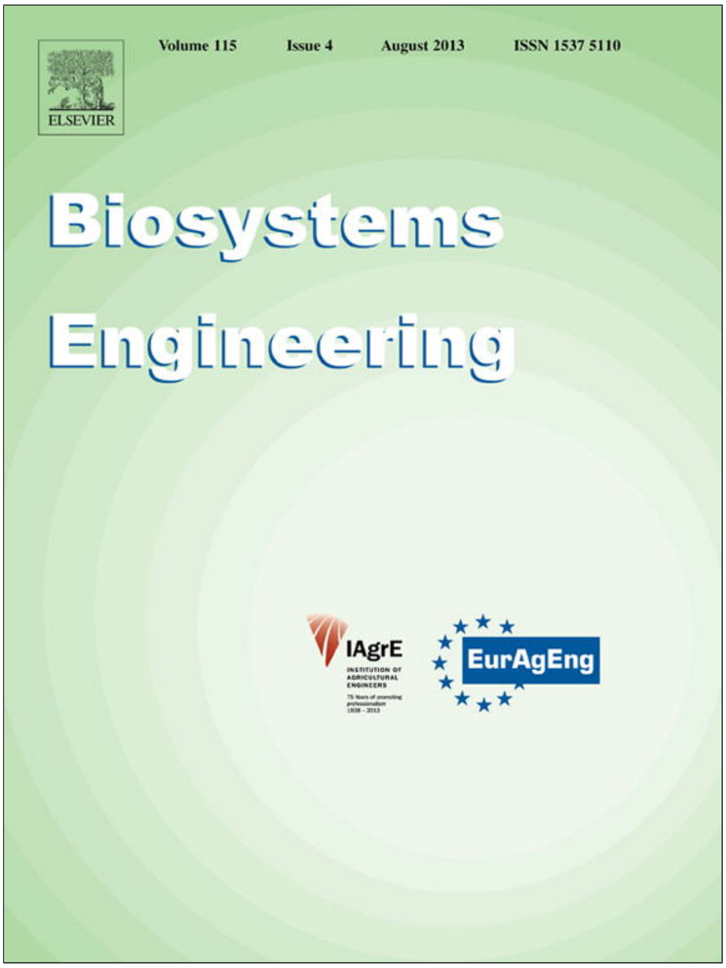
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Research Paper

Leaf recognition of woody species in Central Europe

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A system for recognition of woody species in Central Europe according to the images of their leaves is described. Our own data set, which includes 151 species at this moment, with at least 50 leaves per species was used. After segmentation, the contour of the leaf was traced. Fourier descriptors normalised to translation, rotation, scaling and starting point of the boundary, were used. The size of the leaf, if known, was used as a separate feature. The nearest neighbour classifier was used. The algorithm is available through a web application.

1. Introduction

Plant characterisation, the comparative analysis of visible characters (features in pattern recognition), forms the fundamental practical step in the daily work of many professions related to applied botany such as agriculture, forestry, nature conservation and also in many situations of general public interest. Among the various plant parts suitable for characterisation, leaves are readily availability and are abundant during the growing season; they also have sufficient specificity. That is why most researchers use foliar characters for species recognition. In addition, there are certain scientific fields where leaves offer the only opportunity for species recognition. For example palaeontologists often do not have any other plant remnants available for interpretation of the fossil record. Therefore, it is understandable that this problem attracts considerable interest.

There are many foliar characteristics recognised by botanists (Ellis et al., 2009), but in pattern recognition three main suites of characters are used represented by:

- leaf contour
- leaf surface texture – includes primarily venation, hairs, rough leaves
- features unavailable from single leaf image (leaf arrangement on stem (axis), heterophylly presence, blade reverse side)

The most commonly used suite of characters is leaf contour, perhaps because of the texture variability according to season (phenology phase) and individuals across one species or the requirement of very tiny venation details.

Here we focus on leaf contour recognition applying Fourier descriptors on a newly created public data set associated with a web application to make the proposed algorithm accessible. Our research provides a functional unit stemming from a theoretical concept and resulting in a real-life application.

2. State of the art

The current data sets and the leaf recognition approaches are discussed.

2.1. *Leaf data sets*

The most important publicly available data sets are:

- Flavia – had originally 1800 samples of 32 species, most of them are common plants in the Yangtze Delta, China, introduced in (Wu et al., 2007). It now has 1907 samples of 33 species, the images contain only blades, without petioles. It can be downloaded from Flavia (2009).

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Nomenclature

C++	Programming language
DPI	Dots Per Inch, unit of image resolution
HOG	Histogram of Oriented Gradients
ICL	Intelligent Computing Laboratory, Chinese data set
ImageCLEF	Cross Language Evaluation Forum, Mediterranean data set
MEW	Middle European Woody plants, our data set
NN	Nearest Neighbour classifier
OpenCV	Open source Computer Vision library
PHP	Hypertext Preprocessor, programming language
PNG	Portable Network Graphics, image file format
RGB	Red–Green–Blue colour space
SIFT	Scale-Invariant Feature Transformation
SOAP	Simple Object Access Protocol

Mathematical symbols:

Y	Brightness
T_k	Threshold in kth iteration
$\mu_0(T)$	Mean value of pixels $< T$
$\mu_1(T)$	Mean value of pixels $\geq T$
m_{pq}	Image moment in Cartesian coordinates
$A_{n\ell}$	Image moment in polar coordinates
$P_p(x)$	Polynomial of pth degree
$F(u)$	uth harmonic of Fourier spectrum
a_u	Amplitude feature
φ_u	Phase feature
$\tilde{a}_u, \tilde{\varphi}_u$	Normalised features
i	Imaginary unit, $i^2 = -1$
d_m	Set length (distance of the two most distant points in the set)
d_x	Maximum set length in the data set
$d(\ell,q)$	Distance of the leaves ℓ and q in the feature space
$t(\ell,q)$	Similarity of the leaves ℓ and q

- The Swedish data set – introduced by Söderkvist (2001), it contains 75 samples from each of the 15 species of Swedish trees. It can be downloaded from Sweden (2012).
- ICL (Intelligent Computing Laboratory) – the introductory paper (Hu, Jia, Ling, & Huang, 2012) presented 6000 samples (30 samples from each of the 200 species) growing in China. Currently 16,851 samples from 220 species can be downloaded from ICL (2010); the individual species have from 26 to 1078 samples.
- ImageCLEF (Cross Language Evaluation Forum) – aims to provide an evaluation forum for the cross-language annotation and retrieval of images. ImageCLEF (2011) includes plant images of 71 tree species from the French Mediterranean area. It contains 6436 pictures subdivided into 3 different groups of pictures: scans (3070), scan-like photos (897) and free natural photos (2469). They can be downloaded from ImageCLEF (2011). The data set was used e.g. in Yahiaoui, Mzoughi, & Boujemaa, 2012).

Many authors also use their own data sets that are not publicly available, e.g. Fiel and Sablatnig (2010), or their data sets are limited both in the number of species and in the number of samples. Some publicly available data sets also render low quality of images.

2.2. *Leaf recognition*

Recently, many papers dealing with leaf recognition have been published, therefore our survey cannot be regarded as being complete. In the contemporary literature various approaches can be found. The most frequently used features are polar Fourier transformation either as stand-alone (Kadir, Nugroho, Susanto, & Santosa, 2011a) or in combination with others (Kadir, Nugroho, Susanto, & Santosa, 2011b; Kadir, Nugroho, Susanto, & Santosa, 2011c; Kadir, Nugroho, Susanto, & Santosa, 2012a), image moments (Jiming, 2012; Kadir et al., 2011b, 2011c; Kadir, Nugroho, Susanto, & Santosa, 2012b; Pauwels, de Zeeuw, & Ranguelova, 2009; Söderkvist, 2001; Wang, Huang, Xu, & Heutte, L, 2008) and various versions of shape contexts: Zhi, Hu, and Wang (2012) use arc length shape context, Nanni, Brahnam, and Lumini, (2012) use the combination of inner distance shape context, shape context and height functions.

Also various simple geometric features are popular, e.g. diameter, length, width, area, aspect ratio, rectangularity, narrow factor, convex area ratio, sphericity, circularity, eccentricity, form factor, etc. (Corney, Clark, Tang, & Wilkin, 2012; Kadir et al., 2011c, 2012a; Kaur & Kaur, 2012; Pauwels et al., 2009; Shabanzade, Zahedi, & Aghvami, 2011; Söderkvist, 2001; Wu et al., 2007). Their descriptions of the leaf form are not complete, but if a large number of them are combined, they can express the most important properties of the leaf. Zhang, Zhao, and Wang (2011) and Zhang and Lei (2011) directly use pixels of the leaf image of a normalised size 32×32 and Sumathi and Kumar (2012) and Cope and Remagnino (2012b) use Gabor filters.

A group of features is based on various histograms: histogram of oriented gradients (HOG) – (Xiao, Hu, Zhang, & Wang, 2010), directional fragment histogram (Yahiaoui et al., 2012), red–green–blue (RGB) histogram (Pattanasethanon & Attachoo, 2012) or histograms of curvature over scale (Kumar et al., 2012). We found specific approaches described only in one paper, Cope and Remagnino (2012a) who used dynamic time warping inspired by stereoscopic vision. Ren, Wang, and Zhao (2012) used local binary patterns, Fiel and Sablatnig (2010) used scale-invariant feature transformation (SIFT), Hu et al. (2012) used multiscale distance matrix, and Chen, Lin, and He (2011) used a simplified curvature of the leaf contour called velocity.

Some authors use Fourier descriptors. Yang and Wang (2012) use Fourier descriptors computed from distances of the contour points from the centroid; in our experience this method is advantageous for smaller data sets. Singh, Gupta, and Gupta (2010) use a similar approach, except that the contour was parameterised by angle, not by distance. Neto, Meyer, Jones, and Samal, (2006) use elliptic Fourier descriptors.

Most authors use the simple nearest neighbour (NN) classifier, sometimes in the k-NN version. Other authors use neural network (Kadir et al., 2011c, 2012b; Kaur & Kaur, 2012; Pattanasethanon & Attachoo, 2012; Söderkvist, 2001; Sumathi & Kumar, 2012; Wu et al., 2007) or support vector machine (Fiel & Sablatnig, 2010; Ren et al., 2012).

3. Data set used

Our data set is called Middle European Woody Plants (MEW). It contains native or frequently cultivated trees and shrubs of the Central Europe Region. The current number of species in the data set reaches 153 including at least 50 samples per species and a total of 9745 samples; the data set can be downloaded from MEW2012 (2012). More specifically, *Hedera helix* is divided into fertile and sterile forms and *Maclura pomifera* is divided into female and male, thus 151 botanical species result in 153 recognisable classes.

Leaves were scanned at 300-DPI resolution, 24-bit colour with solid white background in lossless compression format PNG. The used scanners: Epson Perfection V33[1], Mustek ScanExpress A3 USB 2400 Pro[2] and Hewlett Packard scanjet 3500c[3]. Examples from our data set are shown in Fig. 1.

MEW differs from the previously existing data sets in several aspects:

- it is botanically supervised as far as the diversity of Central Europe woody plants and the correct sample determination are concerned.
- it contains a suitable quantity of good quality samples
- it has a unique approach to compound leaves

The compound leaf issue and the differences in our approach are discussed. Other data sets use the botanical leaf definition based on descriptive systems as previously mentioned (Ellis et al., 2009) and collect images of whole compound leaves. This botanically correct definition omits subtended axillary buds and has a definite arrangement in their insertion along the axis (Fig. 2). Hence the difference between a branch with leaves and a pinnately compound leaf with leaflets is based only on present or absent auxiliary buds along the axis. In our method a lack of knowledge or thoughtlessness in the lay human recognition is expected and it is considered possible to detect buds using automated recognition. Therefore it may be useful to collect and recognise only the separate leaflets of compound leaves. This idea can evolve to considering any leafy-shaped organ of a vascular plant as a leaf – such as the enlarged stipules of a pea (*Pisum sativum*), the cladodes of a knee holly (*Ruscus aculeatus*) or the phyllodes of thorntrees (*Acacia* spp.).

These few examples should demonstrate the existing incompatibility between the botanical leaf definition and the theoretic model of a leaf suitable for automatic pattern recognition. Information about leaf type, if available, should be one of the meta-data descriptions applied independently.

Another, less sophisticated feature, is the true leaf size. Leaving aside the large leaves of Palmae (Arecaceae) and the many tropical plants with potentially complicated sampling, several major issues were encountered in our area of interest. Aside from the Tree of Heaven (*Ailanthus altissima*) or Catalpa (*Catalpa* sp.) with leaves mostly exceeding A3 size, the Kentucky Coffeetree (*Gymnocladus dioicus*), occasionally cultivated in gardens, has bipinnately compound leaves up to 1 m long. Moreover leaflets often fall from trees separately, so only an experienced botanist is able to describe correctly the structure of such a leaf.

For the reasons mentioned above our data set consisted of simple leaves and separate leaflets of compound leaves. In a future version of the data set (MEW2013) we anticipate preparing additional samples of complete compound leaves allowing evaluation of the leaflet separation process.

4. Preprocessing

Leaves were scanned by the scanner to obtain green leaves on white background and to enable simple segmentation by thresholding. Photographs of plucked leaves on a white sheet of paper shot by a camera are also acceptable as query images. The colour image was converted to grey levels using

$$Y = 0.299R + 0.587G + 0.114B, \tag{1}$$

where Y is brightness, R, G and B are red, greed and blue channels respectively. Then the Otsu's threshold (Otsu, 1979) was computed iteratively

$$T_{k+1} = \frac{\mu_0(T_k) + \mu_1(T_k)}{2}, \tag{2}$$

where $\mu_0(T)$ is the mean value of the pixels with Y less than threshold T and $\mu_1(T)$ is the mean value of the pixels with Y greater than threshold T. At the beginning, $\mu_0(T_0) = \min(Y)$ and $\mu_1(T_0) = \max(Y)$. When $|T_{k+1} - T_k| \langle 0.5$, T_{k+1} is the result.

The Otsu's threshold method is not always optimal, therefore manual correction was enabled. In the case of the MEW2012 data set, the threshold was manually adjusted at 109 leaves for the correct segmentation, it is 1.12%. The success rate of the recognition was 1% worse without this correction.

The contours in the binary image were then traced. The image was sought sequentially and if some object pixel was found, its 4-neighbourhood was searched for a next boundary point. This process was repeated until the whole contour was traced. The advantage of the 4-neighbourhood was that adjacent boundary points have the same x or y coordinate and their distance is always 1, so the boundary is parameterised by distance, see Fig. 3.

Only the longest boundary in the image was used, the other boundaries of both objects and holes were considered as noise. The boundary tracing was used as the noise filter as well as data preparation for feature computation. An example of the boundary can be seen in Fig. 4.

[1] Seiko Epson Corporation, 3-3-5 Owa, Suwa, Nagano 392-8502, Japan.
[2] Mustek Systems, Inc., 25, R&D Road 2, Science-Based Park, Hsin-Chu, Taiwan.
[3] Hewlett–Packard Company, 3000 Hanover Street, Palo Alto, California, 94304-1185, USA.

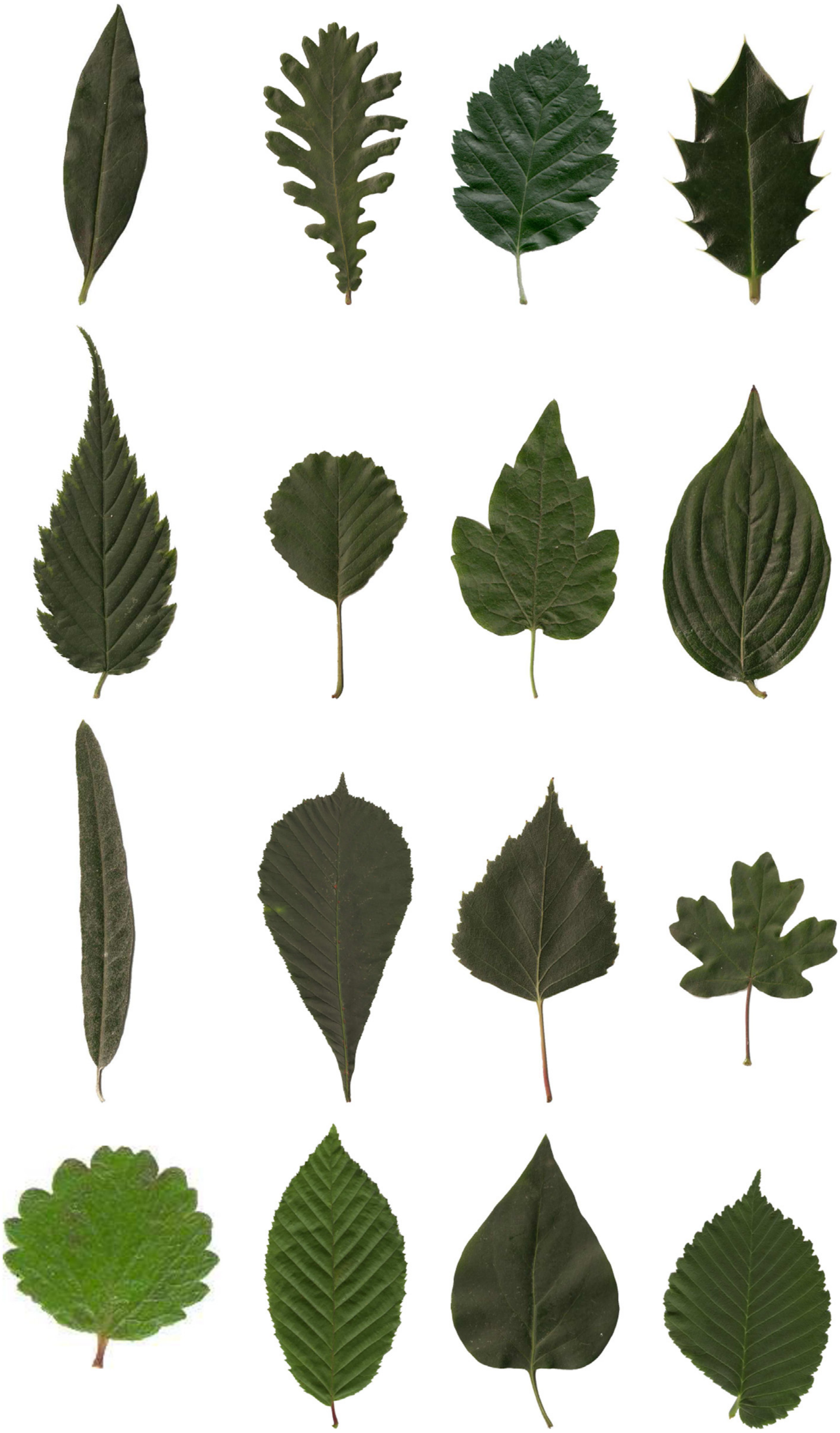

Fig. 1 – Samples of our data set (numbers 1–4 represent rows – scans were cleaned for this printed presentation): 1 – *Ligustrum vulgare*, *Quercus frainetto*, *Sorbus intermedia*, *Ilex aquifolium*, 2 – *Kerria japonica*, *Alnus glutinosa*, *Clematis vitalba* (leaflet of pinnately compound leaf), *Cornus mas*, 3 – *Elaegnus angustifolia*, *Aesculus hippocastanum* (leaflet of palmately compound leaf), *Betula pendula*, *Acer campestre*, 4 – *Betula nana*, *Carpinus betulus*, *Syringa vulgaris* and *Ulmus laevis*.

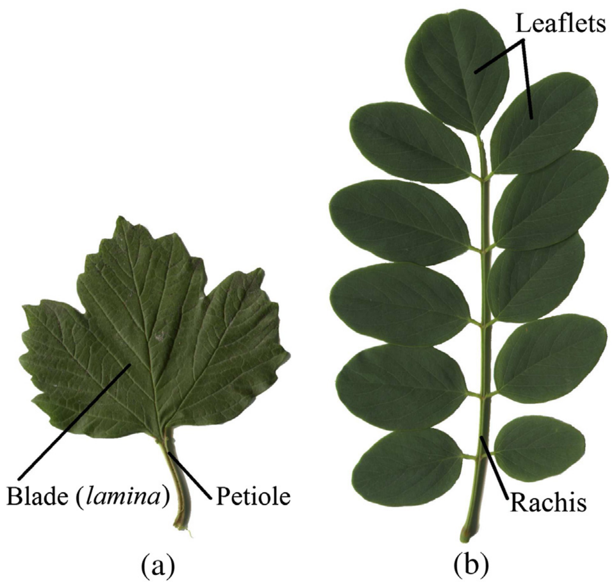

Fig. 2 – (a) Simple leaf (*Viburnum opulus*). (b) Pinnately compound leaf (*Robinia pseudoacacia*).

5. Features

Various types of features computed both from the boundary and from the texture of the leaf were explored. Two most popular features used are image moments and Fourier descriptors. Both were tested extensively.

5.1. *Image moments*

The term *moment* of probabilistic distribution comes from statistics; however moments can be computed directly from an image. The general image moment (Flusser, Suk, & Zitová, 2009) is defined by

$$m_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} G_{pq}(x,y) f(x,y) \mathrm{d}x\mathrm{d}y, \tag{3}$$

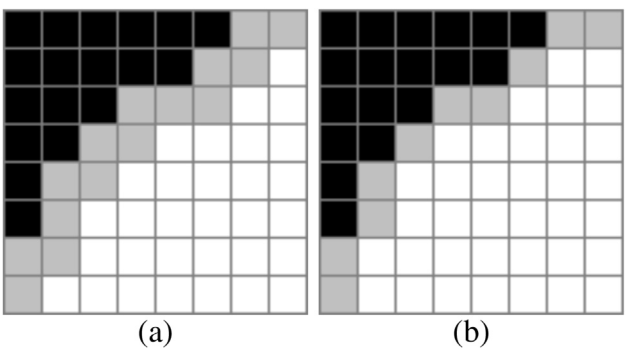

Fig. 3 – Oblique boundary tracing. Grey object pixels are the boundary points found. (a) 4-neighbourhood was used in the tracing – the distance of adjacent points is always 1. (b) 8-neighbourhood was used in the tracing – the distance of adjacent points is somewhere 1 and somewhere $\sqrt{2}$, the boundary is not parameterized by distance.

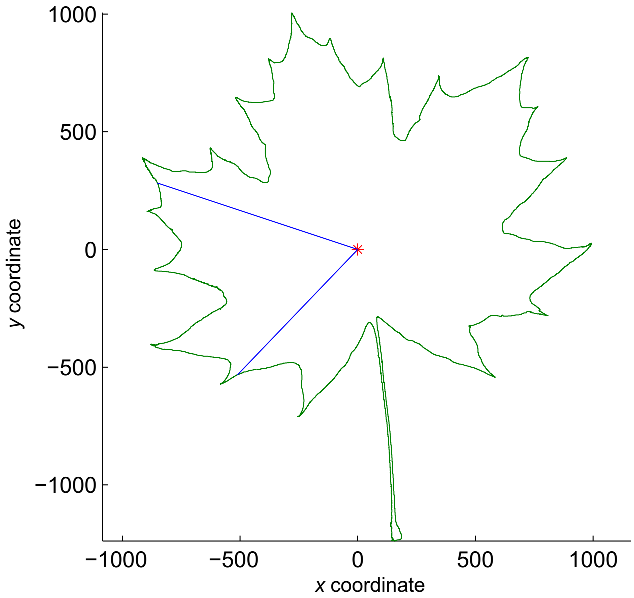

Fig. 4 – The traced boundary of the leaf image (*Acer platanoides*) with the marked centroid.

where $f(x,y)$ is the image and $G_{pq}(x,y)$ are polynomials of the $(p+q)$th degree. They are often separable, so they can be expressed as a product $G_{pq}(x,y) = P_p(x)Q_q(y)$, where $P_p(x)$ and $Q_q(y)$ are polynomials of the pth (qth) degree. The sum of indices $p+q$ is called *order* of the moment. The simplest *geometric* moments have $P_p(x) = x^p$ and $Q_q(y) = y^q$. They have problem with numerical precision of high orders, both high x and high p leads to overflow of x^p. To overcome this problem, orthogonal moments can be used, e.g. Chebyshev moments of the 1st kind have ($P_0(x) = 1$)

$$P_p(x) = \frac{p}{2} \sum_{k=0}^{\lfloor p/2 \rfloor} (-1)^k \frac{(p-k-1)!}{k!(p-2k)!} (2x)^{p-2k}. \tag{4}$$

The leaves can translate and rotate in a scanner, therefore it is useful to use features invariant to translation and rotation. The coordinates of the centroid $x_c = m_{10}/m_{00}$, $y_c = m_{01}/m_{00}$ were subtracted from all coordinates to obtain the moments invariant to translation (so called *central* moments).

The rotation invariance can be obtained by two approaches (Flusser et al., 2009). One of them uses *complex* moments with the kernel functions $P_p(x) = (x+iy)^p$ and $Q_q(y) = (x-iy)^q$ ($i = \sqrt{-1}$ is imaginary unit). The rotation invariants can be obtained simply as their products. The complex moments can be converted to another type of moments, e.g. geometric or orthogonal Gaussian–Hermite (Yang & Dai, 2011) and obtain the rotation invariants in the form of their polynomials.

The second approach is normalisation to rotation. $G_{pq}(x,y)$ can be used in the form

$$A_{n\ell} = \int_0^{2\pi} \int_0^1 R_{n\ell}(r) \exp(-i\ell\varphi) f(r,\varphi) r \mathrm{d}r \mathrm{d}\varphi, \tag{5}$$

where the radial function $R_{n\ell}(r)$ is some polynomial of the nth degree (e.g. Zernike or Chebyshev) and $f(r,\varphi)$ is the image in polar coordinates. Then a phase of some moment (typically A_{31})

can be used for the normalisation of all other moments with respect to the rotation.

The best success rate 68.65% of moments themselves was achieved by discrete Chebyshev moments normalised to rotation. The advantage of using image moments lies in the possibility to compute them from both binary and grey level images, therefore image moments were planned for use as supplementary features with lower weight.

5.2. Fourier descriptors

The traditional Fourier descriptors (Lin & Chellapa, 1987) computed from the boundary of the binary image yielded better results. They are defined as Fourier transformation of the boundary

$$F(u) = a_u \exp(i\varphi_u) = \sum_{k=1}^{n} (x_k + iy_k)\exp(-2\pi iku/n), \quad (6)$$

where (x_k, y_k) are coordinates of the kth boundary point, n is the number of boundary points, u is the relative frequency (harmonic), amplitude $a_u = |F(u)|$ and phase $\varphi_u = \text{angle}(F(u))$ are computed features. The natural range of values of u is 0, 1, $\ldots n - 1$. Then the Fourier descriptors create a complete description of the boundary. Nevertheless, the same number of features from all leaves is required, therefore the range needs to be limited. We can write it as $u = -r, -r+1, \ldots r$ because the Fourier descriptors of the negative harmonics can be computed from $F(-u) = F(n-u)$. Theoretically, r should be less than $n_m/2$, where n_m is the length of the shortest boundary in the data set. There is $n_m = 400$ in our data set (*Vaccinium vitis-idaea*, sample number 26). An optimal value of r was sought. The local maximum of success rate was $r = 185$ slightly under the limit 200. In our experience it can be slightly higher than this limit in some data sets which means that some descriptors of the smallest leaves are used twice.

The centroid coordinates are subtracted from the boundary points to reach translation invariance. If an s-times bigger leaf is being recognised, then its boundary is s-times longer and the size of its serrations (amplitude of the boundary oscillations) is also s-times larger, therefore normalised descriptors a_u/n^2 are invariant to scaling.

The magnitude of a_u falls quickly with u and the appropriate weight of the features in the classifier is required. Therefore $\tilde{a}_u = 10(|u|+1)a_u/n^2$ is used. The value 10 is derived from the condition that the features with u around zero would have the value around one and the coefficient $(|u|+1)$ reduces the fall of the magnitude. The magnitude of a_u and $\tilde{a}_u$ can be compared in Fig. 5.

The rotation of the leaf in a scanner causes both rotation of the coordinates and a change of starting point. The result is a phase shift of the descriptors, therefore the phase must be normalised to both. The first harmonics can be used as follows:

$$\vartheta = (\varphi_1 + \varphi_{-1})/2, \quad \rho = (\varphi_1 - \varphi_{-1})/2. \quad (7)$$

The normalised phase is then

$$\tilde{\varphi}_u = \varphi_u - \vartheta - u\rho. \quad (8)$$

The phase is much more sensitive to noise than the amplitude, yet it still does provide certain information. In theory such features should be used with a very low weight. The result of our optimisation is the weight of φ_u

$$0.008/|u|. \quad (9)$$

The zeroth phase cannot be utilised, φ_0 is always zero from definition and φ_{-1} and φ_1 cannot be used either, if previously used for rotation normalisation.

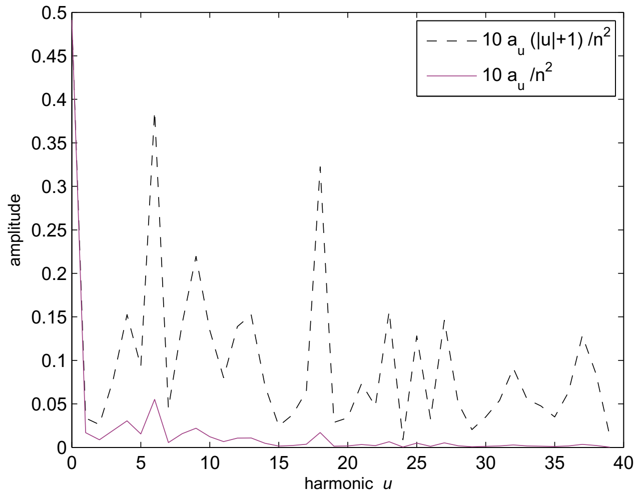

Fig. 5 – Fourier spectrum of the boundary.

5.3. Leaf size

An interesting question arises with the size of the leaves. The botanical rule implies that the largest adult leaf on a tree is approximately twice as large as the smallest. This suggests that the information on size is somewhat interesting, but not too reliable. Another question is how to feed this information to a computerised system. When using a scanner, it can usually calculated from its resolution, but when a camera is used, a problem arises and the user must enter the size information separately. These data, if accessible, are used in the form

$$f_s = 1.04\, d_m/d_x, \quad (10)$$

where the value 1.04 is result of our optimisation, d_m is the distance of the two most distant points in the leaf and d_x is the maximum value of d_m in the data set (in our data set it is *Catalpa bignonioides*, sample number 34 with value 4139.17).

6. Classifier

A simple NN classifier with optimised weights of individual features was used. While the size f_s and amplitudes $\tilde{a}_u$ are just coordinates in the feature space, the phase $\tilde{\varphi}_u$ is an angle. So, for comparison of two phases, we must consider, if the clockwise or anticlockwise distance in a circle is the smaller and if the lesser distance contains the transition $\pi \to -\pi$. Only after that can the weight of these features be used, so our distance is computed by

$$d(\ell,q)=\left[\left(f_s^{(\ell)}-f_s^{(q)}\right)^2+\sum_{u=-r}^{r}\left(\tilde{a}_u^{(\ell)}-\tilde{a}_u^{(\ell)}\right)^2\right]^{\frac{1}{2}}+0.008 \times \sum_{\substack{u=-r\\|u|>1}}^{r}\min\left(|\tilde{\varphi}_u^{(\ell)}-\tilde{\varphi}_u^{(q)}|,2\pi-|\tilde{\varphi}_u^{(\ell)}-\tilde{\varphi}_u^{(q)}|\right)/|u|. \quad (11)$$

In the training phase, the features of all leaves in the data set are computed. In the classification phase, the features of the query leaf are computed, they are labelled by index (q) in Eq. (11), while the features labelled (ℓ) are successively all data set features. Only one nearest neighbour from each species was considered. The distances were sorted and ten species with the minimum distances were offered as an answer. The number of ten was determined after a consideration for possible number of similar species in our data set.

The distance in the feature space is not very intuitive for the user, therefore in the solution a variation of the Tanimoto similarity[4] (Rogers & Tanimoto, 1960) but with a different coefficient $\lambda = 0.2$

$$t(b,q) = 100\%\cdot 2^{-\lambda d(b,q)}, \quad (12)$$

where b is the index of the leaf of the species with minimum distance to the query leaf q. If we compare two identical leaves, $t(b,q) = 100\%$, if $t(b,q) < 20\%$, the species is not included in the list of results. If there is no leaf with $t(b,q) \geq 20\%$ in the data set, the answer given by the software is "the query is not in the data set". It is a guarantee against the queries that are not leaves at all.

7. Results

The system was in two types of tests. Firstly, the data set was randomly divided into two halves, one was used as a training set, and the other as a testing set. If there was an odd number of samples of a specific species, the training set was larger by one. In the second test one sample was used as a testing set and rest of the data set as a training set. It was successively repeated for all leaves in the data set.

The results of our method using our data set MEW2012 was compared with the other data sets described in Section 2. From ImageCLEF only scan pictures were used (scan-like and natural photographs were omitted), while complete sets were used with other data sets (Table 1).

In these types of tests, the declared success rate should be related to the number of species. The more species, the more difficult is the recognition. The original success rates were based on slightly different type of tests. They were adopted from Wu et al. (2007) (10 against rest), Yahiaoui et al. (2012) (1 against all scan pictures) Hu et al. (2012) (1 against 29 randomly chosen samples of 50 randomly chosen species) and Söderkvist (2001) (25 against 50).

A plot of recognition rates, as a function of the maximum species match rank k as presented in Kumar et al. (2012) is shown in Fig. 6. The result for $k = 5$ is 98.97%, for $k = 10$ is 99.63%.

[4] It was originally proposed for binary features with $\lambda = 1$.

Table 1 – Success rates of our method on various data sets. The column labelled #s contains the numbers of species.

Data set	#s	$\frac{1}{2}\times\frac{1}{2}$	$1\times$ all	Original
MEW2012	153	84.92%	88.91%	
Flavia	32	91.53%	93.66%	90.31%
ImageCLEF	62	77.36%	81.58%	77.83%
ICL	220	79.68%	84.62%	74.20%
Sweden	15	95.86%	96.53%	81.96%

8. Web application

As part of the output of this research, a simple web application was created, which is capable of determining an unknown leaf in the following stages:

- single image uploading
- thresholding with user-correction
- user-correction of calculated image size
- top ten results with similarity rate
- filtering results by leaf type meta-data

The application code has been written in PHP, image processing uses ImageMagick Studio LLC (2013) and C++ (including OpenCV library (2013)). The direct access is accompanied by a Web Service interface for exchanging structured information based on SOAP (Simple Object Access Protocol) standards. This extension was built with regard to the planned incorporation into a key guide of trees and shrubs based on web services. The application would be a probability module of such a key.

Application, data set and other information can be found on (MEWProjectSite, 2012).

9. Discussion and future work

Many issues still remain open. If the leaf is compound the query image is required to contain only one leaflet. Information concerning whether the image includes a whole simple leaf or a leaflet of a compound leaf can be entered separately. In the future it is intended that compound leaves will be automatically fully processed, i.e. the application would be capable of discerning whether a leaf is simple or compound and if compound the segmentation to individual leaflets would occur.

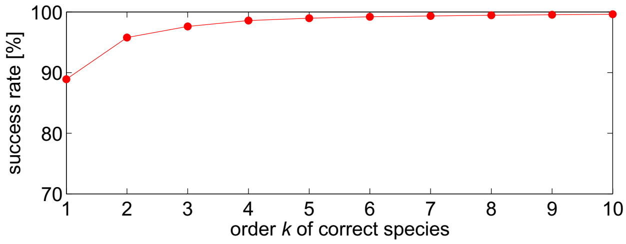

Fig. 6 – The success rates, when the first k species are considered. k is on horizontal axis.

At the moment, a leaf cannot be segmented without the white background at this time, we would like to develop some method of the leaf segmentation that does not require a background.

Currently, only the contour of the leaf is used. In the future we would like to use information from the inner part of the leaf (texture), too. This will probably use grey level images only, colour provides primarily information about the season and the health status of the plant.

The query image currently needs to include the petiole. In the future it would be advantageous if images both with and without petioles were used. The present algorithms used for searching petioles are not sufficiently reliable.

The success rate may be increased by inserting additional features or by using an improved classifier. The main source of mistakes is leaves with plain contours or without any serrations. Perhaps simple geometric features such as eccentricity could help.

The evaluation of results appears simple at first glance; comparison of success rates appears sufficient. Upon closer examination, the success rates in tests on closed data sets strongly depend on the number of species and also on the ratio of test and training samples. The data sets with a lesser number of species have better success rates. In real-life applications, users send query images and the more species in the data set, the greater probability the query is of being among them. A greater number of species is then advantageous.

Conifers cannot be recognised by our algorithm. Fiel and Sablatnig (2010) experimented with images of needles. They found very detailed images in high resolution were necessary for recognition of such different species as spruce (*Picea abies*) and fir (*Abies alba*).

10. Conclusions

A system for the recognition of woody species according to images of their leaves is proposed. Fourier descriptors computed from boundaries of binary images are used. The system is accompanied by a data set focused on Central European species of woods. A web application has been created that compares query leaf images with the data set. Currently, the leaf images must have a white background. The success rates found during testing were promising, thus it could become a part of determination keys.

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REFERENCES

Chen, Y., Lin, P., & He, Y. (2011). Velocity representation method for description of contour shape and the classification of weed leaf images. *Biosystems Engineering, 109*, 186–195.

Cope, J. S., & Remagnino, P. (2012a). Classifying plant leaves from their margins using dynamic time warping. In J. Blanc-Talon, W. Philips, D. Popescu, P. Scheunders, & P. Zemčík (Eds.), *Advanced concepts for intelligent vision systems ACIVS'12* (pp. 258–267). Springer volume LNCS 7517.

Cope, J. S., & Remagnino, P. (2012b). Utilizing the Hungarian algorithm for improved classification of high-dimension probability density functions in an image recognition problem. In J. Blanc-Talon, W. Philips, D. Popescu, P. Scheunders, & P. Zemčík (Eds.), *Advanced concepts for intelligent vision systems ACIVS'12* (pp. 268–277). Springer volume LNCS 7517.

Corney, D. P., Clark, J. Y., Tang, H. L., & Wilkin, P. (2012). Automatic extraction of leaf characters from herbarium specimens. *Taxon: International Journal of Plant Taxonomy, Phylogeny and Evolution, 61*, 231–244.

Ellis, B., Daly, D. C., Hickey, L. J., Johnson, K. R., Mitchell, J. D., Wilf, P., et al. (2009). *Manual of leaf architecture*. New York: Cornell University Press.

Fiel, S., & Sablatnig, R. (2010). *Automated identification of tree species from images of the bark, leaves or needles*. Technical Report CVL-TR-3. Vienna University of Technology, Faculty of Informatics.

Flusser, J., Suk, T., & Zitová, B. (2009). *Moments and moment invariants in pattern recognition*. Chichester: Wiley.

Hu, R., Jia, W., Ling, H., & Huang, D. (2012). Multiscale distance matrix for fast plant leaf recognition. *IEEE Transactions on Image Processing, 21*, 4667–4672.

Jiming, L. (2012). A new plant leaf classification method based on neighborhood rough set. *Advances in Information Sciences and Service Sciences, 4*, 116–123.

Kadir, A., Nugroho, L. E., Susanto, A., & Santosa, P. I. (2011a). A comparative experiment of several shape methods in recognizing plants. *International Journal of Computer Science and Information Technology, 3*, 256–263.

Kadir, A., Nugroho, L. E., Susanto, A., & Santosa, P. I. (2011b). Foliage plant retrieval using polar Fourier transform, color moments and vein features. *Signal & Image Processing: An International Journal, 2*, 1–13.

Kadir, A., Nugroho, L. E., Susanto, A., & Santosa, P. I. (2011c). Neural network application on foliage plant identification. *International Journal of Computer Applications, 29*, 15–22.

Kadir, A., Nugroho, L. E., Susanto, A., & Santosa, P. I. (2012a). Experiments of distance measurements in a foliage plant retrieval system. *International Journal of Signal Processing, Image Processing and Pattern Recognition, 5*, 256–263.

Kadir, A., Nugroho, L. E., Susanto, A., & Santosa, P. I. (2012b). Performance improvement of leaf identification system using principal component analysis. *International Journal of Advanced Science and Technology, 44*, 113–124.

Kaur, G., & Kaur, G. (2012). Classification of biological species based on leaf architecture. *International Journal of Engineering Research and Development, 1*, 35–42.

Kumar, N., Belhumeur, P. N., Biswas, A., Jacobs, D. W., Kress, W. J., Lopez, I., et al. (2012). Leafsnap: a computer vision system for automatic plant species identification. In A. W. Fitzgibbon,

S. Lazebnik, P. Perona, Y. Sato, & C. Schmid (Eds.), *The 12th European conference on computer vision ECCV'12, Part II* (pp. 502–516). Springer volume LNCS 7573.
Lin, C. C., & Chellapa, R. (1987). Classification of partial 2-D shapes using Fourier descriptors. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 9*, 686–690.
Nanni, L., Brahnam, S., & Lumini, A. (2012). Local phase quantization descriptor for improving shape retrieval/classification. *Pattern Recognition Letters, 33*, 2254–2260.
Neto, J. C., Meyer, G. E., Jones, D. D., & Samal, A. K. (2006). Plant species identification using Elliptic Fourier leaf shape analysis. *Computers and Electronics in Agriculture, 50*, 121–134.
Otsu, N. (1979). A threshold selection method from gray-level histograms. *IEEE Transactions on Systems, Man, and Cybernetics, 9*, 62–66.
Pattanasethanon, P., & Attachoo, B. (2012). Thai botanical herbs and its characteristics: using artificial neural network. *African Journal of Agricultural Research, 7*, 344–351.
Pauwels, E. J., de Zeeuw, P. M., & Ranguelova, E. B. (2009). Computer-assisted tree taxonomy by automated image recognition. *Engineering Applications of Artificial Intelligence, 22*, 26–31.
Ren, X.-M., Wang, X.-F., & Zhao, Y. (2012). An efficient multi-scale overlapped block LBP approach for leaf image recognition. In R. Goebel, Y. Tanaka, & W. Wahlster (Eds.), *Proceedings of the 8th international conference on intelligent computing theories and applications ICIC'12* (pp. 237–243). Springer volume LNAI 7390.
Rogers, D. J., & Tanimoto, T. T. (1960). A computer program for classifying plants. *Science, 132*, 1115–1118.
Shabanzade, M., Zahedi, M., & Aghvami, S. A. (2011). Combination of local descriptors and global features for leaf recognition. *Signal & Image Processing: An International Journal, 2*, 23–31.
Singh, K., Gupta, I., & Gupta, S. (2010). SVM-BDT PNN and Fourier moment technique for classification of leaf shape. *International Journal of Signal Processing, Image Processing and Pattern Recognition, 3*, 186–195.
Söderkvist, O. J. O. (2001). *Computer vision classification of leaves from Swedish trees*. Master's thesis. Linköping University.
Sumathi, C. S., & Kumar, A. V. S. (2012). Edge and texture fusion for plant leaf classification. *International Journal of Computer Science and Telecommunications, 3*, 6–9.
Wang, X.-F., Huang, D.-S., Xu, J.-X. D. H., & Heutte, L. (2008). Classification of plant leaf images with complicated background. *Applied Mathematics and Computation, 205*, 916–926.
Wu, S. G., Bao, F. S., Xu, E. Y., Wang, Y.-X., Chang, Y.-F., & Xiang, Q.-L. (2007). A leaf recognition algorithm for plant classification using probabilistic neural network. In *7th international symposium on signal processing and information technology ISSPIT'07* (pp. 6). IEEE.
Xiao, X.-Y., Hu, R., Zhang, S.-W., & Wang, X.-F. (2010). HOG-based approach for leaf classification. In D.-S. Huang, M. McGinnity, L. Heutte, & X.-P. Zhang (Eds.), *Proceedings of the advanced intelligent computing theories and applications, and 6th international conference on intelligent computing ICIC'10* (pp. 149–155). Springer volume LNAI 6216.
Yahiaoui, I., Mzoughi, O., & Boujemaa, N. (2012). Leaf shape descriptor for tree species identification. In *International conference on multimedia and expo ICME'12* (pp. 254–259). IEEE.
Yang, B., & Dai, M. (2011). Image analysis by Gaussian–Hermite moments. *Signal Processing, 91*, 2290–2303.
Yang, L.-W., & Wang, X.-F. (2012). Leaf image recognition using Fourier transform based on ordered sequence. In R. Goebel, Y. Tanaka, & W. Wahlster (Eds.), *Proceedings of the 8th international conference on intelligent computing theories and applications ICIC'12* (pp. 393–400). Springer volume LNAI 7390.
Zhang, S., & Lei, Y.-K. (2011). Modified locally linear discriminant embedding for plant leaf recognition. *Neurocomputing, 74*, 2284–2290.
Zhang, S.-W., Zhao, M.-R., & Wang, X.-F. (2011). Plant classification based on multilinear independent component analysis. In D.-S. Huang, Y. Gan, P. Gupta, & M. M. Gromiha (Eds.), *Advanced intelligent computing theories and applications. With aspects of artificial intelligence. Proceedings of the 7th international conference on intelligent computing ICIC'11* (pp. 484–490). Springer volume LNAI 6839.
Zhi, Z.-D., Hu, R.-X., & Wang, X.-F. (2012). A new weighted ARC-SC approach for leaf image recognition. In R. Goebel, Y. Tanaka, & W. Wahlster (Eds.), *Proceedings of the 8th international conference on intelligent computing theories and applications ICIC'12* (pp. 503–509). Springer volume LNAI 7390.

WEB REFERENCES

Flavia. (2009). *Flavia at a glance*. http://flavia.sourceforge.net/.
ICL. (2010). *Homepage: Intelligent Computing Laboratory, Chinese Academy of Sciences*. http://www.intelengine.cn/English/dataset/index.html.
ImageCLEF. (2011). *Image retrieval in CLEF*. http://www.imageclef.org/.
ImageMagick Studio LLC. (2013). *Image Magick*. http://www.imagemagick.org/script/index.php.
MEW2012. (2012). *Download middle European woods*. http://zoi.utia.cas.cz/node/662.
MEWProjectSite. (2012). *Recognition of woods by shape of the leaf*. http://leaves.utia.cas.cz/index?lang=en.
OpenCV library. (2013). *Opencv (open source computer vision library)*. http://opencv.org.
Sweden. (2012). *Sweden*. http://www.isy.liu.se/cvl/ImageDB/public/blad/.