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Structure Extraction from Complex Textures using Gradient based Relative Total Variation

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Abstract- It is universal that expressive arrangements are shaped by or seem over textured exteriors. Extracting them under the difficulty of texture patterns, which could be consistent, near-regular, or uneven, is very challenging, but of great real-worldsignificance. This paper presents a review on texture segmentation and analysis of different techniques. The comparisons among available techniques are also drawn in order to find the best suitable one. To overcome the existing problems of texture extraction a new extended relative total variation technique is proposed. The proposed technique has ability to extract textures from complex background images using gradient based methods and median filtering. The proposed method has shown accurate results even in highly noisy images. The comparison has shown that the proposed method is quite significant over the available methods.

Index terms: Dark regions, gradients, texture, texture patterns, texture segmentation.

I. INTRODUCTION

Many natural scenes and human-created art pieces contain texture. For instance, graffiti and drawings can be commonly seen on brick walls, railroad boxcars, and subways; carpets, sweaters, and other fine crafts contain various geometric patterns.

Fig. 1. Meaningful structure extraction from textured surfaces

Fig. 1 is showing the input images on the left part and right part contains the meaning full texture extracted image.

In human history, mosaic has long been be an art form to represent detailed scenes of people and animals, and imitate paintings using stone, glass, ceramic, and other materials. When searching in Google Images, millions of such pictures and drawings can be found quickly. They share the similarity that semantically meaningful structures are blended with or formed by texture elements. We call them “structure + texture” images. It is particularly interesting that human visual system is fully capable to understand these pictures without needing to remove textures. In psychology, it is also found that “the overall structural features are the primary data of human perception, not the individual details”.

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Image segmentation can be considered as partitioning the image into mutually exclusive components or region where the intersection between each component/region is null i.e. non-overlapping and each of the component/region is separated by a set of attribute(s). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s).

Several general-purpose algorithms and techniques have been developed for image segmentation. Since there is no general solution to the image segmentation problem, these techniques often have to be combined with domain knowledge in order to effectively solve an image segmentation problem for a problem domain.

Applications of image segmentation range from filtering of noisy images, medical imaging, locating objects in satellite images (roads, forests, etc.), automatic traffic controlling systems, machine vision to problems of feature extraction and recognition.

II. RELATED WORK

Li et al. (2006) [1] has proposed an improved method of threshold selecting, through the Gray level and Gradient Mapping function. It provides good foundation for the character selection, object recognition, and tracking processing. This algorithm has a widespread application prospect. The Ostu method is one of the applied methods of image segmentation in selecting threshold automatically for its simple calculation and good adaptation. They describe an improved method of threshold selecting, through the Gray level and Gradient Mapping function.

Hu et al. (2009) [2] has studied color space conversion is the core matter in color management. Printers and Image setter express color with CMYK space. But if color is edited and corrected in the CMYK space, it will cause a greater loss of color, and the Computing of computer will also be slowed down. So it often needs to be converted to a LAB uniform color space. Among the previous conversion methods, there is a widespread problem that is dark color tones is a little larger. In view of the problem above, They put forward a non-uniform segmentation method: with Prism geometry linear interpolation method, doing color modeling for color inkjet printer, realizing the conversion of CMYK and LAB color space.

Wang et al. (2010) [3] has suggested a segmentation method to extract object based on color and texture features of color tree images. Firstly, reduce noise of the color tree image by the use of anisotropic filter. Then, select Lab color space as the space for image segmentation. And the color image of RGB space is transformed into Lab space. Next, due to the negative end of a-channel reflects the color feature of trees, the L, a, and b channels are split. Green is the main feature of tree images, so segmentation by two-dimension OTSU of automatic threshold in a-channel. Based on the color segmentation result, and the texture differences between the background image and the object tree, we extract the object tree by the gray level co-occurrence matrix for texture segmentation. Finally, the segmentation result is corrected by mathematical morphology methods. This method not only segmentation speed is faster, and without human participation, but also the segmentation result is ideal when there are not green plants which are so close to the object tree in the tree image background.

Yu Jian (2010) [4] presented a novel texture image segmentation method based on Gaussian mixture models and gray level co-occurrence matrix (GLCM). The feature space was formed by eight statics generated by gray level co-occurrence matrix (GLCM) including mean, variance, angular second moment, entropy, inverse difference moment, contrast, homogeneity and correlation. The parameters of Gaussian mixture models were estimated by expectation maximization algorithm.

Kumar et al. (2011) [5] has proposed a new approach for color textured image segmentation. It is a two-stage technique, where in the first stage, textural features using gray level co-occurrence matrix (GLCM) are computed for regions of interest considered for each class. ROI act as ground truths for the classes. Ohta model is the color model used for segmentation.

Which adopts the features of both gray level co-occurrence matrix and Markov Random field model using Ohta color space to segment color textured image. GLCM represents the distance and angular spatial relationships over an image sub-region of specified size from which several textural measures may be computed. The performance of the proposed approach is compared with that of using GLCM and Maximum Likelihood classifier and with the one, which uses GLCM and Markov Random field in RGB color space. The proposed method is found to be better in terms of accuracy.

Suruliandi et al. (2011) [6] has studied three texture models. Texture is one of the high level featdiagnosis. Image segmentation can be isolated lesion and background. The accuracy of its identification has important implications. They propose a new image segmentation algorithm, which is based on super-green features and OSTU methods. This segmentation algorithm is good, easy to implement and suitable for the pretreatment of corn disease identification work. It can provide a good pre-treatment of disease identification results, to improve recognition accuracy.

Babu et al. (2012) [9] has described a new method on textons, for an efficient rotationally invariant texture classification. The proposed Texton Features calculates the relationship between the values of neighboring pixels. The proposed classification algorithm evaluates the histogram-based techniques on Texton Features for a precise classification. The experimental results on various stone textures indicate the efficiency of the proposed method when compared to other methods.

The proposed method is computationally attractive as it computes different Texton Features with limited number of selected pixels. The present paper proposed two methods to classify the textures among the class of textures based on Texton features

Prabha et al. (2013) [10] has demonstrated the segmentation methodology on flower images consists of five steps. Firstly, the original image of RGB space is transformed into Lab color space. In the second step 'a' component of Lab color space is extracted. Then segmentation by two-dimension OTSU of automatic threshold in 'a - channel‟ is performed. Based on the color segmentation result, and the texture differences between the background image and the required object, they extract the object by the gray level co-occurrence matrix for texture segmentation. The GLCMs essentially represent the joint probability of occurrence of grey-levels for pixels with a given spatial relationship in a defined region. Finally, the segmentation result is corrected by mathematical morphology methods. The algorithm was tested on plague image database and the results prove to be satisfactory.

Xu et al. (2012) [13] has discussed that the texture usually refers to surface patterns that are similar in appearance and local statistics. Texture synthesis can produce a large seamless texture map from small examples. For near-regular textures, spatial relationship is used to detect and analyze regularity, enabling image texture separation in de-fencing. These methods count on the symmetry and regularity of texture and require prior pattern knowledge. Image analogy needs examples and may have difficulty removing texture when details are complex and irregular.

Wang et al. (2013) [14] It is very important to extract high quality texture features from images. This is, however, often laborious, because the randomness in the color distribution patterns for texture elements makes texture measurement very difficult, despite these elements having a very similar visual appearance. In this paper, we propose the use of multi-scale color histograms to measure the effect of color distribution patterns efficiently and without having to compute the actual patterns, which saves considerable effort. Meanwhile, the hue-saturation-intensity color model is mainly adopted to take the advantage of human visual experiences in texture recognition.

Arivazhagan, S., and R. Benitta (2013)[15] roposes a new approach to extract the features of a color texture image for the purpose of texture classification. Four feature sets are involved. Dominant Neighbourhood Structure (DNS) is the new feature set that has been used for color texture image classification. In this feature a global map is generated which represents measured intensity similarity between a given image pixel and its surrounding neighbors within a certain window.

III. PROPOSED ALGORITHM

We do not undertake or manually define the type of textures, as the shapes could vary a lot in many examples. The proposed method contains a general pixel-wise windowed total variation measure, written as

$$\mathscr{D}_x(p) = \sum_{q\in R(p)} g_{p,q} \cdot \left|(\partial_x S)_q\right|,$$
$$\mathscr{D}_y(p) = \sum_{q\in R(p)} g_{p,q} \cdot \left|(\partial_y S)_q\right|, \quad (1)$$

whereq belongs to R(p), the rectangular region cantered at pixel p.$D_x(p)$ and $D_y(p)$ are windowed total variations in the x and y directionsfor pixel p, which count the absolute spatial difference withinthe window R(p). g(p, q)is a weighting function defined accordingto spatial affinity, expressed as

$$g_{p,\,q} \propto \exp\left(-\frac{(x_p - x_q)^2 + (y_p - y_q)^2}{2\sigma^2}\right) \quad (2)$$

Whereσcontrols the spatial scale of the window. In an image withsalient textures (Figure 2(a)), both the detail and structure pixelsyield large D, the windowed totalvariation is responsive to visual saliency.

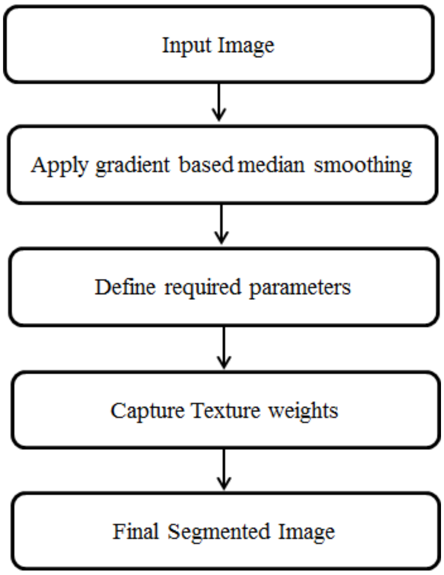

Fig. 2 Proposed algorithm flowchart

Fig. 2 is showing the flowchart of the proposed algorithm. Subsequent are the different steps required to accomplish this research work. Each step has its own significant to produce the results.

Step1: First of all an input image will be passed to the proposed algorithm for texture analysis. This step may also be known as for reading the image from secondary device and put it into the RAM of the electronic machine.

Step2: Now gradient based median smoothing will be come in action to reduce the noise and other parameters from the images.

Step3: At this stage different parameters required to accomplish this work will be defined like lambda, sigma, sharpness factor etc.

Step4: Now defined equations 1-2 will come in action to capture texture weights.

Step5: This step will provide the final segmented image.

IV. EXPERIMENTAL SET-UP

The proposed algorithm is designed and implemented in MATLAB using image processing and data analysis toolbox. For the cross validation we have also implemented the existing algorithm proposed by Xu et al. (2012) [13]. 20 different images are also taken as shown in Table 4.1 for the experimental purpose.

Table 4.1 Images taken for experimental analysis

Image name	Extension	Size in K.Bs
image1	.jpg	221
image2	.jpg	82
image3	.jpg	152
image4	.jpg	47
image5	.bmp	284
image6	.jpg	358
image7	.jpg	59
image8	.jpg	136
image9	.jpg	121
image10	.jpg	64
image11	.jpg	67
image12	.jpg	184
image13	.jpg	165
image14	.jpg	111
image15	.jpg	146
image16	.bmp	452
image17	.jpg	72
image18	.jpg	36
image19	.tif	345
Image20	.bmp	324

V. EXPERIMENTAL RESULTS

This section contains the result for the image2. Following are the outputs of the traditional method and proposed method.

Fig. 5.1 (a) Input image (b) Gradient smoothed image

Fig. 5.1 (a) has shown the input image going to be processed in tradition method. It is clearly shown that the image is heavily corrupted by the noise and will produce poor results. Fig. 5.1 (b) is showing the output of gradient smoothed image using the proposed algorithm. It is clearly shown that the image is visibly restored and will produce better results.

Fig. 5.2 Texture image using (a) old method (b) Proposed method

Fig. 5.2 (a) has shown the textured segmented output of the traditional method. It is clearly shown that the image is over segmented so will not have significant results. Fig. 5.2 (b) has shown the output of the proposed method and it is quite effective and seems to be much accurate than that of existing method.

Fig. 5.3 Canny edge detected image using (a) old method (b) Proposed method

Fig. 5.3 (a) has shown the canny edge detected output of the traditional method. It is clearly shown that the image contains many undesired edges so not having significant results. Fig. 5.2 (b) has shown the output of the proposed method and it is quite effective and seems to be much accurate than that of existing method as it does not produce any unwanted edge.

VI. PERFORMANCE EVALUATION

Table 6.1 and Fig. 6.1 are showing the comparative analysis of the Mean square error (MSE). As MSE need to minimize; so our goal is to reduce them MSE as much as possible. Table 6.1 and Figure 6.1 have clearly shown that MSE is less in the case of the proposed algorithm; therefore proposed algorithm is providing quite better results.

Table 6.1 MSE Evaluation

Image name	Existing method	Proposed algorithm
image1	11540	1595
image2	11341	1284
image3	11398	1276
image4	11456	1590
image5	11498	1764
image6	11384	1869
image7	11041	1911
image8	13120	1773
image9	14315	1803
image10	11344	1952
image11	18139	1733
image12	17151	1886
image13	22139	1945
image14	17211	1911
image15	13414	1952
image16	18319	1733
image17	11751	1886
image18	21239	1945
image19	11711	1911
Image20	11631	1971

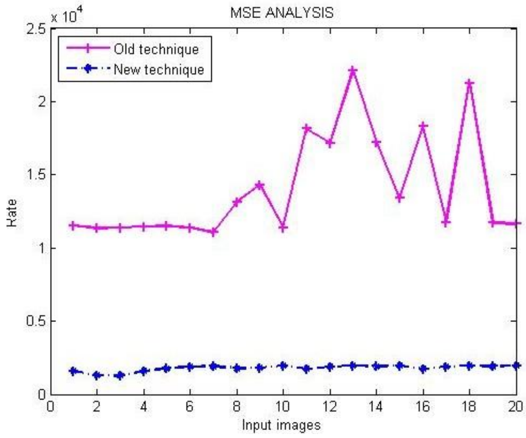

Fig. 6.1 Mean square error (MSE) evaluations

Table 6.2 and Fig. 6.2 are showing the comparative analysis of the Peak Signal to Noise Ratio (PSNR). PSNR contains the power of the input signal over the noisy signal; i.e. the ration of the noise and the ratio of the input signal. As it is required by us is to increase the ratio of the signal over the ratio of the noise. Therefore PSNR need to be maximized; so our goal is to increase PSNR as much as possible. Table 6.2 and Fig. 6.2 have clearly shown that PSNR is quite more in case of proposed algorithm than the available algorithm therefore it has proven that the proposed algorithm is quite effective for the noisy and corrupted images.

Table 6.2 PSNR Evaluation

Image name	Existing method	Proposed algorithm
image1	8	18
image2	7	19
image3	8	21
image4	8	20
image5	7	20
image6	7	21
image7	9	21
image8	8	21
image9	8	20
image10	9	19
image11	10	18
image12	11	19
image13	10	19
image14	7	21
image15	9	19
image16	11	18
image17	9	19
image18	8	19
image19	7	21
Image20	9	20

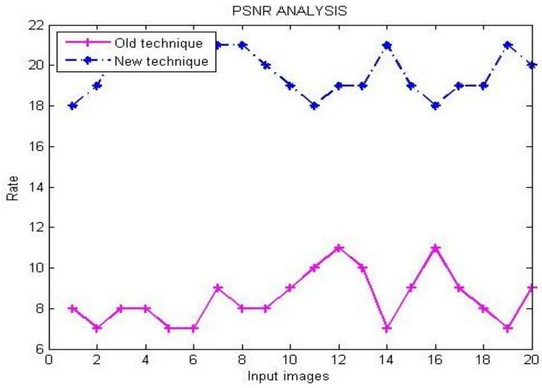

Fig. 6.2 PSNR evaluations

Table 6.3 and Fig. 6.3 are showing the comparative analysis of the Maximum Difference. As Maximum Difference needs to be minimized; so our goal is to reduce them Maximum Difference as much as possible. Table 6.3 and Fig. 6.3 are clearly shown that Maximum Difference is less in the case of the proposed algorithm over the available technique.Therefore proposed algorithm is providing better results.

Table 6.3 Maximum difference

Image name	Existing method	Proposed algorithm
image1	146	103
image2	139	105
image3	131	109
image4	122	101
image5	147	119
image6	158	134
image7	154	132
image8	164	141
image9	145	125
image10	133	128
image11	138	123
image12	142	114
image13	174	134
image14	147	129
image15	133	128
image16	138	123
image17	142	114
image18	174	134
image19	147	129
Image20	131	121

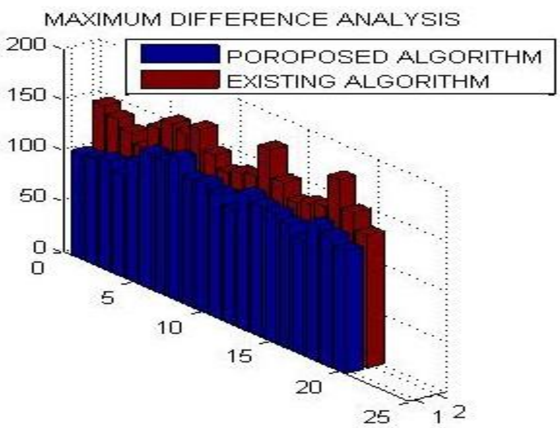

Fig. 6.3 Maximum difference evaluations

Table 6.4 and Fig. 6.4 are showing the comparative analysis of the Mean Difference. As Mean Difference needs to be minimized; so our goal is to reduce the Mean Difference as much as possible. It is clearly shown in Table 6.4 and Fig. 6.4 are that the proposed algorithms has successfully achieve the better results for mean difference also.

Table 6.4 Mean difference

Image name	Existing method	Proposed algorithm
image1	22.31	1.03
image2	21.17	1.05
image3	20.18	1.09
image4	19.19	1.01
image5	17.12	1.19
image6	19.91	1.34
image7	18.99	1.32
image8	28.01	1.41
image9	32.11	1.25
image10	36.36	1.28
image11	34.35	1.23
image12	31.91	1.14
image13	16.14	1.34
image14	15.16	1.29
image15	19.71	1.28
image16	14.25	1.23
image17	13.72	1.14
image18	12.82	1.34
image19	11.92	1.29
Image20	18.25	1.21

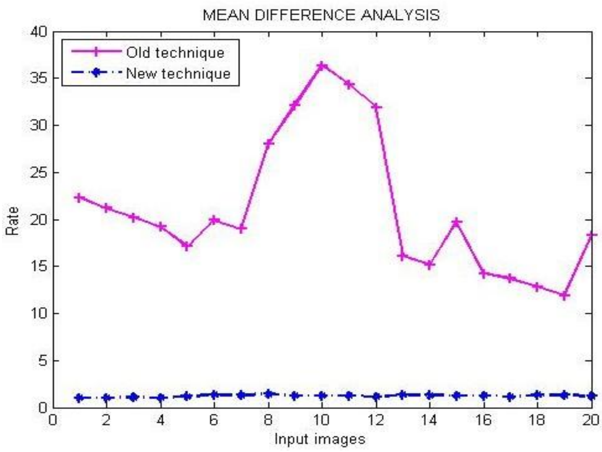

Fig. 6.4 Mean difference evaluations

Table 6.5 and Fig. 6.5 are showing the comparative analysis of the Absolute Mean Square Error (AME). AME is derive form the MSE it defines the actual ration of the noise over the input signal or image. As AME needs to be minimized; so the main attention is to reduce them AME as much as possible. Table 6.5 and Fig. 6.5 are clearly shown that AME is less in our case therefore proposed algorithm is providing quite effective results.

Table 5 Normalized absolute error

Image name	Existing method	Proposed algorithm
image1	.32	.22
image2	.35	.26
image3	.41	.15

image4	.31	.19
image5	.39	.21
image6	.37	.22
image7	.31	.18
image8	.30	.19
image9	.29	.19
image10	.26	.17
image11	.29	.14
image12	.31	.15
image13	.37	.16
image14	.34	.18
Image15	.31	.19
Image16	.39	.21
Image17	.37	.22
Image18	.31	.18
Image19	.30	.19
Image20	.29	.19

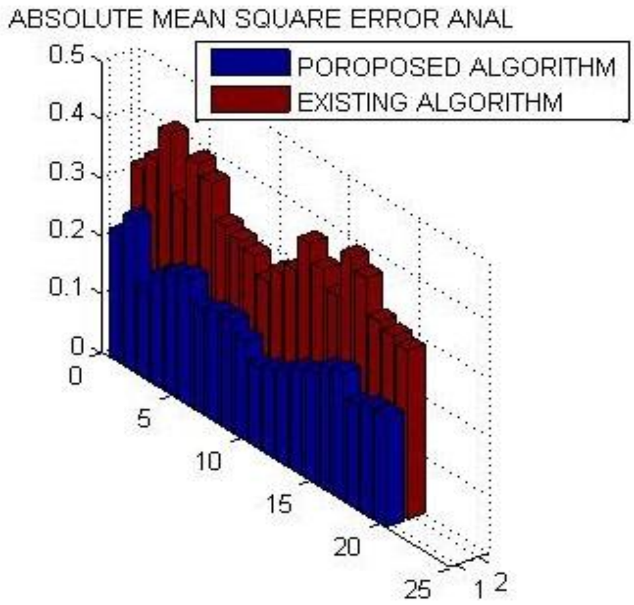

Fig. 6.5 AME Analysis

VII. CONCLUSION AND FUTURE WORK

This paper has presented a review on different techniques. Extracting the meaningful structure from textures or complex background images is found to be important and critical task in vision processing. It is found that much research done in this field to extract textures by using segmentation and some other techniques. It is found that most of the existing researchers have neglecting the issue of haze and noise in images; so most of the existing techniques found to be inaccurate in case of any kind of disturbance in the image. So to overcome this problem we have proposed a new technique which uses gradient based smoothing to reduce the effect of the noise as well as the effect of over-segmentation. The comparative analysis has shown quite significant results over the traditional methods. In near future we will extend this work by integrating it with visibility restoration algorithm to enhance the results further.

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