Proceedings of the International Conference on Machine Vision and Machine Learning
Prague, Czech Republic, August 14-15, 2014
Paper No. 130

Classification of Fungus Spore Images Using Ridgelet Transform and ANN

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Abstract **-** In this study, various fungi were classified by using microscope images of their spores. Ridgelet transform which is one of the new generation multi-resolution analysis techniques was used initially for classifying fungi by this study. Feature extraction was implemented on microscope images by using Ridgelet transform and they were classified utilizing artificial neural network (ANN). A database containing 250 fungus microscope images (50 images of each genus: *Diatrype, Lactarius, Chroogomphus, Discina* and *Galerina*) was generated. Two of five genuses were chosen for each classification process. Accuracy rate of some applications reached 96%.

Keywords**:** Fungus images, Classification, Artificial neural network, ridgelet transform.

1. Introduction

Fungi are classified as analyzing morphologic and microscopic characters by specialist biologists. However, it is necessary to investigate various characteristics in micro and macro level like shape, color and size to count a fungus in a group. This method is seriously time-consuming. Considering this situation, mathematical methods which could achieve classification of fungi were proposed.

El-Shakawy et. al (2004), classified 3000 fungus samples with accuracy of 98,6% as edible / poisonous in their study which they compared performances of decision tree and neural network by using character descriptions. Matti (2010), also achieved a mobile application for deciding whether fungi were edible / poisonous. Pujari et. al (2014), studied on diagnosing fungus disease on plants by using wavelet feature extraction and principal component analysis.

In this study, Ridgelet based feature extraction was applied on fungus images. Ridgelets were proposed by Candes (1998). Discrete form of it was developed by Carre et. al (2004) and applied on 2D datas. Ridgelet transform was effectively used for image analyses (Chen et al., 2007). Wrap-around effect was restricted the denoising performance of Ridgelet transform and Wang (2010), tried to eliminate it in his study.

In this paper, fungus spore images from the same and different phylums were classified by taking advantages of Ridgelet transform and ANNs. The applications had completely taxonomic purposes, they were not actualized to identify the images as diseased / poisinous. The goal of the study was decreasing the workload of biologysts.

Features of used data were mentioned in Section 2 and used methods were elaborated in Section 3. In Section 4, experiments and results were detailed.

2. Used Data

Fungus spore images, used for carrying out the applications, were taken from Selcuk University Mushroom Application and Research Center. The images were obtained by examining the fungus samples microscopically and saving them into computers in JPEG format. Images of fungus spores were arranged as containing just one spore and image sizes fixed (256x256). Place of used fungus samples in fungi kingdom were given in Table 1.

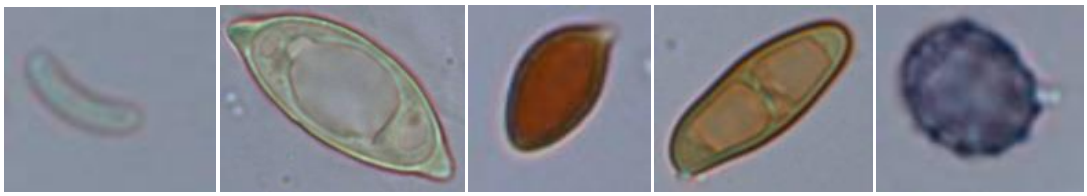
Table 1. Place of used fungus samples, in fungi kingdom

Kingdom	Phylum	Subphylum	Class	Order	Family	Genus	Species
Fungi	Ascomycota	Pezizomycotina	Sordariomycetes	Xylariales	Diatrypaceae	Diatrype	Diatrype disciformis
			Pezizomycetes	Pezizales	Discinaceae	Discina	Discina perlata
	Basidiomycota	Agaricomycotina	Agaricomycetes	Agaricales	Cortinariaceae	Galerina	Galerina marginata
				Boletales	Gomphidiaceae	Chroogomphus	Chroogomphus rutilus
				Russulales	Russulaceae	Lactarius	Lactarius deliciosus

Various characteristics like spore shape and habitat, should be analyzed together for fungus classification. In Table 2, habitats, macroscopic and microscopic features of fungi which were used for experiments were given (Breitenbach et. al, 1984-2005). In Fig. 1, spore image samples of related fungi were presented.

Table 2. Characteristics of used fungus samples

	Sample				
Feature	Diatrype disciformis	Discina perlata	Galerina marginata	Chroogomphus rutilus	Lactarius deliciosus
Habitat	On died branches of Fagus (beech), rarely on other broadleaved trees. Winter-spring. Common.	On rotting wood. Especially conifer stumps. April - June.	Usually gregarious to clustered on dead conifer wood such as stumps, branches, roots, wood chips, etc. Summer-fall. Common.	In coniferous forests. Summer-fall. Widespread.	Usually gregarious near *Pinus* and *Juniperus communis* on dry to damp, alkaline to acidic soils. Late summer-fall. Widespread but not common.
Macroscopic Features	Perithecia black, 0.2-0.4 mm, embedded in one or two layers in a superficially brown-black stroma which is whitish within. The cushionlike stroma, which is flat above and usually circular, emerges from the bark and can be solitary or a few can grow together. The surface is slightly rough and distinctly dotted with the perithecial ostioles.	Fruiting body 30-150 mm. Its shape is as a cup when young, then expanded. strongly deformed, with sinuous margin. Color is red-brown to chestnut- brown. Outer surface withish to ochre. Stalk 10-30 mm long. Flesh odorless.	Pileus 1 5 -25 (40) mm across, hemispherical when young, later convex to plane, in the center with umbo, surface smooth, reddish to ocher-brown when moist. Stipe cylindrical, solid when young, hollow when old, 30-50 (75) X 1.5-6 mm. Lamellae light ocher when young, later reddish- brown. Flesh light ocher to brown, thin, odor and taste farinaceous.	Pileus 40-80 (100)mm, conic to hemispherical when young, later turbinate and plane, surface smooth, gray- to ocher-brown with a copper-red tint, margin acute. Stipe 50-120 X 6-17 mm, clindrical, surface mottled to banded with fibrils, sometimes wine-reddish toward apex. Lamellae broad, olive-ocherish when young, gray-black-olive when mature. Flesh thick, odorless, taste mild, nutty, orange-ocher to salmon-colored, turning violet when chewed.	Pleus 40-80 (100) mm across, planoconvex when young, later expanded and infundibuliform, surface somewhat uneven, spotted and sometimes zoned with deep orange to brown-orange on a cream to light ocher-orange background. Stipe 30-50 (60) X 12-25 mm, cylindrical, solid only when young, soon hollow, surface orange-guttate on a whitish to light orange background, apex whitish. Lamellae cream-orange when young, later orange. Flesh whitish, odor weak and pleasantly spicy with a fruity component, taste mild, herbaceous.
Microscopic Features	Spores smooth, slightly brownish, allantoid, 6-9 X 1.5-2 µm. Ascus eight spored, spores irregularly. Paraphyses not seen.	Spores elliptical, 23-30 X 12-14 µm, hyaline, when mature reticulate and with 3 oil drops and a pointed hyaline appendage of 3-6 µm on each end. Ascus eight spored, 300-360 X 15-17 µm. Paraphyses slightly clavate, cylindrical, with septa.	Spores ocher, elliptical to ovoid, moderately verrucose, 7- 11 X 4.5-6.5 µm. Basidia clavate to cylindrical, with 4 sterigmata and a basal clamp. Cheliocystidia and pleurocystidia similiar, lageniform to fusiform.	Spores smooth, brown-yellow, fusiform-elliptic, 15-20 X 6-7.5 µm. Basidia clavate, with 4 sterigmata, without basal clamp. Cheliocystidia and pleurocystidia clindric, in part incrusted with abrownish amorphous substance.	Spores elliptical, 7-9 X 5.5-7 µm, ornaments projecting up to 0.5 µm. Basidia clavate, with 4 sterigmata. Cheliocystidia present in two forms. Pleurocystidia fusiform to subulate.



a) b) c) d) e)

Fig. 1. Fungus spore image samples used for experiments: a) Diatrype disciformis, b) Discina perlata, c) Galerina marginata, d) Chroogomphus rutilus, e) Lactarius deliciosus.

Considering Fig. 1, it is seen that these spores could be classified visually. However, the aim of the study was not to carry out a process that could not be done visually, via computer. Our purpose was taking human factor away from fungus classification and building up a system which could classify fungi automatically.

3. Methods

Fungus spore images were pre-treated as mentioned in Section 2. A classification system had two steps (feature extraction and classification) were proposed. The system was realized in MATLAB. In feature extraction step, Ridgelet transform which is effectively used in image processing applications were utilized. In addition to that, five different statistical features (mean, standard deviation, skewness, kurtosis, moment) were calculated. In classification stage, ANN were employed. Ridgelet transform and statistical feature extraction calculations were explained in Section 3.1. The ANN model designed for this study was mentioned in Section 3.2. Performances of classification processes were analyzed by using different evaluation criteria.

3. 1. Feature Extraction Methods

Ridgelet transform and statistical feature extraction methods were given in two seperate sections.

3.1.1. Ridgelet Transform

During calculation of WT which is the basis of multi-resolution analyses, wavelet functions are used. Similarly, Ridgelet functions are used for calculating Ridgelet transform (RT). Ridgelets are obtained by Eq.1, where $\theta \in [0, 2\pi)$ is angle parameter, $s > 0$ is scale parameter, $p \in R$ is shift parameter and $\psi(.)$ states wavelet function:

$$\psi_{s,p,\theta} = s^{-1/2}.\psi((x_1.\cos\theta + x_2.\sin\theta - p)/s) \tag{1}$$

Ridgelets are constant along lines. So, $x_1.\cos\theta + x_2.\sin\theta$ =*constant* (Chen, 2007). Angle parameter in the formula provides to apply RT as multi-directional. RT of a bivariate function $f(x, y)$ is equal to multiple of Ridgelet function and $f(x, y)$:

$$R_f(s, p, \theta) = \int \psi_{s,p,\theta} f(x, y) dxdy \tag{2}$$

Radon transform of a bivariate function $f(x, y)$ is obtained with Eq.3, where δ is Dirac function. If Eq.1 and Eq.3 were evaluated together, it could be seen that RT was achieved by appliying 1D WT on Radon slices.

$$RA(\theta,t)=\int f(x,y)\delta(x.\cos\theta+y.\sin\theta-t)dxdy \tag{3}$$

It is possible to calculate RT with Fourier transform. This process is equal to apply 1D WT on Radon slices (Chen, 2007). If the following procedure is implemented on an image respectively, RT coefficients are obtained (Fig. 2): 1) Perform 2D fast Fourier transform. 2) Interpolate the result along straight lines. 3) Apply 1D inverse Fourier transform along interpolation ways. 4) Perform 1D WT on obtained result.

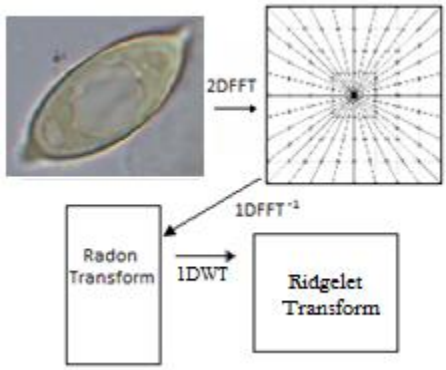


Fig. 2. Scheme of Ridgelet transform

3.1.2. Statistical Methods

Five different statistical methods were used for feature extraction. They were; mean, standard deviation, moment, skewness and kurtosis.

While x_n states a sequence of numbers and n denotes number of components, aritmetic mean is calculated as follows:

$$\overline{x}=\frac{1}{n}\sum_{i=1}^{n}x_i=\frac{x_1+x_2+\ldots+x_n}{n} \tag{4}$$

While $\overline{x}$ states mean value, standard deviation and k^{th} moment were given in Eq.5 and Eq.6 respectively.

$$\sigma=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i-\overline{x})^2} \tag{5}$$

$$m_k=E(x-\overline{x})^k \tag{6}$$

Skewness (Eq.7) and kurtosis (Eq.8) are statistical values of assymmetry nearby mean value.

$$s=\frac{E(x-\overline{x})^3}{\sigma^3} \tag{7}$$

$$k=\frac{E(x-\overline{x})^4}{\sigma^4} \tag{8}$$

3. 2. Classification Method (Artificial Neural Network)

Artificial neural network (ANN) was developed by modelling communication mechanism of human neural system cells. Reactions against to signals which come to sense organs are produced by a series of parallel transactions between neurons. Similarly, it is expected ANN to produce an answer to inputs. Targets are also submitted to the system with input values. Multiplying input values with weights, inputs are tried to approximate to the target values with lots of iterations. ANN has a three-layered (input layer, hidden layer, output layer) structure. Each layer has neurons. According to nature of the problem, ANN parameters are determined and systems are modelled. ANN structure was given in Fig. 3, simply.

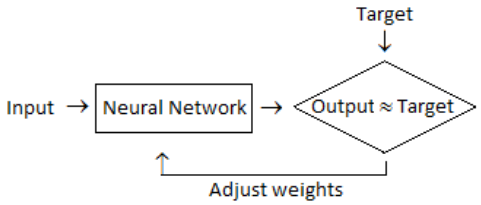


Fig. 3. A simple structure of artificial neural networks

3.3. Performance Evaluation Criteria

Five different performance criteria was calculated to evaluate performance of classification. These were: precision, sensitivity, specifity, accuracy and F_1 score. In Table 3, calculation of related criteria were given. In order to obtain these values, it is necessary to know true positive (TP), true negative (TN), false positive (FP) and false negative (FN) values. Among the fungus images of two classes used in classification, the ones included in first class and determined as in the first class correctly by ANN, gave TP value. Despite they were members of first class, number of the images incorrectly described as second class members by the ANN system were FN value. Similarly, number of correctly classified second class fungus images were TN and number of inaccurate classified second class fungus images were FP.

Table 3. Calculation of performance evaluation criteria

Precision	Sensitivity	Spesifity	Accuracy	F1 Score
$\frac{TP}{TP+FP}$	$\frac{TP}{TP+FN}$	$\frac{TN}{FP+TN}$	$\frac{TP+TN}{TP+FP+FN+TN}$	$\frac{2\times TP}{2\times TP+FP+FN}$

4. Experiments and Results

A system, could be used in taxonomic studies of specialist biologysts, for five different fungi were designed. 5 different species from 3 different classes of fungi were used. A database had 250 microscope images (50 spore images of each species) was generated. Classification procedure was repeated six times as using different species. Each classification process was used to seperate two species (Table 4). So, 100 spore images used for each classification process.

Firstly, RT was performed on spore images. Feature extraction was implemented to obtained transform coefficients with five different statistical methods (mean, standard deviation, moment, skewness, kurtosis). The feature vectors were given as inputs to ANN and classification results of ANN were evaluated. In order to analyze classification results, specifity, sensitivity, accuracy, precision and F_1-score values were calculated and given in Table 4. The scheme of designed system was given in Fig. 4.

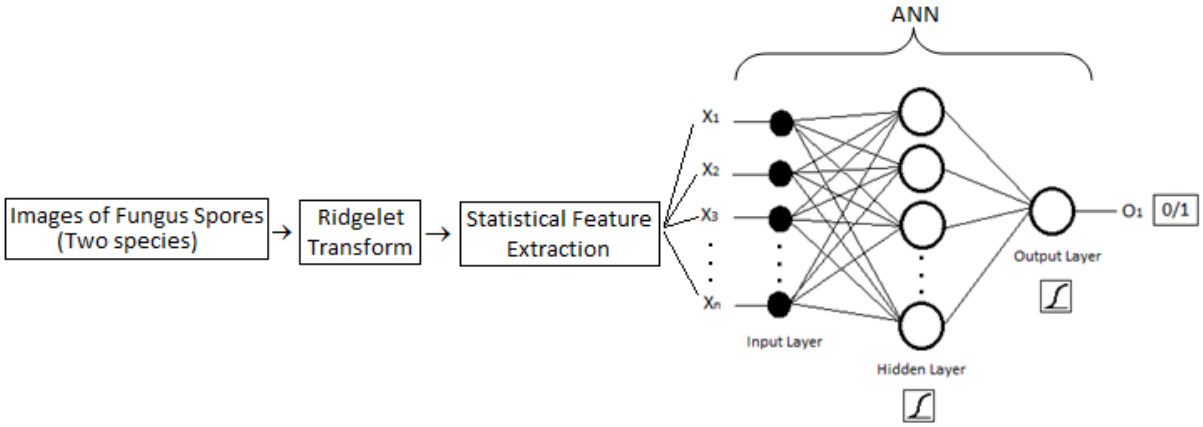


Fig. 4. Sheme of designed classification system.

Relevant epoch number was determined as 480 for first two classification processes in Table 4 and 70 for the others. Learning rate was 0.7 in all processes. 30 neurons were used in hidden layers and one neuron was used in output layers of ANNs. The results were achieved by using 2-fold cross validation and logarithmic sigmoid was used as activation functions of both hidden and output layers. The process time of each classification was enrolled and given in Table 5.

Table 4. Results of classification

Species	Precision	Sensitivity	Specifity	Accuracy	F_1-score
Diatrype disciformis - Discina perlata	70,90%	78%	68%	73%	0,7429
Galerina marginata - Diatrype disciformis	90,70%	76%	90%	83%	0,8172
Discina perlata - Lactarius deliciosus	94,23%	98%	94%	96%	0,96
Galerina marginata - Lactarius deliciosus	80,70%	92%	78%	85%	0,86
Chroogomphus rutilus - Lactarius deliciosus	92,60%	100%	92%	96%	0,9615
Diatrype disciformis - Lactarius deliciosus	90,74%	98%	90%	94%	0,9423

It was seen from Table 4 that accuracy rate reached %96 while classifying some species. It was really a high value for a classification process.

Table 5. Process time of classification

Species		Diatrype disciformis - Discina perlata	Galerina marginata - Diatrype disciformis	Discina perlata - Lactarius	Galerina marginata - Lactarius deliciosus	Chroogomphus rutilus - Lactarius deliciosus	Diatrype disciformis - Lactarius deliciosus
Process Time	in seconds	1967,4492	2015,2048	2007,087	2094,2635	1957,6164	1945,7548
	in minutes	32,79	33,58	33,45	34,9	32,62	32,42

5. Conclusions

This paper was a preliminary study which proved that fungus classification was possible as analyzing just microscopic spore images by intelligent systems. The fungi had more similar spore shapes could be classified by using more advanced systems with higher accuracy rates. In this study, common species in nature were chosen. Instead of very long time-consuming researches, a hundred of fungus samples correctly classified with high accuracy rates in approximately 30 minutes with this study.

The greater number of species with more similar spore shapes will be tried to be classified as future studies. Firstly, it would be studied in limited areas (only a city or a town). Thus, it could be enough that a specialist biologyst to test a microscopic spore image of fungi which found in related areas to define its species. Hours-long literature reviews would be unnecessary.

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