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Birds scaring system for agricultural field using image processing

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Abstract— **Fruits and vegetable crops are vulnerable to wild birds. These wild birds and animals can cause critical damage to the produce. Traditional methods of scaring away birds such as scarecrows are not long-term solutions but short term solutions. This is a huge problem in several areas.**

A more effective and permanent system needs to be put into place. Monitoring systems in agricultural settings could potentially provide a lot of data for image processing. Most current monitoring systems however don't focus on image processing but instead really heavily on sensors. Just having sensors for certain systems work, but for birds, monitoring it is not an option because they are not domesticated like pigs, cows etc. in which most these agricultural monitoring systems work on. Birds can fly in and out of the area whereas domesticated animals can be confined to certain physical regions.

The most crucial step in a smart scarecrow system would be how a threat would be detected. Image processing methods can be effectively applied to detecting items in video footage. This paper will focus on bird detection and will analyze motion detection with image subtraction, bird detection with template matching and bird detection with the viola jones algorithm.

Methodology

To save the crops from birds using image processing.

I.INTRODUCTION

Arduino is a single-board microcontroller to make using electronics in multidisciplinary projects more accessible. The hardware consists of an open-source hardware board designed around an 8-bit Atmel AVR microcontroller, or a 32-bit Atmel ARM. The software consists of a standard programming language compiler and a boot loader that executes on the microcontroller.

Arduino boards can be purchased pre-assembled or as do-it-yourself kits. Hardware design information is available for those who would like to assemble an Arduino by hand. It was estimated in mid-2011 that over 300,000 official Arduinos had been commercially produced.

A arduino board with a RS-232 serial interface (upper left) and an Atmel ATmega8 microcontroller chip (black, lower right); the 14 digital I/O pins are located at the top and the six analog input pins at the lower right.

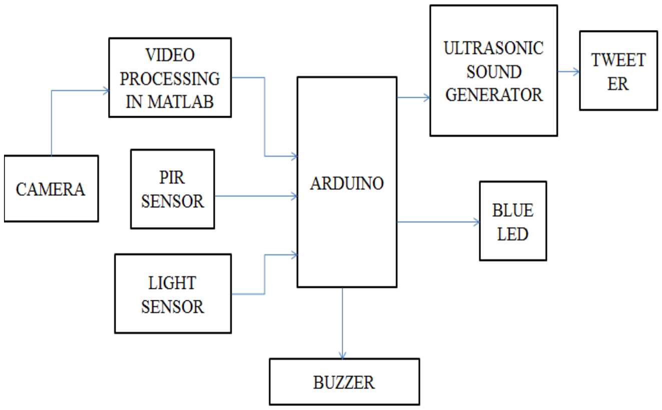
An Arduino board consists of an Atmel 8-bit AVR microcontroller with complementary components to facilitate programming and incorporation into other circuits. An important aspect of the Arduino is the standard way that connectors are exposed, allowing the CPU board to be connected to a variety of interchangeable add-on modules known as shields. Some shields communicate with the Arduino board directly over various pins, but many shields are individually addressable via an I²C serial bus, allowing many shields to be stacked and used in parallel. Official Arduinos have used the megaAVR series of chips, specifically the ATmega8, ATmega168, ATmega328, ATmega1280, and ATmega2560. A handful of other processors have been used by Arduino compatibles. Most boards include a 5 volt linear regulator and a 16 MHz crystal oscillator (or ceramic resonator in some variants), although some designs such as the LilyPad run at 8 MHz and dispense with the onboard voltage regulator due to specific form-factor restrictions. An Arduino's microcontroller is also pre-programmed with a boot loader that simplifies uploading of programs to the on-chip flash memory, compared with other devices that typically need an external programmer.

At a conceptual level, when using the Arduino software stack, all boards are programmed over an RS-232 serial.

This 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 . 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 . 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. Structure of dataset 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 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 , a widely used learning algorithm in the computer vision field. This algorithm is often combined with image features such as Haar-like or Histogram of Orientated Gradients (HOG) 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 is a sequence of images of a scene at a wind farm, and it provides annotations of bird information appearing in the images. 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, Histogram of Orientated Gradients (HOG) features, or RGB features (image pixel values without transformation) combined with AdaBoost knot bird species in offshore waters.This can be explained in the same way as expect 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. 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. On each group, we conducted holdout validation using 800 hawks and 150 crows for training data and others for test data.

IV.PROPOSED ARCHITECTURE

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.



ULTRASONIC SOUND GENERATOR

- Ultrasonic applied to sound refers to anything above the frequencies of audible sound and nominally includes anything over 20,000Hz
- Frequencies used for medical diagnostic ULTRASOUND scans extend to 10MHz and beyond
- The sensor has 2 openings on its front. one opening transmits ultrasonic waves the other receives them

PIR SENSOR

- A passive infrared sensor (PIR sensor) is an electronic sensor that measures infrared (IR) light radiating from objects in its field of view.
- They are most often used in PIR-based motion detectors
- All objects with a temperature above absolute zero emit heat energy in the form of radiation.
- Usually this radiation is invisible to the human eye because it radiates at infrared wavelengths, but it can be detected by electronic devices designed for such a purpose.

LIGHT SENSOR

- A light sensor is an electronic device used to detect light
- A photocell or photo resistor is a small sensor which changes its resistance when light shines on it
- A photo resistor is made of a high resistance semiconductor. If light falling on the device is of high enough frequency, photons absorbed by the semiconductor give bound electrons enough energy to jump into the conduction band.
- The resulting free electron (and its hole partner) conduct electricity, thereby lowering resistance

BUZZER

- A buzzer or Beeper is an audio signalling device which may be mechanical, electromechanical or Piezo electric
- Piezo buzzer is an electronic device commonly used to produce sound

DESCRIPTION

The most crucial step in birds scaring system would be how a threat would be detected. Image processing methods can be effectively applied to detecting items in video footage. This paper will focus on bird detection and will analyze motion detection with image subtraction, bird detection with template matching, and bird detection with the Viola-Jones Algorithm.

MOTION DETECTION

One of the traditional motion detection algorithms used for tracking objects (usually humans) has been the Kalman Filter . Optical flow and Mean Shift tracking has also been used for bird detection. These methods however are much more computationally intensive than other simpler methods such as background subtraction, or difference subtraction because of all the extra calculations in trying to predict the object's next future positions. Both of these studies', main goal was to be able to track birds. For our case, tracking the bird is not necessary because bird detection should be enough for a smart scarecrow to operate properly. In our case we can avoid storing past information and calculations when new image frames come in from video footage.
Although motion detection gives really high accuracy results, motion detection needs to be supplemented with another image processing technique (such as template matching and bird detection using the Viola-Jones algorithm) because anything moving in the scene will be detected as a bird. This is why the next chapters go into object detection tailored to birds specifically.

TEMPLATE MATCHING

Object recognition and object detection has had an increased importance with many fields such as biometrics, robotics, and other image processing applications. One of the oldest methods of object recognition is template matching. Template matching consists of sliding the template over the search area (usually an image in which we are trying to locate an object in) and, at each position, calculating a "distortion" or "correlation" measure that estimates the degree of dissimilarity or similarity, between the template and the candidate. This template matching technique gives high accuracy.

RESULTS

IV.CONCLUSION AND FUTURE WORK

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

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