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Illumination Normalized based Transformation Techniques for Texture Classification

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Abstract: The image transformation is also known as spectral enhancement method. The transformed image may have properties that make it more suited to the particular purpose than original input image. Illumination normalization is an important task in the field of computer vision and pattern recognition. In this paper a novel approach by combining different transformation techniques with illumination normalization methods are suggested. The transformation techniques; Haar, Hadamard, and Walsh are utilized. For illumination normalization, gamma correction and small scale retinex (SSR)methods are used. For the assessment of the efficiency of the suggested method VisTex database is utilised. Classification is done by using k-Nearest Neighbour (k-NN).

Introduction

Texture contains the vital part of information among all the characteristics present in an image. Still, the performance of texture classification is affected by two vital factors such as the change in pose and illumination conditions of the subjects. In literature, many authors have tried to compensate the illumination variation by proposing different methods.

In image analysis, contains two important properties of image is texture and colour. Many authors ignore the color information and use various texture features extraction and classification techniques for gray texture imagesIn texture classification there are many kind of methods, texture features description are important in texture analysis. In the field of texture analysis,many local texture descriptors like gray level co-occurrence matrix (GLCM), law mask and local binary pattern (LBP) are suggested [1-3]. Several multi-resolution techniques have been proposed for wavelets frame transform, Gaborfilters and Dyadic wave transform [4-6]. In addition, many authors have introduced hybrid model to improve the classification rate and achieved. From past few years, many researchers have worked on the problem of illumination variance which controls the stability of an image under illumination changes. They are many existing techniques which are deal with the illumination problems. Du and Ward have suggested a new approach of histogram equalization in which it is used as low frequency and emphasizes on high frequency components for face recognition.Jobson have proposed multi-scale retinex(MSR) for illumination normalization method in which low frequency is eliminated by dividing the image by a smoothed version of itself [7].Dash et al. proposed illumination method based on homomorphic filtering techniques to enhance face recognition with challenging illumination conditions [8]. Dash and Senapati have suggested normalization for texture classification by using gray level run length matrix (GRLM) based on wavelet normalization and Tan and Trigg normalization [9]. Amiri and Hassanpour have proposed that actual appearance of many imaging devices of objects cannot display due to technical limitations. This process is called as gamma distortion, which disturbs the image. The gamma distortion is not monotonic. Adjacent pixels are mainly depends to the relative illumination reflection of objects. It may also depends to the depth, texture, and relative reflection of objects in the image. Texture and depth gamma distortion of an image may vary from one object to other [10].Tan and Triggs have suggested that Normalization technique is also used for the enhancement of local texture features. For illumination normalization in pre-processing stage Gamma correction, Difference of Gaussian filtering, Masking (optional) and Contrast equalization have been used. For feature extraction, Local Ternary Patterns (LTP) and Gabor filter are used. [11]. More recently, an illumination normalization technique is implemented through homomorphic filtering and histogram equalization for face recognition [12].

Even though in the literature there are many efficient texture descriptors are available but few authors have also proposed texture analysis using some transformation techniques. Lonnestad has recommended texture features based on haar transform [13] Huang has proposed a fast method of analysis of texture using Discrete Cosine Transform (DCT) [14].Nassiri et al. have suggested extracting the texture features utilizing slant-hadamard transform [15].

Hence, after a complete study in this paper a novel approach of texture analysis based on illumination normalization based transformation technique is recommended. Three different transformation techniques like haar, hadamard, and walsh are utilized for the texture feature extraction. For illumination normalization: small scale retinex (SSR) and gamma intensity correction methods are implemented.

The paper is arranged as follows. A brief review of transformation techniques and illumination normalization methods are narrated in Section 2. Details of proposed method are discussed in section 3. Experiments and results are given in section 4. The conclusion is given in section 5.

2. Review of Transformation Techniques and Gamma intensity correction

2.1. Haar Transformation

The Haar Transform (HT) was originally presented in the onedimensional, continuous case**.** Haar is then extensioned to the 2D and discrete case was straightforward. Within image processing, the Haar Transformation can be suited to data coding, edge detection, and possibly multiplexing. The HT is an orthonormal transform like the Fourier transform, but it hassome interesting properties.The HT uses rectangular basis functions, no trigon-metric functions are involved. The HT is real, not complex like them, allowing simple implementation, simple computation, aswell assimple visualization and interpretation.The HT is the fastest of the orthonormal transforms described in the literature, being of order N^2, compared to $N^2 \log_2 N$ for Fast Fourier Transform.
The discrete, 2-D Haar transform H(u,v) of image F(x,y) of size N^2 where $N=2^n$ is defined by

$$H(u, v) = \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x, y)\, H\ (x, y; u, v) \qquad (1)$$

Where the separable forward transformation kernel H can be defined by a product of Haar basic function h.

$$H\ (x, y; u, v) = h_u(x)\, h_v(y) \qquad (2)$$

The index u(v) can be uniquely decomposed into integers p and q as

where $0 \leq p \leq q-1$ and $q \in \begin{Bmatrix} 0,1 & for\ p=0 \\ 1 \ldots 2^p & for\ p \neq 0 \end{Bmatrix}$

p = frequency index

q = position in the original image

2.2. Hadamard Transformation

The Hadamard transformation H_m is a 2^m x 2^m matrix, the Hadamard matrix, that transforms2^m real numbers x_n into 2m real numbersx_k. The Hadamard transform can be defined in two ways recursively or by using binary representation of the indices nand k.

Recursively, we define the 1×1 hadamard transform H_0 by the identify H_0=1, and define H_m for m>0

$$H_m = \frac{1}{\sqrt{2}} \begin{pmatrix} H_{m-1} & H_{m-1} \\ H_{m-1} & -H_{m-1} \end{pmatrix} \qquad (3)$$

2.3. Walsh Transformation

Walsh transform consists of basic function values are only 1 and -1. They have the form of squares waves. This function can be implemented more efficiently in a digital environment than the exponential basic function of the Fourier transform.
We define now the 2-D Walsh transform as a straightforward extension of the 1-D transform:

W(u,v) $=\frac{1}{N}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)\left[\prod_{i=0}^{n-1}(-1)^{b_i(x)b_{n-1-i}(u)+b_i(y)b_{n-1-i}(v)}\right]$ (4)

The above is equivalent to

$$W(u,v)=\frac{1}{N}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)\left[(-1)^{\sum_{i=1}^{n-1}(b_i(x)b_{n-1-i}(u)+b_i(x)b_{n-1-i}(u))}\right] \quad (5)$$

We define now the inverse 2-D Walsh transform. It is identical to forward 2-D Walsh transform.

$$f(x,y)=\frac{1}{N}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} W(u,v)\left[\prod_{i=0}^{n-1}(-1)^{b_i(x)b_{n-1-i}(u)+b_i(y)b_{n-1-i}(v)}\right] \quad (6)$$

The above is equivalent to

$$f(x,y)=\frac{1}{N}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} W(u,v)\left[(-1)^{\sum_{i=1}^{n-1}(b_i(x)b_{n-1-i}(u)+b_i(x)b_{n-1-i}(u))}\right] \quad (7)$$

2.4. Gamma Intensity corrections

Various devices utilized for capturing, printing or displaying the images normally apply a transformation that is known as power law transformation or gamma correction. It is applied on each pixel of the image that has nonlinear effect on luminance.The gamma transformation contains the basic form

$$m = kn^{\gamma} \quad (8)$$

where k and γ are positive constant, n is raised to the power γ,m is output value

Gamma correction controls the overall brightness of an image. When the quantity of$\gamma<1$, the transformed image turns into lighter than the original image. When thequantity of $\gamma>1$, the transformed image turns into darker than the original image. As the gamma correction is applied to the image pixel intensities, hence the knowledge of gamma is necessary for the enhancement of image.

2.5. Singlescale Retinex

TheLand[16]proposedthat image I(x,y) is the product of two components, illumination L(x,y) and the reflectance R(x,y)

$$I(x,y) = L(x,y)\, R(x,y) \quad (9)$$

The single scale Retinex is defined for a point (x, y) is an image as

$$R_i(x,y) = \log I_i(x,y) - \log\left[f(x,y) \otimes I_i(x,y)\right] \quad (10)$$

Where $R_i(x,y)$ = Retinex output

$I_i(x,y)$ = image distribution

i^{th} = spectral based

There are three spectral bands-one each for red, green, and blue.

The object comprises the information regarding the reflectance and scene of geometric properties of illumination. The light spotting on the image identifies the small feature.However, the effect of spot it may overlook the identification and have negative effect on the normal quality of restored image. Human eye is more sensitive for the gray edge, such as high frequency information because of convolution function in low pass function, the low frequency information removes from original, which is single-scale Retinex, received original description of high-frequency part, that corresponds to the edge of the image.

3. Suggested Normalization based Transformation methodology

This section describes the suggested approaches, whose principles are given on the steps shown on Fig. 1.

The focus of this work to improve the classification accuracy by proposing illumination normalization techniques integrated with transformation techniques. Two types of illumination normalization, gamma intensity correction and SSRtechniques are used. Three different types of transformation techniques like haar, hadmard and walsh are used. Texture features like mean, standard deviation, kurtosis, and skewness are extracted from the transformed images. To validate the efficiency of the proposed method, experiments are conducted on the VisTex database.K-NN classifier is utilized in the classification task.

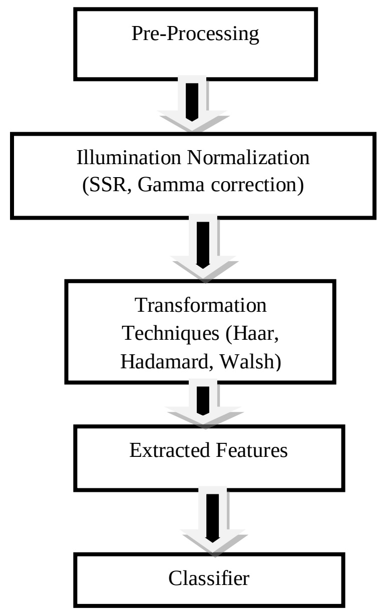

Fig. 1. Steps of the recommended approach.

The various steps of the recommended methods are explained below.

a. Gamma intensity correction normalization: The image may consist of several of texture and depth; the gamma distortion may not be similar on all the objects. Thus in this method local gamma correction is employed. Fifteen different gamma values (from 0.1 to 1.5 with interval 0.1) are applied to each image.
b. small scale retinexnormalization: In this technique the parameter that controls the bandwidth of the Gaussian filter is varied with different values (from 1 to 15 with interval 1) and that is required for the SSR technique.
c. In the next step texture features like mean, standard deviation, kurtosis, and skewness are extracted using various transformation techniques.
d. In the last step classification is done with the help of k-NN classifier.

4. Experimental results and discussion

The effectiveness of the recommended methodology is tested using the VisTex dataset.In pre-processing 25 images from VisTex database of size 512×512 pixels are selected and are shown in Fig. 2. The image are converted into gray then each image is subdivided each 512×512 pixels image into 128×128 pixels. Thus, total 400 images are generated from which 200 images are used for testing and remaining 200 for training.

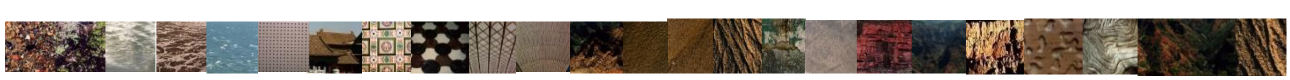

Fig.2. Examples of VisTex dataset.

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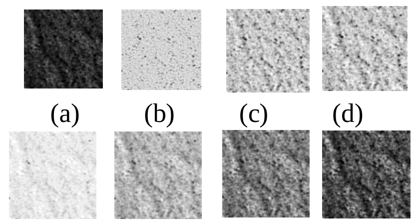
The normaliztaion techniques are appled to the orginal images both on traing and testing sets. Few examples of normalized images generated from various values of the normalized approches are presented in Fig. 3.



(a) (b) (c) (d)

(e)(f) (g) (h)

Fig.3. Examples of normalized images. (a) original image (b) normalized image at SSR=1 (c)normalized image at SSR=5 (d)normalized image at SSR=10 (e)normalized image at Gamma=0.1(f)normalized image at Gamma=0.5 (g)normalized image at Gamma=1 (h)normalized image at Gamma=1.2.

In our first experiment, theoriginal transformation techniquessuch as haar, hadamard, and walsh are applied to the original images and used for feature extraction. For each image, five texture features are extracted using all the transformation techniques. The classification successes rates are shown in the Table 1. It is noted that the maximum success rate of 36.50%, 35%, and 34% on haar, hardamad, and walsh transformation techniques respectively.

Table1: Classification results on traditional transformation techniques

Transformation techniques	**Classification Accuracy(%)**
Haar	36.50
Hadamard	35.00
Walsh	34.00

In the second experiment SSR illumination normalization technique is applied to the original dataset. Texture features are extracted by using the same three transformation techniques. The results are shown in Table 2. From the Table 2 it is noted that the classification accuracy increased to 40% for the haar transformation, 39% for the hadamard transformation, 35.50% for the walsh transformation at the value of SSR=13. Also for many other values of SSR increased classification accuracy is observed.

Table 2: Classification results of proposed SSR normalization based transformation techniques

Transformation techniques	**Classification Accuracy(%)**
Haar+SSR	
SSR=1	26.50
SSR=2	27.50
SSR=3	27.50
SSR=4	29.00
SSR=5	30.50
SSR=6	30.00
SSR=7	33.00
SSR=8	33.50
SSR=9	34.50
SSR=10	36.50

SSR=11	37.50
SSR=12	38.50
SSR=13	**40.00**
SSR=14	39.50
SSR=15	39.00
Hadamard+SSR	
SSR=1	23.50
SSR=2	23.50
SSR=3	24.50
SSR=4	25.00
SSR=5	26.00
SSR=6	30.00
SSR=7	32.00
SSR=8	31.50
SSR=9	35.50
SSR=10	36.00
SSR=11	37.50
SSR=12	38.50
SSR=13	**39.00**
SSR=14	38.00
SSR=15	37.00
Walsh+SSR	
SSR=1	22.00
SSR=2	22.50
SSR=3	23.00
SSR=4	23.00
SSR=5	26.00
SSR=6	27.50
SSR=7	27.00
SSR=8	28.50
SSR=9	29.00
SSR=10	31.50
SSR=11	33.00
SSR=12	34.50
SSR=13	**35.50**
SSR=14	34.00
SSR=15	34.00

In the third experiment Gamma illumination normalization technique is applied to the original dataset. Texture features are extracted by using the same three transformation techniques. The results are shown in Table 3. From the Table 2 it is noted that the classification accuracy increased to 38.50% for the haar transformation at Gamma value 1.1, 46.50% for the hadamard transformationat Gamma value 1, and 41% for the walsh transformation at Gamma value 1.3. In addition to above, increased in classification rates are also observed for othervalues of Gamma.

Table 3: Classification rates of the suggested Gamma normalization based transformation techniques

Transformation techniques	Classification Accuracy (%)
Haar+Gamma	
Gamma=.1	23.00
Gamma=.2	29.00
Gamma=.3	33.00
Gamma=.4	34.00
Gamma=.5	33.00
Gamma=.6	33.00
Gamma=.7	34.50
Gamma=.8	35.50
Gamma=.9	35.50
Gamma=1	37.00
Gamma=1.1	**38.50**
Gamma=1.2	36.50
Gamma=1.3	37.50
Gamma=1.4	36.50
Gamma=1.5	37.00
Hadamard+Gamma	
Gamma=.1	27.00
Gamma=.2	34.00
Gamma=.3	36.50
Gamma=.4	39.00
Gamma=.5	39.50
Gamma=.6	39.50
Gamma=.7	43.00
Gamma=.8	43.00
Gamma=.9	45.00
Gamma=1	**46.50**
Gamma=1.1	45.50
Gamma=1.2	45.50
Gamma=1.3	46.00
Gamma=1.4	45.00
Gamma=1.5	45.00
Walsh+Gamma	
Gamma=.1	28.50
Gamma=.2	34.00
Gamma=.3	36.50
Gamma=.4	38.00
Gamma=.5	38.50
Gamma=.6	38.50
Gamma=.7	38.00

Gamma=.8	39.00
Gamma=.9	39.00
Gamma=1	40.00
Gamma=1.1	38.00
Gamma=1.2	39.50
Gamma=1.3	**41.00**
Gamma=1.4	36.50
Gamma=1.5	36.50

Fig. 4 represents the classification success rate of the original transformation techniques. Fig. 5 and Fig. 6 show the classification success rates of the recommended approaches.

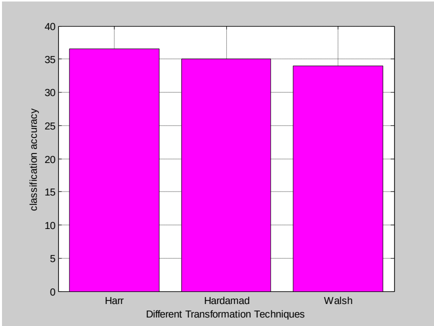


Fig. 4. Performance results of the original transformation techniques.

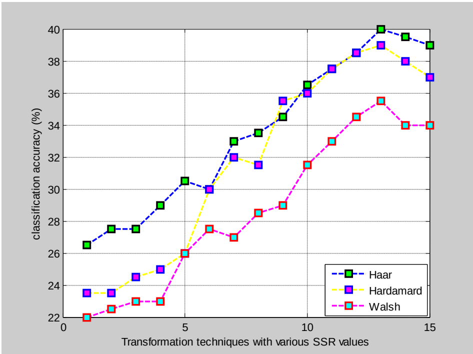


Fig. 5. Classification results of proposed SSR normalized based transformation approaches.

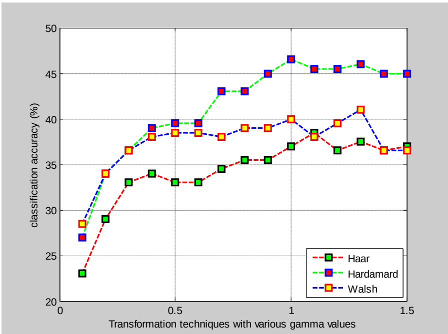


Fig. 6. Classification results of proposed SSR normalized based transformation approaches.

5. Conclusions

In this paper, two illumination normalization techniques, which are combined with transformation techniqueslike Haar, Hadamard, and walsh is recommended for texture classification.The gains of the recommended methods are confirmed experimentally by the classification on VisTex database. The suggested approach is effective at accomplishing illumination invariant. The increment in classification accuracy is 3.5% on haar transformation with SSR normalization.The increment in classification accuracy is11.5% on hadamard transformation with Gamma normalization. The increment in classification accuracy is7% on walsh transformation with Gamma normalization.

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