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Automatic feature-queried bird identification system based on entropy and fuzzy similarity

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Abstract

Birdwatching is one of the very interesting hobbies and most important work. Many birdwatching assistant systems have been developed. However, most of them do not have any intelligence and cannot tolerate noises either. A bird identification system, BirdID is proposed and implemented. To identify birds, BirdID imitates bird experts to automatically direct birdwatchers to provide features. It also tries to list the most likely species after each feature is entered. In BirdID, entropy and fuzzy similarity are used to select most appropriate queried features and calculate similarity, respectively, which makes BirdID more intelligent and noise-tolerant. The experiments on a dataset with 106 species show that BirdID works well.

Keywords: Bird identification; Entropy; Fuzzy similarity

1. Introduction

Birdwatching, also called birding, means learning to identify birds and understand what they are doing. It has become one of the fastest-growing hobbies in the European countries and United States (Mullarney, Svensson, Zetterstrom, & Grant, 2001; http://www.birdwatching.com/index.html). Birds always delight people because of their beauty and their power of flight, which attracts people of all ages. Changes in bird populations can reflect the health of the environment, for example, global warming, which also causes environmental scientists to watch birds. As a result, birdwatching has become one of very interesting hobbies and most important work.

Traditionally, birdwatchers always carry a pair of binoculars, a field guide and a little notebook (Mullarney et al., 2001; http://www.birdwatching.com/index.html). They watch birds through binoculars and try to record all the features in the notebook until they think they have recorded sufficient features to identify the observed bird. Based on these features, birdwatchers will look up the field guide to check which species birds they have watched are most likely.

Traditional birdwatching has some drawbacks. First, it is inefficient. Birdwatchers have to write down what they have seen in the notebook when they are watching birds. They always need to record as many features as they can. It depends on birdwatchers themselves to decide when to stop recording. Birdwatchers do not try to identify birds until they think they have got enough features for bird identification. If the observed bird could not be identified, they have to use additional, unrecorded features, which in many cases is not possible. In addition, traditional birdwatching is error-prone. Birdwatchers have to try to record as many features as possible, which makes them unable to focus on specified features. Sometimes, some vital features are ignored or fail to be recorded. In this case, species are often misidentified.

Currently, there are some systems to help birdwatchers to identify birds, such as YardBirds, WhatBird etc. But unfortunately, most of them are searching system. That is

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to say, these systems only act as online field guides. None of them are able to direct birdwatchers to identify birds. They cannot tolerate noises either. Considering the challenges birdwatchers have faced so far, we develop an automatic feature-queried bird identification system based on entropy and fuzzy similarity, BirdID, to assist birdwatchers to identify birds. BirdID is a PDA-based system. Birdwatchers can bring a PDA with BirdID system installed with them to go out for birdwatching. Unlike traditional birdwatching, in BirdID, the bird features are not given a priori. The system determines which features to acquire next, that is, BirdID automatically asks birdwatchers to provide features. After each question the system tries to identify the species according to features currently available and determines whether further features need to be requested. When the system has got sufficient information, the most likely species will be listed in order for birdwatchers. An important feature of the proposed system is that it is robust to situations where the user either is unable to provide requested features, or has provided incorrect information.

The remainder of this paper is organised as follows. Section 2 describes the proposed bird identification system, BirdID. Section 3 discusses similarity calculation methods for different type of features in BirdID. Section 4 presents a criterion for next queried feature selection. Some experimental results are given in Section 5. Section 6 outlines conclusions and future work.

2. The proposed system

Shown in Fig. 1 is a brief flowchart of how the proposed system, BirdID works. Starting with a new answered question, the system retrieves and ranks a set of most similar species from a knowledge base, which includes bird species and bird expert knowledge. The most likely species are presented to birdwatchers as references for the new observed bird. This process repeats until the observed bird has been identified. In some rare cases, BirdID may not identify the bird and also no further questions could be provided. This is mostly because too many incomplete or incorrect answers are given by birdwatchers. Ideally, the information provided should be retained and sent back to bird experts who will be asked to evaluate and label this new bird. Based on the popularity of the new bird, bird experts would suggest birdwatchers to update the knowledge base with the information of new bird to make the knowledge base more complete and competent. To make knowledge consistent, bird experts may also be allowed to append or modify knowledge base directly.

In the proposed system, species matching among a variety of birds and query feature selection among all the describing features are the two main challenges. An appropriate similarity metric is desired. The metric is supposed to distinguish between the actual species and all other species stored in the knowledge base. Query feature selection is to select one or more features to ask birdwatchers to provide their values. It is intended to identify birds as quick as possible. In our knowledge base, four types of features, i.e., nominal, continuous, ordinal and coloured are used to describe birds. Therefore, it is important for BirdID how to be able to deal with these four types of features to make queried features more reasonable and species matching more accurate. In Section 3, we will provide more details.

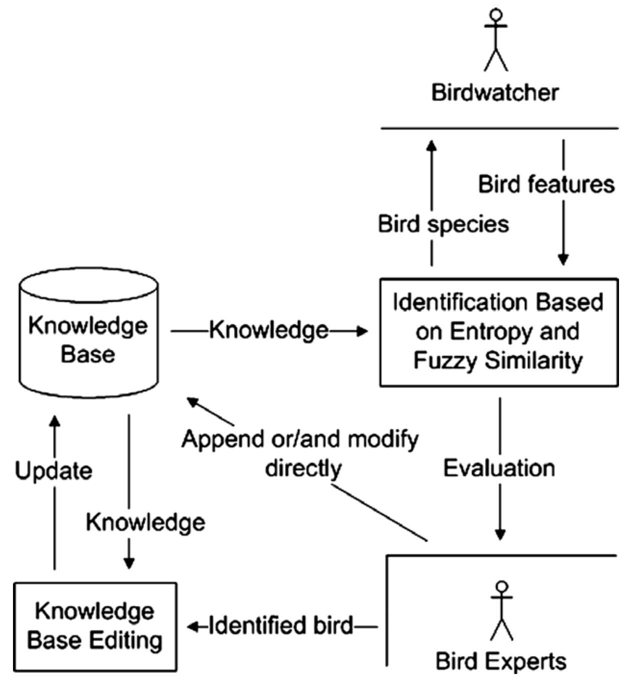

Fig. 1. Flowchart of BirdID system.

3. Species matching

As mentioned in Section 2, Species matching is one of the challenges for bird identification application. In BirdID, we calculate similarity between the features provided by the user and a set of features for a bird from the database by using of weighted sum of mixed features. The following formula is used to calculate species similarity (Hyung, Song, & Lee, 1994; Wang, 1997)

$$S(x,y) = \frac{\sum_{i=1}^{N} \alpha_i \cdot \mu_{y_i}(x_i)}{\sum_{i=1}^{N} \alpha_i}, \tag{1}$$

where $\mu_{y_i}(x_i)$ is similarity between bird x and y for the ith feature. α_i is the weight for the ith feature. N is total number of features to illustrate birds. To calculate species similarity, we have to calculate similarity for each feature. Since similarity for same type of features can be calculated in similar way, species similarity between two birds is easily and flexibly presented as long as a similarity calculation for each feature type is available. Let us discuss similarity calculation for each type of features in detail.

3.1. Nominal features

A nominal feature is one that has two or more categories, but there is no clear ordering to the categories. In

BirdID, the following formula is used to calculate the similarity between two nominal features. It is simply to compare one nominal feature to the other. Similarity sets 1 if two nominal features have same value. Otherwise similarity has 0 value

$$\mu_{y_i}(x_i) = \begin{cases} 1 & x_i = y \\ 0 & x_i \neq y_i \end{cases}, \tag{2}$$

where x_i and y_i are two values for given nominal feature.

3.2. Ordinal features

An ordinal feature is similar to a nominal feature. The difference between the two is that there is a clear ordering of the features. Therefore, we cannot calculate the similarity between two ordinal features the same way as nominal features. In BirdID, we defined the similarity for two ordinal features as follows:

$$\mu_{y_i}(x_i) = 1 - \frac{|n_{x_i} - n_{y_i}|}{K-1}, \tag{3}$$

where n_{x_i} and n_{y_i} are scores assigned to x_i and y_i. K is the number of different values for ordinal feature. Scores $1, 2, 3, \ldots$ is assigned to each value for ordinal features in order, respectively. Let us take an example to illustrate how BirdID calculate the similarity between two ordinal features. For example, we have feature 'tartus' with three values, that is, shorter, normal and longer. According to the definition above, we have n_{shorter} valued 1, n_{normal} valued 2, n_{longer} valued 3, and N valued 3. Therefore $\mu_{\text{shorter}}(\text{longer}) = \mu_{\text{longer}}(\text{shorter}) = 1 - |3-1|/(3-1) = 0$ and $\mu_{\text{normal}}(\text{shorter}) = 1 - |2-1|/(3-1) = 0.5$, which means that shorter is more similar to normal than to longer, as one would intuitively expect.

3.3. Continuous features

It is impossible for birdwatchers to enter the continuous value because it is very difficult for them to get the value precisely. In order to facilitate birdwatchers, in BirdID, we categorize continuous features into ordinal ones. Birdwatchers need only to provide relative values. Take feature 'leg' for example. First, we transform leg values into relative values by using of leg values divided by bird lengths. Then bird experts will determine the separators to categorize relative leg values. Therefore, bird legs are categorized as shorter, normal and longer. After categorization, similarity for continuous features is calculated using the same criterion used for ordinal features.

3.4. Colour features

Colour features are used to illustrate birds since they are easy to observe. For example, it is generally easy for birdwatchers to observe wing colour. Literately, colour feature seems to be nominal feature. But actually, they are not. We could not say two colours are absolutely different although they have different colour names. For instance, dark brown and black should be treated as more similar than yellow and black because dark brown is more like black than yellow from human eyes perspective. Therefore, we cannot treat colour feature as a nominal feature. An alternative way has to be found for colour features' calculation to imitate human eyes.

According to colour science (Westland & Ripamonti, 2004), colour difference is very simple to calculate in CIELAB colour space as following:

$$\Delta E_{x_iy_i} = \left(\Delta L^{*2}_{x_iy_i} + \Delta a^{*2}_{x_iy_i} + \Delta b^{*2}_{x_iy_i}\right)^{1/2}, \tag{4}$$

where

$$\Delta L^*_{x_iy_i} = L^*_{x_i} - L^*_{y_i}$$
$$\Delta a^*_{x_iy_i} = a^*_{x_i} - a^*_{y_i}$$
$$\Delta b^*_{x_iy_i} = b^*_{x_i} - b^*_{y_i}.$$

Here L^*, a^* and b^* are used conventionally to describe all the colours visible to the human eye. $\Delta E_{x_iy_i}$ reflects the colour difference between colour x_i and y_i. However L^*, a^* and b^* values cannot be derived from colour name, that is to say, we do not know L^*, a^* and b^* values for a given colour name. But fortunately, we do know X, Y and Z values in CIEXYZ colour space given specific environments. And also L^*, a^* and b^* values can be easily computed from X, Y and Z values. Formula (5) is to implement the transformation from X, Y and Z values to L^*, a^* and b^* values

$$\begin{aligned} L^* &= \begin{cases} 116 * (Y/Y_n)^{1/3} - 16 & \text{for } Y/Y_n > 0.008856 \\ 903.3 * Y/Y_n & \text{otherwise} \end{cases} \\ a^* &= 500 * [f(X/X_n) - f(Y/Y_n)] \\ b^* &= 200 * [f(X/X_n) - f(Z/Z_n)], \end{aligned} \tag{5}$$

where

$$f(t) = \begin{cases} t^{1/3} & \text{for } t > 0.008856 \\ 7.787 * t + 16/116 & \text{otherwise.} \end{cases}$$

Here X_n, Y_n and Z_n is White Point. When computing CIELAB values from XYZ values it is necessary to define the White Point. It is very effective in differentiate colours difference and influences human observation. In BirdID, we only considered White Point under D65 Illuminant/10 Degree 1964 Observer conditions. Under this condition, $X_n = 94.811$, $Y_n = 100.000$ and $Z_n = 107.304$.

After we have the $\Delta E_{x_iy_i}$ value, $\mu_{y_i}(x_i)$ is simply computed by

$$\mu_{y_i}(x_i) = 1 - \frac{\Delta E_{x_iy_i}}{\Delta E_{\max} - \Delta E_{\min}}, \tag{6}$$

where $\Delta E_{\max}$ is the maximum ΔE among all the colours and $\Delta E_{\min}$ is the minimum one.

4. Query feature selection

The other challenge for BirdID is query feature selection. BirdID should not query feature for birdwatchers in a fixed order. The currently queried feature has to be influenced by the features birdwatchers have already provided. In addition, BirdID should query as few features as possible to complete the bird identification. Considering these two conditions, we propose formula (7) as a criterion to select the next queried feature. Here information entropy (Shannon, 1948) is introduced as criteria

$$S = \sum\nolimits_{i=1}^{n} p_i \log_n p_i = \frac{\sum\nolimits_{i=1}^{n} p_i \log_2 p_i}{\log_2 n}, \tag{7}$$

where n is the number of different values for given feature. p_i is the proportion of the ith value to the sum of values for given feature.

From formula (7), we know that BirdID queries at most $M = \lceil \log_2 N \rceil$ features to identify birds if each queried feature is provided with correct value, where N is the number of features to illustrate birds.

When BirdID identifies birds, formula (7) is used to select the next queried feature. BirdID asks birdwatchers to provide a value. After the birdwatchers have entered the value, BirdID will select next queried feature. It should be noticed that, to make identification faster, only the current top 10 species are used to compute S in formula (7).

5. Experimental results

Fig. 2 is part of BirdID system interface. Shown in Fig. 2 is bird, grey wagtail, which is ranked top one after several questions. From the interface we can see that BirdID is very convenient and easy to use for birdwatchers.

We have tested BirdID on the database with 106 bird species, which were provided by bird experts. First, we tested BirdID under noise-free circumstances, that is, answers provided by birdwatchers are totally correct. Fig. 3 is the results BirdID obtained. Horizontal axis is the number of features BirdID queried. Vertical axis is the number of species ranked top one after questions corresponding to horizontal axis were provided.

We have also tested our system, BirdID in the presence of noises, that is, inaccurate answers, which include wrong, incomplete and unknown answers. We generated the noises for each of 106 species in random to test BirdID

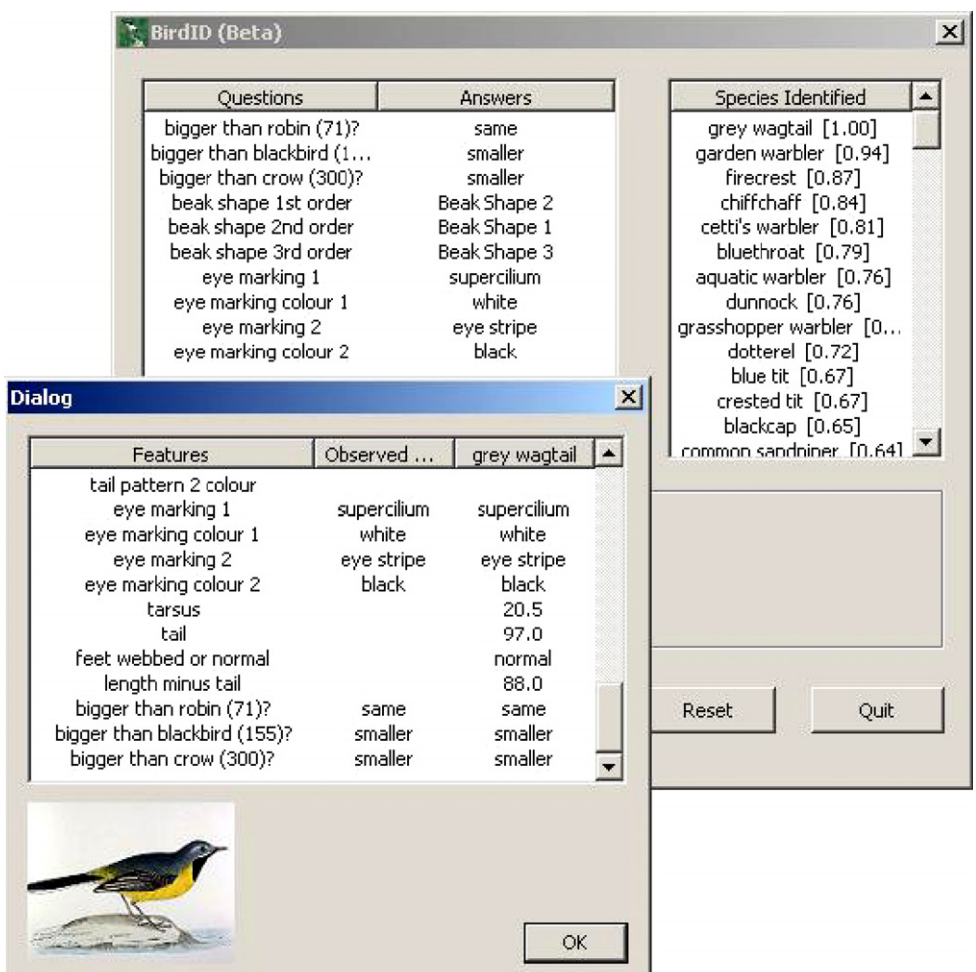

Fig. 2. Part of BirdID system interface.

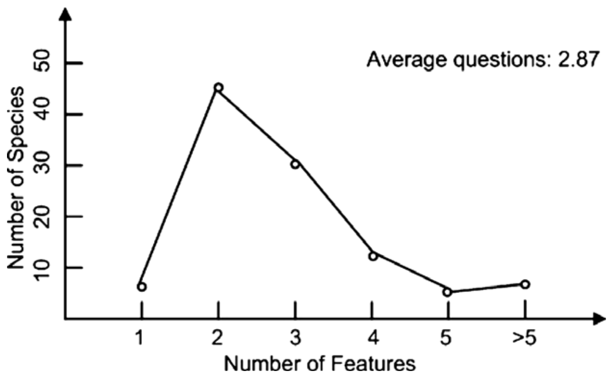

Fig. 3. Noise-free results.

performance. To generate noises, we randomly selected some features and treated them as noises. When BirdID queried these features during bird identification, we entered inaccurate answers for them. Fig. 4 is the results BirdID got when one inaccurate answer was provided. Figs. 5 and 6 are the results obtained when two and five inaccurate answers were entered, respectively. Here horizontal and vertical axes have the same meaning as those in Fig. 3.

From above figures, we can conclude that BirdID could identify birds using as few features as possible. And BirdID could also identify birds effectively although some inaccurate values were presented.

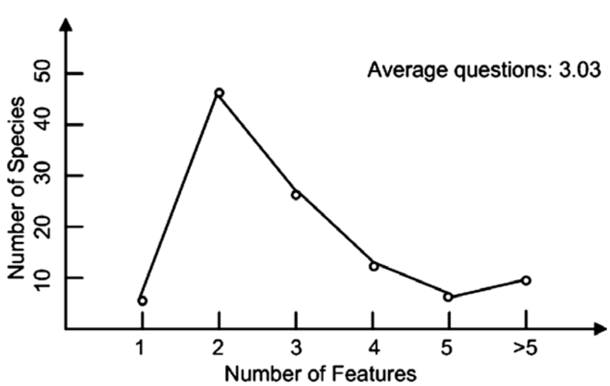

Fig. 4. 1-Noise results.

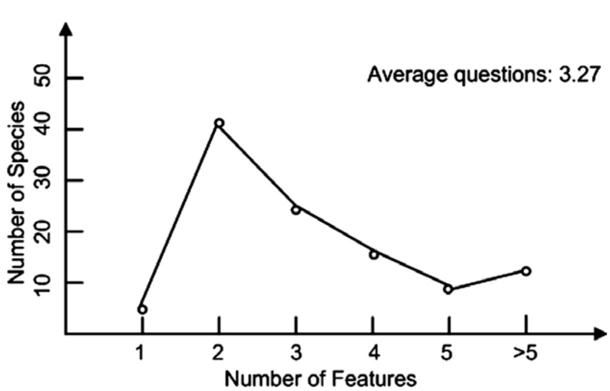

Fig. 5. 2-Noise results.

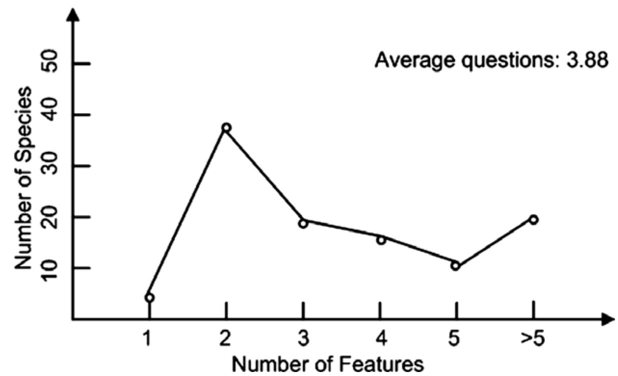

Fig. 6. 5-Noise results.

In our database, only 27 features are used to illustrate birds. Theoretically, at most 5 ($\lceil \log_2 27 \rceil$) questions are enough to identify birds. Therefore in figures above we only limited our horizontal axis to six units, that is, one to five question(s) and more than five questions.

Except for testing BirdID ourselves, we also asked bird experts to help us evaluate BirdID. They confirm that, BirdID could ask reasonable questions and can identify birds with higher precision as well.

6. Conclusions and future work

In this paper, we propose an automatic feature-queried bird identification system, BirdID, which assists birdwatchers to identify birds. Based on entropy and fuzzy similarity, BirdID is able to imitate bird experts to direct birdwatchers to provide features they have seen and identify birds utilizing features as few as possible. In the experiments on the database with 106 bird species, we can see that BirdID works well.

We intend to carry out our work in following two aspects. First, currently some PDAs have some built-in devices, such as GPS and microphone. These devices can be used to screen out some species. For instance, using PDA with GPS built-in, we automatically know where we are watching birds. Therefore birds habituated out of the site where you are watching should not be considered completely. This will obviously speed up our system. Second, although BirdID has been designed for bird identification, it is not restricted to bird identification only. The same techniques could be also used to identify animals or plants. We have tried our best to keep the system more general to make it be suitable to plants or animals identification, which is one of our future targets.

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