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RESEARCH ARTICLE

Create regularly textured images using Texture analysis filters and Walsh Hadamard Transform

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Abstract

In this paper, Create regularly textured images using Texture analysis filters and Walsh Hadamard Transform is presented. In particular, we analyze the effectiveness of the Texture analysis filters and Walsh Hadamard Transform in automatic image annotation and content based imageCreate regularly textured. This algorithm registers images of the same or different modalities. Each image bit is lengthened in terms of Fast Walsh Hadamard basis functions. Each basis function is a notion of determining various aspects of local structure, e.g., horizontal edge, corner, etc. The experimental results show that Walsh Hadamard transform accomplished better results than the conventional Walsh transform in the time domain. Also Walsh Hadamard transform is more reliable in Create regularly textured image registration consuming less time.

Introduction

Pattern recognition is the ultimate goal of most computer vision research. Shape feature extraction and representation are the bases of object recognition. It is also a research domain which plays an important role in many applications ranging from image analysis and pattern recognition, to computer graphics and computer animation. shape descriptor is some set of numbers that are produced to describe a given shape feature. A descriptor attempts to quantify shape in ways that agree with human intuition (or task-specific requirements). Good retrieval accuracy requires a shape descriptor to be able to effectively find perceptually similar shapes from a database [1].

The work proposed in this paper uses Walsh Hadamard Transform (WHT) for image texture analysis .The coefficients obtained are normalized to determine a unique h in turn represents the digits in a particular range. The experiments conducted on clinical images show that proposed algorithm performed well than the conventional Walsh Transform (WT) method in for image texture analysis . EXTURE can be used in the analysis of images in several ways: in the segmentation of scenes into distinct objects and regions, in the classification or recognition of surface materials in detection of defects and abnormalities, and in the computation of shape from surface. Although an implicitly known term, an exact definition of texture either as a surface property or as an image property has never been adequately given. Although the concept of a surface texture as a pattern of variations in macroscopic surface topology is easy to accept, real-world surface textures are extremely difficult to model mathematically. Texture modeling as a function of surface attributes is yet more complex, since an accurate model must incorporate descriptions of both theoptical properties of the surface materials and of the geometries of the lighting sources and imaging system. In general, real texture modeling is a complex and hard to solve problem, regarding infinite combination of illumination, reflexes, surface topologies, shadows, and soon[2].

In many machine vision and image processing algorithms, simplifying assumptions are made about the uniformity of intensities in local image regions. However, images of real objects often do not exhibit regions of uniform intensities. For example, the image of a wooden surface is not uniform but contains variations of intensities which form certain repeated patterns called visual texture. The patterns can be the result of physical surface properties such as roughness or oriented strands which often have a tactile quality, or they could be the result of reflectance differences such as the color on a surface[3].

The paper is organized as follows; Section 2: contain the discussion for many techniques used for Texture analysis filters and Walsh Hadamard Transform. Section 3: deals with Texture analysis filters and Walsh Hadamard Transform, section 4: The proposed method, Section 5: gives the overview of algorithm with results and last section 6: ends the paper with conclusion.

Related Work

There are several texture feature extraction methods namely [4]:

Gray-level co-occurrence matrix(GLCM) method

Statistical method

Run Length method

Texture Spectrum method

Tamura's method

Wavelet based method

Gabor filters method

Law's method

Many techniques used for Walsh Hadamard Transformnamely:

In 2006 S. AMIRHASSAN MONADJEMI and PAYMAN MOALLEM they get on proposes a novelWalsh-Hadamard-based feature extraction approach to texture classification,
called Directional Walsh-Hadamard Transform,2008 M. J. Nassirithey used , texture feature extraction using Slant Hadamard Transform was studied and compared to other signal processing-based texture classification schemes.

In 2009 Claudio Moraga using walshhardmard matrix in digital signal processingondescribes a technique that utilizesWalsh function for the successful generation of periodic waveforms in their digital form and illustrates its implementation in Field Programmable Gate Array (FPGA) Technology. And in 2011 H.B.Kekre and Dhirendra Mishra him used presents the idea of using salcal density distribution in complex Walsh transform sectors to generate the feature vector for content based image retrieval This paper compares the performance of 8 , 12 and 16 sectors of Walsh Transform.

3.Texture Analysis Filters And Walsh Hadamard Transform

Texture is another feature that can help to segment images into regions of interest and to classify those regions. In some images, it can be the dawning characteristic of regions and critical in obtaining a correct analysis, Texture gives us information about the spatial arrangement of the colors or intensities in an image [10].

The analysis of texture requires the identification of those texture attributes which can be used for segmentation, discrimination, recognition, or shape computation,and the development of computational approaches for accomplishing these tasks. Here, low-level segmentation ofimages based on texture is considered, viz. without scrutinization, higher-level interpretation, or a priori knowledge of the texture types that may be encountered . Thus, discrimination is modeled as well, since the discrimination problem is embedded in the segmentation problem. However, recognition of real-world surface textures can only be achieved in a rudimentary sense using low-level processing. As with shape recognition, texture recognition requires the integration of computed low-level information with high-level knowledge. Thus, recognition of real-world textures is not considered; only textures occurring in images are considered, and texture will be regarded as being synonymous with image texture unless otherwise indicated[9].

Use entropy H to measure randomness of gray-level distribution[6]:

$H = -\sum_{i}.\sum_{j} N_d(i,j)\log_2 N_d(i,j)$……….(1)

Using a Gray-Level Co-Occurrence Matrix (GLCM)

A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix[11].

In addition, these features are also useful[6]:

$\text{Energy} = \sum_i . \sum_j N_d^2(i,j)$ … … … …(2)

$\text{Contrast} = \sum_i . \sum_j (i-j)^2 N_d(i,j)$……….(3)

$\text{Homogeneity} = \sum_i . \sum_j \frac{N_d(i,j)}{1+|i-j|}$…………(4)

$\text{Correlation} = \frac{\sum_i . \sum_j (i-\mu_i)(j-\mu_j) N_d(i,j)}{\sigma_i \sigma_j}$……….(5)

Walsh transform [5]matrix is defined as a set of N rows ,denoted Wj, for j = 0, 1, ... , N - 1, which have the following properties:

• w_j takes on the values +1 and -1.

• w_j [0] = 1 for all j.

• $w_j \times w_k^T = \begin{cases} 0 & \text{if } j \neq k \\ n & \text{if } j = k \end{cases}$

• Wj has exactly j zero crossings, for j = 0, 1, ., N-1.

• Each row Wj is either even or odd with respect to its midpoint.

Walsh transform matrix is generated using a Hadamard matrix of order N. The Walsh transform matrix row is the row of the Hadamard matrix specified by the Walsh code index, which must be an integer in the range [0, ..., N - 1]. For the Walsh code index equal to an integer j, the respective Hadamard output code has exactly j zero crossings, for j = 0, 1, ... , N - 1.

The system of Walsh functions is the basis for Walsh transform. Walsh functions are orthogonal and have only +1 and -1 [5] In general, the Walsh transform can be generated by the Hadamard matrix as follows:

$H_{2^k} = \begin{bmatrix} H_{2^{k-1}} & H_{2^{k-1}} \\ H_{2^{k-1}} & -H_{2^{k-1}} \end{bmatrix}$for k=1,2,3,….n

For k = 1, the 2 × 2 Hadamard matrix H2 is defined by:

$H_2 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$.

For k = 2, the 4 × 4 Hadamard matrix H4 can be easily obtained using the formula:

$H_4 = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & -1 & 1 \end{bmatrix}$ or $H_4 = \begin{bmatrix} H_2 & H_2 \\ H_2 & -H_2 \end{bmatrix}$

Lemma:

Let H_n be an Hadamard matrix of order n. Then:

$$H_n = H_n^t$$

$H_n . H_n^t = nI_n$, where I_n is the identity matrix of order n

$\det(H_n) = (n)^{\frac{n}{2}}$ for $n \geq 4$.

Theorem :

Let H_n be an Hadamard matrix of order n. Then the inverse Hadamard matrix be:

$$H_n^{-1} = \frac{1}{n} H_n$$

The Fourier Transform consists of a projection onto a set of orthogonal sinusoidal waveforms. The FT coefficients are called frequency components and the waveforms are ordered by frequency. The Hadamard Transform consists of a projection onto a set of square waves called Walsh functions. The HT coefficients are called sequence components and the Walsh functions are ordered by the number of their zero-crossings.

The Walsh functions are real (not complex) and take only the values +1 or -1. A Hadamard matrix H_jj is a symmetric JxJ matrix with elements +1 and -1.

The Hadamard matrix of second order is given by Hadamard matrices of orders other than powers of 2 exist, buty they are not widely used in image processing. The Hadamard transform given by :

$$F = H_m f H_n$$

The Hadamard transform and its inverse are given by:

$$f = \frac{1}{mn}(H_m F H_n)$$

It can be seen that only matrix multiplication is necessary to compute a Hadamard transformation, and further, only additions are computed during it. The Hadamard transform is sometimes called a Walsh-Hadamard transform, since the base of the transformation consists of Walsh functions.

4.The Proposed Method

The algorithm for this work explain how to extract ideal features that can reflect the Texture analysis content of the images as complete as possible is still a Create regularly textured problem and how can use Walsh Hadamard Transform to shown regularly textured images. Algorithm

1- Start
2- input image
3- FindProperties of gray-level co-occurrence matrix
   3-1 **Contrast:** Returns a measure of the intensity contrast between a pixel and its neighbor over the whole image.
   3-2 **Correlation:** Returns a measure of how correlated a pixel is to its neighbor over the whole image.
   3-3 **Energy:** Returns the sum of squared elements in the GLCM.
   3-4 **Homogeneity:** Returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.
4- Find Entropyof image
5- Find Global image threshold using Otsu's methodof grayscale image
6- Create gray-level co-occurrence matrix from image and Properties of gray-level co-occurrence matrix
7- Convert image values to double values
8- Find Fast Walsh–Hadamard transform for values
9- Find Hadamard matrix for values
10- Bit reversing of the binary index and Pre-allocate memory
11- Binary to integer sequence indexthen 1-based indexing
12- Find Hadamard index and multiply it by mean ofProperties of gray-level co-occurrence matrix toshown regularly textured image
13- if we need to process anther image go to step 2 else go to step 14
14- End

5.Experimental Results

In this section, the results are presented which are obtained by applying different Properties of gray-level co-occurrence matrixandWalshHadamard Transform to shown regularly textured images. The proposed method has been applied using images with different size(n*m) ,format are(.tif and.png) of an coins.png , rice.png , testpat1.png ;kids.tif , pout.tif ,onion.tif ,cameraman.tif, ,spine.tif,board.tif and peppers.png.

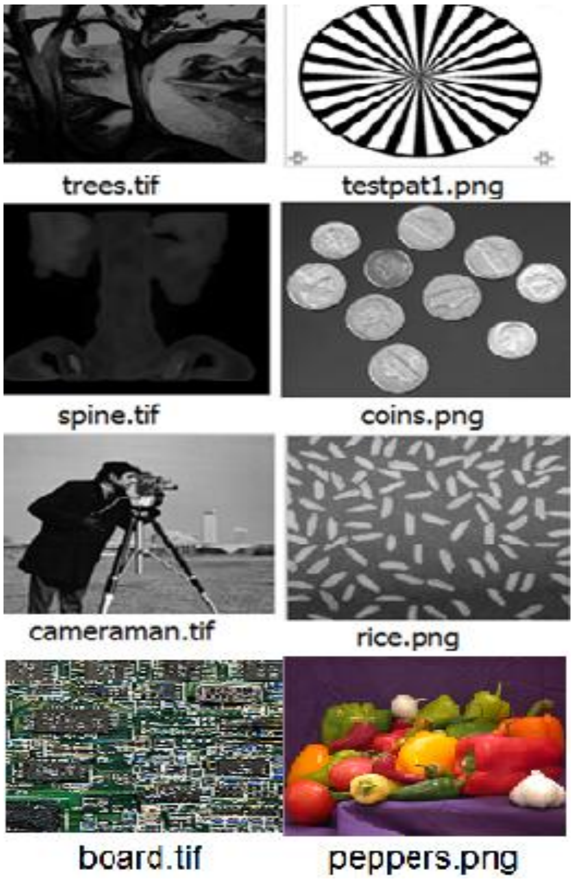

Fig. 1: Sample of data base for gray scale image use in this work .

Using GLCM texture feature extraction method, Contrast, Correlation ,Entropy and Homogeneity values are extracted for six samples shown in table(1).

Table 1: GLCM texture feature extractionProperties values

Image name	Contrast	Correlation	Energy	Homogeneity
Cameraman.tif	0.5006	0.9269	0.1636	0.8925
Rice.png	0.2985	0.8931	0.1909	0.8843
coins.png	0.1677	0.9633	0.3987	0.9450
spine.tif	0.0082	0.9838	0.4920	0.9960
trees.tif	0.1676	0.9461	0.2455	0.9315
testpat1.png	1.6235	0.9149	0.4173	0.8918
peppers.png	0.0886	0.9758	0.2371	0.9591
board.tif	3.3268	0.6012	0.0681	0.6889

It is observed that high Contrast for board.tifimage,highCorrelation 0.9838 for spine.tif image ,high Energy 0.4920 for spine.tif image and high Homogeneity0.9960spine.tif image.

It is observed that low Contrast0.0082 for spine.tif image image,lowCorrelation0.6012for board.tifimage ,low Energy 0.0681board.tif image and low Homogeneity0.6889board.tif image.

The main purpose of texture feature extraction is to obtain relationships among the pixels that belong to a similar texture, such as spatial gray level dependence. Table(2) shown energy and Global thresholdvalues.

Table 2: Energy and Global thresholdvalues.

Image name	entropy	Global threshold
Cameraman.tif	7.0097	0.3451
Rice.png	7.0115	0.5137
coins.png	6.3162	0.4941
spine.tif	4.0935	0.0627
trees.tif	5.7006	0.2392
testpat1.png	2.4763	0.5137
peppers.png	6.9917	0.3961
board.tif	7.4568	0.5059

The results of compute gray-level co-occurrence matrix (GLCM) values for these images can be seen in Figure 2, Figure 3,Figure 4 and Figure 5 respectively.

```
glcm =

  Columns 1 through 4

       11133          576          138           77
         560         1965          382          165
         184          310         1080          496
         109          182          488         5656
          45          157          167         2093
          14           96          100          110
           1           37           23           52
           0            2            3            7

  Columns 5 through 8

          73           34           15            0
         128           90           28            1
         159          115           31            0
        2024          151           44            4
       15430         1415           42           19
        1426        16842          136           23
         122           74          252           33
          12           10           46           93
```

Fig.2: Gray-level co-occurrence matrix (GLCM) values for Cameraman.tif

```
glcm =

  Columns 1 through 4

       14800          580          413          314
         609          188           81           79
         420           84          137           45
         304           93           46           81
         237           79           84           27
         248          114           49           68
         123          213           78           74
           0          141          303          261

  Columns 5 through 8

         245          268          121            0
          88          100          210          137
          86           63           77          279
          29           61           66          269
          61           42           88          309
          33          155           75          434
          78           71          103          595
         307          416          595        39446
```

Fig.3: Gray-level co-occurrence matrix (GLCM) values for Testpat1.png

```
glcm =

  Columns 1 through 4

       95173         668           8           0
         673       82386          45           0
           3          50         457           0
           0           0           0           0
           0           0           0           0
           0           0           0           0
           0           0           0           0
           0           0           0           0

  Columns 5 through 8

           0           0           0           0
           0           0           0           0
           0           0           0           0
           0           0           0           0
           0           0           0           0
           0           0           0           0
           0           0           0           0
           0           0           0           0
```

Fig.4: Gray-level co-occurrence matrix (GLCM) values for Spine.tif

```
glcm =

  Columns 1 through 4

       35451        2634         133          37
        2515       12242        1732         235
         185        1705        8013        1267
          65         194        1336       22298
           0           0           0           0
           0           0           0           0
           0           0           0           0
           0           0           0           0

  Columns 5 through 8

           0           0           0           0
           0           0           0           0
           0           0           0           0
           0           0           0           0
           0           0           0           0
           0           0           0           0
           0           0           0           0
           0           0           0           0
```

Fig.5: Gray-level co-occurrence matrix (GLCM) values for Trees.tif

Figure (6) shown Gray-level co-occurrence matrix (GLCM)shape ,the same figure between spine.tif image and trees.tif image the values in figure (4) and figure(5) respectively.

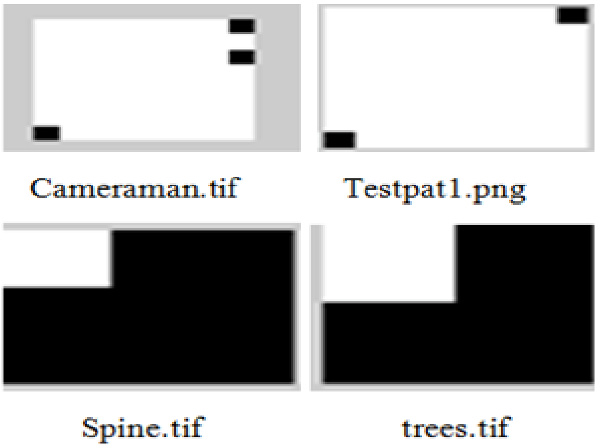

Fig. 6: Gray-level co-occurrence matrix (GLCM) shape

The results show clearly the advantages of using Walsh Hadamard Transform(WHT)sequence order for selecting features, especially when the features vector consists of a very few features figure (7) shown Walsh Hadamard Transform(WHT) for Cameraman.tif,peppers.png and board.tif.

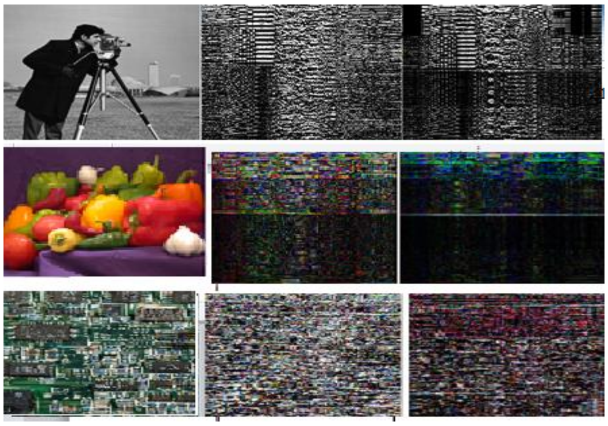

Fig. 7: Walsh HadamardTransform(WHT) for Cameraman.tif,peppers.png and board.tif.

For Each window size, texture features are calculated and the difference between the feature value for the previous window size and the difference will be less as we approach the correct window and again it will increase.

To find different patterns repeated regularly in a same image. out optimal window size for all those patterns is a level and window size may be different for each pattern.

In figure(7) shown sample window values for Contrast of different types of texture. The values of contrast are varied with respect to types of textures taken for analysis.

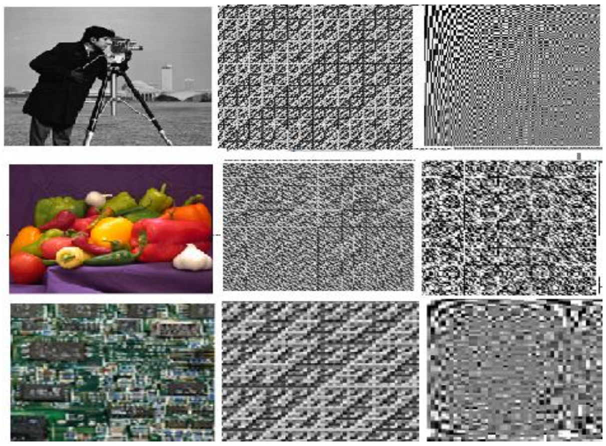

Fig.7: Sample window values for Contrast of different types of texture

Finley after find Hadamard index and multiply it by mean of Properties of gray-level co-occurrence matrix to shown regularly textured image ,figure(8) shown regularly textured image for Cameraman.tif,peppers.png and board.tif.

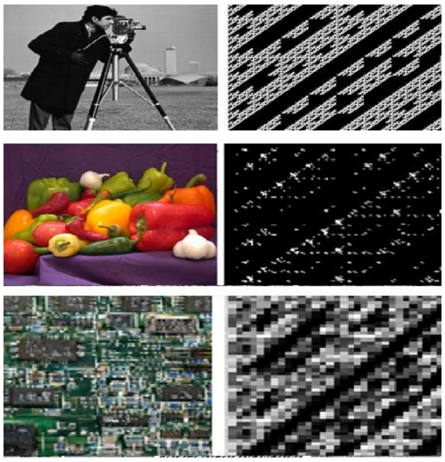

Fig.8: regularly textured image for Cameraman.tif,peppers.png and board.tif

6.Conclusion

The proposed method is decrease the computation time with generate high quality of Create regularly textured images by use Texture analysis and Walsh Hadamard Transform . Experiment results have demonstrated that the proposed scheme for Create regularly textured images works satisfactorily for different levels digital images. Another benefit comes from easy implementation of this method.

We alsodetermined the importance of the parameter setting to obtaineffective features. Tests were focused on natural randomtexturesanalysis, where the analysiswindowsimage isusually more difficult.

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