A Remote Mycological Assistant

Abstract

Inspired in the active field of content based image retrieval (CBIR), we propose the design of a remote system for assisting mycological amateurs to categorize the mushroom samples they find in the nature. The query to a remote database will be performed trhough a mobile phone with incorporated digital camera. The system is a blend of CBIR and rule based expert system. In its current state of development we have implemented a shape based CBIR system complemented by a rule based expert system that achieves a high success rate over a in-house collected image database. The paper also describes the global system architecture.

Keywords: Expert Systems, CBIR, Mycologic, Pattern Recognition, Remote Assistant, Distributed Systems

1 Introduction

New mobile phone generations have features that make them versatile multimedia terminals, that can be used in many different tasks and applications. The ability to generate and transmit multimedia infomation, both image and video, allows them to act as input point for applications such as multimedia database content based retrieval, more precisely content based image retrieval (CBIR) systems. This paper describes some aspects of a patent pending system that applies those innovative mobile phone features in a mycological context, providing a remote assistant for the average user. Mycology is a science that deals with mushrooms and fungi in general[3, 5, 4, 2, 9]. The research goal is a system that allows the onsite mushroom identification, on the picking place. A specific goal is to discriminate between edible and dangerous (venomous) species.

Mushrooms posses some visual identificative features that may help the consumer to distinguish between them: the hat shape, the skin texture, peel details, color and brightness, etc. Information about these features may be combined into some morphological analisis rules that may allow to identify it and decide about safe comsumption. Other identificative festures are not visual like smell, habitat, taste and hardness. The set of features needed for exhaustive classification of any mushroom specimen covers some 70 of them, but only 20 are needed to discriminate among the most common species. The system must take into account that the user may be unable to answer properly some questions posed by the system to perform the search for the correct species identification. For instance, the agreement about a color or other image features may be small, or their characterization subject to uncertainty. It is even possible that the user is unable to understand the question because he lacks the mycologycal knowledge. The basic approach taken to ease the user shortcomings is the use of images as queries to the database system. So the user asks the identification of the examplar sending the image of the sample mushroom. The identification problem is therfore partly a problem of content based image retrieval, because que we use a database of mushroom images to look for the most similar ones and to decide the sample mushroom classification.

Image indexing in the database of mushroom images is performed on the basis of 20 features that we extract from the images using computer vision algorithms. We have tested several classification approaches (K*, RIPPER, C4.5 y Naive Bayes). In some instances, the visual features are not discriminant enough to identify the sample mushroom specie. Ambiguity arises when several species have the same or similar prediction probability. In some instances, no one of the species exceeds the recognition threshold, so that no decision can be taken on its identity. To overcome this situation we employ an “ad hoc” expert system with rules tailored to ask the user for information that may lead to the resolution of each conflict situation.

Our previous work towards the definition of the system involves the construction of classification systems based on shape features [10]. There we extract the mushoom contour using active contour techinques (snakes) and we test several approaches to the extraction of shape features. Here se use more mycological oriented features based on expert knowledge, instead of the abstract general feature extraction algorithms tested in [10]. Besides we test other classification approaches.

The system architecture is described in the following sections. We have structured this description into four aspects:

- Hardware technolgies involved are described in section 2.
- Software architecture that realizes the information system is described in section 3.
- Visual feature extraction is described in section 4.
- The "ad hoc" expert system is described in section 5.
- The final section is devoted to conclusions and further work directions.

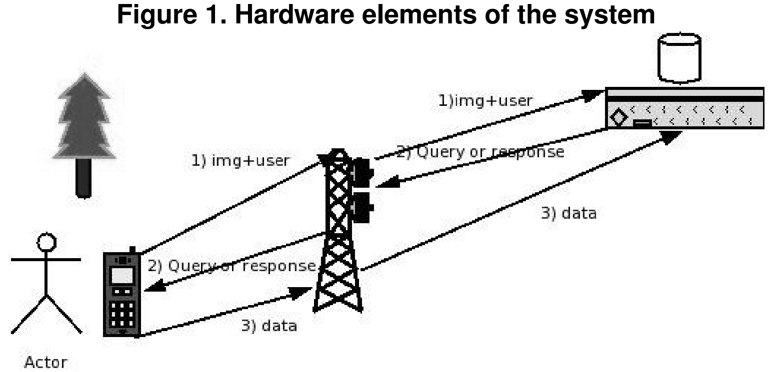
2 Hardware technologies

The essential hardware techonologies involved in the realization of the mycological assistant are:

1. A mobile communication device, a mobile phone, incorporating a digital camera, screen and the ability to establish communication with an internet server (WAV, GSM, UMTS...), and the ability to execute Java and XHTML.
2. A wireless communication network, allowing the connectivity of the user device over wide areas, including the wild areas where the mycological amateurs may need to use the system.
3. An internet server managing the content based image retrieval system, including XML, XSLT and Java tools.

Figure 1 shows the physical realization of the communication protocol. 1) The user transmits his identification and the query image to the server through the wireless network. 2) If the server is able to determine the most likely species with enough confidence, it answers the user with information related to the identified species and the ones closely related found in the database. 3) In case of ambiguities or no high confidence, the system asks for more information to the user to build confidence.

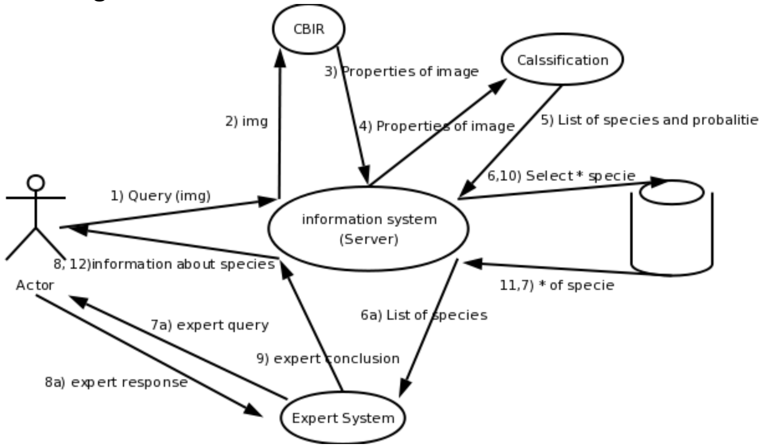
Figure 1. Hardware elements of the system



3 Sofware architecture

The schema in figure 2 shows the main software components of the information system and the flow of information between them. The process consists of the following informaiton exchanges:

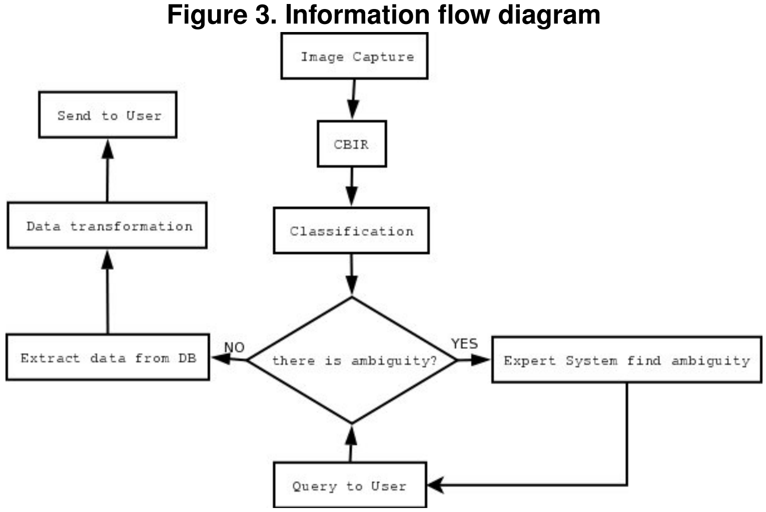
Figure 2. Sofware structure and information flows



1. The user captures the image that is sent to query the system.
2. The CBIR module extracts the visual features of the sample mushroom in the image.
3. The feature vector is sent to the classifier, which returns the closest species, ordered according to their prediction probabilites.
4. If there is confidence enoguh for the classification, the data related to the identified mushroom species is sent to the user.
5. if there is not enough confidence, the system starts to interact with the user sending optimized questions designed to discriminate between conflicting species.
6. The data related to the identified species is sent to the user.

Figure 3 shows the information flow diagram and the decision realized by the system.

Figure 3. Information flow diagram

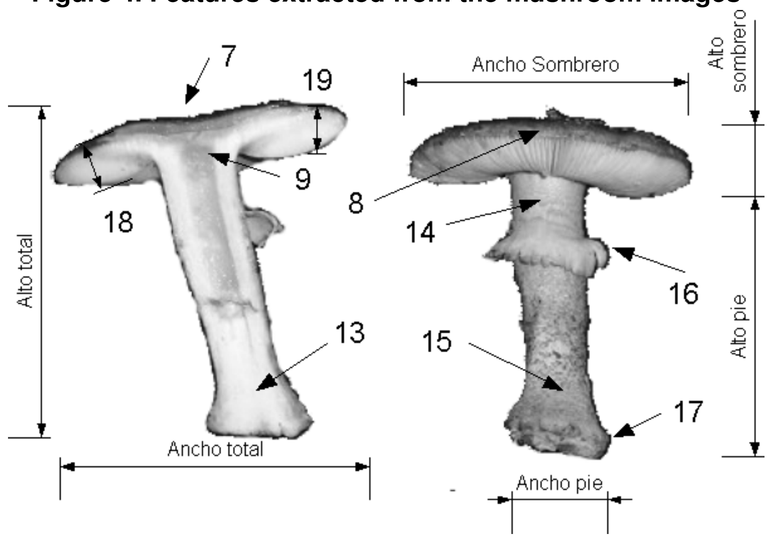


4 Visual feature extraction

For visual feature extraction we perform classical binarization and extraction of connected components[6]. That way we localize the mushroom in the image, then we extract the features that will be used for the search of the most similar images in the mushroom image database. Some of these features are the heigh, width, area of the whole mushroom and the hat and foot. We also detect the existence of accidents like the ring in the foot, the color of the cuticle, internal meat and foot. Figure 4 illustrates the localization of the features extracted. In the following we detail some of the feature extraction algorithms.

Images are characterized by a black backgroung, where the sample mushroom cut in half is placed. One of the half is disposed with the meat to the camera, the other with the cuticle towards the camera. Besides a reference size label with a mark of a centimeter is included in the image, to obtain the corresponding physical size of the pixels. The first step, algorithm 1 localizes each half in the image computing their area, height and width. The next step, described in algorithm 2, is the separation of the hat and foot of the mushroom given the contour of the half mushroom, which can be computed using a simple laplacian convolution mask on the binary image.

Figure 4. Features extracted from the mushroom images



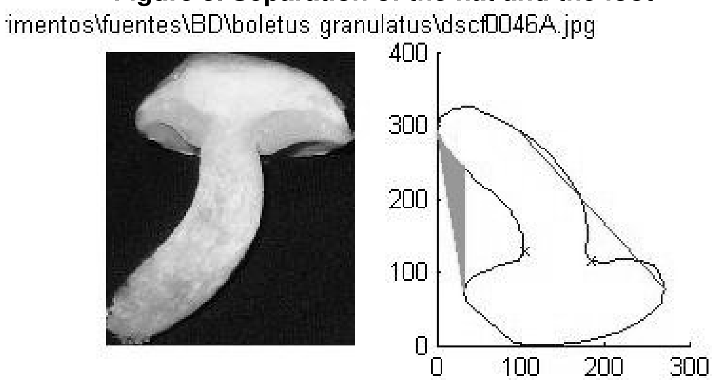
Algorithm 1 localization of the half parts of the mushroom

1. Obtain a grelevel image from the original color image
2. Estimate an optimal binarization threshold, using minimum variance algorithms [6]
3. Compute the image binarization
4. Dilate and erode twice with a 3x3 binary structural element
5. Detect the three biggest connected components
6. Compute the connected components centroids
7. Compute the size of each pixel according to the reference label
8. Compute the minimal bounding box for each half

Algorithm 2 Separation of hat and foot

1. Find the bottom and the rightmost points in the contour.
2. While there is no point with distance >0 between those points.
   (a) Move the contour point on the foot to the next right pixel following the contour.
3. Find the maximum in this interval (right cut point)
4. Find the bottom and the leftmost points in the contour.
5. While there is no point with distance >0 between those points.
   (a) Move the contour point on the foot to the next left pixel following the contour.
6. Find the maximum in this interval (left cut point)
7. Follow the conotur line between the cut points, keeping the maximum distances and separate the foot and the hat. Figure 5

Figure 5. Separation of the hat and the foot



Once the hat and the foot are isolated, we can compute their size parameters (height, width, area) . We can also extract the color representatives of the interest zones: bottom part of the foot, upper part of the foot, cuticle, meat both of the foot and the hat. Besides it is also possible to analyze the contour line of both hat and foot to detect accidents like the ring. For the foot we can compute an vertical projection (algorithm 3) that shows the distribution of foot widht along is height. The north projection (algorithm 4) reveals the shape of the upper part of the hat. Finally, an horizontal projection (algorithm 5) reveals the mass distribution of the hat.

4.1 Classification

There are many classification algorithms that may be applied to the task of finding the exemplar class. We have experiment with RIPPER[1], C4.5[12], Naive Bayes[8] and K*[15], all of them implemented inside Weka [7]. We have also experimented with the Associative Morphological Memories (AMM) [10] over the contour lines obtained applying snakes. Best results were obtained using K* over the above told features. The color space used is RGB, altough it is usually recognized that other color spaces are more robust to illumination changes. We assume that illumination conditions will be usually good daylight. Table 1 shows the classification results obtained with a database of mushroom images. To validate the approaches, we measure the algorithms performance as in a conventional classification experiment, with a one-leave-out validation strategy.

[1] Propositional rule learner, Repeated Incremental Pruning to Produce Error Reduction (RIPPER), which was proposed by William W. Cohen as an optimized version of IREP.

Algorithm 3 Vertical projection

1. Find the bottom point of the contour image.
2. Initalize contour following to the right and to the left.
3. While not reached the end upper point
   (a) Advance the contour following in both directions.
   (b) FInd the distance between the contour following pointers.
4. Find the mean distances in 10 steps of the height.

Algorithm 4 North projection

1. Find the leftmost point
2. while not reached the rightmos point, and going over the upper part of the hat
   (a) keep the distance to the upper boundary of the image.
3. Obtain the average of 10 intervalas of the projection.

Rows in table 1 correspond to a different number of species considered for the experiment. The conclusion is that large number of species (32) degrades the performance, due to the existence of some classes with few samples. For a reduced number of classes the results are quite good taking into account the high variability of the mushroom sizes and shapes. The system gives good recognition results for 10 species, selected attending to the number of samples.

Table 1. Micological classification experiment results

Especies	K*	Naive Bayes	C4.5	RIPPER
32	0.7201	0.6238	0.4541	0.3440
15	0.8425	0.7007	0.5590	0.44888
10	0.8988	0.8202	0.7303	0.6404
5	0.9130	0.9130	0.8474	0.7173
3	0.92	0.84	0.84	0.88

5 Expert system

When we find ambiguities (two or more species with high probability) and loss of confidence (no one species with enough probability to be selected) we resort to a localized, ad hoc expert system, whose rules are tuned to improve the discrimination between competing species. Traditionally, expert systems are built up with inference rules clustered in diverse modules according context. In our application we create the inference rules in an “ad hoc” fashion with the information contained in the database.

Fuzzy rules are *if-then* rules where the antecedent and consequent are fuzzy sets, that is, linguistic results with an associated mathematical semantic. These rules, are stated by an expert in natural language incorporating his knowledge[14]. Ideally this system must be able to learn and adapt to new situations and environments, even through structural modifications. In our case study, we have all the relevant information in a specialized database, so that our next step is to try to ascertain from the database information and the classification probabilities returned by the classifier the new features that will maximize discrimination between the conflicting species. Those features will not be detectable from the image, correspond to non

Algorithm 5 Horizontal projection

1. Detect the leftmost contour point. of the hat
2. Initialize the contour following above and below the hat.
3. while we do not reach the rightmost point
   (a) move to the next right point in the contour above and below
   (b) find and keep the distance between both
4. Find the average in 10 intervals of the projection.

visual features: odor, habitat, texture, taste. The task is therefore to search in the database for the descriptive variable that has maximum variability (maximum entropy) in order to minimize the number of questions that the user must answer to determine the correct species. The user is questioned about this variable for the sample under study.

Let us consider a brief example, the system has selected as most probable species: *Agaricus Campestris, Russula Capives y Hebeloma Radicosum* . We know that the habitat is different for each species: lawn for *Agaricus campestris;*white fir for *Russula Capives;* beech forest for *Hebeloma Radicosum.*

Therefore we construct from the database information thre inference rules:

1. if habitat is lawn then species is *Agaricus campestris*
2. if habitat is forest of white fir then species is *Russula Capives*
3. if habitat is forest of has then species is *Hebeloma Radicosum*

Finally, we send the question about the species habitat to the user. It is not needed to know these rules beforehand or to store them after a conflicting situation, because we can always recover them from the database. Note that we follow the same strategy than decision tree construction algorithms to select the next decision variable from a branch. Algorithm 6 illustrates the process.

Algorithm 6 Generation of *ad hoc* expert system

1. Select non visual attributes from the database for the conflicting species
2. Find the most variable atribute
3. Ask the user about the value of the selected attribute.

6 Conclusions and future works

We present a remote system for mycological information deliver, characterized by the use of visual information extracted from the transmitted image that realizes the user's query. We are able to extract 25 numerical features from the image that give high precision for a limited number of species. The system and the validation experiment are based on an "in house" database which actually growing in the number of images. We propose, and apply, an ad hoc expert system approach based on the actual database information about non visual features. This approach generates questions to the user that allow to solve conflicting situations with low confidence or ambiguities. The approach minimizes the number of questions needed to obtain an identification.

There are several features whose detection is under development. Color gradients [13] and texture analysis[1, 11, 6] are techniques that can be of use for these goals. The final objective is to avoid as much as possible asking questions to the user.

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