Plant Texture Classification Using Gabor Co-Occurrences

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Abstract. Leaves provide an important source of data for research in comparative plant biology. This paper presents a method for comparing and classifying plants based on leaf texture. Joint distributions for the responses from applying different scales of the Gabor filter are calculated. The difference between leaf textures is calculated by the Jeffrey-divergence measure of corresponding distributions. This technique is also applied to the Brodatz texture database, to demonstrate its more general application, and comparison to the results from traditional texture analysis methods is given.

1 Introduction

In the field of comparative biology, novel sources of data are continuously being sought to enable or enhance research varying from studies of evolution to generating tools for taxon identification. Leaves are especially important in this regard, because in many applied fields, such as studies of ecology or palaeontology, reproductive organs, which may often provide an easier form of identification, are unavailable or present for only a limited season. Leaves are present during all seasons when plants are in growth. There are also millions of dried specimens available in herbaria around the world, many of which have already been imaged. While these specimens may possess reproductive organs, the main character features are often concealed in images through being internal or due to poor preparation. However, almost all specimens possess well-preserved and relatively easily imaged leaf material.

Traditional methods employed by botanists for describing leaves rely on terminology and are largely qualitative and open to some level of interpretation [8]. In recent decades plant science has begun to use a range of quantitative morphometric methods in comparative studies [20, 13]. However, such data currently exist for a small minority of plant taxa, largely due to the limitations imposed by manual data capture.

In recent years there has been an increased interest in applying computer vision techniques to the problem of plant classification. Most of these studies have involved the analysis of leaf shape [7, 22, 11] or venation patterns [9, 16, 18], with leaf texture having been largely ignored. Backes et al. have applied multi-scale fractal dimensions [1] and deterministic tourist walks [2] to plant classification by leaf texture, although their experiments involved very limited datasets (just five species in the latter case) and so may not work as well for a wider range of plant species. Casanova et al. [4] used Gabor filters on a larger dataset and acheived reasonable results, whilst Liu et al. have presented a method based on wavelet transforms and support vector machines [17]. Generalized Fourier descriptors were applied to leaf images acquired using a scanning electron microscope [14], although this data capture method is impractical for most purposes due to the specialist equipment required.

This paper presents a method for plant texture classifaction based on the joint distributions of Gabor filter responses. Section 2 describes a simple method for extracting consistent texture samples from leaves. Our method of texture analysis and classification is given in section 3. In section 4 details of experiments using our method and a number of traditional methods on both leaf texture datasets and the popular Brodatz dataset [3] are given, with the the results presented and discussed in section 5.

2 Plant Texture Extraction

Much of the texture present on a leaf is due to the venation, with other sources of texture including hairs and glands. This venation can be separated into two main groups: the low order (primary and secondary) vein framework, and the higher order vein fabric. If texture samples (windows) are extracted randomly from a leaf, the level and quality of the vein framework present in a sample may vary greatly, and the sample may contain leaf damage, depending on the precise position of the sample on the leaf. For these reasons, we suggest a simple method of extracting samples which as far as possible contain only the vein fabric, as the contents of these samples should be more consistent. (figure 1).

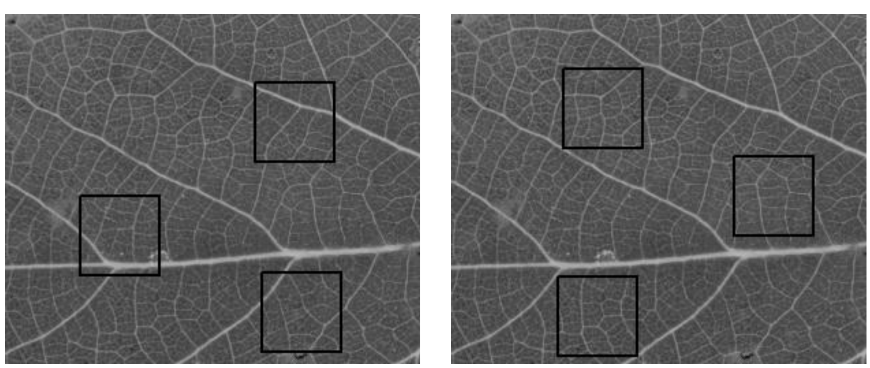

Fig. 1. Random sampling (left) compared with desired sampling (right)

The first stage is to reduce the scale of the image by convolving it with a Gaussian kernel and then sub-sampling. This has the effect of smoothing out much of the detail in the vein fabric, whilst retaining the main venation. Next, the image background, the paper on which the leaf is mounted, is removed. This can be done using Otsu's thresholding method [19]. An edge detection operator is then applied to the foreground of the image to provide a rough measure of the areas with strong edges in this scale space. A large number of potential windows are sampled at random from the foreground (containing only the leaf) and are sorted according to the sum of the squared edge magnitude for all the pixels within the window. The desired number of non-overlapping sample windows with the lowest sum can then be selected for use. A number of examples of windows selected by this method are given in figure 2.

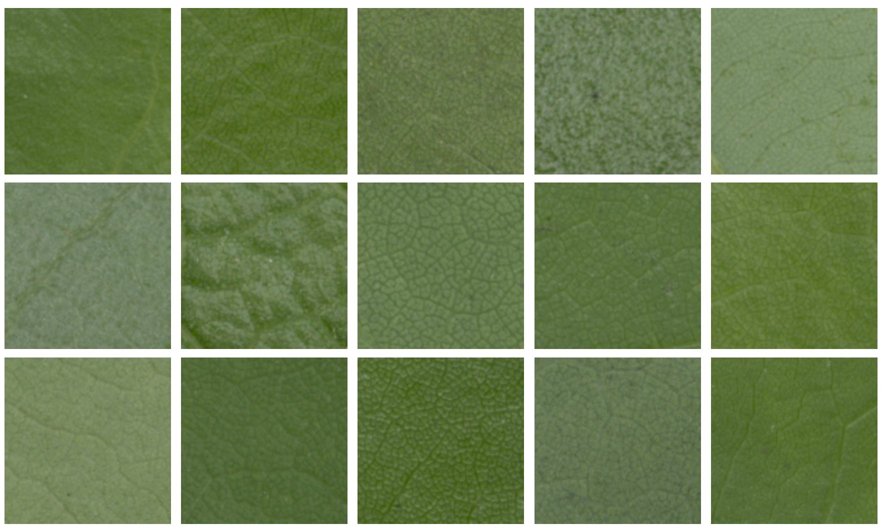

Fig. 2. Extracted texture samples from 15 species of Quercus (Oak)

3 Texture Analysis And Classification

3.1 Gabor Filters

The texture analysis method presented in this paper is based around the joint distributions of Gabor filters. A Gabor filter [6] is essentially a sinusoid modulated by a Gaussian function. It can be expressed as follows:

$$G(x, y) = \exp(\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}) \cos(\frac{2\pi x'}{\lambda} + \psi) \quad (1)$$

Where:

- $x' = x \cos\theta + y \sin\theta$
- $y' = y \cos\theta - x \sin\theta$
- θ is the orientation of the filter.
- γ is the filter aspect ratio.
- σ is the standard deviation of the Gaussian.
- λ is the wavelength of the sinusoid.
- ψ is phase offset.

Gabor filters have been applied to a large range of computer vision problems including image segmentation [21] and face detection [12]. Of particular interest are the links found between Gabor filters and the human visual system [5].

3.2 Texture Analysis From Gabor Co-Occurrences

A bank of 128 Gabor filters is created, where for filter G_{mn}, $\sigma = 1.5 * 1.2^{m-1}$, $\lambda = \frac{\sigma\pi}{2}$ and $\theta = \frac{n\pi}{16}$, with $m = 0..7$ and $n = 0..15$ refering to the filter scale and angle respectively. For all filters, $\gamma = 1$ and $\psi = 0$. The full set of filters is applied to each texture, but for each scale only the value corresponding to the highest absolute value for all the orientations is recorded for each pixel. This ensures that the method is rotation invariant. The results of the filtering for an image are combined into a series of co-occurrence matrices [10], whereby for each pair of scales, the resulting matrix describes the probability of a pixel producing one response value for the first scale, and another for the second.

$$C_{kl}(i,j) = \sum_x \sum_y \begin{cases} 1, \text{ if } g_k(x,y) = i \text{ and } g_l(x,y) = j \\ 0, \text{ otherwise} \end{cases} \tag{2}$$

Where $g_m(x,y) = \max_{n=0..15}(G_{mn}(x,y) * I(x,y))$ is the maximum response from convolving the filters for scale m with the image I at point (x,y), and (i,j) is a pair of response values. Examples of these matrices are given in table 1.

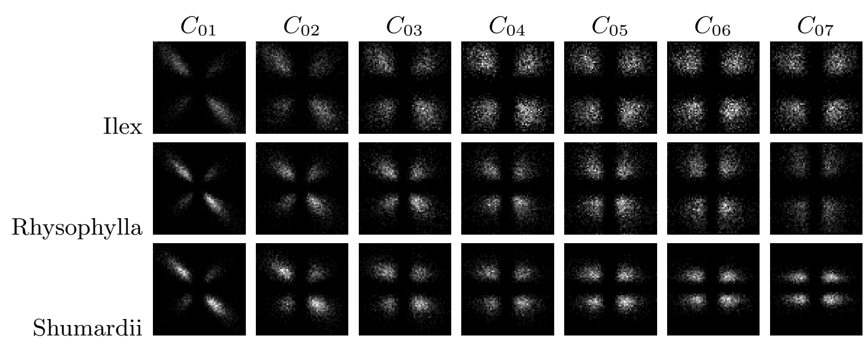

Table 1. Examples of Gabor co-occurrence matrices for 3 species of Quercus

3.3 Classifying Textures

To classify textures, the corresponding co-occurrence matrices for different textures are directly compared. This is done by treating the co-occurrence matrices as probability distribution functions (pdfs), by simply dividing each value by the sum of all values, and using the Jeffery-divergence distance measure. For two pdfs, f_a and f_b, the distance between them, $JD(f_a, f_b)$, is calculated as follows:

$$JD(f_a, f_b) = \sum_i \sum_j f_a(i,j) log \frac{2f_a(i,j)}{f_a(i,j) + f_b(i,j)} + f_b(i,j) log \frac{2f_b(i,j)}{f_a(i,j) + f_b(i,j)} \tag{3}$$

The distance between two images A and B is then:

$$D(A, B) = \sum_k \sum_{l, l \neq k} JD(C^A_{kl}, C^B_{kl}) \tag{4}$$

Where C^A_{kl} and C^B_{kl} are respectively the co-occurrence matrices at scale k,l for images A and B. The final classification is performed using the the k-nearest neighbour method, with $k = 3$. The modal class of the 3 closest texture samples to the one being classified is chosen. In the case that all 3 classes are different, the class of the single closest texture sample is used instead. This strategy was chosen as it reduces the risk of classification errors due to outliers.

4 Experiments

4.1 Datasets

The method was evaluated using four texture datasets. The first dataset was constructed using the method described in section 2. For each of 8 leaves from 32 different species, 8 64×64 windows were selected. This window size was chosen to allow the windows from leaves with dense vein frameworks to fit between the main veins. Eight windows were then used to provide an adequate overall sample size, whilst more would require more computation and may not be possible for particularly small leaves. Each of the 8 samples for a leaf was filtered before they were combined into a single set of co-occurrence matrices. The second dataset used 8 windows sampled at random from the same leaves, to illustrate the value of our texture extraction method.

The remaining two datasets came from the Brodatz texture database [3], with the first of these using a 40-class subset of the full 111 texture classes used in the second on these sets. From each of the classes, 9 200×200 non-overlapping samples were selected. The second of these sets is particularly difficult, due to the weak intra-class homogeneity present in some classes [15].

Fig. 3. Randomly extracted texture samples from 15 species of Quercus

4.2 Comparison Methods

For comparison, the above datasets were also used with a number of traditional texture analysis methods:

- Fourier Descriptors:
  The Fourier Transform of each image was calculated. From this, a vector of 64 features was found, whereby the i^{th} feature $f_i = \sum_{\theta=0}^{\pi} F(i\frac{w}{64}, \theta)$, where $F(r, \theta)$ is the Fourier Transform in polar form, and w is half of the image width.
- Gabor Filters:
  The set of Gabor filters used in section 3.2 is applied to each image. The energy in each resulting image is then calculated as $e_{\sigma\theta} = \sum_x \sum_y (G_{mn}(x, y) * I(x, y))^2$. The set of energies for each scale are then averaged resulting in 8 rotationally invariant features. This is similar to the approach used in [4]
- Co-occurrence Matrices:
  The traditional co-occurrence matrices were produced, using angles of $0rad$, $\frac{\pi}{4}rad$, $\frac{\pi}{2}rad$ and $\frac{3\pi}{4}rad$ and distances of 1,2 and 3. For each distance, a set of 14 textural features is calculated, as described by Haralick [10].

5 Results

The results for the experiments are given in tables 2 and 3. For the two leaf datasets, all the algorithms performed better on the dataset created as described in section 2, showing the value of our method of leaf texture extraction. For all

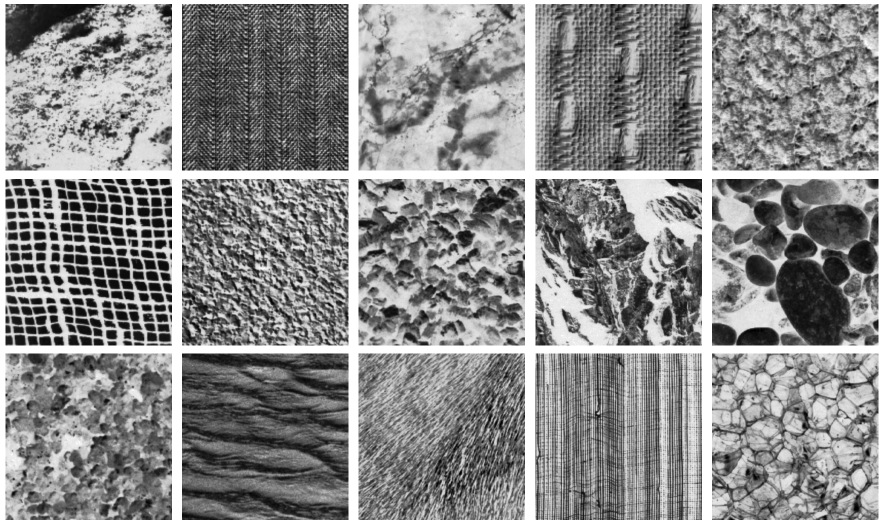

Fig. 4. Fifteen texture samples from the Brodatz dataset

datasets our method performed best, with the basic Gabor method performing worse. For the leaf datasets, the Fourier descriptors outperformed the co-occurrence matrices, whilst for the Brodatz datasets, co-occurrence matrices did better. It seems likely that the Fourier method is better at capturing finer detail, whilst the co-occurrence matrices perform best in images with higher contrasts between nearby pixels. This is supported by the greater improvement in quality for the Fourier method between the two leaf datasets.

	Vein Fabric	Random
Our Method	85.16	79.69
Gabor	50.78	45.70
Fourier	82.42	62.89
Co-occurence Matrices	69.14	61.72

Table 2. Results for the two leaf datasets

6 Conclusions

This paper has presented a method for texture classification that outperforms a number of traditional methods. It was found to be effective in the difficult task of classifying plants based on leaf texture, for which extracting texture samples from the vein fabric was shown to produce better results. The method also achieved high classification rates on the Brodatz texture database, performing only slightly worse on the entire 111 classes than on a 40 class subset.

	40 Class Subset	Entire Brodatz
Our Method	97.50	95.50
Gabor	63.61	52.55
Fourier	77.50	74.47
Co-occurence Matrices	87.50	81.18

Table 3. Results for the two Brodatz datasets

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