IJCTA, 9(12), 2016, pp. 5569-5575

A Survey on Texture Image Transformation Techniques

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Abstract : DigitalImage & Transformation of imagesis presently a fast growing needand trust area in theresearch. To identifyt he different transformation schemes in its features for texture images, A surveyon various texture images was applied todifferent transformation techniques.This paper gives detailed information about the survey carried out by considering different Transformation methods on Texture Images. The filter selection algorithm results are compared on various texture features like Markov random field Co-occurrence & Gabor with Ohanion and Daubechies. For Less detailed images Daubechies Family produces a better Compression Ratio (CR), leverage value of Peak Signal to Noise Ratio(PSNR)with the less Bit Error Rate(BER)than Haar. Discrete Cosine Transform (DCT)gives good resultona transform property energy compaction, but has limitation over Mean Squre Error(MSE).After comparative analysis, Harr and Daubechies functions gives best one because it has less MSE and high Energy Retained (ER). From the above, we concluded that Discrete Wavelet Transformation (DWT) with MultiWavelet Transform(MWT)that are the best of all texture features for less, medium and high detailed images.

Keywords : DWT, DCT, Discrete WaveletFrames(DWF), ContinuousWavelet Transform(CWT),Gray Level Co-occurrence Matrix (GLCM).

I. INTRODUCTION

The texture is described as spatial arrangement of color intensities in selected region of an image. The images that are visualized in a computer vision & used automated computational methods to retrieve the visual information and understanding the image content based on textural properties. There are two main approaches used for spatial arrangment; one is structural approach, a set of primitive texels in some regular or repeated relationship of a texture Second is statistical approach, a quantitative measure of the arrangement of intensities in a region of a texture.

There are several techniques used for classifying the textures,some of them are, the DWT Techniques [6] which gives better PSNR,MSE,CR and maintains good quality of images. The multi wavelet transform and interpolation techniques[7] identifies a DWT preserves the edge information with interpolation of Adjacent Pixel Algorithm to obtain the interpolation of high frequency sub bands and reaches the high resolution of an input image for resolution enhancement of satellite images. The HSV (Hue, Saturation, Value) based Color Texture Image Classification uses Wavelet Transform and Motif Patterns [16] which identifies color texture classification.

The First-Order Statistical (FOS)[8] method identifies Support Vector Machines(SVM) and it classifies microscopic images based on statistical features such as mean,standard deviation,skewness and kurtosis to be established considerable signatures of several images at distinct level by the Daubechies wavelet families which is used as decomposition filter for analysis of performance. It also investigates by considering some parameters such as kapppa statistics, Mean Absolute Error (MAE), F-mean,True Positive (TP), False Positive(FP)rates, precision, Recall, Receive Operating Characteristic(ROC) & Precision Recall curve(PRC).

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The image classification of texture uses GLCM [9] which identifies to extract texture features such as Energy, Entropy Moment of inertia & Correlation.Texture classification on images uses Multi resolution Transforms [1] which identifies a Pyramidal wavelet transform to extract relevant information from natural texture images and synthetic texture images by using various factors such as mean, variance, entropy and energy. The comparsion & analysis of Haar and Daubechies,DCT wavelet for image compression [3] identify a series of finitely large data points in terms of a sum of oscillating cosine functions at different frequencies. The Effect of Symlet filter eleminates noisy of natural images[4].

A comparison between Haar and Daubechies wavelet transform on Field Programmable Gate Array (FPGA) Technology [5] identifies the design of high performance systems and investigated the wavelets on texture feature like BER. The Texture classification uses Spectral Histograms [10] identifies features of minimum distance classifier and gain. The Wavelet approach for detecting clouds and shadows [11] from images based on time series. The Color Image uses WT based on Human Visual System (HVS) [12] is a new robust scheme based on Discrete Wavelet domain and gives better transparency and good robustness to noise, filtering, compression and cropping.

The Lung Tissue Classification uses Wavelet Frames [13] identifies the High Resolution Computational Tomography (HRCT) with Lung Tissue patterns of effected interesting Lung Disease (ILD) by defining wavelet coefficients and gray level histograms with the help of Knearest neighbor classifiers and computed the Euclidian distance between normalized feature vectors. The texture classification by Local Binary Pattern (LBP) based on CWT [14] describes mother wavelet satisfies the conditions Admissibility, Regularity and vanishing moments expressed according to scaling function and a scaling factor. The feature Extraction and Classification of High Resolution Satellite Images uses GLCM & Back Propagation Technique [15] identifies the feature extractions like Homogeneity, Entropy, Angular Second Moment, Dissimilarity, Correlation, Mean, Variance, Contrast from the filtered image.

We describe the details of the paper in the following Sections: Section II describes the Analysis of different schemes, and Finally, Section III describes the conclusion of the paper.

2. ANALYSIS OF DIFFERENT SCHEMES

A. DWT, DWF & CWT

1. **DWT :** Wavelet Transforms are systematically arranged as continuous and discrete. For extending a relatively great length signals CWT is time consuming, so as it needs combined at all the times. DWT can be usually a specially shaped object designed to do a particular task through sub band coding and useful because it can localize signals in scale and time, whereas DCT can localize signals in the domain frequency.The DWT is valid by filtering the signal among a sequence of digital filters of different scales.The scaling operation is done with changing the resolution of the signal through sampling.

   DWT is a multi-resolution decomposition which divides a spatial domain image into four sub-band images in frequency domain.Due to the filter ability of wavelet transform, the input image is filtered by low pass and high pass filters.The filtered signals represent spatial information within sub-band images.Therefore, the texture images are transformed to sub-band images by wavelet transform before texture feature extraction.

Ll1	Hl1
LH1	HH1

Fig. 1. Level-1 decomposition by DWT

The wavelet transform of 1-D signal $f(x)$ is defined as :

$$(\mathrm{W}_y f)(a, b) = \bigcup f(x)_{(a,b)} y dx,$$

$$y\text{–}b_{(a,\ b)} = \frac{1}{\sqrt{a}^{\,y}} x(a)$$

where as a denotes the scaling factor, b is the translation parameter, and $\Psi_{(a,b)}{}^{*}(x)$ is the transforming function. Due to applying the wavelet transform in a 2-D image, the transforming results are calculated by using a separable product of 1-Dimensional filter to the image:

$$\mathrm{LL} = {}_{\mathrm{I}}\mathrm{H}_{\mathrm{X}} * \mathrm{H}_{\mathrm{Y}} * \mathrm{I}_{\varnothing 2,1},{}_{\varnothing 1,2}(b)$$
$$\mathrm{HL} = {}_{\mathrm{I}}\mathrm{G}_{\mathrm{X}} * \mathrm{H}_{\mathrm{Y}} * \mathrm{I}_{\varnothing 2,1},{}_{\varnothing 1,2}(b)$$
$$\mathrm{LH} = {}^{\mathrm{I}}\mathrm{H}_{\mathrm{X}} * \mathrm{IG}_{\mathrm{Y}} * \mathrm{I}_{\varnothing 2,1},{}_{\varnothing 1,2}(b)$$
$$\mathrm{NH} = {}^{\mathrm{I}}\mathrm{G}_{\mathrm{X}} * \mathrm{IG}_{\mathrm{Y}} * \mathrm{I}_{\varnothing 2,1},{}_{\varnothing 1,2}(b)$$

Since, I is the input image, Hx and Hy are low pass filters, Gx and Gy are high pass filters, $b \in \mathrm{R}^2$, Ψ^* is the convolution operator, $\downarrow 2$ to designate the down-sampling operation. The mentioned four sub-band images are refer to LL, LH, HL,and HH include the wavelet coefficients to present detailed characteristics of an image. According to sub-band images LH, HL, and HH, the image information including vertical, horizontal and diagonal features can be obtained from these three sub-band images respectively. If the image is processed with further decomposition, the first level LL sub-band image will be shown in Fig-1 is decomposed by above procedures.

DWT transforms the image into vertical, horizontal and diagonal distributions of sub bands. Motif patterns are extracted from the motif co-occurrence matrix into vertical, horizontal, diagonal distributions taken from sub bands. SVM is used to learn and texture classes by extracting features in color, texture image database.The DWT shows texture classification on color, which is based on HSV Color Space for extracting texture features to obtain accurate color statistics, because Wavelet Statistical Features,Wavelet Adaptive Neuro-fuzzy Inference System (W-ANFIS) gives an incorrect classification. The WSF-WCF method introduced wavelet co-occurrence & statistical features for texture classification. On the other hand, the W-ANFIS method also uses wavelet transform and information theory to obtain features, and then ANFIS is able to be put to learn and classify texture classes [16].

The Wavelet approach uses the wavelet image fusion (WIF) to fill the missing information to detect clouds and their shadows and subsequently fill out the missing information of the satellite images based on time series [11].

The DWT to preserve the edge information with interpolation of an Adjacent Pixel Algorithm to obtain the interpolation of high frequency sub bands and reach high resolution of an input image.The DWT describes HDL to remove the nosing of an image. It gives good visualization by losing the high frequency contents. The DWT with MWT shows inter sub band correlation technique and describing the continuous frequency to get continuous high resolution of an image to make a clear enhanced image without blurring effects. MWT produces less artifacts and gives performance improved in terms of PSNR, and reduced MSE. So, the MWT can have a right to choose a classification technique to obtain high resolution of an image [7].

The DWT with FOS texture features using linear SVM classifies on microscopic images by choosing the debauches wavelet families used as decomposition filter. The FOS will classify the image based on statistical features such as mean, standard deviation and skewness used to obtain considerable signatures of those images at distinct levels. It also investigated some parameters kappa statistics, MAE, TP, FP, F-mean, precision, recall, ROC and PRC. Daubechies family transform has given Lower value is expected for FP and for the rest of the parameters higher values are expected for better performance of the classifier. For Daubechies family transforms based texture features the superlative accuracy is obtained at the highest level of image decomposition [8].

2. **DWF :** DWF decomposition consists of analyzing the input image $f(x)$ is expressed in over complete group of related templates.

$$\mathrm{S} = \{g_1(x-l), \ldots, g_{\mathrm{I}}(\mathrm{x}-l)h_i(x-l)\}_{l \in z}{}^{2} \tag{3}$$

Since, h_i, stands for a low pass filter at iteration i and g_i, a related group of high pass filters with $i = 1,...,$ I. The related decomposition algorithm is

$$G_i(x) := \langle g_i(x-1), f(x) \rangle l_2$$
$$H_I(x) := \langle h_i(x-1), f(x) \rangle l_2 \quad (4)$$

Since, $\langle\cdot,\cdot\rangle l_2$ is the l_2 scalar product, G_i include coefficients produced by the convolution of the image with the high pass filters at its iteration and H_I the convolution of the image with the low pass filter at its last iteration I.

Wavelet Frame feature extraction algorithm is used to determine the frame coefficients $G_i(x)$ and $H_I(x)$ directly carry out the equation (4). A related group of B-Splines of third order are used as wavelet starting point. The coefficients $H_I(x)$ resulting from the convolutions with low pass filters h_i are supported for each iteration in order to caary out the continuous components of the lung tissue patterns at distinct scales. The l_2– norm made up of different coefficients $C_i(x)$ yields for each iteration as follows:

$$C_i(x) = \sqrt{(G_x H_y)_i^2(x) + (G_y H_x)_i^2(x)} \quad (5)$$

Since, $(Gx\,Hy)_i(x)$ and $(GyHx)_i(x)$ are the coefficients produced using the convolution with the high pass filter on x and with the low pass filter on y, and vice versa. The required level of both is computed for reason that we believe no directionality and have something with in in lung tissue textures.To extract higher-frequency features at smaller scales, the input images are up sampled by a factor of 2^n. The images contain some standards in H.U. The mean (μ) and the variance (σ) of the coefficients $G_i(x)$, $C_i(x)$ and $H_i(x)$ are yields over all ROIs for each iteration to create the feature vector is

$$(\mu, \sigma(G_1(x_R))\ \mu, \sigma(C_1(x_R))\ \mu, \sigma(H_1(x_R))\ \mu, \sigma(G_I(x_R))\ \mu, \sigma(C_I(x_R))\ \mu, \sigma(H_I(x_R)) \quad (6)$$

Since, x_R denotes the points belonging to the ROI.

The DWF identifies HRCT with Lung Tissue patterns for effected ILD. The extraction is done by defining wavelet co-efficients and gray level histograms and specific features. It uses K-nearest neighbors classifiers with Euclidian distance computed between normalized feature vectors. The accuracy is improved by maximum no of iterations from each feature realization of each feature normalized. It shows to be complementary which allows a classification of multiple patterns with a good accuracy. It has low resolution scales compared with the DWF decomposition, along with the required feature weighing while merging features from different origins [13].

3. **CWT :** A continuous wavelet transform (CWT) is already put to use to divide a continuous-time function into wavelets. The CWT dominate the ability to construct a time-frequency that offers very good time and frequency localization in representation of a signal. The CWT is a continuous, square-integrable function $x(t)$ at a scale $a > 0$ and translational value $b \in \mathrm{R}$ is expressed by the following integral.

$$X_W(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t)\, y^*\left(\frac{t-b}{a}\right) dt$$

Whereas $\Psi(t)$ represents a continuous function in both the time domain & frequency domain also called Mother wavelet and * represents operation of complex conjugate . The mother wavelet is to contribute a source function to produce the daughter wavelets and that are simply the translated and scaled versions of the mother wavelet. To get well the original signal $x(t)$, the inverse continuous wavelet transform can be utilize.

The Mother Wavelet follows some conditions like admissibility, regularity and number of vanishing moments and they expressed according to scaling function and a scaling factor. So,CWT proposed a novel LBP and compared to all other methods. The scaling function improves the coverage of wavelet spectrum and scaling factor compress a signal by decreasing the no of wavelets to cover the entire spectrum. The scale factor does not last complete duration of the signal and result graph is in more detailed. High scale factor does the signal stretched out and gets a less detailed graph. It is robust to histogram equalization and random rotation and has computational simplicity. The features can be obtained with fewer calculations and comparison without image filters [14].

B GLCM

GLCM uses Support Vector Machine which is core algorithm using kernel mapping technology that reproduces a strong ability which promotes the general learning model and gives more flexibility with high Accuracy. It was compared with the Minimal Hyper-Sphere which retstrain methods used to ascertain the accuracy of the classification [9]. The GLCM extracts features like homogeneity, entropy, angular second moment, dissimilarity, correlation, mean, variance contrast from the filtered image and classified by BPANN. It ensures that classification has good accuracy in all types of multispectral satellite image.

C. DCT, Haar and Daubechies, Symlet & Coieft families

DWT Techniques[6]give better PSNR,MSE,CR, encoding time, transforming time and decoding time.The Haar has given good result on accuracy, but the average time for computation is to be reduced than Co-occurrence Matrix for all original, noisy, noisy with contrast and rotated images [2].

The DCT gives good result of a transform property called energy compaction, but has some limitation over the parameter MSE.After comparative analysis, Harr and Daubechies functions gives best one because it less MSE and High ER.The Haar and Daubechies have to improve the property that to removal of redundancy between neighboring pixels [3].

The Symlet12 gives better performance with increased CR and ER on grayscale images with optimum filter.The Visual quality of the reconstructed image is better for higher compression ratios to same threshold value.Sym4 slowly degrades the image for higher compression ratios than other Symlet families. The reconstructed image visual quality is rapidly reduced for higher compression ratio even if number of decomposition increases caused by analyzing the order of the filters [4].

The Daubechies on FPGA technology gives less BER between input and output signal. So it is improved more efficient than Haar wavelet. The demerit of Haar is the averages generating for next level and each set of coefficients by having more wavelets and is not suitable for compression and removal of noise in audio signal processing [5].

The Haar is analyzing the signals with sudden transitions.But Haar is not continuous and it does not have step function and gives poor energy compaction for image.

Daubechies has scaling functions that have compact support, which is orthogonal and continuous. Symlet wavelets have closer identical with linear complex phase with set of roots. So,reconstructed image is improved with better PSNR with a good de-noised signal.Coieft constructs vanishing moments and scaling function. It allows good approximation at different resolutions with good visualization on any frequency of interest.The DWT provides qualifying frame work that is precise for the analysis and characterization of a signal at different scales [6].

The minimum distance and gain critically depend on filters selected by the filter selection algorithm and results have compared on various texture features like Markov random field co-occurrence & Gabor with ohanion and daubechies.The spectral Histograms give robust distance measures for comparing textures with wide range integration scales and test to train ratios and to obtain satisfactory results on natural texture data sets[10].

As per comparative analysis of haar and daubechies wavelet for hyper Spectral imageclassification[18] Daubechies preserves the energy of signals while Haar did compression which involves averaging and differencing and found that Daubechies filters gives better classification results than Haar but takes more computational time due to longer support of scaling and wavelet coefficients.

The Comparative Analysis on some measuring metrics

The comparative analysis with objective fidelity measuring metrics such as MSE,PSNR and CR with BER.

(*a*) Mean Square Error

It is related to a sort of average or sum of squares of the error between two images.In comparision to a standard deviation,charming the square root of MSE and surrender the root mean squared error.

1. The Monochrome images are stated by $\frac{1}{N^2}\sum_{i}^{N}\sum_{j}^{N}[X(i,j) - Y(i,y)]^2$ (8)

2. The Color images are stated by $\frac{1}{N^2}\sum_{i}^{N}\sum_{j}^{N}\{[r(i,j)\} - r^*(i,j)]^2 + [g(i,j) - g^*(i,j)]^2 + [b(i,j) - b^*(i,j)]^2\}$ (9)

   Where $r(i, j)$, $g(i,j)$ and $b(i,j)$ illustrates the color pixels at location (i,j) of the original image, $r^*(i,j)$, $g^*(i,j)$ and $b^*(i,j)$ illustrates the color pixel of the reconstructed image, while NXN mark the size of the pixels of the color images.

(*b*) Peak Signal to Noise Ratio

It is the proportion between signal variance and reconstruction error variance. The PSNR is usually declared in decibel scale and used as a common measure of the quality of restoration in image compression.

$$\mathrm{PSNR} = 10 \log_{10} \sqrt{\frac{255^2}{\mathrm{MSE}}}$$

Here 255 stands for the maximum pixel value of an image, when the pixels are represented using 8 bits per sample.The PSNR values fluctuate between infinity for identical images and zero for images that have no commonality.The PSNR is conversely proportional to MSE and CR as well. *i.e* PSNR decreases as the compression ratio increases for an image.

(*c*) Compression Ratio

Compression ratio is determined as the ratio between the original image size and compacted image size.

Compression Ratio = Original Image Size/Compressed Image Size.

Bit Error rate

The Bit Error Rate is determined the number of bit errors divided by the total number of transferred bits during a planned time interval.The BER is a unit less performance criterian. It is a standardized signal-to-noise ratio (SNR) measure and particularly useful when comparing the bit error rate performance of different digital modulation schemes without taking bandwidth into account.

3. CONCLUSION

The present paper identifies that Haar Transform analyzes the signals with sudden transitions, is not continuous and also gives poor energy compaction for an image. As per the analysis, Daubechies wavelet transformation has been identified as good for accuracy and average computation time is high when compared to Haar due to longer support of scaling and wavelet coefficients.The accuracy of classification algorithm mainly based on number of training sample of each class and consistency in classifying same matter as the same class. Hence the DWT with MWT Technique is enough for various texture images and classifications.

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