construct a model as various clustering techniques provide approximation, while for every new context histogram is developed for all possible values which exist in the sample image.

Below is the block diagram of the system. Explanation of all blocks in detail i.e. what happens at each level is discussed below.

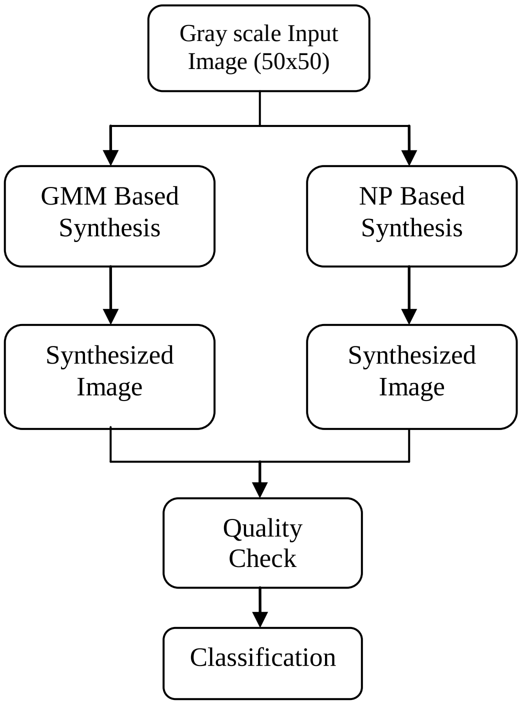


Fig.(1). Block diagram of system

Before so all sample images are queried. A good model haven't been found for catching statistical processes so the non parametric sampling technique is used even being simple but powerful.

We model Markov Random Field (MRF) for texture. In this model, we consider that the probability distribution of the luster values for a pixel given the luster values of its dimensional neighbourhood is independent of the rest of the image. The neighbourhood of a pixel is shaped as a square window around that pixel. Here size of the window is a free parameter which shows or specifies how imaginary user believes the texture to be. In detail, the size of the window should be on the scale of the massive regular feature if the texture is count on mainly regular at high spatial frequencies and mainly imaginary at low spatial frequency.

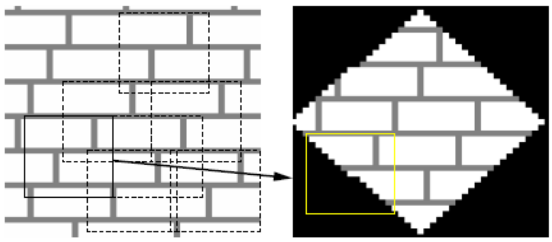


Fig.(2) Algorithm overview

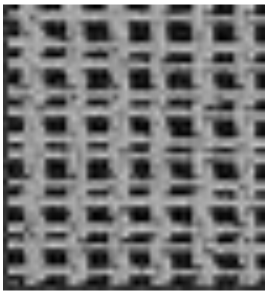
In the above figure, a sample texture image is shown in left and a new image is being synthesized shown in the right by one pixel at a time. To start with the synthesis process the algorithm will find all the neighbourhoods in the sample image which are equivalent to the pixel's neighbourhood and then it chooses one neighbourhood randomly and takes its centre for synthesizing new pixel.

There are in total seven blocks in our block diagram namely Gray scale input image, GMM based synthesis, NP based synthesis, 2x Synthesized image, Quality check & Classification.

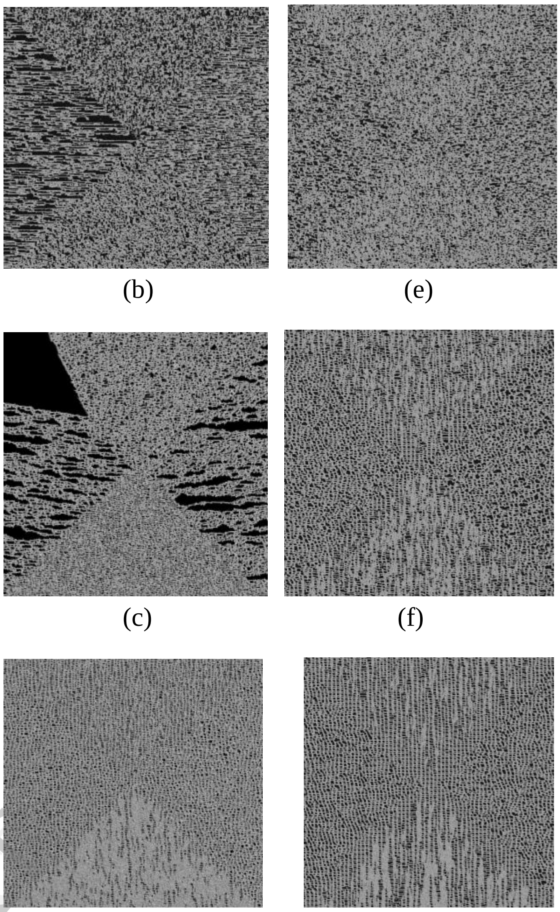
- First the gray scale input image is taken of size 50x50.
- Then both GMM (Gaussian Mixture Model) & NP (Non Parametric) Synthesis algorithm are applied to the input image taken.
- Synthesized image is obtained by both the algorithms.
- Now both the synthesized images are compared and qualitative analysis of images is carried out by calculating different parameters like mean, variance, signal to noise ratio, wavelet transform,etc.
- So after the analysis results can be obtained that synthesized image obtained by NP algorithm is better in quality compared to that of GMM algorithm synthesized image.
- Classification is also included in the project. Here the database is formed by taking different texture images. Mean, variance & other different parameters are calculated of those images and data is stored in database.
- Now whenever any unknown texture image is given as input to the system, mean, variance & other parameters are calculated of that image and compared to the data available in database. So the texture image from the database which suits best to the input texture image is shown as output.

IV. RESULTS

Different texture sample images are taken and synthesis process is carried out. Obtained results are shown below.



(a)



(b) (e)

(c) (f)

(d) (g)

Fig (3). Texture synthesis output. (a) input image, (b)-(c)-(d) output synthesized images with GMM based synthesis with the window size 3-5-7 respectively, (e)-(f)-(g) output synthesized images with non-parametric sampling method with the window size 3-5-7 respectively.

V. CONCLUSION

In this paper, two methods have been used for texture synthesis namely Guassian Mixture Method (GMM) & Non-Parametric (NP) Sampling method. By comparing both results, better method for synthesizing texture image can be identified. Comparison of both results will be carried out by calculating parameters like signal to noise ratio of the output texture images. To find the exact sampling region boundaries using image segmentation, the constrained synthesis process can be enhanced further. As a lossy compression technique, small patch of each region can be stored along with region boundaries while texture synthesis is used to restore each region separately. By synthesizing the background into the foreground segment, foreground removal can be done if ground segmentation is possible and background is like texture. The horizon of the texture synthesis can be extended by exploring a large number of new applications which are based on our algorithm.

REFERENCES

[1] Muhammad Rizwan Khokher, Abdul Ghafoor & Adil Masood Siddiqui, "*Image Segmentation using Fuzzy Rule Based System and Graph Cuts*," International Conference on Control, Automation, Robotics & Vision, 5-7th December 2012 (ICARCV 2012).

[2] Jitendra Malik, Serge Belongie, Thomas Leung & Jianbo Shi," *Contour and Texture Analysis for Image Segmentation*," International Journal of Computer Vision, 43(1), 7–27, 2001.

[3] Alexei A. Efros and Thomas K. Leung, "*Texture Synthesis by Non-parametric Sampling*," IEEE International Conference on Computer Vision, Corfu, Greece, September 1999.

[4] Suyash P. Awate, Tolga Tasdizen, and Ross T. Whitaker, "*Unsupervised Texture Segmentation with Nonparametric Neighborhood Statistics*," ECCV 2006, Part II, LNCS 3952, pp. 494–507, 2006.

[5] Rahman Farnoosh, and Behnam Zarpak, "*Image Segmentation Using Gaussian Mixture Model*," IUST International Journal of Engineering Science, Vol. 19, No.1-2, 2008.

[6] J. Bigun, G. H. Granlund, and J. Wiklund,"*Multidimensional orientation estimation with applications to texture analysis and optical flow*" IEEE Trans. Pattern Anal. Mach. Intell., 13(8):775–790, 1991.

[7] M. Rousson, T. Brox, and R. Deriche," *Active unsupervised texture segmentation on a diffusion based feature space*"In Proc. IEEE Conf. on Computer Vision and Pattern Recognition, pages 699–706. IEEE Computer Society, 2003.

[8] G. Doretto, D. Cremers, P. Favaro, and S. Soatto.,"*Dynamic texture segmentation*," In Proc. Int. Conf. Computer Vision, pages 1236–1242, 2003.

[9] R. Boomgaard and J. Weijer,"*Robust estimation of orientation for texture analysis*,"In 2nd Int. Workshop on Texture Analysis and Synthesis, 2002.

[10] J. S. de Bonet and P. Viola,"*Texture recognition using a non-parametric multiscale statistical model*," In Proc. IEEE Conf. on Comp. Vision and Pattern Recog., pages 641–647, 1998.

[11] S. Esedoglu and Y.-H. R. Tsai,"*Threshold dynamics for the piecewise constant mumford-shah functional*," Number CAM-04-63, 2004.

[12] K. Popat and R. Picard,"*Cluster based probability model and its application to image and texture processing*," IEEE Trans. Image Processing, 6(2):268–284, 1997.