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# OKIRAKU Search: Leaf Images based Visual Tree Search System

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## Abstract

*This paper addresses leaf images based visual tree search system called OKIRAKU Search. A user photographs an isolated leaf on a white background, and inputs the photographs to the system. The system automatically extracts the leaf region and computes shape features and color features, and searches it in the known species. The system shows the user the top matched species. The point of our approach is to accept either front leaf image or rear leaf image, or both images. We investigate the effectiveness of the features and images. In our experiment, 297 classes (278 species) are uniquely collected in the fields around our campus. The experimental results reveal that our proposed method obtains high performance. Moreover, we have developed a prototype tree search systems for mobile phone version and web-based version implemented the proposed method.*

## 1 Introduction

When we go outside, we can see a number of trees. However, most of people rarely know their names. For expanding our interest, we develop an application which can identify a tree name easily. In respect to the image based recognition of plants, a large number of researchers are interested in flowers [1, 2, 3, 4]. Flowers are more attractive than leaves and barks which have simple shapes and boring color. However, flowers can be taken only in specific time because their blooming period is restricted. On the other hand, although there is a number of deciduous trees, the existence period of leaves is longer than flowers. Another possibility is to use the bark texture which is easy to be influenced by the environment and also more various than leaves. Based upon the above reasons, we focus on the leaves.

The Image CLEF 2013 plant identification task is a system-oriented test bed dedicated to the evaluation of image-based plant identification technologies. In this task, five different types of view of the plant (leaf, flower, fruit, stem and entire) were prepared. Summaries of the retrieval approaches employed by the participating groups, and an analysis of the main evaluation results are described in [5]. Belhumeur et al. have built a computer vision system that aids in the identification of plant species [6]. Their system requires the user to photograph an isolated leaf on a plain white background. The key technology of their system is a shape matching using an inner distance shape contest (IDSC). The surprising contribution of their research is using three datasets containing thousands of single leaf images. Kumar et al. extended [6] and developed the first mobile app for identifying plant species using automatic visual recognition [7]. The key technologies to theirs system are computer vision components for discarding non-leaf images, segmenting the leaf from an untextured background, extracting features representing the curvature of the leaf's contour over multiple scales, and identifying the species from a dataset of the 184 trees. Their project team developed an electronic field guide application for iPhone and iPad called LeafSnap [8].

LeafSnap encourages us to propose a new image based leaf recognition for tree identification. The main contribution of this paper are as follows: (1) Build a larger leaf image dataset than [7], (2) propose a high performance recognition method based on shape features and color features, (3) investigate the effectiveness of the front leaf and rear leaf, and (4) develop a leaf images based visual tree search systems for mobile phone version and web-based version implemented the proposed method.

## 2 System Design

Leaves are usually congregated, and it is difficult to automatically extract them from an unneeded background. For this reason, many of researchers used a scanned or scan-like leaf image, i.e. a leaf image is took by first snipping a leaf from trees. Here, the scan-like image means a photograph with uniform background. In this research, we use not the scanned image but the scan-like leaf image. The advantage of this approach is that a leaf cannot become flat.

The main difference between this research and other researches is a number of acceptable image. Many related researches use only the front leaf images. Although there is a species which is glossy on the surfaces of the leaf, the front color is almost green. On the other hand, the color of a rear side of the leaf has a tendency lighter than the front side. Some species have a white or gold color. Moreover, the vein of the front side is a concave, and the vein of the rear side is a convex. The rear side of the leaf has a variation rather than the front side, and it is assumed that the rear side is useful for the leaf identification. Hence, in our system, not only the front side image but also the rear side image is used. Note that either the front side image or the rear side image can be applied.

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Figure 1. Japanese Beech (left: front leaf image, right: rear leaf image).

front side is a concave, and the vein of the rear side is a convex. The rear side of the leaf has a variation rather than the front side, and it is assumed that the rear side is useful for the leaf identification. Hence, in our system, not only the front side image but also the rear side image is used. Note that either the front side image or the rear side image can be applied.

Figure 1 shows a pair of input photographs. In this figure, a left image is a front leaf image and the right image is a rear leaf image. The name of this leaf is Japanese Beech.

Autumn foliage is a phenomenon that affects the normally green leaves of many deciduous trees, during a few weeks in the autumn season, various shades of red, yellow, purple, and brown. In fact, not only color but also shape is changed. However, many related researches are not taking this phenomenon into consideration. From a botanical standpoint, an important information for identification is the leaf shape. However, the color information is useful for identifying the leaf, and the color features are defined in this research. Thus, our method introduces a two expression levels of class-level and species-level for leaf identification. The former level is used on the recognition task, and latter is used when displaying the recognition result to the user.

## 3 Dataset

We uniquely gathered 20 samples of leaf images from 278 species in the fields around our campus. The number of class is 297. The difference number 19 means that the leaves of 19 species in our dataset have both normal green leaves and autumnal leaves. We took the photos for both sides of front and rear from one leaf. It means that 297 classes × 20 samples × 2 sides = 11880 images are collected. Several compact digital cameras marketed were used for photography. The image size had variations and all images were converted into QVGA size by considering the transfer speed.

## 4 Graph-cuts based extraction

In this research, the leaf image as shown in Fig. 1 is inputted. Such a leaf image is also used in some previous related researches [6, 9, 10]. These researches apply the simple methods, such as a thresholding method and a clustering method. Although we first apply these methods, there are some images in which a leaf region cannot be extracted correctly. Therefore, we apply a graph-cuts based leaf region extraction method.

In [11], the seeds are given by user. To reduce user operation, we propose an automatic seeds detection method. In our method, we define the object is a leaf, and the background is a remaining white region. The process flow of a graph-cuts based region extraction method is as follows: (1) Automatic seeds detection, (2) seeds clustering, and (3) graph cuts based extraction.

In order to detect seed points automatically, a grid scanning line is considered. The background of the image is almost uniform, and a large intensity change can be observed at the boundary of the leaf region. In each scanning line, the point of the large intensity change is detected as a seed point.

By only applying the previous process, the detected seeds are not classified into neither the foreground nor the background. It is desirable that seeds around image are classified into the background, and others are classified into the foreground. However, the seed of the background may be detected except in the region around the image. Thus, the detected seed points are classified into either foreground or background.

After applying the clustering method, the seed points of a leaf region are classified into the foreground, and the remaining seed points are classified into the background. Then, we apply the graph-cuts method and obtain a binary image. Next, we apply a labeling method to obtain a largest region as a leaf region.

## 5 Matching

The most important parts of leave are a base point $P_B = (x_B, y_B)$ and a tip point $P_T = (x_T, y_T)$. Thus, these two points are first detected in this research. To detect these points, the curvature $\rho$ at each contour pixel is calculated. A peak point of left side is detected as $P_B$, and a peak point of right side is detected as $P_T$. After detecting $P_B$ and $P_T$, the following nineteen shape features (F1–F19) are calculated. (F1) The aspect ratio $AR$ of the leaf, (F2) the bias $b$ of the gravity, (F3) $R_{SR}$ is an area ratio between the area of leaf region and area of bounding box, (F4) the second area ratio between an elliptic area inscribed in a bounding box and area of bounding box, (F5, F6) two roundness values, (F7–F13) Seven Hu's moments, (F14, F15) the margin ratios, (F16) the maximum frequency of centroid contour distance spectrum, (F17) a bending angle, (F18, F19) two angles of the base and tip point.

Although the color of the leaf is generally green, there are also yellow leaves and red leaves by which can be seen in autumn. Thus, it is believed that color information is effective for the recognition. This paper defines six features (C1–C6) proposed in [3].

As for the final matching process, the proposed method applies to the random forests [12].

## 6 Experiments

### 6.1 Extraction experiments

For the leaf extraction, the automatic extraction method described in **4** was applied to all 11880 leaf images. The success extraction rate was 98.1%. The number of unsuccessful extraction images was 223 in which 107 leaf images were failed by over-extraction, and the remains 116 leaf images were failed by lack. We investigated the failure reasons. As a result, some

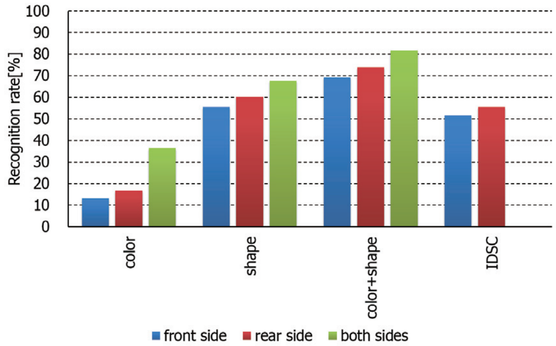


Figure 2. Recognition results with various conditions.

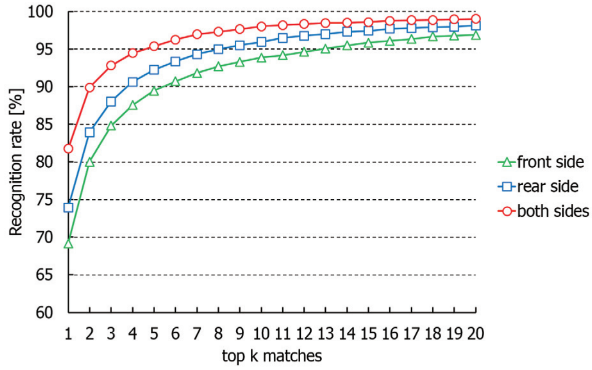


Figure 3. Recognition results.

images consist a shadow of the leaf and those images yielded an excessive extraction. In contrast, since the color of leaf vein is white and which is similar to the background color, the part of main vein was not extracted.

### 6.2 Recognition experiments

We carried out the recognition experiments with three conditions: (i) using only the front leaf, (ii) using only the rear leaf, and (iii) using both sides. To evaluate the performance, we applied a leave-one-out cross validation experiment, in which each sample is removed from the dataset and used as a query. Moreover, we conducted the following four recognition tasks;

1. `color` : using only six color features,
2. `shape` : using only nineteen shape features,
3. `color+shape` : using six color features and nineteen shape features, that is, the number of feature is 25,
4. `IDSC` : inner distance shape context (IDSC) was used in [6].

Here, the number of trees of the random forests was 200 which obtained the best performance. Figure 2 shows the recognition performance of all conditions and tasks. It is found that the rear leaf images could acquire a recognition rate higher than the front leaf images. We guess that the recognition accuracy of the rear side can be improved since there are large variations in color compared to the front leaf image. For both sides, we obtained the highest recognition rate.

IDSC is proposed by Ling and Jacobs, and this method samples points along the boundary of a shape, and builds a 2D histogram descriptor at each point. This method is not included the color information. The reason which the accuracy of our method is higher than IDSC is that the proposed method is specialized for the leaf shape. On the other hand, the IDSC is proposed supposing various shape objects.

Figure 3 shows the performance curves that indicate how often the correct classes for a query is placed among the top $k$ matches, as $k$ varies. In this case, the number of features is 25, i.e., the third condition of `color+shape`. The correct accuracies which appeared in the top five using only front side, rear side, and both sides were 89.4%, 92.2%, and 95.4%, respectively.

Table 1. Selected features for random forest.

| | front side | rear side | both sides |
|---|---|---|---|
| 1 | F5 (0.55) | F5 (0.51) | F5$^{(r)}$ (0.30) |
| 2 | C1 (0.15) | F1 (0.26) | F1$^{(r)}$ (0.25) |
| 3 | F1 (0.14) | C2 (0.13) | F5$^{(f)}$ (0.13) |
| 4 | F15 (0.06) | F14 (0.05) | F1$^{(f)}$ (0.06) |
| 5 | F14 (0.05) | F15 (0.03) | C2$^{(r)}$ (0.16) |

Next, we analyzed the generated trees of random forests. Table 1 shows the ratios of most selected features for root node at each tree. In this table, the numerical value in parenthesis means a rate of the total number of trees. As the result, it was found that F5, roundness, was most selected feature in all conditions. Interestingly, the tendency between the front side and rear side is almost same. Focusing on the both sides, it turned out that the feature on the rear side is more selected than that of the front side.

## 7 OKIRAKU Search

Based on the proposed method, we develop a tree search systems called "OKIRAKU Search" for two versions of Android OS and web-based. "OKIRAKU" means ease in Japanese. The former version can be used only the device which OS is Android, on the other hand, the later version can be used for all devices. The difference between two versions is only design of surface. These systems has the following three functions:

1. Search: Users can search for specific species by the proposed method. In current version, ten candidates are displayed as the search result.
2. Collection: System shows the past collection history.
3. Browse: Users can browse all species in our database. They can toggle between thumbnails of leaves, bark, and whole tree. They can also sort the list by scientific order name, family name, and genus name. Users can click on one of the species to see the detail page.

The above functions are similar to Leafsnap [8]. The back-end server is currently a Cent OS machine with an Intel Xeon E5-2470 CPU at 2.40GHz, and 4GB of RAM.

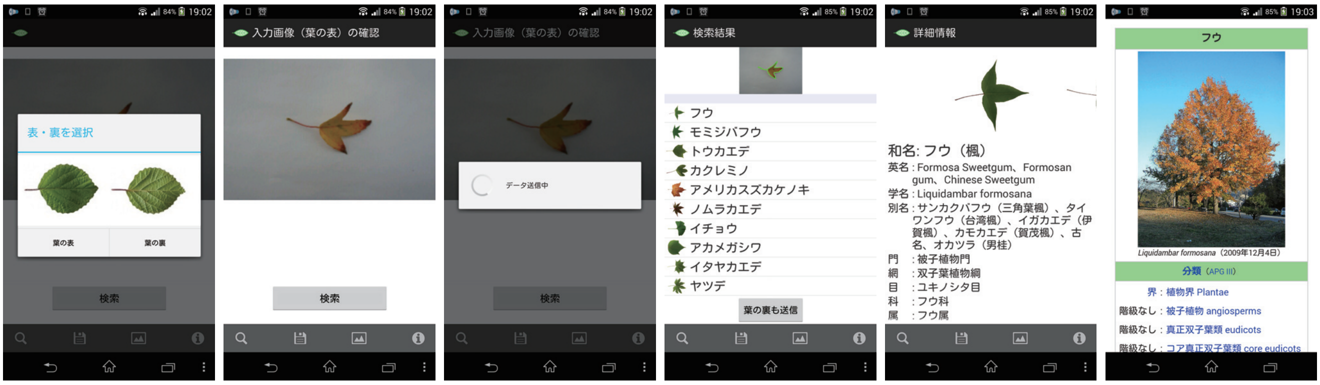

Figure 4. Screen short of our system for Android OS: select front side or rear side, target image, uploading, resulting candidates, detail, corresponding web-site.

The overview of the search function is described as follows: The user takes a photo of a leaf or select a photo in the gallery. Next, our system requires a front image or a rear image of the user. The image and selected answer (front or rear) are sent to the server for the recognition process. The recognition process is down on the server. The server returns a set of ranked matches. Ideally, the correct match will be first in the list, although this is not always true; however, the correct match is almost always within the top ten. To make the final identification, the user can click on a result to see the detail page and verify if it is the correct species by looking at other characteristics of the tree.

Figure 4 shows the some screen shots of the developed system for Android OS. Our systems can be download from [13].

## 8 Conclusion

This paper proposed a leaf image based visual tree search system called OKIRAKU Search. This paper has the following contributions. Firstly, we built a large leaf image dataset. Secondly, we proposed a high performance recognition method for leaf image. This is confirmed by comparison experiment. Thirdly, the comparison verification between the front leaf and rear leaf which was not investigated in the related researches was carried out, and the experimental results reveal an interesting knowledge: the recognition accuracy of the rear side is higher than that of the front side. Finally, we developed a whole search system for mobile phone.

The developed system will be released. It is expected that non-leaf image is inputted. Leafsnap has implemented discrimination processing of a leaf image and a non-leaf image. Our system also needs the same processing. Our dataset is larger-scale than other research groups. However, it is said that thousands of species of tree can be seen in Japan. Thus, one of the future works is to collect a lot of species.

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