

ROTATION AND SCALE INVARIANT FEATURE EXTRACTION FOR MRI BRAIN IMAGES.

¹NAVEEN KISHORE GATTIM, ²V RAJESH.

¹ Research Scholar, Dept. Of Electronics And Communications, K L University (Klef), Vaddeswaram, Guntur, Ap.

² Professor, Dept. Of Electronics And Communications, K L University (Klef), Vaddeswaram, Guntur, Ap
E-Mail: ¹ naveengattim@kluniversity.in ² rajesh71@kluniversity.in

ABSTRACT

Texture classification of images with varied orientations and scale changes is a challenging and considered to be important in image analysis. Feature extraction can be used to increase the efficiency of texture classification using log polar wavelet energy signatures. For the image to be rotation and scale invariant two major steps are applied which involves applying log polar transform and adaptive row shift invariant wavelet transform. Log polar transform eliminates the rotation and scale effects and causes a row shifted log polar image, which undergoes adaptive row shift invariant wavelet transform to remove the row shift effects. Finally they obtained output wavelet coefficients are rotation and scale invariant. The complexity of $O(n \log n)$ is efficient with adaptive row shift invariant wavelet packet transform. From the log polar wavelet energy signatures a feature vector is generated which are extracted from each sub band of wavelet coefficients. In the experiments the features are extracted for images considering different orientation and scale changes and simultaneously experiment is simulated for few wavelet families. The experiment results show the efficiency of few wavelets in extracting the features of a given image. The overall accuracy rate for this approach is 87.05 percent representing that the extracted energy signatures are effective rotation and scale invariant features.

Keywords - *Log polar transform, Row shift invariant wavelet transform, Rotation and scale invariance, Feature extraction.*

1. INTRODUCTION

Texture analysis has its importance in pattern recognition of different types of surface texture. It has an extensive range of applications in many practical areas like medical diagnosis, robotic sensing, Industrial monitoring, etc. Recent events of image analysis in time and frequency domains such as Gabor filters, the transformed wavelets and wavelet frames provide good resolution for feature extraction and classification tools. With this approach high accuracy rates can be achieved. The existing methods assumed the images to be with the same texture orientation and scale which is not realistic for most of the practical applications. Taking into consideration the example of the images obtained from scanning photographs, which are usually subject to certain random oblique angles and the photographs of the same objects at different distances cause different scales of objects. The performance of these methods is found inefficient

when the assumption is not valid. Works done by Kashyap and Khotanzad [6] proposed a model for rotation and scale invariant texture classification. This involved the development of an auto regressive (AR) model. With a database of 12 Brodatz textures, good results were achieved. Leung and Peterson [8] proposal was a mental transformation approach which estimated the rotation and scale of the texture by first passing the texture spectra through log polar Gabor filters. But this involves a high computational complexity when the number of texture classes to be classified or the texture size is large. Gabor filters gives the spatial and frequency analysis of an image given by Hayley and Manjunath [5] Teuner et al. [12]. Multiresolution of an image is analyzed by using wavelet transforms Chang and Kuo [1], Laine and Fan [7] wavelet frames detailed by Unser [13] which provides best multiresolution for texture analysis and classification. It has been assumed that texture images have the same orientation and scale which is not realistic for most practical applications

i.e. they undergo certain random skew angles and the assumption is not valid. Rotation and scale parameters are estimated with the extended 2D Gaussian markov random field (GMRF) model which is explained in Cohen et al. [2] A tuning algorithm which uses a single convolution mask to classify and segment rotated scaled textures was described in You and Cohen [14]. Rotation-invariant features are extracted by multi channel gabor filters. Fountain and Tan [3], Fountain et al. [4], Potter and Canagarajah [9]. Haley and Manjunath [5] explained about rotation-invariant texture classification with space-frequency gabor wavelet model showing a favorable result. However, high computational complexity for feature extraction is required. The discrete wavelet decomposition are combined with opposite energy signatures which are used as features for rotation invariant texture classification as explained by potter and canagarajah [9]. Rajesh and Rajesh Kumar [10] [11] explained the transformation of signals into feature sets and classify the robustness of data using wavelets. Thus the existing algorithms involve high computational complexity and are accurate over a small set of selected image classes. The efficiency of a texture classification/segmentation algorithm can be increased by using a module for feature extraction followed by classification. David G [15] proposed a method for matching objects which is robust to rotation and scale invariance which identifies the objects among clutters.

2. METHODOLOGY

The method followed in this paper is to develop such a module for rotation and scale invariant feature extraction. The rotation and scale invariant feature extraction for a given image involves applying a log-polar transform to eliminate the rotation and scale effects, but at same time produce a row shifted log-polar image. Adaptive row shift invariant packet transform is incorporated to overcome the row shift effects. The adaptive row shift invariant wavelet packet transform is quite efficient with the complexity of $O(n \log n)$. A feature vector is generated from the most dominant log-polar wavelet energy signatures which are extracted from each sub band of wavelet coefficients as given in the block diagram fig. 1. In the experiments, the features are extracted for images

considering different orientation and scale changes and at the same time the experiment is simulated for different wavelet families. The experimental results show the efficiency of few wavelets in extracting the features of a given image. The overall accuracy rate for joint rotation and scale invariance obtained is 87.05 percent demonstrating that the extracted energy signatures are effective rotation and scale invariant features. Concerning its robustness to noise, this extraction scheme performs better than the other methods.

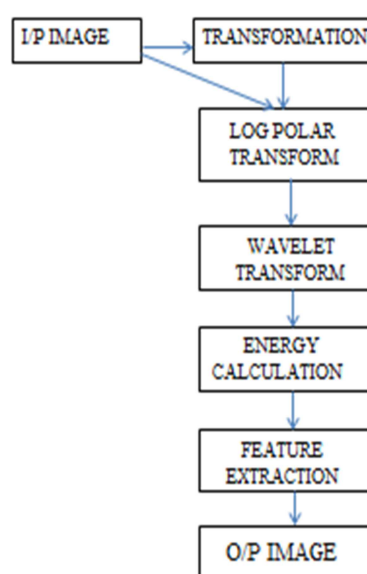


Fig. 1 Block diagram

3. TRANSFORMATIONS

The main idea of the project is to develop the model for rotation and scale invariant feature extraction of texture images. In this regard transformation is applied to the image. The transformation indicates that the process of rotation and scaling which is done manually in the sense giving an angle of rotation which in turns experimentally can go for the angle by which the image get transformed automatically. The process of scaling will also helps the image to get its threshold levels get improved which gives some more clear visualization or perception of the image for the later stages involved in the method developed. In the real time situation the transformation indicates the changes that occur in the image automatically during capturing process

of image due to changes like angle and distance of capturing an image etc

4. LOG POLAR TRANSFORM

Log polar transform is applied to eradicate the rotation and scale effects of the input image. This log polar image is scale invariant and rotation invariant but is row shifted. The log polar transform algorithm is divided into two key steps. In the foremost step, the radius of the largest circle inside the given square image is used as scan line to sample S times from 0 to 360 degrees to create its equivalent S x S [N/2] polar form. Normally polar form p(a,r) of the given N x N image f(x,y) can be explained as follows:

$$p(a,r) = f\left(\left[\frac{N}{2}\right] + \left[r \cos\left(\frac{2\pi a}{S}\right)\right], \left[\frac{N}{2}\right] - \left[r \sin\left(\frac{2\pi a}{S}\right)\right]\right)$$

For a=0,....., S-1, and r=0,.....,[N/2]-1

The second step performs the logarithm functions where the radii values in the polar form and their outputs are then quantized into R bins. Hence the produced image is S x R log polar image for the given N x N image. The step wise procedure is as given in below fig. 2

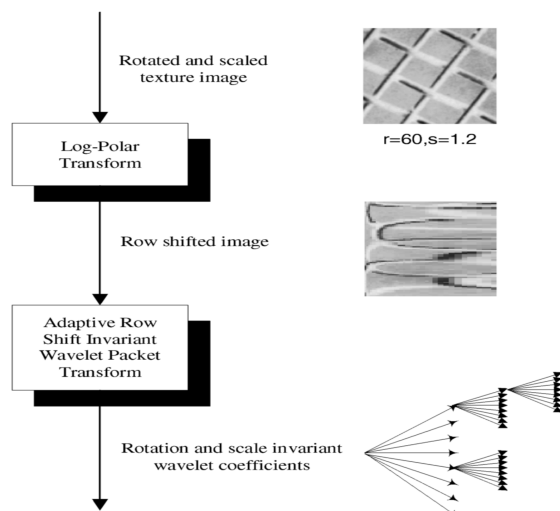


Fig. 2 Process of rotation and scale invariant wavelet Coefficients

5. ADAPTIVE ROW SHIFT INVARIANT WAVELET TRANSFORM

In 2D-DWT analysis, an image is split into one approximation image and three detail images and the approximation image is further split into second level approximation image and detail images and this cycle is repeated continuously. Thus for an n level decomposition, there are n+1 levels to encode the image. The advantage of DWT over FFT is that, it can be analyzed in both time and frequency domains. Hence, this is a Multi resolution technique by which different frequencies are analyzed with different resolutions. And also by using this technique smooth and filtered outputs can be obtained.

By applying log polar transform, we get row shifted image. To eliminate these row shifts DWT is considered as its row shift invariant technique. This process computes wavelet coefficients which are used in the calculation of energy signatures

5.1 Log Polar Wavelet Energy Signatures For Rotation And Scale Invariant Images.

Discrete Wavelet Transforms gives the frequency and time locality are represented by wavelets with finite duration and has been found very useful for image investigation. The 1D Discrete wavelet transform uses a high pass and low pass filters that are derived from wavelet functions. The input signal is decomposed into two sub band components: approximation and detailed respectively

The approximation sub band is decomposed recursively to generate the succeeding level of the order. The distinct feature of the original signal can be obtained by using an orthonormal wavelet basis. Although DWT has a major drawback of invariance to the shifting of the input signal due to the dyadic structure of the wavelet expansion, where in 2D DWT have different wavelet coefficients with different rotational and scale changes

The implementation process of 2D DWT requires the application of a filter bank along columns and rows of an image. As the horizontal and vertical directions are separable they are strongly oriented in

these directions which make it very tedious to extract the features of rotation invariant from the wavelet coefficients. In this section an algorithm is implemented for rotation and scale invariant feature extraction which can be obtained by applying a log polar transform and adaptive row shift invariant wavelet packet transform. After applying these two process an energy signature is computed for each sub band of the output rotation and scale invariant wavelet coefficients where the necessary feature extraction process is obtained.

5.2 Rotation And Scale Invariant Wavelet Energy Signature Extraction

In the former step of the process the image is directly given to the log polar transform and then non-linear transformation is done and their energies are calculated for their feature extraction.

Where as in the second step the image is undergone some transformations like rotation and scaling which can give some threshold increase which helps in visualizing the image with more fineness and then the log polar is applied and the remaining process is followed. But as per the process done in second step that is rotation and scaling the image will undergo some changes and the main idea of our project is to develop a model which will give a rotation and scale And then the image is gone for energy calculations and by selecting the more dominant values of the image pixels we will go for comparison with the image pixels of the first step image which is not transformed and will finally show the output image as a rotation and scale invariant image.

In this process we go for log polar transform because it reduces time or complexity when compared to Fourier coefficients as the total butterfly process is involve for FFT. and it is also useful for normalization which is nothing than merging same sort of image pixels that is grouping the pixels with same properties. And also used for removing pre-defined noises like additive white Gaussian noise and whatever the type of noise present in it. And also the process involved here is linear transformation where in the later step that is in wavelet transform the image undergoes some non-linear transformation which in turn helps to take the

pixels randomly for comparing with the first step process involved image.

In the wavelet transformation technique the main advantages are filtered and smooth output and the TOE (Time of Execution) is very less when compared with other transforms and it gives 85% accuracy theoretically and the remaining is due to the mismatch of images. And the total process involved is for feature extraction and these features are extracted by using the wavelet frequencies by considering more dominant values and also by LL, HL, LH, HH frequencies like which in turn gives A, H, V, D respectively and then we go for comparison that is whether the pixels are matching to the first step image or not. Due to the pixels match we can say that the images are rotation and scale invariant.

6. RESULTS

The effectiveness of the proposed log polar wavelet signature for rotation and scale invariant feature extraction is tested on the set of MRI brain images courtesy from from satya scan centre, Kakinada. The MRI images of size pixels with 256 gray levels are taken with different orientations and different scales (120 degree orientation and 1.2 scaling factor). The orientation and scaling factor for different values can be used to compare the energy signatures. Different wavelets are applied to the MRI brain images. Haar and Daubechies wavelets gives the comparison of the two wavelets with a normal image and a rotated and scaled image where after applying the log polar transform followed by adaptive row shift invariant wavelet packet transform gives the same energy signatures of both the brain images. Therefore even the images are rotated and scaled by applying the log polar transform and adaptive row shift invariant wavelet packet transform we obtain the same features of both the compared images. It is executed in the MATLAB R2013a software shown below.

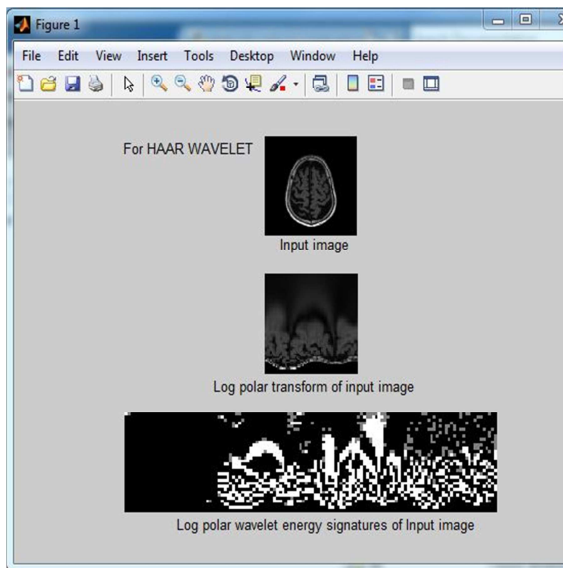


Fig. 3. Using Haar Wavelet To Normal Image

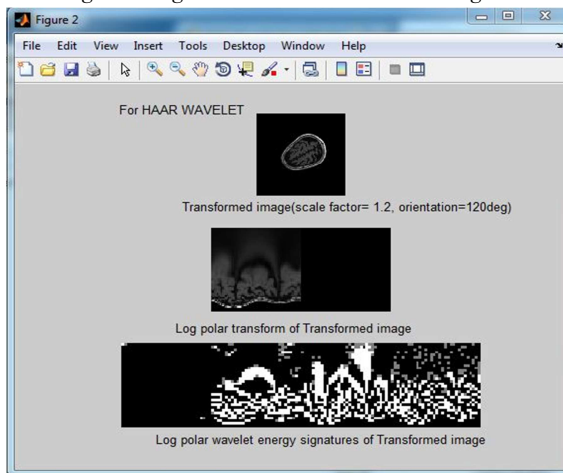


Fig. 4. Using HAAR Wavelet With A Scaling Factor 1.2 & 120 Degrees Orientation

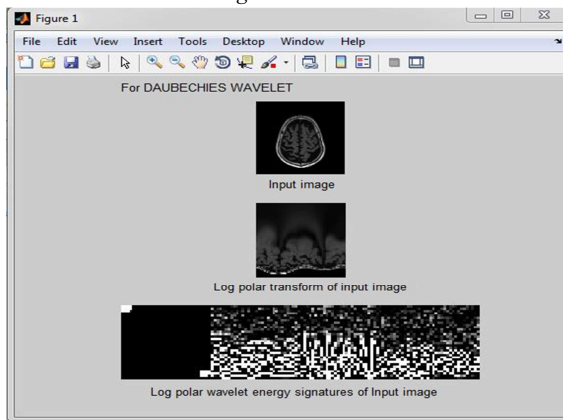


Fig. 5. Using DAUBECHIES Wavelet To Normal Image.

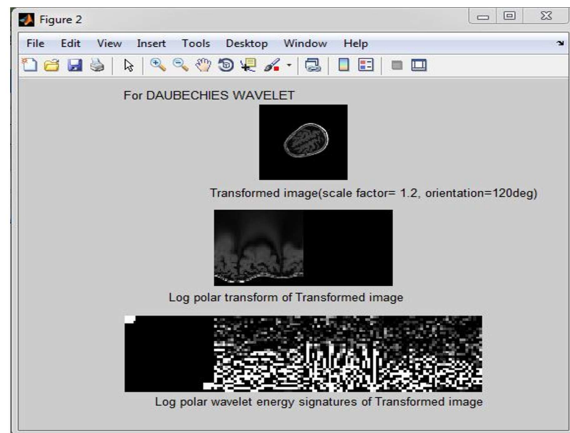


Fig. 6. Using DAUBECHIES Wavelet With A Scaling Factor 1.2 & 120 Degrees Orientation

In the above experimental results shown in Fig (3) and Fig (4) are for HAAR wavelet which gives the same energy signatures of the brain image given irrespective of the rotation and scaling. In the same way the experimental results shown in Fig (5) and Fig(6) are for DAUBECHIES wavelet where in this wavelet also give the same energy signatures of the brain image given irrespective of the rotation and scaling. The overall accuracy rate is 87.05 percent.

7. CONCLUSION

Rotation and Scale invariance of images are necessary in addressing the problem of image analysis. This paper propose a effective technique for log polar transform and adaptive row shift invariant wavelet packet transform which gives feature extraction process for rotation and scale invariant wavelet coefficients with the complexity of $O(n \log n)$ where n is the number of pixels in the given image. These techniques are useful due to their distinctiveness in showing the rotation and scale invariant images. The change of illumination of the same image can be identified using feature extraction which leads to robustness. The technique used is useful for medical. The approach described uses adaptive row shift invariant wavelet packet transform for row shift invariance. The experimental results are obtained using Haar and Daubechies wavelet with different rotations and scales where the features extracted show that the proposed technique are effective for rotation and scale invariant features and the overall accuracy rate is 87.05%. Further

research in rotation and scale invariant feature extraction can be done for illumination changes.

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