International Journal of Computing Academic Research (IJCAR)
ISSN 2305-9184, Volume 6, Number 5 (October 2017), pp.136-144

http://www.meacse.org/ijcar

Determination of Leaf Type by Image Processing Techniques

Emre AVUÇLU[1] and Abdullah ELEN[2]

[1]Department of Computer Technology and Computer Programming,
Aksaray University, Aksaray/TURKEY
[2]Karabuk University, Department of Computer Technology and Computer Programming,
Karabuk/TURKEY

Abstract

There have been many studies in various fields such as engineering, medicine, military applications, geographical applications, space studies with image processing methods. In this study, by applying image processing techniques of digitized leaf images, leaf type was determined according to morphological characteristics. The average of each leaf area is taken in itself. Mean area-based leaf type detection was developed in the C # application environment. In the study, 90 leaf types were determined and a total of 795 leaf images were studied.After the application, 85% recognition was done in 25 leaf types. Recognition of 100% in 65 leaf types was performed. The other findings obtained are presented in the conclusions.

Keywords: Image processing, Leaf type determination, Areacalculate.

1. Introduction

Every image transferred to electronic medium is actually a 2 dimensional matrix.Each element of this two-dimensional matrix is the point that we will call it a point of view.When considered numerically, each element of a matrix that forms a digital picture is actually the numerical value that will enable the color to be formed in that pixel.The values of these numeric values are relevant to the type of image.If the image is a color image, there is a numerical value that contains the RGB (Red-Green-Blue) color corresponding to each pixel.For the simplest color scheme (8 bits), each of these numbers is in the range 0-255.If the picture consists of black and white and the gray shades between them, each pixel consists of decimal numbers from 0 to 1.If the picture consists of just black and white, the value of each black dot is 0, and the value of each white dot is 1.Such pictures are called binary pictures.In many image processing applications, image files are converted to binary (binary) mode [1].Image classification (GI) and product classification are used for classification both in terms of size and quality.An example of classifying in terms of quality is Karhan and his colleagues [2].In this study, it was tried to determine the stains that are formed as a result of leaf-penetrating disease in apricots.Mathematical morphology and morphological image processing technique were used in the study.

As a result of image processing based on the retrieval and manipulation of input images with different techniques, either a new image is obtained or a meaningful result is obtained from the image.

Another study on the classification of agricultural products by GI was carried out by Bul and colleagues [3]. In this study, bean grains were used as data set. In this study, the image of each bean was taken with a digital camera and transferred to the computer system in the size of 302x200 * .jpeg format and processed with MATLAB with GI technique.In this study, while the length and length of the bean grains were determined, a classification was made for the beans as good and bad quality using Artificial Neural Networks method.In another study done by Sabancı and his colleagues, it was aimed to classify the potatoes with the help of image processing techniques and artificial neural network.Prior to classification, potatoes with external surface and deformity were identified using Otsu method and morphological processes and were excluded from classification.Later, the classification of smooth potatoes as size was carried out [4].Different studies on image processing and classification have been done [5-8].

In the literature, artificial neural networks were used in general.In this study, the classification process was carried out with a different thought. With the application, the process of determining the class of 90 leaf species was determined with high success rate.In this study, leaf type was determined using image processing techniques. Image types are found according to the areas of the leaf species.

2. Materials And Methods

2.1.Image processing

Image processing is an expression involving all the operations performed by a computer on any image file recorded in electronic media.Operations on image files can also change properties such as light, color, contrast, sharpness or sharpness in the image; It can also be a noise, roughness or disorder in the picture.Image processing techniques are used in many areas:

- Medicine and biology (biomedical images),
- Geosciences (cartography and meteorology),
- Restoration in Visual Arts (repair of damaged images),
- Space science,
- The defense industry (night vision, unmanned aerial vehicles, intelligent rocket systems)
- Industrial applications (product inspection, classification)
- Safety systems (iris and fingerprint recognition, plate reading)
- Agricultural applications (herd management, product quality determination and classification) [9].

This database called MEW (Middle European Woods) was originally with name LEAF created for experiments with recognition of wood species based on a leaf shape (see Recognition of woods by shape of the leaf). It contains leaves of wood species growing in the Czech Republic, both trees and bushes; native, invasive and imported (only those imported species which are common in parks are included). The leaves were scanned with 300 dpi, thresholded (binarized) , preprocessed (denoising and cleaning) and saved in PNG format. The name of each file includes the latin name of the species and the label of the sample [10].

Erosion is often used to separate two or more objects connected to each other with a subtle noise [11].In image processing, they are often used as pre- or post-processing, such as morphological filtering, thinning, pruning [12].

In this study, 795 leaf images taken from site [10] were studied.A portion of the database image containing the images used is shown in Fig.1 below.

Fig. 1:A partial view of the database

As shown in Fig. 2 a below, the color image is first converted to gray scale.Fig. 2 b shows a gray scale converted image.

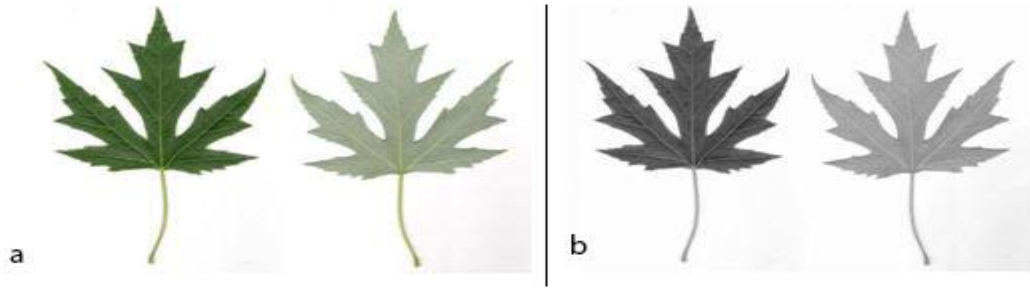

Fig. 2: Colored leaf image

Then the binary form is transformed into different methods.These methods have developed new methods to determine the best of each leaf type.Fig. 3 a and b below show binary forms of different leaf species.

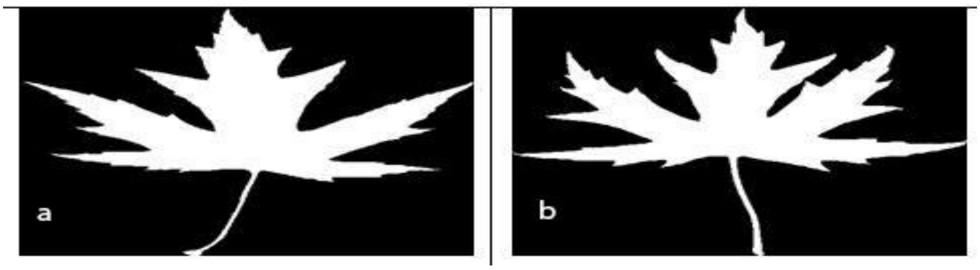

Fig. 3: Binary leaf image (rooted)

In Fig. 4 a and b below, the stemless leaf images are shown.There is no need to take any action to separate these leaves from their stems.The area in which the leaf area is located is sufficient to identify such leaves.

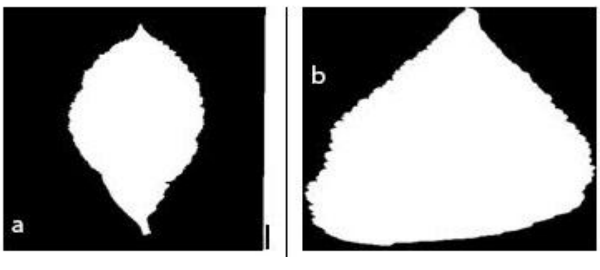

Fig. 4: Binary leaf image (without root)

In Fig. 5 a and b below, rooted leaf images are shown.

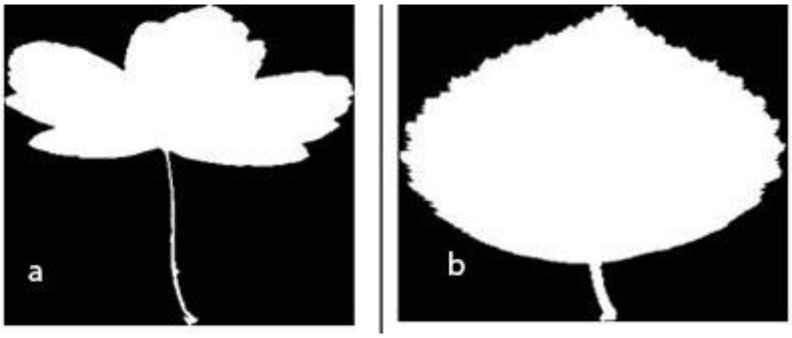

Fig. 5: Different rooted leaf images

The leaf image is scanned horizontally (line by line). The number of white pixels on each line is summed.Thus, a one-dimensional image sequence is obtained according to the horizontal axis.In order to separate these leaves from their stems, a red lane method was used in Fig. 6 below.This method determines the roots of any leaf-rooted root.After the determination, the root zone is cropped and only the stem remains on the leaf.This prevents unnecessary area scanning. The foliage part of the fence is sufficient to determine its own course.

2.2. Leaf Root Determination

To determine the root of the leaf, the red stripe shown in Fig. 6 below scans all pixelles starting at point 0,0 in the upper left corner on the x and y axes.The first scan is scanned from point 0,0 to point x 0. X is the last pixel here.Then a pixel 0,1 is pivoted and the second pixel is scanned.Then the pixel (0,2), (0,3), (0,4) … (0, y) is scanned to the point (x, y).Thus, all the pixellas on the PictureBox are scanned.

In Fig. 6 below, during the scanning of the indicative pixels, 1 white region is detected on the red line numbered 1.There are four different white areas with red lane number two. There are 3 different zones of red ribbon 3.There are one white zone in the strips numbered 4, 5, and 6. Since there are no different numbers of white regions after these lines, the last numbered red banner with the white region identified is located at the beginning of the root.This is the first lane after the red strip that is outside the detected area, the first spot where the root begins.

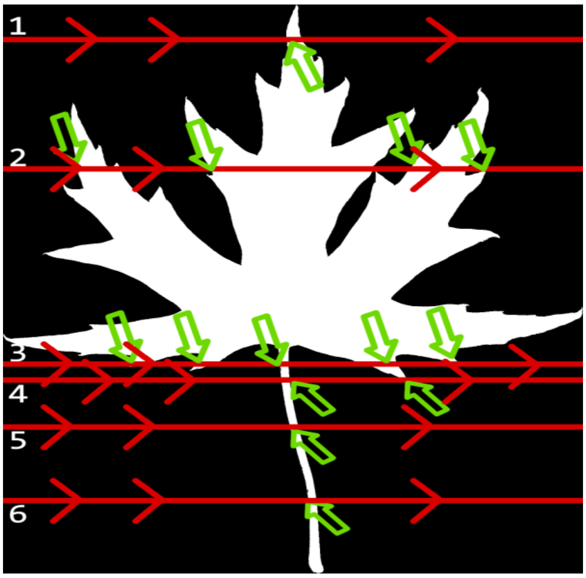

Fig. 6: Root detection

After this point, the leaf is trimmed because the body part is finished, and the following is as shown in Fig. 7. After this screening, the roots of the leaf were identified.

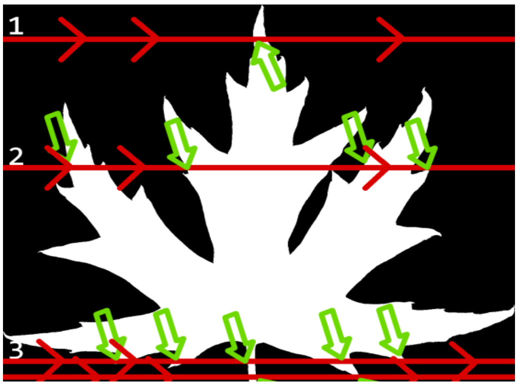

Fig. 7: Root-clipped leaf

In Fig. 8 below, one white zone is detected in all the red strips, so it can be seen that there are no roots of these and similar leaf species.The trimming of the roots of these leaf species is not performed.

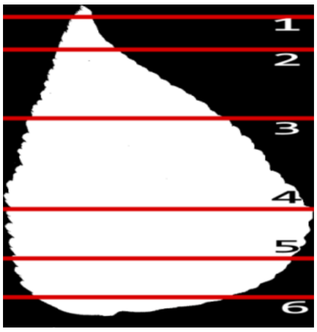

Fig. 8: Rootless leaf

The flow diagram of the implemented application is shown in Fig. 9 below.

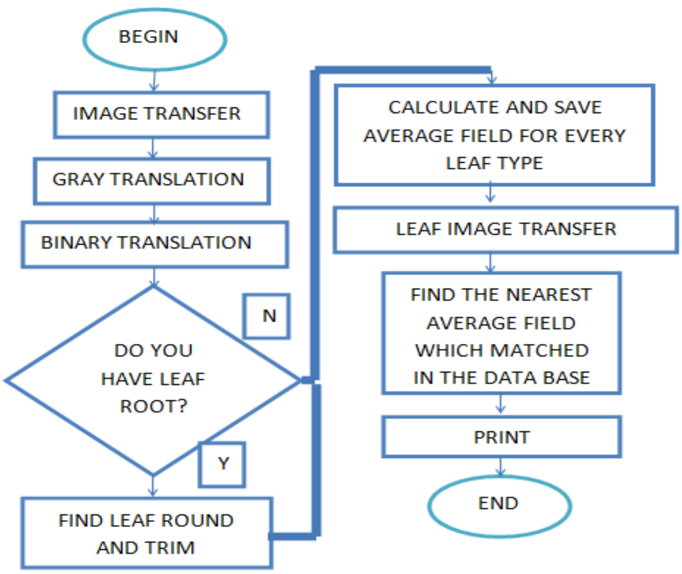

Fig.9: Flow Diagram of the Application

3. Conclusions

Some of the values obtained from the developed application and leaf species are given in Table 1 below.When the actual area is calculated, the number of white pixels in which the leaf is found is taken.The number of leaf species in the database and the results of the experimental results obtained are given in Table 1 below. The leaf to be detected is determined according to the leaf type closest to itself.

Table 1. Experimental data and results

Leaf Species	Piece	Test Piece	Average Area Value (Pixels)	Correct Detection Rate
Acer campestre	3	1	872303	%100
Acer ginnala	7	3	518815	%100
Acer negundo	4	2	348792	%85
Acer platanoides	3	1	1347078	%100
Acer pseudoplatanus	7	3	1669685	%100
Acer saccharinum	7	3	713670	%85
Acer tataricum	8	3	299406	%100
Aesculus carnea	13	5	2073343	%100
Aesculus hippocastanum	12	5	591047	%100
Ailanthus altissima	5	2	1611411	%100
Alnus glutinosa	3	1	615941	%100
Alnus orientalis	17	5	305804	%85
Amorpha fruticosa	7	3	90270	%100
Aronia melanocarpa	6	3	405207	%85
Berberis vulgaris	7	3	67275	%100
Betula pendula	3	1	113916	%100
Betula pubescens	5	2	124164	%100
Carpinus betulus	23	8	408931	%85
Castanea sativa	7	3	3019414	%100
Catalpa bignonioides	7	3	2451920	%100
Celtis occidentalis	10	4	402278	%85
Cercidiphyllum japonicum	15	5	458009	%100
Colutea arborescens	14	5	81781	%100
Cornus mas	5	2	282489	%100
Corylus avellana	18	6	1710355	%100
Corylus colurna	14	5	1434080	%85
Corylus maxima	6	2	777796	%85
Cotinus coggygria	13	4	625257	%100
Cydonia oblonga	3	1	513721	%100
Elaeagnus angustifolia	7	2	128308	%100
Fagus sylvatica	23	8	756926	%85
Fallopia aubertii	4	2	117017	%100
Forsythia intermedia	10	3	153656	%100
Frangula alnus	6	2	174513	%100
Fraxinus ornus	5	2	243356	%85
Ginkgo biloba	7	2	376651	%100
Hamamelis japonica	9	3	613420	%100
Hamamelis virginiana	5	2	473233	%85
Hedera helix	7	2	635256	%100
Hydrangea petiolaris	4	1	1084909	%85
Ilex aquifolium	22	8	100158	%85
Juglans nigra	25	9	473861	%85
Juglans regia	6	2	759195	%85
Koelreuteria paniculata	6	2	386761	%100
Ligustrum ovalifolium	8	3	195960	%100
Liquidambar styraciflua	19	6	1436461	%85
Liriodendron tulipifera	15	5	1555055	%100

Magnolia hypoleuca	5	2	4737350	%100
Magnolia soulangeana	15	7	1214853	%85
Mahonia aquifolium	9	3	271174	%100
Mespilus germanica	8	2	655935	%100
Morus alba	3	1	474925	%85
Parthenocissus inserta	7	2	474925	%85
Parthenocissus tricuspidata	5	1	1563806	%100
Paulownia tomentosa	17	5	2314471	%100
Phellodendron amurense	7	2	607859	%100
Platanus hybrida	4	1	2035434	%100
Populus alba	20	8	576587	%100
Populus nigra	3	1	490805	%100
Populus nigra Itallica	5	1	367653	%100
Populus tremula	7	2	556393	%100
Prunus armeniaca	2	1	343758	%85
Prunus mahaleb	8	3	244967	%85
Prunus spinosa	10	3	162501	%100
Pyracantha coccinea	19	5	105546	%85
Quercus cerris	8	2	718940	%85
Quercus frainetto	20	8	771359	%85
Quercus petraea	8	2	893412	%100
Quercus robur	19	9	827022	%100
Quercus rubra	5	2	1163310	%100
Ribes alpinum	6	2	62773	%100
Robinia pseudacacia	5	2	195878	%100
Salix alba Pendula	17	5	37019	%100
Sambucus nigra	4	1	420361	%100
Sophora japonica	5	2	158094	%100
Sorbus aria	7	2	640938	%100
Sorbus domestica	10	3	138560	%100
Sorbus intermedia	7	2	660145	%100
Symphoricarpos albus	7	2	183652	%100
Syringa josikaea	7	2	449177	%100
Syringa vulgaris	3	1	411955	%100
Tilia cordata	4	1	215070	%100
Tilia platyphyllos	6	1	982624	%100
Ulmus glabra	7	2	353658	%100
Ulmus laevis	9	2	1217206	%85
Ulmus minor	9	2	304682	%85
Ulmus pumila	9	2	147381	%100
Vinca minor	8	2	125644	%100
Vitis riparia	8	2	1055189	%100
Vitis vinifera	3	1	2737619	%100

The Salix alba Pendula was formed with the smallest area required for the leaf type structure and formed on an average of 37019 pixels Fig. 10(a).Magnolia hypoleuca has the largest area of leaf-like structure, with a mean of 4737350 pixels Fig. 10 (b).

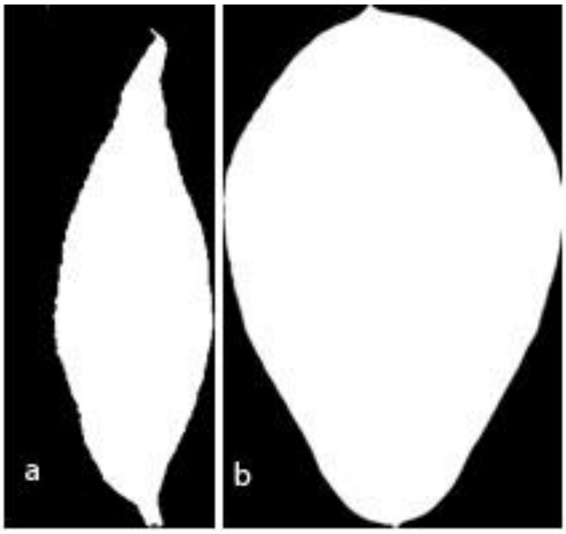

Fig.10: Leaves with the most and least average area

Table 1 above shows that the values of the leaf area of the detection rate are very close to each other.The areas of the following leaf types are very close together.Because of this, the correct detection rate has been reduced in these leaf types during the test phase.These leaves;

Ilex aquifolium andPyracantha coccinea,
Fraxinus ornus and Prunus mahaleb,
Ulmus minor and Alnus orientalis,
Prunus armeniaca and Acer negundo,
Celtis occidentalis, Aronia melanocarpa andCarpinus betulus,
Hamamelis virginiana, Juglans nigra, Morus albaand Parthenocissus inserta,
Acer saccharinumandQuercus cerris,
Fagus sylvaticaand Juglans regia,
Quercus frainettoand Corylus maxima,
Magnolia soulangeanaand Ulmus laevis,
Corylus colurnaand Liquidambar styraciflua,
Leaf types.

In this study, instead of artificial intelligence in the literature or classifying by machine learning techniques, which is new in the literature, it was tried to determine leaf type with a different thought.The average area of all of the leaves belonging to their class was taken.These mean values were determined by comparison with the externally entered leaf image795 leaf images were worked on.Determination for 90 leaf types was performed.With the application, 85% recognition was performed on 25 leaves.Recognition of 100% in 65 leaf types was performed.

References

[1] Balcı M., Altun A., Taşdemir Ş., "Görüntü İşleme Teknikleri kullanılarak Napolyon Tipi Kirazların Sınıflandırılması", Journal Of Selcuk-Technic , vol. 15, no. 3,2016.

[2] Karhan M, Oktay M. O., Karhan Z., Demir H., Morfolojik Görüntü İşlemeYöntemleri ile Kayısılarda Yaprak Delen (Çil) Hastalığı Sonucu Oluşan LekelerinTespiti, 6 th International Advanced Technologies Symposium (IATS'11), Elazığ,Türkiye,2011, pp. 172-176.

[3] Bul E., Gelen G., Altun H., Görüntü İşlemeye Dayalı Tarımsal Ürün Sınıflandırma,Accessed on: May. 20, 2017, [Online] Available:http://www.emo.org.tr/ekler/3287fcce194dbd9_ek.

[4] Sabancı K., Aydın C., Ünlerşen M.F., "Görüntü İşleme ve Yapay Sinir AğlarıYardımıyla Patates Sınıflandırma", Parametrelerinin Belirlenmesi, Iğdır Üniversitesi FenBilimleri Enstitüsü Dergisi, vol. 2, no. 2, pp. 59-62, 2012.
[5] Avuçlu E., Başçiftçi F.,"Face to Recognize and Position Reporting System Design", Journal of Selçuk University Natural and Applied Science, vol. 4, no.2, pp.1-10, May. 2015.
[6] Turan MK.,Elen A.,Şehirli E., "Analysis Of Dna Gel Electrophoresis Images With Backpropagation Neural Network Based Canny Edge Detection Algorithm", Yayın Yeri:International Journal Of Scientific And Technological Research, vol.2, no. 2,pp. 55-63, 2016.
[7] Avuçlu E., Altun A., Elen A., "Real Time Pca Based Face Recognition For Following Staff", Yayın Yeri:Journal Of Selcuk-Technic , vol. 16, no.1,2017.
[8] Avuçlu E., Başçiftçi F.,"The Missing Persons Finding Sensitive To Movements With Image Recognition System And Numeric Data People Of Loss In Turkey". The Online Journal Of Science And Technology , vol. 6, no. 2,2016.
[9] Öztaş O., Görüntü İşleme Teknikleri-1, İstanbul Üniversitesi Mühendislik FakültesiBilgisayar Mühendisliği Bölümü, Accessed on: May. 14, 2017, [Online] Available:http://www.oguzhanoztas.com/gi/ders1.pdf
[10] Tree Leaf Database MEW2010, Accessed on: Feb. 28, 2017, [Online] Available: http://zoi.utia.cas.cz/tree_leaves
[11]Abacı B., Morfolojik Görüntü İşleme,Accessed on: Jun. 01, 2017, [Online] Available:http://www.cescript.com/2012/08/morfolojikgoruntu-isleme.html
[12] Gonzalez R. C., Woods R. E., Eddins S. L., Digital Image Processing UsingMatlab, Gatesmark Publishing, 2009.