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Image texture analysis using second order statistical model

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Abstract: Image texture analysis is very crucial research topic for various vision-based applications. In this paper, robust gray-level co-occurrence matrix (GLCM)-based statistical model is explored and exploited for various image texture analysis. After demonstrating the model, experimental analyses are accomplished with datasets to demonstrate the performances of the statistical model. It illustrates that these statistical modules can be very much functional for image texture understanding.**.** Initially, we run our model in some ground-truth images covering few basic patterns, so that we can vividly compare the results on various images on datasets. The experimental dataset is the standard 'building surface dataset', where the experimental results relate the ground-truth data significantly.

Keywords: Co-occurrence matrix, GLCM, Texture analysis.

1 INTRODUCTION

Texture analysis is an attractive area of research because of its wide applicability in many fields. We can define texture as the surface of the objects. Several researchers define texture as a number of combined structurizing elements. Haralick et al. [7] assume texture as a spatial statistical distribution of gray pixels. We know that we can differentiate various image surfaces, objects, etc. A machine usually fails to identify an object based on its surface of similar patterns [10]. In these circumstances, identify complex surface using texture cue from a single image is an intricate problem [10]. In this paper, we explore statistical models for various image texture surfaces in order to develop a robust recognition and classification system. It is known that identification of similar objects under various real-world lightings is very challenging task for a machine/robot vision system. From the experimental results based on our analyzed statistical models, we achieve promising hypothesis by employing a benchmark dataset along with our ground truth dataset for in-depth analysis. To the best of our knowledge, these models in the building dataset along with ground truth analysis have not been undertaken by others.

Section 2 demonstrates some related works of this topic. Section 3 describes the statistical methodology exploiting the Gray Level Co-occurrence Matrix for texture analysis. Then, in Section 4, we illustrate some experimental results using a benchmark dataset. Finally, conclusion is presented in Section 5.

2 RELATED WORK

Texture analysis is very important research area in Machine vision system. Many researchers did their research based on different patterns of texture image. This research is very important for industry, medical experiment, and garments sector for automatic inspection of product. Texture analysis describes a variety of image-analysis techniques that quantify the variation in surface intensity or patterns, including some that are imperceptible to the human visual system. Quality control is important in textile industry. Texture analysis plays an important role in the automated visual inspection of texture images to detect their defects. For this purpose, Ozdemir *et al.* [1] did comparative experiment based on deferent textile sample. Model-based and feature-based methods are implemented and tested for textile images in a laboratory environment. Texture features, such as energy, entropy, contrast, homogeneity, and correlation, are then derived from the co-occurrence matrix. Several works have reported using co-occurrence matrices to detect defects, such as [2-7]. For example in [6], Iivarinen *et al.* applied co-occurrence texture features to detecting defects in paper web where the normal textures have characteristic frequency. Texture analysis is a valuable and adaptable implement in neuro-MR imaging. Texture analysis plays a encouraging role in the medical image interpretation. In some cases, however, statistical or spectral textural features have outperformed visual assessment in discriminating between or among intracranial tumors, as well as in discerning subtle anatomic changes associated with a high risk of seizures in patients with epilepsy.

3 METHOD

We explored the 2nd order statistics, called Gray Level Co-occurrence Matrix (GLCM). It is a way of extracting 2nd order statistical texture features. A GLCM is a matrix where the number of rows and columns is equal to the number of distinct gray levels or pixel values in the image of that surface. GLCM is a matrix that describes the frequency of one gray level appearing in a specified spatial linear relationship with another gray level within the area of investigation [11-12]. Fig. 1 shows the system flow diagram of this work.

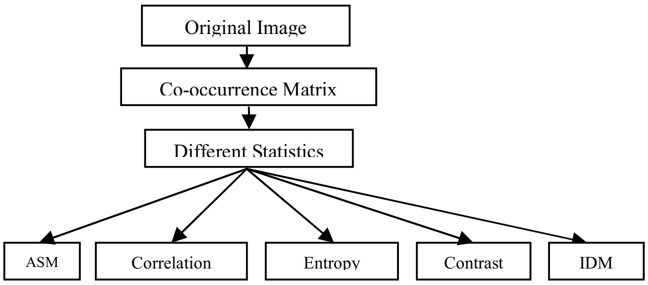


Fig. 1. System flow for this method.

In this paper, we exploit the Gray Level Co-occurrence Matrix (GLCM) for texture analysis. Given an image, each with an intensity, the GLCM is a tabulation of how often different combinations of gray levels co-occur in an image or image section. Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity (i.e., image texture) at the pixel of interest. Typically, the co-occurrence matrix is computed based on two parameters, which are the relative distance between the pixel pair *d* measured in pixel number and their relative orientation θ. Normally, θ is quantized in four directions (e.g., 0º, 45 º, 90 º and 135 º) [11-12], even though various other combinations could be possible. As our dataset is based on buildings – it is not necessary to explore all different angles. The other parameter *d* is also important. Based on our experiment, we consider *d* as 1. If we have an image that contains *N* gray levels from 0 to *N*–1, and if we consider *f*(*m*,*n*) is the intensity at sample *m*, line *n* of the neighborhood, then we can have the gray level co-occurrence matrix as,

$$p(i,j \mid \Delta x,\Delta y) = WQ(i,j \mid \Delta x,\Delta y) \tag{1}$$

where,
$$W = \frac{1}{(M-\Delta x)(N-\Delta y)}$$

$$Q(i,j \mid \Delta x,\Delta y) = \sum_{n=1}^{N-\Delta y}\sum_{m=1}^{M-\Delta x} A$$

where,
$$A = \begin{cases} 1 & \text{if } f(m,n) = i \text{ and } f(m+\Delta x, n+\Delta y) = j \\ 0 & \text{otherwise} \end{cases}$$

The resultant texture images show the pixel-based spatial distribution of magnetic anomalies, associated with elements of subsurface structure, with much higher lateral resolution than the original magnetic images. In this paper, we consider seven different cues based on GLCM texture features. These features are – angular second moment (ASM), contrast, correlation, variance, inverse difference moment, sum entropy and information measures of correlation. The features are thoroughly promising [7].

Angular Second Moment (ASM):

$$ASM = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p_{ij}^2 \tag{2}$$

It is also known as energy, uniformity, and uniformity of energy, returns the sum of squared elements in the GLCM. ASM ranges from 0.0 for an image with many classes and little clumping to 1.0 for an image with a single class.

Contrast:

$$Contrast = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i-j)^2 p_{ij} \tag{3}$$

It provides a measure of the intensity contrast between a pixel and its neighbor over the whole image. Contrast is also known as variance and inertia.

Correlation:

$$Corr = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}} p_{ij} \tag{4}$$

It returns a measure of how correlated a pixel is to its neighbor over the whole image. We also explored *entropy*.

Entropy:

$$Entropy = -\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p_{ij} \times \log(p_{ij}) \tag{5}$$

It is a statistical measure of randomness that can be used to characterize the texture of the input image. We use he normalized GLCM as it is the joint probability occurrence of pixel pairs with a defined spatial relationship having gray level values of an image.

Inverse difference moment (IDM):

$$IDM = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{1}{1+(i-j)^2} p_{ij} \tag{6}$$

The inverse difference moment is another textural measure that attains a maximum value when all the image pixels that are compared have the same value, then yields a strong response at the central locations of the features of interest. IDM ranges from 0.0 for an image that is highly textured to 1.0 for an image that is untextured (such as an image with a single class).

4 EXPERIMENT AND RESULT

In this paper, we present a ground truth analysis for the GLCM-based image features. In Fig. 2, the ground-truth data contains 5 images – full white, strips in black and white – vertical direction and horizontal direction, gray, etc. This dataset shows comparative robust intuition of this concept. We cover different building images to analyze the statistical model features and some frames are shown in Fig. 3.

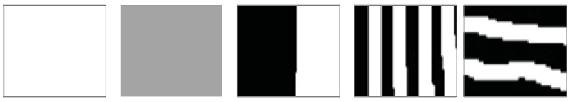


Fig.2 Ground-truth images.

Fig.3 Sample frames for the Building surface dataset.

In Fig. 4, we demonstrate the ASM. We can see that for bld-14, the ASM value is higher than others. We think that bld-14 has less texture elements and the pixels are very similar. The GT data for gt1 and gt2 has similar pattern with higher ASM value. Similarly, Fig. 5 shows contrast for ground-truth (GT) and building dataset. Similar to Fig. 4, it is evident that bld-14 has very less contrast. Contrast is zero when the neighboring pixels have constant values. The bld-6 has higher contrast values.

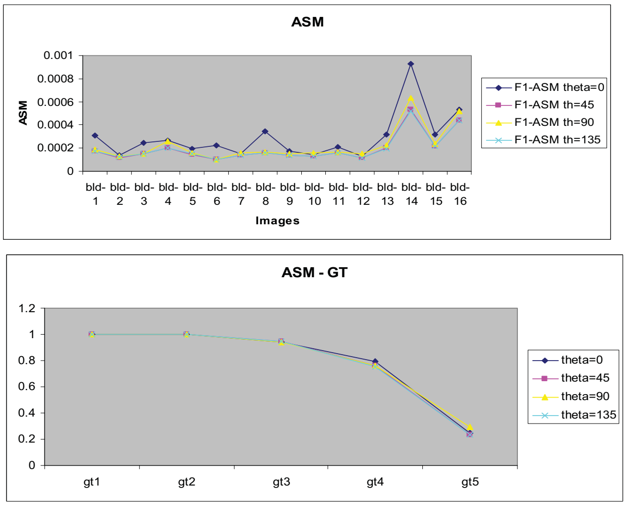


Fig.4 ASM for four angles with ground-truth (GT) and building dataset.

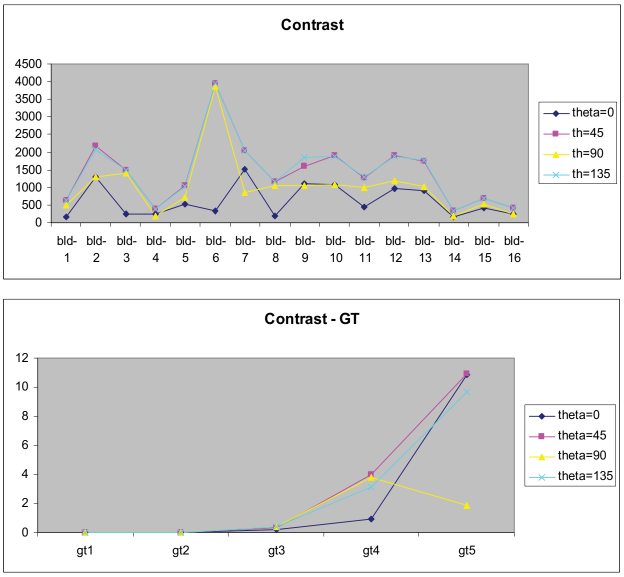


Fig.5 Contrasts evaluation for four angles.

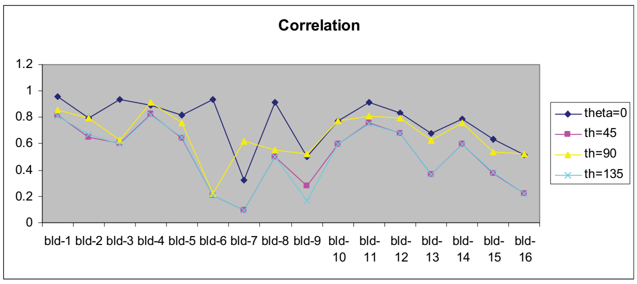
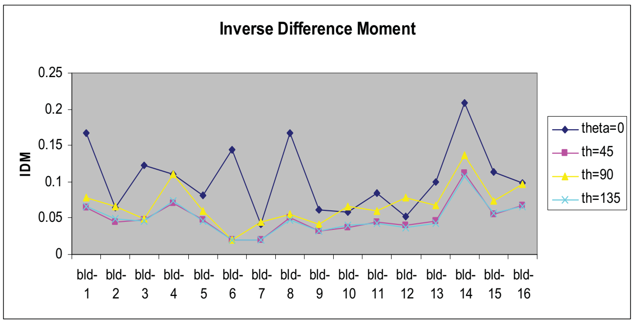


Fig.6 Correlation measures for four angles.

In Fig. 6, correlation measures are analyzed for the building surface dataset. Finally, the inverse difference moment (IDM) is computed as well for four angles for the ground-truth (GT) and building surface images. From the

GT graph in Fig. 7, it is visible that the IDM has higher value when all elements of the image are same. The bld-14 image has higher values for IDM and ASM.



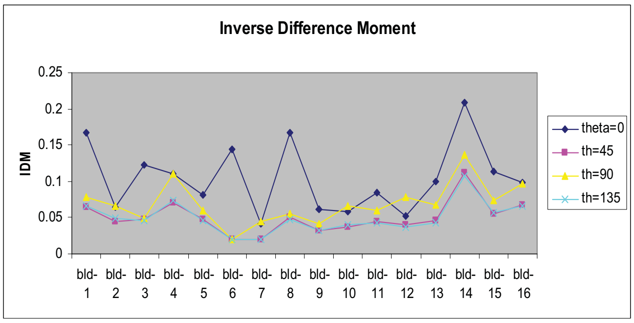


Fig.7 Graph for inverse difference moment.

5 CONCLUSIONS

In this paper, we explored image texture analysis, which is an important area for different real-life applications. Here, we exploited some of the robust gray-level co-occurrence matrix (GLCM)-based statistical measured for various image texture analyses. The gray-level co-occurrence matrix is a way of extracting 2nd order statistical texture features. In this paper, we computed and analyzed the angular second moment (ASM), correlation, contrast and inverse difference moment (IDM) based on the gray-level co-occurrence matrix. After demonstrating the model, we accomplished some experimental analyses by using a dataset to demonstrate the performances of the statistical model. It illustrates that these statistical modules can be very much functional for image texture understanding.. Initially, we ran our model in some ground-truth images covering few basic patterns, so that we can compare the results on various images on datasets. The experimental dataset is the standard 'building surface dataset', where the experimental results relate the ground-truth data significantly. In future, we will extract more features based on GLCM for texture analysis and evaluation, and we will classify various textures by employing classifiers. We will also analyze by using other datasets.

REFERENCES

[1] Ozdemir S, Baykut A, Meylani R, Ercil A, Ertuzun A (1998), Comparative evaluation of texture analysis algorithms for defect inspection of textile products. Int. Conf. on Pattern Recognition, pp.1738-1740.
[2] Bodnarova A, Williams J, Bennamoun M, Kubik K (1997), Optimal textural features for flaw detection in textile materials. IEEE TENCON, PP.307-310.
[3] Siew L, Hodgson R, Wood E (1998), Texture measures for carpet wear assessment. IEEE Trans. on Pattern Analysis and Machine Intelligence 10, pp.92-105.
[4] Iivarinen J, Rauhamaa J, Visa A (1996), Unsupervised segmentation of surface defects. Int. Conf. on Pattern Recognition, pp.356-360.
[5] Shiranita K, Miyajima T, Takiyama R (1998), Determination of meat quality by texture analysis. Pattern Recognition Letters, 19, pp.1319-1324.
[6] Iivarinen J (2000), Surface defect detection with histogram-based texture features. SPIE Intelligent Robots and Computer Vision XIX: Algorithms, Techniques, and Active Vision, pp.140-145.
[7] Haralick R, Shanmugam K, Dinstein I (1973), Textural features for image classification, IEEE Trans. on Systems, Man and Cybernetics, 3, pp.610-621.
[8] Latif-Amet L, Ertuzun A, Ercil A (2000), An efficient method for texture defect detection: Subband domain co-occurrence matrices. Image and Vision Computing, 18(6-7), pp.543-553.
[9] Kassner A, Thornhill R (2010), Texture analysis: a review of neurologic MR imaging applications, AM Journal Neuroradiol ,31, pp.809-16.
[10] Hossain S, Serikawa S (2010), Statistical analysis and psychological evaluation of surfaces under various illumination, Int. Journal of Applied Machines and Materials, 36, pp.422-429.
[11] Baraldi A, Parmiggiani F (1995), An investigation of the textural characteristics associated with GLCM matrix statistical parameters, IEEE Trans. on Geos. and Remote Sensing, 33(2), pp.293-304.
[12] Mokji1 M, Bakar S (2007), Gray level co-occurrence matrix computation based on Haar wavelet, Computer Graphics, Imaging and Visualisation.
[13] Adelson E (2008), Image statistics and surface perception, SPIE-IS&T Electronic Imaging, 6806, pp.1-9.
[14] Dror R, Willisky A, Edelson E (2004), Statistical characterization of real-world illumination, Journal of Vision, 4, pp.821-837.
[15] Koudelka M, Magda S, Belhumeur P, Kriegman D (2003), Acquisition, compression and synthesis of bidirectional texture functions, 3rd Int. Workshop on Texture Analysis and Synthesis.
[16] Sharan L, Li Y, Motoyoshi I, Nishida S, Adelson E (2008), Image statistics for surface reflectance perception, Journal of Optical Society America, 25(4).