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Texture Feature Extraction using 2-D Gabor Filters

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***Abstract*— Texture feature extraction is a procedure of computing and describing the features and characteristics of image which numerically describes that texture image properties. This paper investigated texture feature extraction using 2-D Gabor Filter to extract the texture features of Inverse Fast Fourier Transform (IFFT), texture energy and transformed IFFT. The Gabor filter bank experimented on seventy two collected samples of skull-stripped T1-weighted, T2-weighted and FLAIR MRI brain images utilizing four frequencies and four orientations. Results showed that texture feature extractions of two highest frequencies with all four orientations produced the highest acceptance rate.**

***Keywords*— Texture feature extraction, Gabor Filters, IFFT, Texture Energy, Transformation of IFFT, MRI images**

I. Introduction

The medical texture image segmentation algorithms had been extensively studied during the past few decades. There are many applications applicable in pattern recognition which describes the region based on texture, shape and colour. The colour features are well defined but its limitations are to identify and distinguish image objects. Shape features are mostly applied to the applications where objects are well identified such as industry object recognition, trade mark retrieval and graphical design. Texture features are very effective, useful and have been used practically in image processing domain [1]. Besides, the texture features can also differentiate between objects with similar colours and shapes. Thus, this feature extraction task is a challenging task to extract good feature sets for classification [2]. Several studies have applied the texture feature extraction such as industrial inspection, searching for oil, cancer diagnosis, cancer characterization and ophthalmology [3].

Texture feature extraction refers to the process of computing characteristic of image which numerically describes texture image properties [4] as well as to derive some measurements that can be used to classify the image texture. Numerous texture extraction techniques can be categorized using four approaches: structural approaches, statistical approaches, model-based and transform methods.

The structural methods are based on defining the rules of grammar that can be used to characterize the texture [3] - [5]. The advantage of the structural approach is it provides a good symbolic description of the image. This method is also more useful for synthesis compared to analysis task [4]. Conversely, it performs poorly for noisy and low contrast input data [6].

The statistical approach for texture analysis is based on statistical properties of the intensity histogram [5] [8]. These statistical methods are based on second-order and have been shown to achieve higher discrimination rates [4]. Several methods of statistical approaches include co-occurrence matrix [1] [2] [10] and autocorrelation features [7]. The co-occurrence matrix approach is based on studies of the statistics of pixel intensity distributions [11] by statistically sampling the way certain grey-levels occur in relation to other grey-levels [5]. The common measures of texture obtained from this algorithm are contrast, correlation, inertia, energy and entropy [5] [8]. However, these texture features are difficult to capture effectively within a small region with large number of grey levels [12].

Model-based methods are based on attempting to interpret the application of texture of the image and generating the texture image model using fractal and stochastic model. The limitation of the stochastic model is the increased of computational complexity for its parameters. The advantage of the fractal model are it is useful for modelling some of the natural textures and can be used for texture analysis discrimination but it lacks orientation selectivity and is not suitable for describing the local image structures [4].

The transform methods represent image in a frequency domain in which the interpretation of the coordinate system is closely related to the characteristics of texture [4]. These methods generate the Fourier Transform of the image and then group the transform data to obtain a set of measurements [13] as well as analyses the texture images by decomposing the image into frequency and orientation components [7]. Numerous algorithms have been used in the transform methods such as Fourier Transform, Gabor filter [14] - [18] and wavelet transforms [4]. Several studies on Gabor filter found this method provides means for better spatial localization [4] and highly non-orthogonal. The results are significant in correlation between texture features but this method is linearly independent [1] [17]. Gabor filters have been successfully used in segmentation and classification of textured images [7]. The advantage of Gabor filter are it is able to capture the texture features at various orientations and frequencies as well as it can achieve the optimal localization in spatial and frequency domain. Besides, Gabor filter texture feature can significantly extracts texture features and has been shown to outperform other methods [1] as well as very efficient compared to others [18].

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Therefore, this paper studied and investigated texture feature extraction using a bank of Gabor filters to extract the texture features of Inverse Fast Fourier Transform (IFFT), texture energy and transformed IFFT.

II. Methodology

In this paper, the aims are to describe texture feature descriptions of MRI skull-stripped brain images as well as to evaluate the performance of the experimented texture features. **Figure 1** shows the process flow of the proposed algorithms.

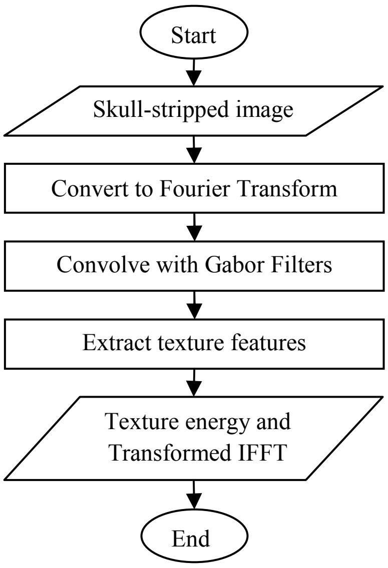


Figure 1: Process flow of the experiment process

A. Data Collection and Skull Stripping

The two-dimensional MRI data sets of adults ranging from 18-60 years old are collected from Hospital Sungai Buloh in Selangor. A total of 72 MRI brain images for all image sequences are utilized as the test images. Details of image sequences used in the experiments are:

- T1-Weighted of axial orientation (24 images)
- T2-Weighted of axial orientation (24 images)
- Fluid Attenuated Inversion Recovery (FLAIR) of axial orientation (24 images)

The MRI data sets are pre-processed prior to texture feature extraction as non-cerebral tissues of the brain will considerably affect the extraction results. To remove the non-cerebral tissue, skull stripping process using mathematical morphology is applied on all 72 MRI images [9]. An example skull stripping process is illustrated in **Figure 2**.

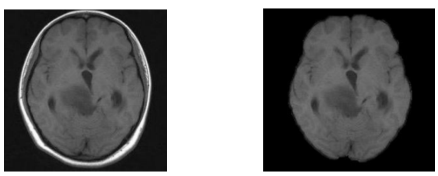


Figure 2: Skull stripping process

B. Gabor Filter

Gabor filter is one of the most established texture descriptors introduced by Gabor in 1946 [19]. It is applied to extract features by analysing the frequency domain of the image [15]. Gabor filter is basically a Gaussian function modulated by complex sinusoidal of frequency and orientation. It has the ability to perform both in spatial and frequency domain [20] and can be in any number of dimensions. These filters are more desirable since they provide the finer distinctions of the different textures [20]. The Gabor filter is analysed by taking the Fourier transform of the image and multiplying it with the Gaussian function centred at various frequencies and taking the IFFT of the results. The choice of the central frequency of each Gaussian is important to ensure all the frequencies of the image are covered [3].

This research applied the 2-D Gabor filter since the data sets collected are two-dimensional medical images. The aim of this experiment is to extract the texture features by analysing the frequency domain of the image using different frequencies and orientations.

1) Gabor Filter Bank: The 2-D Gabor filter consists of a Gaussian function modulated by complex sinusoidal of frequency and orientation. It can be computed as Equation (1).

$$G(x,y) \equiv e^{-\frac{(x-x_0)^2}{2\sigma_x^2}-\frac{(y-y_0)^2}{2\sigma_y^2}} e^{j(\omega_{x0}x+\omega_{y0}y)} \quad \textbf{(1)}$$

where:

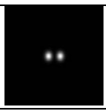
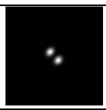
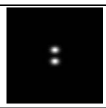
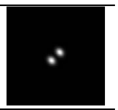
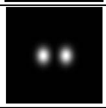
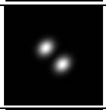
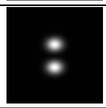
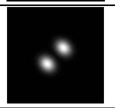
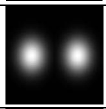
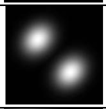
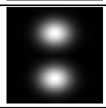
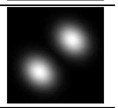
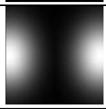
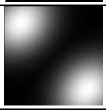
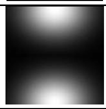
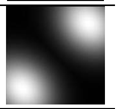
ω_{x0}, ω_{y0}	=	centre frequency of x and y directions which is the frequency in which the filter produces the greatest response.
σ_x, σ_y	=	standard deviation of the Gaussian function along x and y directions.
x, y	=	pixel position of the image.

Several parameters of the Gabor filters are defined in our experiment. The number of all orientations, $L = 8$ orientations are applied for the Gabor filter. Then, the orientation bandwidth is calculated as, $\Delta\theta = \frac{360}{8} = 45^{\circ} = 0.7857$ rad. Thus, the orientation, θ used in this experiment are $0^{\circ}, 45^{\circ}, 90^{\circ}$ and 135°. The centre of the frequency i can be computed as Equation (2).

$$\rho_i = \frac{\omega_i + \omega_{i-1}}{2} = \frac{1}{2}(2^i\omega_0 - 2^{i-1}\omega_0) = 2^{i-1}.3\omega_0 \quad \textbf{(2)}$$

For an input image of size 256×256, a total of 16 Gabor filters (4 orientations and 4 frequencies) are used for this experiment. **TABLE** I illustrates the frequencies and orientations of these Gabor filters.

TABLE I
THE TWO-DIMENSIONAL OF EXPERIMENTED FREQUENCIES AND ORIENTATIONS OF GABOR FILTER

Frequency	Gabor Filter			
	$\theta = 0$	$\theta = 45$	$\theta = 90$	$\theta = 135$
F1				
F2				
F3				
F4				

C. Texture Feature Extraction

Three texture features are extracted using Gabor filters which are Inverse Fast Fourier Transform (IFFT), texture energy and transformed IFFT.

1) Conversion of Fourier Transform: The Fourier Transform (FT) is a way of mapping signals into the component frequencies [13] in frequency domain. The coordinate system in the frequency domain spanned by $F(u,v)$ with u and v variables. The discrete FT image can be computed as Equation (3) below [8].

Let $f(x,y)$ for $x = 0,1,2,\dots,M-1$ and $y = 0,1,2,\dots,N-1$ of $M \times N$ image. The FT of f, $F(u,v)$:

$$F(u,v) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)e^{-2\pi j\left[\frac{ux}{M}+\frac{vy}{N}\right]} \qquad \textbf{(3)}$$

where:
u = $0,1,2,\dots,M-1$
v = $0,1,2,\dots,N-1$

2) Convolution with Gabor Filter: Response image refers to the result of the convolution between the Fourier Transform of skull-stripped image and Gabor Filter. The convolution process can be performed by applying Fast Fourier Transform (FFT) multiplication which is in the frequency domain. For example, the convolution of one image, $F(u,v)$ with another image, $P(u,v)$ where the convolution process is denoted by '$*$'.

3) Inversion of Convolved Image: The result of the FT is a complex number and it is difficult to view the results. Therefore, the convolved image have to be inversed back to the spatial domain which requires Inverse Fast Fourier Transform (IFFT) [13]. The inverted convolved image refers to the result of response image which is transformed back to the spatial domain via IFFT and IFFT is added as a texture feature. The IFFT image can be computed as Equation (4) [8].

Let $F(u,v)$ for $u = 0,1,2,\dots,M-1$ and $v = 0,1,2,\dots,N-1$ of $M \times N$ image. The IFFT, $f(x,y)$:

$$f(x,y) = \frac{1}{MN}\sum_{u=0}^{M-1}\sum_{v=0}^{N-1} F(u,v)e^{2\pi j\left[\frac{ux}{M}+\frac{vy}{N}\right]} \qquad \textbf{(4)}$$

where:
x = $0,1,2,\dots,M-1$
y = $0,1,2,\dots,N-1$

TABLE IV illustrates graphical examples of the steps involved to produce IFFT image of F3 frequency of all orientations. **TABLE III** shows an example of the IFFT images of each orientation and summation of all orientations of frequency F3. Based on the visual inspection from **TABLE III,** the results of the IFFT image for all data sets are difficult to interpret. So, we experimented on all image sequences data sets on 72 MRI brain images of T1-Weighted, T2-Weighted and FLAIR by adding all the IFFT images of all orientations for each four frequencies. As can be seen from **TABLE III,** the new IFFT image which is the image of summation of all orientations is clearer compared to the each orientation results. Therefore, we decided to add all the IFFT image of all orientations for each four frequencies for texture feature extraction.

4) Extraction of Texture Features: The final step is to extract two texture features of the IFFT images. They are texture energy and transformation of the IFFT.

- Texture energy is extracted after obtaining the IFFT image. The texture energy is computed by taking the square of the values of the IFFT. Therefore, we take care of the fluctuations in sign of the IFFT and the values of the texture energy are in positive sign.
- Transformation of the IFFT is computed after getting the results of IFFT. The transformation of the IFFT refers to the absolute values of the IFFT. Some researchers have found that the transformation of the IFFT produce better results compared with the texture energy which is by rectifying the waves and taking the absolute value of the images [3]. The transformation of the IFFT can be defined as Equation (5) below.

$$\varphi(g) = \left|\frac{1-e^{-2\alpha g}}{1+e^{-2\alpha g}}\right| \qquad \textbf{(5)}$$

where:
$\alpha > 0$ = parameter
g = grey value of the IFFT image

If $g \to \pm\infty$, $\varphi(g) \to 1$ and if $g = 0$, $\varphi(g) = 0$. The effect of this transformation is to rectify the IFFT wave by making the graph wave positive and broaden the wave into stripes. Then, we decided to use $\alpha = 2.50$ since α is in the range of g values $[-1,1]$ [3].

III. Results and Evaluation

The experimented algorithm is tested on 72 MRI skull-stripped brain images of T1-Weighted, T2-Weighted and FLAIR of axial orientation. This paper utilized all four frequencies and four orientations of texture feature images to demonstrate the performance of texture features of IFFT, texture energy and transformation.

The purpose of performance evaluation of texture features images is to evaluate the important region of texture features images such as tumour and normal tissues. Performance evaluation of texture features images using visual inspection are subjectively established based on the following categories:

Group 1 (Accept): High contrast between the tumour tissues and its surrounding background.

Group 2 (Reject): Cannot differentiate between the important region such as tumour and normal tissues.

The sample of accepted and rejected images is shown in **Figure 3**.

Figure 3: Sample of accepted and rejected images

The accepted image, A is used to quantify the number of accepted images and it can be computed as follows.

$$A = \frac{A_1}{T} \times 100 \quad \textbf{(6)}$$

where:

A_1 = number of accepted image

T = total image

The rejected image, R is used to quantify the number of rejected images and it can be computed as follows.

$$R = \frac{A_2}{T} \times 100 \quad \textbf{(7)}$$

where:

A_2 = number of rejected image

TABLE II
Visual Inspection of IFFT for T1-Weighted, T2-Weighted and FLAIR Images

Data Set	Frequency	Accept (%)	Reject (%)
T1-Weighted	**F1**	21	79
	F2	46	54
	F3	92	8
	F4	100	0
T2-Weighted	**F1**	44	56
	F2	56	44
	F3	68	32
	F4	96	4
FLAIR	**F1**	67	33
	F2	75	25
	F3	88	12
	F4	92	8

TABLE II shows that visual inspection of IFFT for frequencies F3 and F4 produced higher acceptance rate compared to F1 and F2 for all three types of image sequences. For example, the acceptance rate of IFFT for frequencies F3 T1-Weighted images is 71% and 46% higher than F1 and F2 respectively.

As can be seen from **TABLE II**, we decided to work on two highest frequency acceptance rates which are F3 and F4. **TABLE V** illustrated the sample results of texture features of IFFT, texture energy and transformation of IFFT images for two chosen frequencies of F3 and F4 for T1-Weighted, T2-Weighted and FLAIR image sequences.

IV. Conclusions

The proposed Gabor filter of MRI brain images have been utilized for each image sequences of all T1-Weighted, T2-Weighted and FLAIR MRI brain images. This Gabor Filter experimented on four frequencies of F1, F2, F3 and F4 of $0°, 45°, 90°$ and $135°$ orientations. Therefore, based on the results in **TABLE II** shows frequencies F3 and F4 of Gabor filter produced higher acceptance rate compared to F1 and F2 for all three types of image sequences.

For future work, F3 and F4 frequencies will be used for segmentation and classification task. As for the choice of orientations, all four orientations for two frequencies of F3 and F4 will be applied in segmentation tasks.

TABLE III
The Results of IFFT Image for Frequency of F3

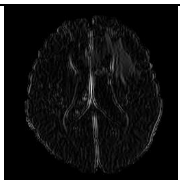
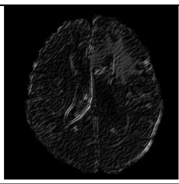
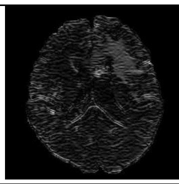
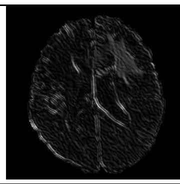
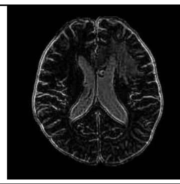
Orientation	0°	45°	45°	135°	Summation of the All Orientations
IFFT					

TABLE IV
THE STEPS INVOLVED TO PRODUCE IFFT RESULTS FOR FREQUENCY OF F3

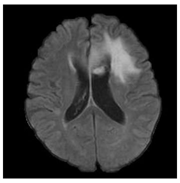
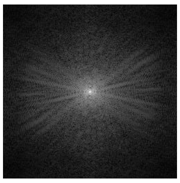
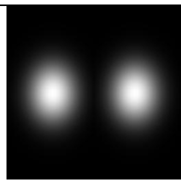
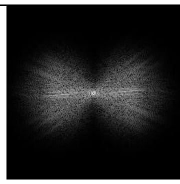
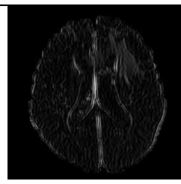
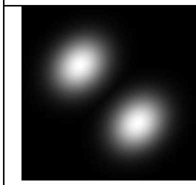
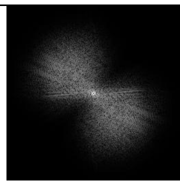
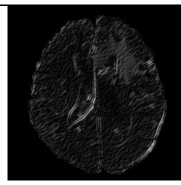
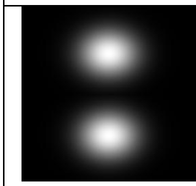
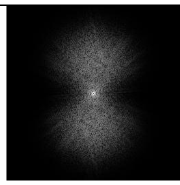
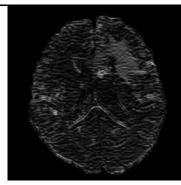
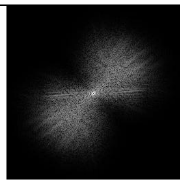
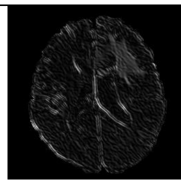
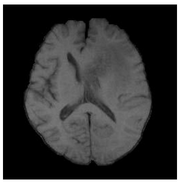
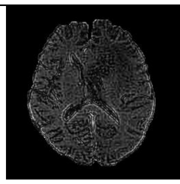
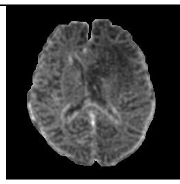
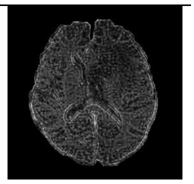
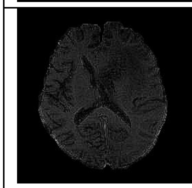
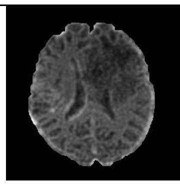
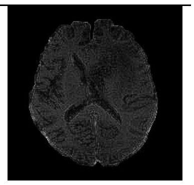
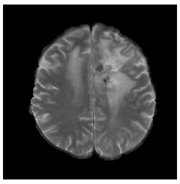
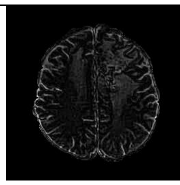
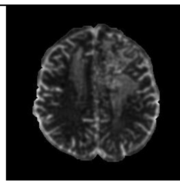
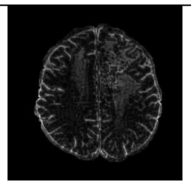
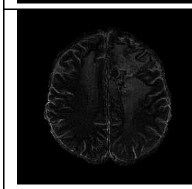
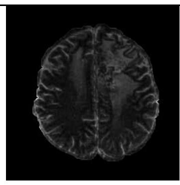
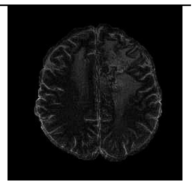
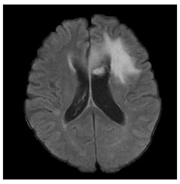
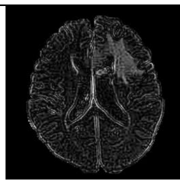
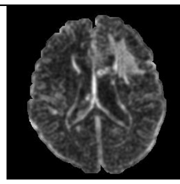
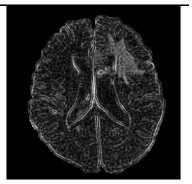
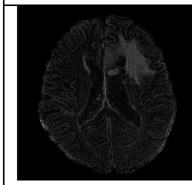
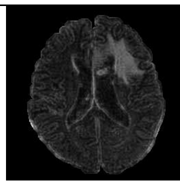
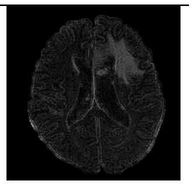
Orientation	Skull-Stripped	FT of Skull-Stripped	Gabor Filter	Response	IFFT
0°					
45°					
90°					
135°					

TABLE V
THE RESULTS OF TEXTURE FEATURES OF IFFT, TEXTURE ENERGY AND TRANSFORMED IFFT

Data Set	Frequency	Skull-Stripped	IFFT	Texture Energy	Transformed IFFT
T1-Weighted	F3				
	F4				
T2-Weighted	F3				
	F4				

FLAIR	F3				
	F4				

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