Bog pools pattern classification using adaptive Gabor filters in the frequency domain

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Abstract

Pattern recognition and classification has so far remained a largely unexplored area of peatland science[7]. The objective of this work is to classify the patterns of bog pools and ridges displayed on aerial photo of a patterned peatland in Western Scotland, UK. The neural network experiments reported in this research present in the first layer the input data as a bank of Gabor filters to be trained. This network enables an automated texture feature extraction in the multichannel texture classification through the modification of the kernel and the connection weights by the back propagation based on the training rule. After training the net , each cluster or pattern can be represented by its respective target. In the testing process different new images are fed in the first layer and separated in a different groups by calculating the Euclidean distances between the output layer vectors and the centroid. The numerical results demonstrate that the two dimensional Fourier power spectrum of bog pool images can reveal information about the frequency and the directions of the ridges. It is concluded that adaptive Gabor filter, as a member of the neural network architecture, is an efficient tool for pattern recognition and classification of bog pools.

1. Introduction

According to Looney [5], there is one operational mode where the system maps each input feature vector into the output vector that represents the class decision. This decision-making is recognition. Before a system can do this, however, it must have first learned the classes of feature vectors through a process that partitions the set of feature vectors. This is classification, which involves training, or machine training.

The most sophisticated machine vision is, undoubtedly, the human visual system [3]. Once image data have been brought into the computer, they are nothing more than numbers that can be manipulated with all the arithmetic operations and logic capabilities of the computer. Usually, the final goal of image processing is segment the objects within an image for classification and recognition.

The Gabor filters are being widely used for extraction of local orientation and scale information of the texture [1], [4] and [6]. Gabor filtering also can be used in multiple orientations and this makes it a powerful tool for the analysis of the directional textures. Therefore, it is a suitable method for classification of these kinds of textures. In addition to its ability to describe the texture directionality, Gabor filtering can be used in multiple scales, which is a desirable property in the classification of non-homogenous natural textures [5].

Although Gabor filters are a good choice for texture analysis, their parameter design is rather difficult. Hence, selection of the filter bands for efficient characterization of the textures within the image is one of the major issues in multichannel filtering. To use an appropriated filter parameters it is introduced in this paper a neural network model which unifies image-filter as input data in the first layer and the classifier in the output layer in the network architecture. The filter parameters and the weights of the classifier stage will both be trained by a method based on the back propagation rule. Kameyama [2] proposed a neural network using multi-channel Gabor Filter, but our approach is quite different: our NNW work in the frequency domain, and used Genetic Algorithm to obtain the optimum parameters of the Gabor Filter and the weights and bias of the network.

We use this method for classifying the patterns of bog pools and ridges displayed on aerial photo of a patterned peatland in Western Scotland, UK. The theoretical analysis is presented in the next section. In section 3 it will be displayed the numerical results. Section 4 discusses the results and shows that the two dimensional Fourier power spectrum of bog pool images can reveal information about the frequency and the directions of the ridges.

2. Theoretical Analysis
2.1. Gabor Filter in the Frequency Domain

A two dimensional Gabor filter, in the visual domain, can be written as,

$$G(x,y) = e^{\{-\pi[(\frac{x'}{\alpha})^2+(\frac{y'}{\beta})^2]\}} e^{(-2\pi j)[u_0 x' + v_0 y']} \qquad (2.1)$$

(2.

where

$$x' = a^{-m} x_r - x_0$$
$$y' = a^{-m} y_r - y_0$$
$$x_r = x\cos\theta + y sin\theta$$
$$y_r = -x sin\theta + y\cos\theta$$

and a is the scale factor, m is a non-negative integer, θ represents the angle of the orientation, u_0 and v_0 denote the spatial frequencies and α and β are the standard deviations of the Gaussian envelope along the x and y directions, respectively.

Note that (x_r , y_r) are obtained by rotating the point (x,y) clockwise of an angle θ, with respect to the origin (0, 0),

After some algebraic manipulations the two dimensional Fourier power spectrum stays,

$$F(u,v) = e^{\{-\pi[(\alpha u')^2+(\beta v')^2]\}} e^{(-2\pi a^m j)[x_0 u_r + y_0 v_r]}$$

where u and v are the spatial frequencies and,

$$u' = a^m u_r - u_0$$
$$v' = a^m v_r - v_0$$
$$u_r = u\cos\theta + v sin\theta$$
$$v_r = -u sin\theta + v\cos\theta$$

Observe that $F(u,v)$ is a complex variable since $j = \sqrt{-1}$

2.2. The image and the filter in the frequency domain

Let us consider a certain image $i(x,y)$ in the visual domain and its Fourier transform $I(u,v)$. Hence, according to the linear system theory, the filtered image at (u,v) can be displayed as

$$\text{Out}\,(u,v) = \text{I}\,(u,v)\ \text{F}\,(u,v) \qquad (2.3)$$

For the whole frequency domain, in terms of each Gabor filter component, the energy is defined as,

$$g(\lambda) = \frac{1}{2}[OutR^2(\lambda) + OutI^2(\lambda)] \qquad (2.4)$$

It is important to remark that for a given input set l in which the *parameters* α, β, θ, x_0, y_0, u_0, v_0, a, m are known, the output from each filter l can be represented by $g(l)$. l is the total number of input layer units or the total number of each output Gabor filter.

2.3. Adaptive filter parameters

From equations (2.1) and (2.2) consider a, m, y_0, u_0, v_0 the fixed parameters and $\sigma = \alpha = \beta$, θ and $\phi = x_0$, the three parameters to be trained using a neural network. Let $\sigma(l)$, $\theta(l)$, $\phi(l)$ be represented by $\lambda(l)$.

Using the network architecture with an input layer unit g(l), a hidden and an output layers units the total error is written as

$$ETot = \frac{1}{2}\sum_{n=0}^{N-1}\sum_{p=0}^{P-1}[t(p,n) - z(p,n)]^2 \qquad (2.5)$$

in which the error $e(p,n)$ is the difference between the target t(p,n) and the neural network output $z(p,n)$. Here P is the number of different images to be trained, L is the number of the input layer units, M the number of the hidden layer units and N is the number of output units. (2.3)

The Genetic Algorithm is used to minimize the function of error (2.5). In this case, it is not necessary to train the network, cause the Genetic Algorithm find the optimum parameters of the neural network, i.e., the parameters of the Gabor Filter (σ, ψ and θ), the weights linking the input and the hidden layer units $wh(m; l)$, the weights linking the hidden and the output layer units $ws(n;m)$ and the corresponding bias represented by $bh(m)$ and $bs(n)$.

3. Numerical Results

In this section is presented the numerical results obtained as an output of a software package in C++ specially developed for this research.

3.1. Data Generation Required for Training

The input image data used in this research was one aerial photo that has been scanned into the computer, obtaining a matrix of grayscale values, to be numerically manipulated.

Figure 1 shows a scanned aerial photo of a patterned bog from Western Scotland, UK. The bog is dominated by a range of patterns formed by linear ridges and pools in which 8 different regions (R) or sub-images have been chosen to analysis. In each region (i), 3 sub-regions (j) are considered for training and testing purposes.

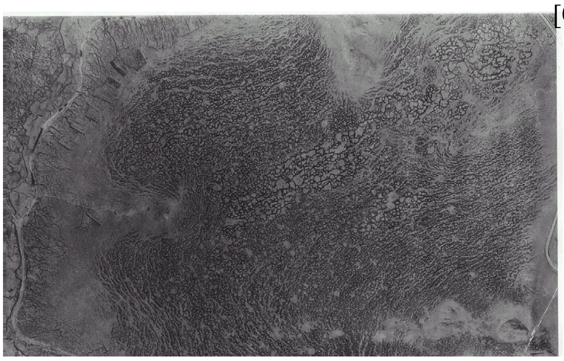


Figure 1. Aerial photo of bog pools

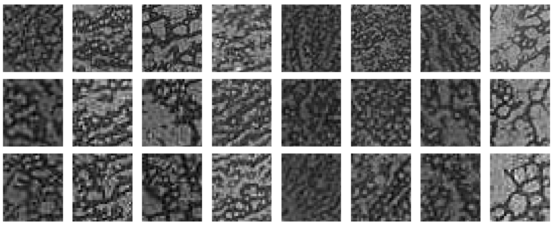
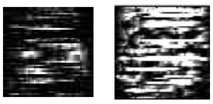


Figure 2.Sub-regions R(i,j) of bog pools; i = 1,8 and j = 1,3

Figure 3 shows two sub-images (R71 and R83) filtered in the visual domain, using Gabor Filter for $\sigma=1$, $\theta = 45^o$ e $u_o = 0$



R71 **R83**

Figure 3. Filtered sub-images R71 and R83

From figure 4 for a given image p to be trained in the NNW, the calculated initial values g(l) for each input layer unit are obtained as follows:

i) transform the image i(x,y) in the visual domain to frequency domain I(u,v);

ii) for one (l) specify the initial Gabor filter parameters σ(l), θ(l), ϕ(l) to be altered in the training process (see table 3.1);

iii) using equation (2.3) the spatial frequency distribution F(u,v) are obtained;

iv) from relation (2.4) the energy g(l) is calculated and is the value of the input layer unit (l);

v) For another l the steps from ii) to iv) are repeated;

vi) all L input data g(l) are normalized in the interval [0,1];

vii) steps **i)** to **vi)** are repeated for all P images.

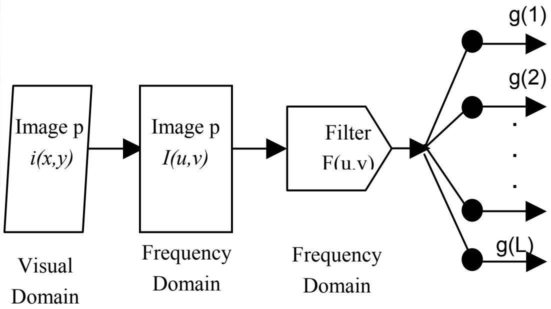


Figure 4. Pre-processing normalized Gabor filter parameters *g(l)* as input data.

The table 1 presents initial Gabor filter parame-ters σ(l), θ(l) and ϕ(l) used for training process.

Table 1 Initial Gabor filter parameters *σ(l), θ(l), ϕ(l)* used for training

	σ(l)	*θ(l)*	*ψ(l)*
l =1	0.5	0	5
l =2	0.1	π/4	1
l =3	2.5	3π/4	0

3.2. The Desired Values of Output Layer Units

As it is well known a supervised neural networks require targets or desired values *(t)* to be reached at the output after the training process is over. Hence, for each image p, each output layer unit n assumes a known value *t(p,n)*. According to relation (2.7) when the total error, including all the P images and all the N output layer units reaches a minimum value previously defined, the Gabor filter parameters and the NNW are said to be trained. To improve the training process, the initial values of weights *(w's)* and biases *(b's)* was randomly generated.

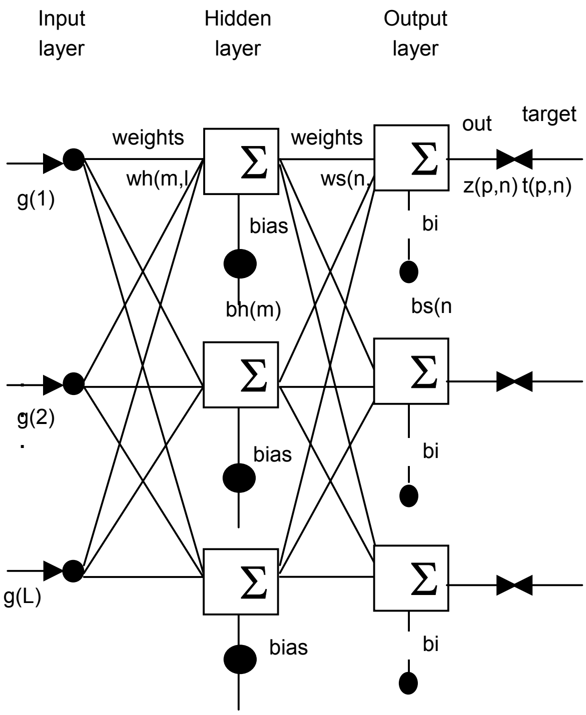


Figure 5. The topology of the NNW

3.3. The Classification Process and Conclusions

The classification of the bog pools, according to figure 6, has been made by supervised neural network in which the values of the input layer units are obtained in the frequency domain.

The topology of the NNW used in this experiment consists of 3 different Gabor filters, 5 hidden layer units and 5 output layer units.

Each trained image can be considered as a cluster or centroid. With all the final Gabor parameters and weights fixed, a new set of non trained K images are selected for the classification process. For each image k, the P Euclidean distances are calculated. The minimum distance between the calculated output z(k,n) and all trained P clusters z(p,n) indicates that the image k belongs to the p group. The results of this criteria are displayed in figure 6 and indicate that the NNW involving the Gabor filter parameters is an efficient method to be used for classifying images.

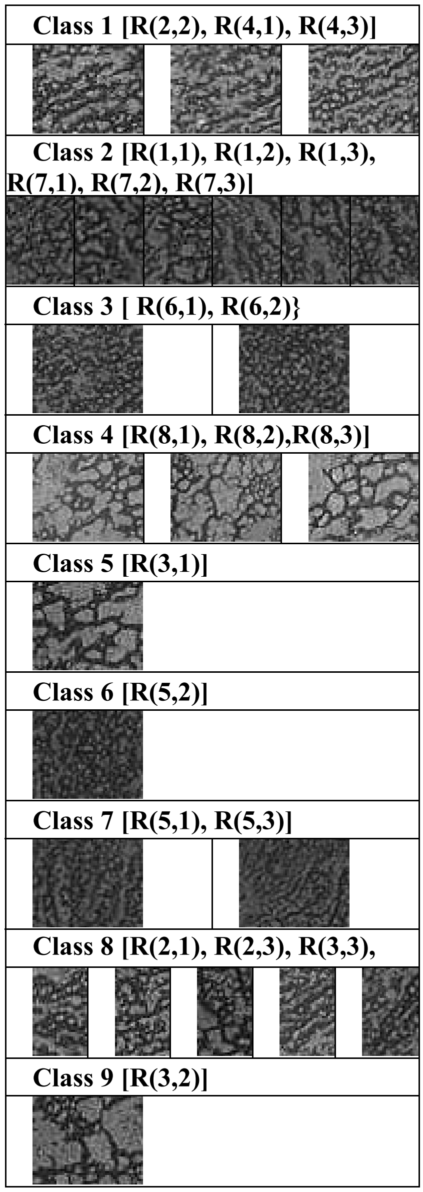


Figure 5. Classification of the 24 images

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