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Universal Texture Clustering

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ABSTRACT

Although texture can be assumed as the richest aspect of images to obtain visual information yet again the existing methods to analyses this field of data are not very effective, there are generally statistical, structural, model based and mathematical transformations based approaches which all are either unable to fully grasp the information or highly complicated and time- computation consuming. At this work a simple, fast and comprehensive statistical like pace is developed which can quickly determine the existence of both micro and macro structures for further computer vision applications.

KEYWORDS
texture analysis, image structures, computer vision.

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Introduction

although the existence of a texture can be interpreted as a repetitive entity made from a comprehendible distribution of gray-lightness levels amongst the pixels (Rosenfeld, 1982) yet again there are no strict definitions of the texture to make it identifiable because this phenomena can be comprised of many possible arrangements of gray levels which could be inferred by human conscience by definitions like uniformity, roughness, density, regularity, frequency, linearity and curves, coarseness, directions, granulation, fineness and even randomness

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(Levine, 1985); this has been approved in scientific surveys decades ago (Brodatz, 1966) by the pioneers of image processing.
there are typically a few kinds of data retrievable by the texture analysis, we would need to either segment the image using the textured areas, classify the textures based on some features and to realize the shapes of some reflected 3D objects with respect to the textures. Above all the texture feature extraction is the first stage because without it this is not possible to discover the texture itself. At this work we first discover the fundamental characteristic of the smallest texture cells (3x3 neighborhoods) and then look for the repetitions of similar features across the image then the algorithm can be repeated for the larger ranges or structures so all the possible texture cases could be discovered. It will be realized that this technic is immune to edge limitations which frustrates most of the previous solutions and also toward phases and directions plus the feature vector can be used to classify and recognize the types of texture which is an essential asset on many object recognition practices.

Previous works:

We attend inspecting the previous works with respect to their fundamental approaches; there are basically four categories for texture processing discussable as follows.

the structural approaches; these tactics assume a primitive micro structure and a spatial arrangement of the microstructures as macros to be matched and found (Haralick, 1979). Although these methods may present fast and reliable solutions but they often require a predefined model for the micro and macro structures while both are highly variable as explicated before. The insistence of further development for these approaches has led to the creation of mathematical morphology (Serra, 1982).

the statistical approaches; as the most usual category they don't explicitly attempt to understand the hierarchical structures among the pixels. Yet they seek un-deterministic first or higher order statistical measures between the gray levels of certain neighborhoods which can be later used to classify and identify the texture segments (Chen, 1994). So far these methods have been most effectively utilized for the medical imaging applications; examples like the histogram matching or co-occurrence matrix technics. Still even the most recent developments fail to present a thorough local analysis of image regions (Chen, 1994).

model based techniques; the general idea here is to try matching the predefined stochastic or geometric-fractal models with the subjected image in order to estimate the model parameters numerically and then utilize them for further analysis. While the fractal modeling has been tried successfully for some rare natural textures like in (Weszka, 1976) still the more confident stochastic routs require complex and voluminous computations, not suitable for many instantaneous exercises of machine vision applications. Examples of these mathematical models are auto regressive (fractal) and Gaussian-Markov or Gibbs random fields (stochastic).

mathematical transformation methods; Fourier, Gabor and wavelet transforms can be applied for this purpose. They can represent a 2D array like an image in another 2D coordinate system which at the axis are corresponding to some characteristics which can be interpreted as texture features. While the Fourier transform performs poorly for the texture analysis (since it only detects frequencies) and the Gabor transform requires to check all filter resolutions (frequencies and phases) which renders is frustrated yet the wavelet transform can be executed more effectively if it's configured for specific applications (William, 2010).

Based on these the need for a fast and universal texture extraction solution is explicit. at this article we arrange a simple, fast and reliable technique which can detect any kind of texture without being sensitive toward frequencies, directions, edges, noise or the range of gray levels- conditions of illumination thus it can hinder all previous methods in one or more ways (Jingjing, 2008).

The current technique:

First we consider disintegrating the gray scale image into the smallest neighborhood 3x3 cells; should the image size does not match with 3's multiplications we can indeed consider one or two columns and rows as expandable or negligible.

$P(i-1,j-1)$	$P(i-1,j)$	$P(i-1,j+1)$
$P(i,j-1)$	$P(i,j)$	$P(i,j+1)$
$P(i+1,j-1)$	$P(i+1,j)$	$P(i+1,j+1)$

Figure 1: 3x3 cell.

Now we comprise a mask matrix at the same size of rows and columns but at the depth of 8 pages, the first depth indicates the distance between the first pixel of the cell with the central pixel and such. This matrix we call as the Feature Vector Matrix (FVM) is immune to the variations of the illumination levels at the original gray image.

$$\begin{cases} FVM(i,j,1) = (P(i-1,j-1) - P(i,j)\,) \\ \quad\quad . \\ \quad\quad . \\ \quad\quad . \\ FVM(i,j,8) = (P(i+1,j+1) - P(i,j)) \end{cases}$$

This *FVM (i, j, :)* can be presumed as a measure over the gray level variations of each cell which if actually the fundamental concept of the texture as mentioned before.

Thus we have a feature vector matrix but the clustering stage still remains. In order to obtain a clustered image we have to categorize each neighborhood upon its corresponding FVM line; for this purpose a measure of the difference between the FVM lines is needed and as for this instant we assume the following measure:

$$D = \sum_{k=1}^{8} \left| \left(FVM_{(i,j,k)} - FVM_{I,J,k} \right) \right|$$

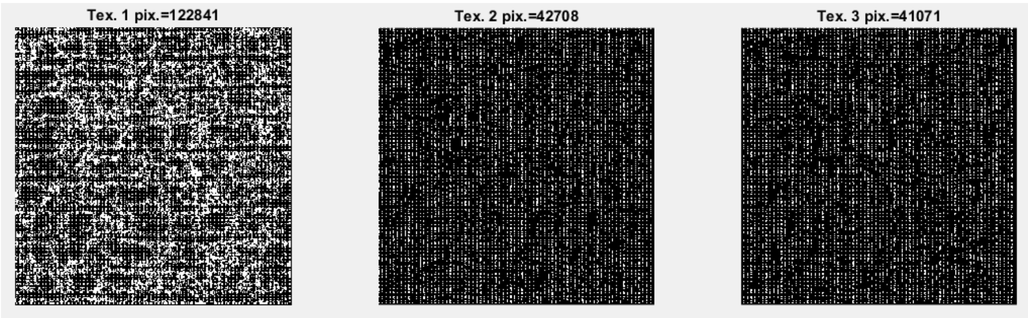
Should this Distance be smaller than a threshold then the corresponding pixels to the two compared FVM lines belong to the same cluster and marked with its signature. The compared feature vectors should also be exempted from the further comparisons. Eventually with respect to the accuracy threshold we had assumed and image's frequencies we will obtain larger or smaller clusters of textures. Assuming the clustering and not segmenting nature of the proposed method we can conclude that the edges could not introduce much of the demise for this approach. For this exercise we assumed the accuracy threshold as the average value of the whole image's gray levels but one may assume utilizing any other standards (Ruchaneewan, 2007).

5- Results and conclusion:

In order to gain a proper estimation over the method's efficiency we assumed running tests over a range of entropies, first we choose an image with entropy of 6.98.

Figure 2- a view of bricks with not much of the similar textures, the left image has marked by the classified texture and the black pixels are those which have not been put under any clusters. those are typically related to the edges or higher frequencies.

This image of 600x600 size has been clustered down to 514 bands of minimal neighborhoods and we show the top three largest.



Now we try lower entropy of 6.47, the results show that the lower frequencies are more likely to be successfully clustered by the smallest neighborhood's categorization.

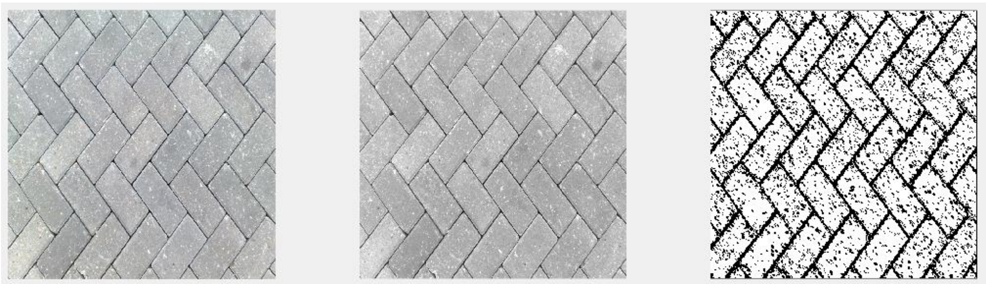
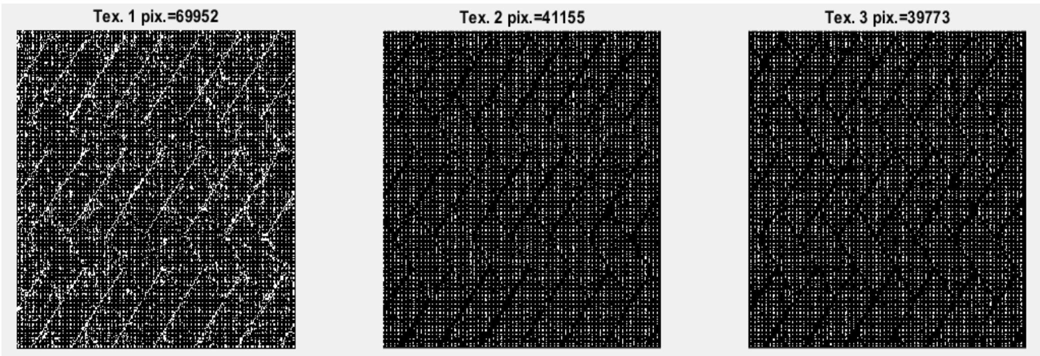


Figure 4- a nearly gray scaled image with small variation of colors can bear better results with the smallest neighborhood analysis.

Figure 5- top 3 largest texture clusters of the previous subject.



As for this subject even though the edges themselves are not classified still they don't prevent the other cells to be successfully categorized. Next we try an image with a little higher entropy of 7.03, a relatively ordered array of gray scale squares; and the results are still within the reason.

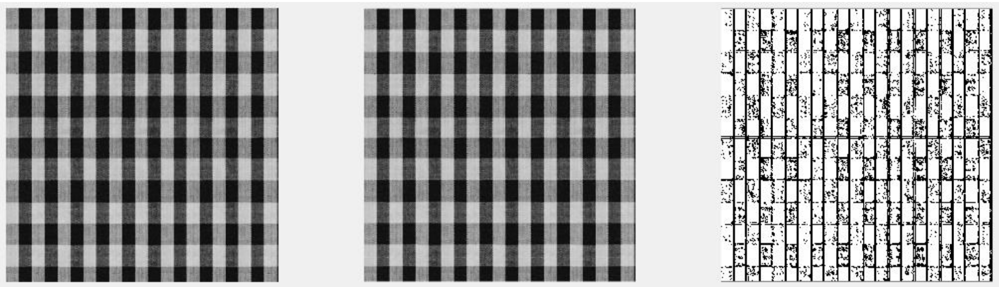


Figure 6- the texture clustering results are still within the interest.

However we should mention that this image is put to 136 clusters with the current categorization threshold.

And finally we inspect even higher entropy, a very stochastic image with the entropy of 7.54.

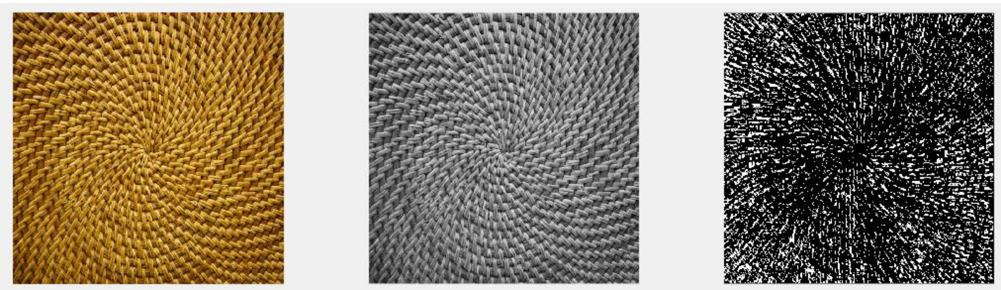


Figure 7- apparently higher frequencies render the method less effective but this is only because we still used the smallest neighborhoods to create FVM.

The method shows great potent for implicit developments and applications, the feature vectors allow the texture not to be only identified and clustered but also classified which is of great use in object recognition application; further the method is nearly improvised toward traditional texture segmentation obstacles like edges and shades and virtually every kind of texture can be analyzed with this simple and fast technique since it's not even sensitive toward directions and phases. Also the method can only be affected by very high levels of noise. Still the approach can be further enhanced by considering better measures of FVMs composition and categorization and also perhaps with altering the standard of clustering threshold even though our experiences confirmed the current one as the most optimistic. At last it should be remembered that one can assume repeating the clustering operation with increased sizes of neighborhoods or to assume regrouping the cells within larger ranges as mentioned before in order to resolve higher frequency situations.

Notes on contributors

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