NOVEL FEATURE EXTRACTION METHODS FOR EFFECTIVE TEXTURE IMAGE AND DATA CLASSIFICATIONS

First Dr.S.Navaneetha Krishnan   Second Dr. P. Sundara Vadivel

Associate Professor- Department of Electronics and Communication Engineering,
SACS MAVMM Engineering College, Madurai, Tamilnadu, India
sundar.me2009@gmail.com

Third Dr. D.Yuvaraj

Associate Professor- Department of Computer Science and Engineering,
Karpagam College of Engineering, Coimbatore, Tamilnadu, India.

Fourth S.R.Mathusudhanan

Assistant Professor- Department of Computer Science and Engineering,
PTR College of Engineering and Technology, Madurai, Tamilnadu, India.

Abstract: *Feature Extraction is a process of capturing visual content of images for indexing & retrieval. Texture is a primary property of natural images which is of much importance in the fields of computer vision and computer graphics. Texture study is a type of image analysis producing measurements of the texture. These measurements may be of low- level, such as statistics of local facade or a result of higher level processing, such as segmentation of an image into different regions or the class of the texture present in an image. Identifying the superficial qualities of texture in an image is an important. The proposed work provides novel feature extraction schemes for identifying texture categories. Three frameworks have been proposed for 2D gray level images for classifying the textures.First two frameworks are designed for classifying the textures of gray scale images. The third frame work is proposed for classifying colour images.*

Keywords: *DTCWT method, SVM classifier, CCM, GLCM,KNN classifier*.

1. Introduction

Image processing plays a significant task in almost all areas of our life. Now a day's more information is represented and processed through digital images. Digital image processing is a universal, with applications Image sharpening and restoration Medical field Remote sensing, Machine/Robot vision, Transmission and encoding, Video processing, Pattern recognition, Microscopic Imaging, Color processing, Others. CT, MRI scans are used to obtain the images of human organs for classification. These scanning images used to find gray level or shape information mainly a difficult task due to the varying form of organs in a stack of slices in the medical images. The scanned gray level intensity overlie in soft tissues. Steady structures within tissues are used to find healthy organs and it alsohas a tissue across multiple slices. This research work proposed a texture investigationfor the classification of tissues, liver, brain and kidney images.

In image processing the textures provides important individuality about the surface and objects detection from airborne or satellite photographs, Radar images for remote sensing, biomedical images, metrological estimates and forecasts.

Textures are color variations or quality intensity that usually originates from the coarseness of object surfaces. For a precise texture, strength variation in general reveals both reliability and uncertainty, and for this reason texture investigation requires cautious propose of statistical events. Most of the proposed methods for describing and analyzing textures mainly depend on the estimation of intensity variations.Texture analysis is a kind of image analysis producing measurements of the texture. These measurements may be low-level, such as statistics of local appearance, or a result of some higher level processing, such as segmentation of an image into different regions or the class of the texture present in an image.

The main objective of this paper is to provide feature extraction schemes for identifying texture categories. The proposed work consists of three frameworks of which the first two frameworks are meant for classifying the textures of gray scale images. The third frame work is used for classifying color images. The first framework uses the combination of Dual Tree Complex Wavelet Transform with Gray Level Co-occurrence Matrix features. Dual Tree Complex Wavelet Transform (DTCWT) with Orthogonal Polynomial Operators (OPO).is used to extract the feature for texture classification. This is the second framework for the proposed work. The third framework is based on the combination of Dual Tree Complex Wavelet Transform (DTCWT) with Color Co-Occurrence Matrix (CCM). Various features were extracted with these combinations and the identified reliable features were used for texture classification of the color images. The proposed frameworks have been applied for finger print and iris recognition which gives promising results in terms of accuracy.

2. Related Work.

One of the defining qualities of texture is the spatial distribution of gray values. The use of statistical features is therefore one of the early methods proposed in the machine vision literature. Haralick's (1973) gray-level co-occurrence matrix approach is based on the studies of statistics of pixel intensity distributions as a function of distance and directionality. However, the decision of suitable distance and direction is critical and the approach is sensitive to illumination changes.

The orthogonal polynomials was proposed for texture description and tested on micro texture in an image in terms of the significance of the orthogonal effects. The spatial variation resulting from textural characteristics had been separated to identify the textured region. A framework using orthogonal polynomials for edge detection and texture analysis had been presented by Ganesan (1997).

An extensive survey on texture analysis has been recorded by Tuceryan and Jain (1999), in which the texture analysis methods are divided into four categories: statistical, geometrical, model based and signal processing.

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Manjunath et al (2001) presented an overview of color and texture descriptors that have been approved for the Final Committee Draft of the MPEG-7 standard. The color descriptors in the standard included a histogram descriptor that was coded using the Haar transform, a color structure histogram, a dominant color descriptor and a color layout descriptor.

Yao and Chen (2003) proposed a new method for color texture retrieval using color and edge features. This method used unified color and edge features rather than simply analyzing only color characteristics. First, the distributions of color and local edge patterns were used to derive a similarity measure. Then, a retrieval method had been used to retrieve texture images from a database of color textures. The effectiveness and practical application of this method had been proved by various experiments.

Guoliang and Xiang-Gen (2003) developed a new Hidden Markov Model, called Hidden Markov Tree (HMT), for statistical texture characterization in the wavelet domain. In addition to the joint statistics captured by HMT, the method also exploited the cross correlation across Discrete Wavelet Transform (DWT) sub-bands. Texture was characterized by using the graphical grouping technique.

The Fractal Dimension Co-occurrence Matrix (FDCM) method, incorporated with fractal dimension and the GLCM, was presented for texture classification. 12 Brodatz's natural texture images were classified by the GLCM method, Sub-Band Domain Co-occurrence Matrix (SBCM) method and the FDCM method. The FDCM method showed the highest classification rate among the methods compared (Kim et al 2006).

Tou et al (2009) tried to deploy the texture classification algorithms onto the Embedded Computer Vision (ECV) platform. Two algorithms were compared; GLCM and Gabor filter. Raw GLCM achieved only 90.86% accuracy as compared to the combination feature (GLCM and Gabor filters) at 91.06% accuracy.

The method was motivated by the observation that there exist distinctive correlations between the sample images of the same texture class. Experimentally, it was observed that this kind of correlation varies from texture to texture.The model parameter of the exponential function was estimated using maximum likelihood estimation technique.

Texture analysis and its classification approach with the linear regression model based on the wavelet transform had been addressed (Wang et al 2008). The distinctive correlations between the sample images of the same texture class are observed by the linear regression model. The experimental result observes that the distinctive correlation varies from texture to texture.

A new image coding scheme based on orthogonal polynomials was proposed by

Krishnamoorthi (2009). The above works were used for edge detection in textured images.

3. Proposed Method for Texture classification

The Discrete Wavelet is used to reduce noise at each level of image compression and also it is the powerful tool for signal analysis and reconstruction. The application of the DWT is the signal is de noised and smoothened without changing of the properties of the original signal. Even though the DWT has four drawbacks,

1) The singularity positive and negative values are oscillated by wavelet coefficients. This oscillation increases the complication of detection and modeling of image compression.
2) The decimated DWT wavelet coefficients are changed by shift variance, which means that the input signal is shifted with time or space.
3) The iterative time discrete operation is the process of calculating wavelet coefficients with low pass and high pass filters. Due to this aliasing will appear on the filter bank side. The aliasing effect canceled by inverse DWT process when without process of wavelet coefficient calculation.
4) The horizontal and vertical edges are successfully detected by DWT,butunnecessary checkerboard artifacts appear when the edges are under an acute angle.

3.1 The Dual-Tree Complex Wavelet Transform (DTCWT)

The DTCWT overcome drawbacks with DWT by its properties.Approximate shift invariance.Good selectivity and directionality in 2-dimensions (2D) with Gabor-like filters (also for higher dimensionality).
Perfect Reconstruction (PR) using short linear phase filters.Limited redundancy, independent of the number of scales = 2:1 for1-D, 2m: 1 for m-D.
Efficient order-N computation- only 2m times the simple DWT for m-D.

3.2 DTCWT

The Energy Extraction formula for DTCWT is

$$E_k = \frac{1}{RC}\sum_{i=1}^{R}\sum_{j=1}^{C}|x_k(i,j)| \tag{1}$$

Where$x_k(i,j)$the pixel value of the kth subimage and R, C is is width and height of the subimage respectively.

3.3 Gray-Level Co-occurrence Matrix (GLCM)

The statistical distribution of experiential combinations of intensities at specified positions is used to compute the statistical texture features. According to count of the intensity pixels in each combination, the statistical texture features are classified in to first order, second order and so on. The second order statistical texture features are computed from the GLCM method. The image P (I, j) has the equal number of rows and columns to the number of gray levels. This matrix is called as graycomatrix function. By calculating how often a pixel with the intensity (gray-level) value i occur in a specific spatial relationship to a pixel with the value creates a gray-level co-occurrence matrix (GLCM). According to co-occurrence matrix Haralick texture feature, in this paper some important features, energy (Angular Second Moment), inertia moment, Correlation, Entropy, and the Inverse Difference Moment are selected for texture classification.

1) Energy

The GLCM of Angular Second Moment is called as Uniformity or Energy.The GLCM of Angular Second Moment is called as Uniformity or Energy. Angular Second Moment measures the image homogeneity by calculating sum of squares of entities in GLCM. When icon has very good homogeneity or when pixels are very analogous the uniformity is high.

$$\mathrm{ASM} = \sum_{\mathrm{i,j}} \mathrm{p(i,j)}^2 \tag{2}$$

2) Inverse Different Moment

The local homogeneity is measured from Inverse Different Moment. When local gray level is uniform and inverse GLCM is high, the Inverse Different Momentis high.

$$IDM = \frac{\sum_{i,j} P(i,j)}{1-(i-j)^2} \quad (3)$$

3) Entropy

The amount of information is calculated by entropy that is important parameter for image compression techniques. The loss of information in a image when the image is transmitted from one channel to another channel is measured from entropy calculation.

$$Entropy = \sum_{i,j} -P(i,j) * logP(i,j \quad (4)$$

4) Correlation

The linear reliance of grey levels of adjacent pixels is the correlation of GLCM. Correlation is used to tracking, displacement, strain, to measure deformation, and optical flow.

$$Correlation = \frac{\sum_{i,j}(i,j)p(i,j) - \mu_x\mu_y}{\sigma_x\sigma_y} \quad (5)$$

K-Nearest Neighbor (KNN) Classifier

The KNN has been both a workhorse and benchmark for classifier. The KNN method attempts to classify any undecided sample to a class according to the majority class membership of its nearest neighbors, whose membership has already been decided. The KNN classification algorithm tries to find the K nearest neighbors of X0 and uses a majority vote to determine the class label of X0. Without prior knowledge, the KNN usually applies Euclidean distances as the distance metric. In order to calculate distances in dimensional feature space, all features were normalized by subtracting their mean and dividing by their standard deviation.

3.3 COLOR IMAGE PROCESSING

The mathematical version of a set of colors is known as color space. In this research work, the three color space models are discussed.

3.3.1 RGB Color Space

Digital cameras create images using combinations of just three colors (Red, Green and Blue (RGB)). These are the primary colors of evident brightness and this how computers demonstrate images on their screens.

RGB colors often become visible brighter and bright particularly since the light is being estimated in a straight line into the eyes of the observer.

In RGB Color dice each peak represents the grouping of the highest and least production of every main. When the amounts of 3 Red, Green and Blue colors are in least levels the black color is created; when the amounts of primary colors are in highest levels, the white color is produced. The fundamental rule of combination in RGB color cube is following

Red+Green+Blue=White

Red+Blue=Magenta

Green+Blue=Cyan

Red+Green=Yellow

3.3.2 YUV Color Space

The NTSC-color system $R_N G_N B_N$ obtained from

$$\begin{pmatrix} R_N \\ G_N \\ B_N \end{pmatrix} = \begin{pmatrix} 0.842 & 0.156 & 0.091 \\ -0.129 & 1.320 & -0.203 \\ 0.008 & -0.069 & 0.897 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \quad (6)$$

The YUV color space is

$$\begin{pmatrix} Y \\ U \\ V \end{pmatrix} = \begin{pmatrix} 0.842 & 0.156 & 0.091 \\ -0.129 & 1.320 & -0.203 \\ 0.008 & -0.069 & 0.897 \end{pmatrix} \begin{pmatrix} R_N \\ G_N \\ B_N \end{pmatrix} \quad (7)$$

3.3.3 HSI Color Space

HSI color space hue, saturation, and intensity are used as coordinate axes. The hue H of the color q characterizes the dominant color contained in q.

$$H = \begin{cases} \delta \text{if} B \leq G \\ 360^\circ - \delta \text{if} B > G \end{cases} \quad (8)$$

where

$$\delta = \arccos\left(\frac{(R-G)+(R-B)}{2\sqrt{(R-G)^2 + (R-B)*(G-B)}}\right) \quad (9)$$

The saturation S of the color q is a measurement of color purity.

$$S = 1 - 3\frac{\min(R, G, B)}{R + G + B} \quad (10)$$

and

$$I = \frac{R + G + B}{3} \quad (11)$$

For the extreme case, I = 0 corresponds to the color black.

4.1 TECHNIQUES FOR TEXTURE FEATURE EXTRACTION

4.1.1 Feature Extraction Stage for gray scale image

In the proposed approach, the energy of all DTCWT subbands, the input texture image is first decomposed by using the DTCWT at five scales. The energy of all the subimage coefficients is used as feature vectors individually. The Uniformity and correlation determined with the GLCM. DTCWT with GLCM features are generate a database.

4.1.2 Classification Stage for gray scale image

In the classification phase, five scale decomposition of DTCWT to an unknown texture image is performed, and obtained the feature vector of this image. Then this vector is processed with the features in the database generated in the feature extraction stage. The classification algorithm is as follows

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4.1.3. Classification Algorithm for Gray Scale Image

The unknown texture image and the feature database are the input of the algorithm. The index of texture to which this unknown texture image is assigned is the input of the algorithm

1) Using DTCWT, the unknown texture image with 5 scale is decomposed.
2) Calculate energy of all coefficients of subimage
3) Using GLCM Calculate the spatial features
4) Perform the following iteration by usingorder all the features into list and (set k=1 at first)
    a. Pick out the k^{th} feature of the unknown image and the same feature set in the database.
    b. Perform KNN classifier to the unknown image dataset and find the index of the texture and store it into the index list
    c. Perform the next iteration by increasing the value of k by 1.
5) Find the maximum frequency of amount of the index and allot the index to the unknown texture image.

4.2 TEXTURE CLASSIFICATION FOR COLOR IMAGES

4.2.1. Feature Extraction for color images

The selected color texture images are first converted into required color space RGB, YUV or HSV color space and then each color plane is decomposed at five scales by DTCWT. Then the energy of all DTCWT subbands and co-occurrence features energy and correlation is extracted for each color plane, all features are fused and stored in the database.

4.2.2. Classification Stage for color image

For classification, an unknown color texture image is converted into any color model and each color plane is decomposed at five stages by using DTCWT. The spatial information calculated by GLCM.

4.2.3 Classification Algorithm for Color Image

[Input] unknown color texture image and the feature database

[Output] the index of color texture to which this unknown texture image is assigned

1. Perform the color conversion for the unknown color texture image.
2. Decompose all the color plane of the given unknown color texture image with 5 scale decomposition of DTCWT.
3. Calculate the energy of all sub image coefficients using DTCWT
4. Calculate the spatial features using GLCM for all individual color planes.
5. Perform feature fusion and order all the features into list and perform the following iteration (set k=1 at first)
    a. Pick out the kth feature of the unknown image and the same feature set in the database.
    b. Apply KNN classifier and find the index of the texture and store it into the index list
    c. Perform the next iteration by increasing the value of k by 1.

d. Find the maximum frequency of occurrence of the index and assign the index to the unknown texture image.

4.3 TEXTURE CLASSIFICATION FOR MEDICAL IMAGES

The procedure of generate image representations of the internal of a body for medical analysis and medical intervention of some tissues is called as Medical imaging. Medical imaging seeks to expose interior structures concealed by the skin and bones. It is used to analyze and care for ailment. Medical imaging also establishes a list of normal structure and physiology to make it achievable to recognize abnormalities. Although imaging of impassive organs and tissues can be performed for medical reasons, such events are usually considered part of pathology as a replacement for of health check imaging.

It is part of biological imaging and incorporates radiology which uses the imaging technologies of magnetic resonance imaging, X-ray radiography, endoscopy, medical ultrasound, tactile imaging, thermography, medical photography and nuclear medicine useful imaging techniques as Single-photon emission computed tomography and positron emission tomography.

In this research the most discriminative texture features of regions of interest are automatically extracted which is automatically identifying the various tissues. The proposed algorithm consists of two stages. First one is Feature Extraction and other one is classification.

5. RESULTS AND DISCUSSIONS

5.1 Gray Scale Image

The performance of the classification Dual Tree Complex Wavelet Transform (DTCWT) with GLCM is applied and verified. From the Brodatz album 40 images with size of 640x 640 obtained is used in the experiments. The original image divided with 256 sample images, size of 128x128 an overlap of 32 pixels between vertically and horizontally adjacent images are extracted from each original image These 10240 texture images are separated into two set and 1600 images are randomly selected as training set and the remaining 8640 images as testing set.

Further the methodology is applied and tested by adding white gaussian noise in the frequencies of of 1db, 5db, 10db and 15db to images before classification. The classification rate is found to be affected by noise except D6, D16, D21, D34, D101, D105 texture images It is noticed that the noise extremely influences the pixel gray value of the texture image.

5.2 Color Image

The VisTex database is a group of texture images. The database was produced with the goal of providing a huge set of high value textures for computer vision applications. The set was ready as a substitute to the Brodatz texture library, which is not liberally accessible for investigate use. The images in VisTex do not match to inflexible forward flat perspectives and studio illumination environment. The goal of VisTex is to make available texture images that are delegate of real world environment. While VisTex can provide as a surrogate for conventional texture collections.

The database has 2 main components:

1) Reference Textures: 100+ homogeneous textures in anterior and tilted perspectives.
2) Texture Scenes: Images with multiple textures. ("real-world") scenes.

The color texture 20 images samples with of size 512x 512, obtained from the VisTex album is applied in the experiments. Every original image divided into 144 sub images size of 128x128 with an overlap of 32 pixels between vertically and horizontally adjacent images. Among the 144 images, 61 images are randomly selected for each color texture images. 30 images are used in the training phase and the remaining 31 images are used for testing phase.

Table 1.
Comparison DTCWT with other techniques

ID	DTCWT with GLCM	Linear Regression Model	F16b	Wavelet and GLCM	TSWT	PSWT	Gabor	Gabor and GLCM
D6	100	100	95.122	100	88.225	68.596	67.639	70.941
D9	97.530	97.531	80.488	95.122	50.941	39.136	24.151	24.583
D11	98.765	97.531	68.298	85.366	55.756	39.074	28.395	30.54
D14	100	93.827	100	100	90.154	73.318	80.201	74.429
D16	100	98.765	95.122	100	95.278	74.799	51.914	46.173
D17	98.765	95.062	80.488	97.651	60.509	44.398	43.719	38.333
D20	100	98.765	95.122	100	98.241	88.812	68.673	95.139
D21	100	100	100	100	100	96.343	99.753	92.963
D22	97.53	93.827	92.683	97.561	84.969	68.889	68.312	58.349
D24	96.296	98.726	70.732	95.122	58.249	42.207	29.907	33.981
D26	98.765	98.765	97.561	100	92.114	68.858	42.762	68.102
D34	100	98.765	97.561	100	81.728	70.833	68.688	85.201
D36	88.888	100	95.122	100	65.679	51.25	26.096	23.38
D41	96.296	90.123	82.927	92.683	45.324	33.827	19.738	17.593
D46	100	98.765	100	100	96.96	90.278	63.457	72.052
D47	100	98.765	100	100	97.886	74.367	36.852	65.602
D51	98.765	96.296	100	100	92.207	69.228	22.022	33.47
D53	100	96.296	100	100	92.577	70.247	41.682	49.259
D55	100	97.531	78.049	100	83.704	57.238	24.63	32.269
D56	100	86.42	97.561	100	91.574	73.133	45.139	43.41
D57	100	98.765	51.22	87.802	75.725	60.694	65.216	65.17
D64	100	98.765	100	100	94.383	61.713	38.287	43.148
D66	98.765	93.827	100	97.561	87.315	73.58	43.796	39.259
D68	100	93.827	100	92.683	87.361	62.685	33.148	26.62
D76	100	96.296	92.683	97.561	67.022	46.713	21.867	41.466
D77	98.765	98.765	97.561	100	77.824	47.824	47.515	35.401
D78	97.531	98.765	85.366	92.683	67.963	46.142	23.935	32.176
D79	95.062	96.296	80.488	90.244	61.188	43.688	21.713	28.056
D80	95.062	100	85.366	87.805	62.114	37.253	20.617	20.123
D82	98.765	98.765	65.854	100	73.904	50	34.306	54.469
D83	98.765	100	70.732	100	71.019	39.182	29.414	44.506
D85	90.124	97.531	87.805	100	62.901	38.92	22.052	26.929
D101	100	98.765	100	100	100	38.904	88.364	96.579
D102	100	97.531	100	100	90.478	87.809	36.296	77.716
D103	98.765	98.765	100	100	99.907	90.571	69.398	62.299
D104	97.531	98.765	100	100	99.846	92.114	61.142	68.318
D105	88.889	98.296	82.927	95.122	76.049	54.815	36.451	37.284
Average	**97.654**	**97.151**	**90.061**	**96.707**	**79.166**	**61.588**	**43.429**	**48.995**

Experiments results with various color planes

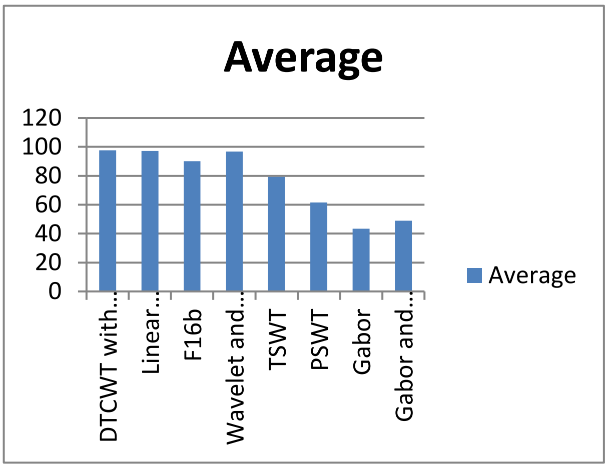

Fig 1. Comparison DTCWT with other techniques

Table 2:
VisTex Color Texture Images used in the experiments results with various color planes

ID	RGB	YUV	HIS
Bark.0006	97.9167	98.6111	77.0833
Bark.0012	100	100	83.3333
Brick.0000	100	98.6111	63.8889
Brick.0004	95.1389	88.8889	72.9167
Food.0009	100	100	97.9167
Fabric.0013	100	100	54.8611
Fabric.0017	98.6111	97.2222	97.2222
Flowers.0006	100	100	84.7222
Fabric.0002	100	100	95.8333
Food.0000	97.9167	98.6111	55.5556
Food.0001	100	100	89.5833
Grass.0001	100	100	77.7778
Leaves.0012	100	100	88.8889
Metal.0002	100	100	80.5556
Metal.0004	100	100	66.6667
Misc.0001	100	100	100
Misc.0002	100	100	59.7222
Sand.0000	100	100	90.9722
Sand.0002	100	100	93.75
Tile.0008	100	100	57.6389
Average	99.47917	99.09722	79.44445

The table reveals that the results are found to be more significant when applied with RGB color space than with other color spaces

5.3 Medical Image

Further, the DTCWT with GLCM was applied and tested with 140 medical images of Kidney, Liver and Brain was collected from medical professionals and other resources. The classification performance with respect to sensitivity, specificity, precision and Classification efficiency was calculated for the images.

Table 3.
Classification performance in % of the DTCWT with GLCM

Performance	Kidney	Liver	Brain
Classification efficiency	88	90	97
Sensitivity	77.78	83.33	95
Specificity	93.75	96.15	98
Positive Predictive value	87.5	95.24	99
Positive Likelihood	1244.44	2166.67	36
Prevalence	36	48	34

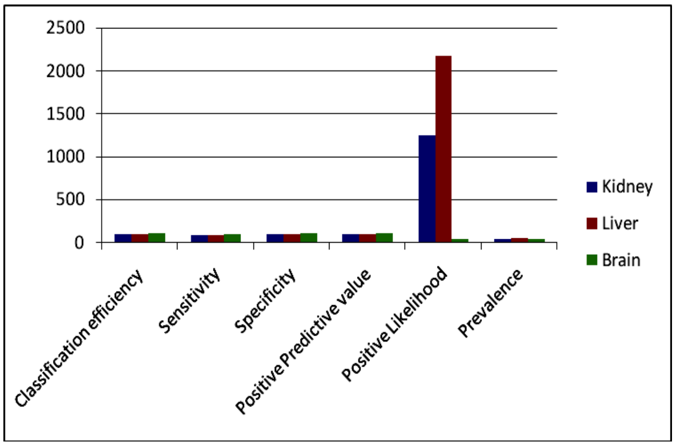

Fig 2.Classification performance in % of the DTCWT with GLCM

6. CONCLUSION

In this work a new approaches introduce for different database of the texture images. The Texture classification based on Dual Tree complex Wavelet transform, GLCM and KNN classifier have been attempted and performance comparisons were done for 2D gray scale, color images and medical images. Experiments were performed on three different databases images with different. Euclidean distance measure has been used to compare the output of segmented images.

The performance for the gray scale image of the proposed method is compared with Linear Regression Modal, TSWT, GLCM, GLCM with Wavelet and other multi resolution methods for gray scale images; it gives classification rate of 97.654% when compared with other methods. It has been observed that, adding white gaussian noise in the frequencies the performance of the proposed method is affected with noise.

In the second work based of the proposed method applied for color images, obtained from the standard color texture base of Vistex. The method performance is satisfactory level for the three different color planes. The classification rate in RGB color plane is 99.47%, YUV color plane is 99.09% and HIS 79.44%. In the three color planes the proposed method gives a good performance for RGB color plane comparatively with the other planes YUV and HIS. From the experimental result, the proposed method is suitable for the RGB color plane than YUV and HIS color planes.

In the third approach, three different tissue images kidney, liver and brain images taken for experiments. The Kidney and liver images are CT –scan images and the brain images are MRI images. The proposed method applied for the medical images and the classification rate is 97% for the Brain images, 90% for Liver and 88 % for kidney. From the classification rate the proposed method is works well for MRI images comparatively with the CT-scan images.

Methods proposed in this paper are unique and perform well in the texture classification for the different database of images. Out of all the techniques, the Dual Tree complex wavelet transform with Gray level co occurrence matrix performs well comparatively with the other methods high efficiency.

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