Evaluation of Bird Detection using Time-lapse Images around a Wind Farm

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Introduction

Environmental concerns in developing wind farms have been highlighted by both the wind-energy community and ecological experts [1–3] as the demand for wind power energy grows rapidly around the world to meet public policies for renewable energy. One of the primary concerns is the increase in bird mortality caused by collision with blades, loss of nesting and feeding grounds, and interception on migratory routes [4–7]. Hundreds of annual bird fatalities, including those of charismatic species, have been reported at several sites [6]. To assess such risks during the establishment and operation of wind farms, investigation of bird ecology and assessment of potential risks are necessary.

Conventional bird monitoring has been carried out by manual observation, which is expensive and laborious [8]. Automation in this task can lower the cost, enable long-term monitoring, and lead to higher accuracy and reproducibility. However, an automatic system is required to perform bird detection as well as classification of bird species.

A few studies about automatic bird monitoring exist. Although radar-based detection has been commonplace for birds [9, 10, 11], image-based detection using cameras is also a promising approach, owing to recent dramatic advances in imaging devices and the computer vision research field. DTBird [12, 13] and APEM [8, 14] are frontier enterprises developing image-based bird detection. However, very few scientific papers discuss whole pipelines designed for bird monitoring.

In addition, accuracy, precision, and recall of general bird detection algorithms remain uncertain. An exception is May et al.'s work reporting that DTBird detected 76% to 96% of total birds in an experimental setting in Smøla [13]. With state-of-the-art methods in computer vision, bird detection in a general object detection competition achieves lower scores compared with detection via persons, buses, and bikes [15, 16]. The reasons for such low scores have not yet been explored.

Our Approach

This paper presents an automated bird monitoring system for wind farms including a whole image processing pipeline. Our system utilizes recent computer vision methods based on machine learning for robust and detection. In addition, to clarify the capability of bird detection and classification methods, we utilize a wild bird image dataset around a wind farm as a benchmark [17] and evaluate the performance of basic machine-learning algorithms.

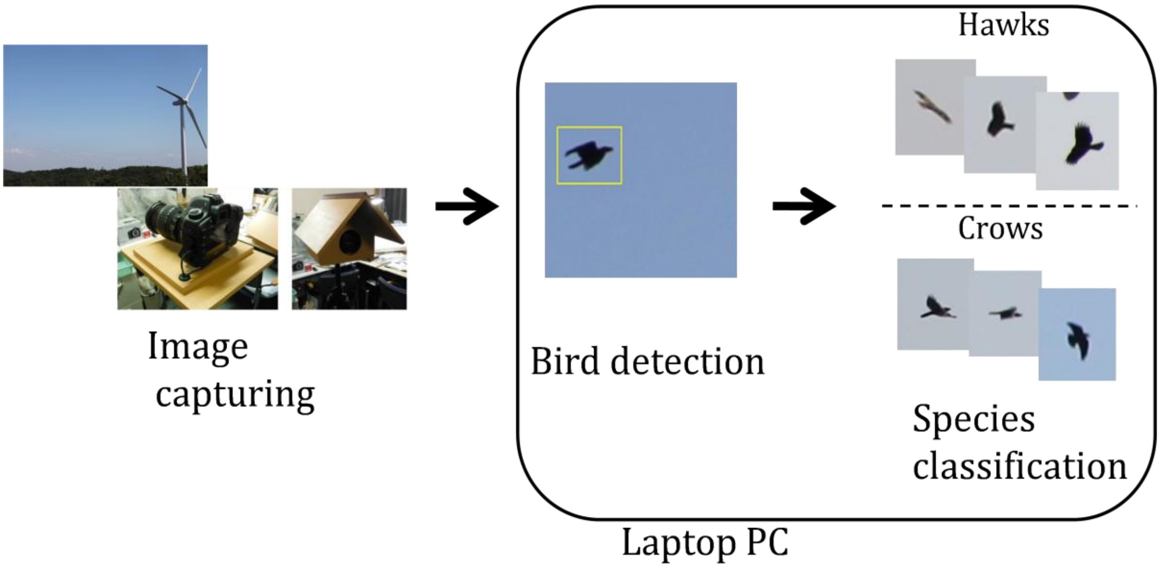

Figure 1. Overview of proposal system for bird detection.

Our system consists of a fixed camera, a laptop computer for control, and recognition software. It captures images automatically and processes them to detect and classify birds (Fig. 1). The core algorithm is based on machine learning for robust detection of birds, and the details are evaluated below. The system is able to discriminate birds from others or a species of birds from others after the training phase. During training, the classifier is optimized in accordance with training images including birds and others.

For the performance evaluation of basic bird detection and classification, we utilize a dataset of birds at a wind farm [17]. This dataset offers open access and has the preferable attributes: containing a large amount of data and presenting a detailed specification of birds. “Detection task” is defined as a classification of birds and non-birds, given the candidate regions suggested from motion information. “Classification task” is defined as a classification between hawks and crows, which is a fundamental and practical task in a bird-monitoring system. They are the most frequent classes of birds in the area and we have sufficient amount of data for accurate evaluation. This two-class classification is also practical, because many endangered species are included in hawks.

Main Body of Abstract

System Overview

Fig. 1 shows an overview of our system. We use a still camera with a telephoto setup to capture a bird with a one-meter wing span 580 meters away that would cover an area of 20 pixels in the image, considering the distance between the camera’s location and the wind turbine. This setup enables us to monitor a wide area suitable for bird investigation, including the wind turbine. The resolution of the sensor is 5616 times 3744 pixels and the field of view is 27 times 19 degrees.

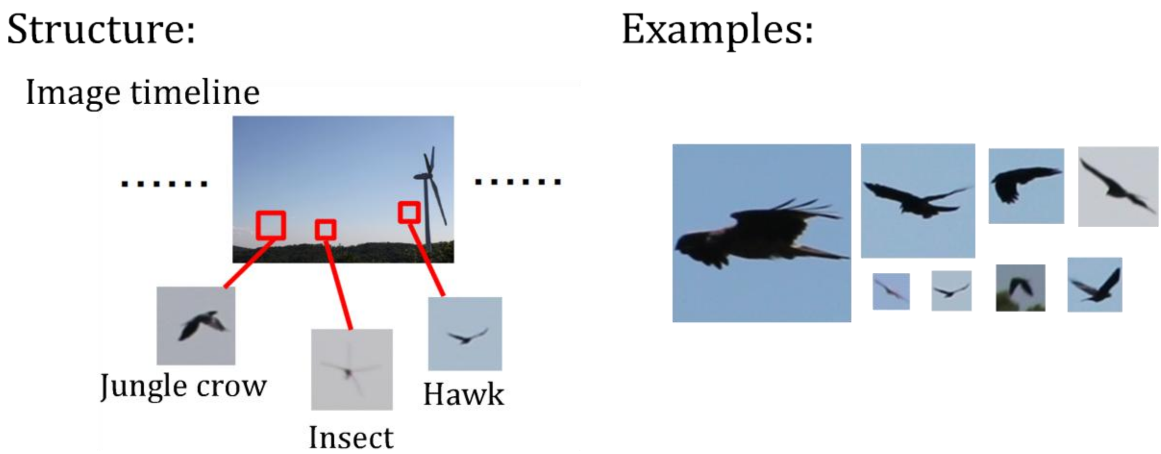

Figure 2. Structure of dataset [17] and bird image examples. Dataset includes time-lapse images, bounding boxes of birds and other flying objects, and their class labels.

The interval of image capture is two seconds because of the transfer rate between the camera and the laptop.

Our algorithm is a combination of background subtraction [18] and object classification. Background subtraction is a method for extracting moving objects from fixed backgrounds and works well on scenes that consist of birds and fixed backgrounds except for wind turbines. However, regions extracted still include some background objects, such as turbine parts, trees, or clouds; thus, we utilize machine learning-based classifiers to filter birds from others. Specifically, we use AdaBoost [19], a widely used learning algorithm in the computer vision field. This algorithm is often combined with image features such as Haar-like [20] or Histogram of Orientated Gradients (HOG) [21] for further robustness. The performance of these methods is known to depend highly both on the types of targets (faces, people, birds, etc.) and scene properties (indoor, street, wind farm, etc.). Thus, in this study, we compare some of the methods to clarify what kind of methods is suitable for bird monitoring in wind farms.

Wild Bird Image Dataset for Training and Evaluation

The dataset [17] is a sequence of images of a scene at a wind farm, and it provides annotations of bird information appearing in the images (Fig. 2). Annotations were added to the images by bird experts who are members of a bird association and have experience in field surveying. They checked the image timelines, found birds, and annotated bounding boxes with class labels for each bird. 32,442 images were processed and 32,973 birds were found.

Evaluation Experiments

Using this dataset, we conducted two recognition experiments: bird detection and two-class species classification. In these experiments, we used Haar-like[20], Histogram of Orientated Gradients (HOG) [21] features, or RGB features (image pixel values without transformation) combined with AdaBoost [19].

Figure 3. Bird image examples grouped by resolutions.

In the experiment of bird detection, we used bird regions in the dataset as positive samples. As negative samples, we used background regions clipped by background subtraction. To experiment on the dataset efficiently, we conducted five-fold cross-validation.

In the experiment of species classification, we used hawks as positive samples and crows as negative samples for the evaluation of species classification. In this experiment, we divided the positive and negative images into groups based on resolution. Species classification is a difficult task to learn for the algorithms, so we experimented on the effect of resolution variation using this task. Hawk and crow images are divided into the groups of 15–20 pixels, 21–30 pixels, and 31–50 pixels (Fig. 3). On each group, we conducted holdout validation using 800 hawks and 150 crows for training data and others for test data.

The results of birds-versus-others classification are shown in Fig. 4. In the graph, the x-axis is the false positive rate, the rate of misrecognizing backgrounds as birds, and the y-axis is the true positive rate, the rate of correctly recognizing birds. These curves in the graph present a trade-off between correct detection of birds and misrecognition of others, and the upper curves show the better results. The best performance is achieved with Haar-like. At the false positive rate of 0.01, over 0.98 of birds are still detected with Haar-like, which is a successful performance.

The results of hawks-versus-crows classification are shown in Fig. 5. This can be explained in the same way as Fig. 4, except that the false positive rate is the rate of misrecognizing crows as hawks, and the true positive rate is the rate of correctly recognizing hawks. Because of visual similarity, species classification is much more difficult than birds-versus-others classification, and lower performance is apparent. However, success of classification to some extent is also observed with RGB features in the 15–20 pixels group and with HOG in the 30–50 pixels group.

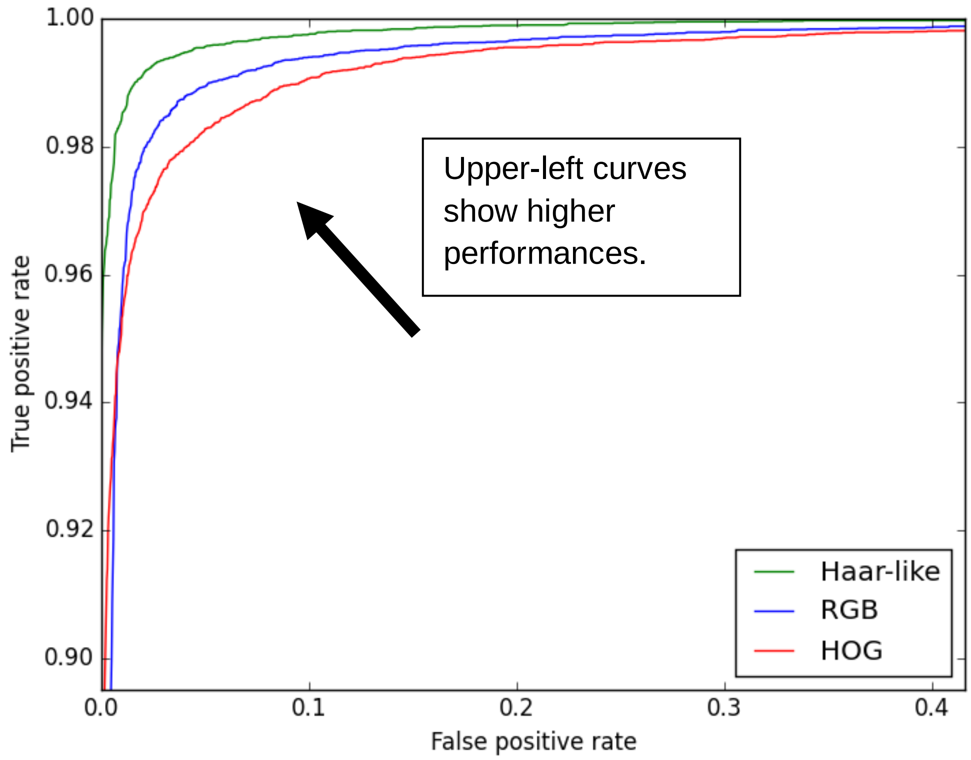

Figure 4. Results of bird detection (bird-versus-others classification).

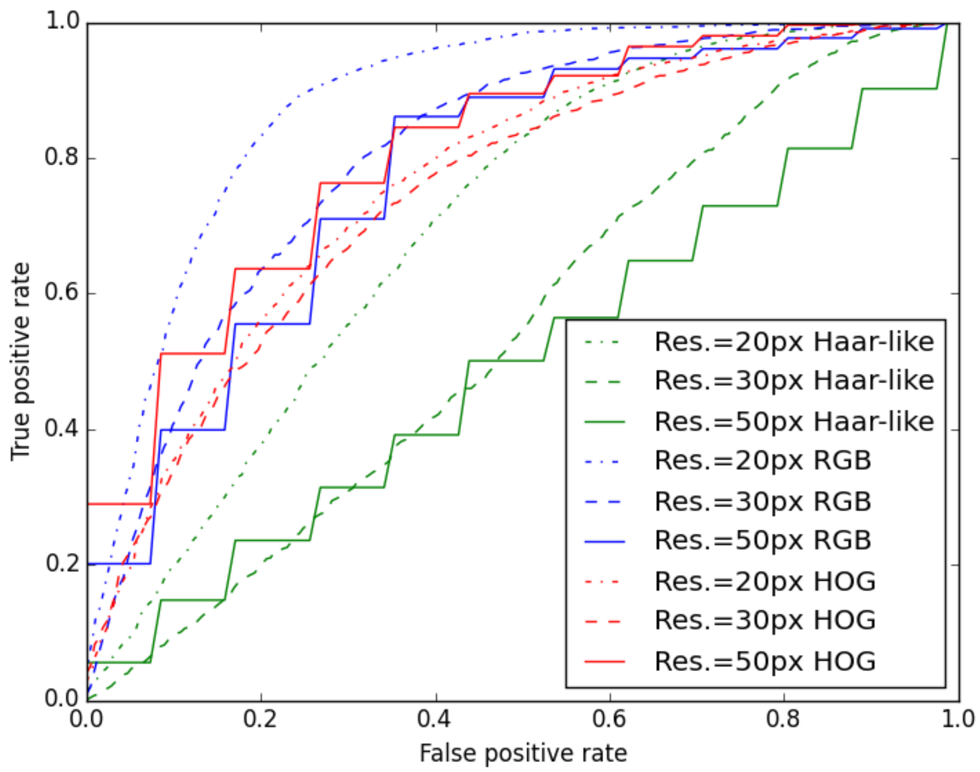

Figure 5. Results of hawk-versus-crow species classification.

Conclusion

We have proposed a bird monitoring system based on time-lapse images and conducted experiments for evaluation of the system. In the experiments, we showed successful results for bird detection and the possibility of species classification using image recognition. However, there is room for performance improvement, especially in species classification. Improvement of the software for more accurate bird monitoring is necessary.

Learning Objectives

Image-based detection and classification is a promising approach for bird monitoring around wind farms. Readers can understand the whole image processing pipeline required for fully automatic bird-monitoring, the performance of established computer-vision methods, and an evaluation methodology. It also introduces an open image database designed for the wind-energy community. The proposed system is a hopeful solution to bird strikes and can contribute to social acceptance of wind energy.

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