International Journal of Computer Science and Engineering Communications,
Volume.5, Issue.6 (2017): Page.1774-1783
www.ijcsec.com

Development and Analysis of an Automated Bird Crash Avoidance System

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Abstract. *Bird Conservation is mandatory in wild life preservation. Aviation hazards by birds are to be reduced. Bird preservation by deterrence to avoid aircraft hazards is proposed. This system has three phases- Bird detection, Bird identification, Bird deterrence, a camera on the aviation environment detects the presence of bird. Bird is classified and identified for enabling its deterrence. The image from the camera is processed to check if it is a bird. Once if it is confirmed to be bird it is identified for its species. The relevant acoustic which is deterrent to the bird is identified; the acoustic deterrent system raises the noise irritable to the bird.*

Keywords: *Image capture, Object detection, Object recognition, Pattern Matching*

1.Introduction

From the day of first powered flight birds have been found hazardous to them, which is true vice-versa also. This collision that occurs between any airborne living being especially birds and an airborne human-made vehicle is termed as Bird strike. This term is used also in places where a bird gets stricken by any human made mechanical or structural units wind turbine or power based systems. Insisting on flight safety when concerned with bird strikes, such accidents lead to even human causalities. Also when concerned with damages to aircraft, it affects globally, which are major contributing factor worldwide for the sudden decline of airborne species decline of many avian species. Bird strikes happen most often during takeoff or landing, or during low altitude flight. Flocks of birds are quite dangerous that leads to multiple strikes, and damages in both sides. Recovery of aircrafts during takeoff and landing depends on the damage caused based on altitude of flight.

1.1 Proposed scheme

A pilot is instructed from the Air Traffic Control room with a good clearance statement to the best of his knowledge, through many ways like runway inspections, the use of Surface Movement Radar etc., the runway is clear of objects which could interfere with the safe take-off and landing of the aircraft. Debris near runways causes heavy damages to aircraft indirectly through bird strikes. Foreign Object Damage on airfield includes bird strikes also and the catastrophic damage is to be concentrated on their detection and removal.

DOI:10.5281/zenodo.1155836

In most cases, concentration is to be adopted on eyesight and vigilance of ground staff to adopt best practice in detection and removal.

The objective of this implementation is to:

- Swing away the bird from aviation environment based upon the image captured from the live camera.
- Safeguard the bird from crash.
- Safeguard the aviation components from damage.
- To create a bird deterrent system to fly away the bird from the area of aviation.

Birds are one of the factors considered as a serious hazard to aviation. Damage to airframe is also an important factor to be considered, even though there is no damage to bird or air-crash. Reasons for Bird strike varies in different airports, which in majority incudes wide-open platform of grass that, attract blackbirds, meadowlarks, starlings, pigeons, and geese. Airports located on the coastline or near wetlands attract waterfowl and gulls. Airports near such areas of water sources may attract many birds during time of their migration. The remainder of this work is organized as follows. Section 2 reviews more related works. After reviewing the related works, Section 3 describes the Design of the proposed system. It introduces the system architecture, description, system design goals. Section 3 gives the implementation details.

2. Related Works

Lorries Nanni et al.,[1], in their paper proposed a novel approach for automatic bird species classification. The proposed strategy is based on features taken from the textural content of spectrogram images of bird vocalization. Several texture descriptors can be used for representing the spectrograms. The approaches tested include local ternary phase quantization, heterogeneous auto similarities of characteristics, and an ensemble of variants of local binary pattern histogram Fourier. Combining this set of descriptors greatly increased classification performance and markedly improves previous ensembles of textures used for describing a spectrogram. Moreover, additional improvement was obtained when the texture descriptors are combined with the acoustic features. SVM classifiers are used in the classification step, with final result computed using 10-fold cross-validation. For a fair comparison with the method in the literature, the experiments are performed on a benchmark database composed of 46 bird species used for this classification task. The best accuracy rate obtained is about 94.5%.

Ming sun et al.,[2], in their paper, propose a shape-guided segmentation algorithm for fine-grained visual classification(FGVC). First, edge information is extracted from the query image and compared with each sample of the training set, which can help us retrieve a subset of candidate proposals. These proposals are used to learn prior shape knowledge by separately estimating the foreground probabilities of correspondent pixels from the query image. Then a redefined energy functions introduced to translate a minimum of energy to a good segmentation, with which can dynamically pick out the most preferable proposal. After that, a label map of the image is obtained at the pixel level. Finally, the high-quality segmentation is used to aid locating semantic parts. One global model and two-part model caffe is fine tuned to extract deep features and use a learned SVM classifier for categorization. Three aspects were tested in the experiment, including foreground segmentation, part localization, and final classification.

The results obtained outperformed the state-of-the-art approaches on the famous Caltech-UCSD birds 2000-2011 dataset.

John et.al.,[3], presents a novel approach for bird species classification based on color features extracted from unconstrained images. Besides, the images present strong variations in illuminations and parts of the birds may be occluded by other elements of the scenario. The proposed approach first applies a color segmentation algorithm in an attempt to eliminate background elements and delimit candidate regions where the bird may be present is split into component planes and from each plane, normalized color histograms are computed from these regions. After the aggregation processing is employed to reduce the number of intervals of the histograms to a fixed number of bins. Experimental results on the CUB-200 data set show that the segmentation algorithms achieve 75% of correct segmentation rate. Furthermore, the bird species classification rate varies between 90% and 8%, depending on the number of classes taken into account.

Nilima.R.kharsan[4], proposed a method with 3 important visual features of an image. As a first step, an image is uniformly divided into 8 divided coarse partitions. By using gray level co-occurrence matrix(GLCM). The texture of an image is obtained. Color and texture features are normalized. To record the shape features, invariant moments are then used. A combination of color and texture feature set for the image retrieval is considered as an efficient feature set.

Nursyakirah mohd Noor[5], indicates the use of freeman chain code(FCC) method in image representation and focus on the shapes as the feature extraction for shape matching. Each shape has a different vector in length of chain code hence it needs to match with the template image of the chain code. By using dynamic time warping(DTW) for classification; we manage to indicate the distance between the input images and template image. The lowest distance shows that the image is the closest image. We tested on various regular and irregular shapes, and the result of the shape matching on regular shapes is precise and acceptable but for irregular shapes, some of the dissimilar shapes have almost the same distance and it's invalid.

A.J.Turatti[6], presents a novel approach for bird species identification that relies on both visual features extracted from unconstrained bird images and acoustic features extracted from bird vocalization. The scale invariant feature transform (SIFT) detects local features in bird images, which are then used to train a support vector machine classifier. The instances that are not classified with a certain degree of certainty are then rejected and reclassified using Mel-frequency cepstral coefficients (MFCCs) extracted from the bird songs is available. An experiment conducted on a dataset of 50 bird species that comprise images from the CUB200-2011 and audio samples from xenon-canto have shown that improvements between 1.2 and 15.7 percentage points are achieved when using an acoustic classifier to reprocess the instances rejected the visual classifier, depending on the rejection level.

3. Proposed system

In order to bring out the bird deterrent system as a valuable output, a systemized architecture is to be dealt with. The design of the entire system is detailed in this section. In general, system architecture deals up with detailing the overall flow of the system.

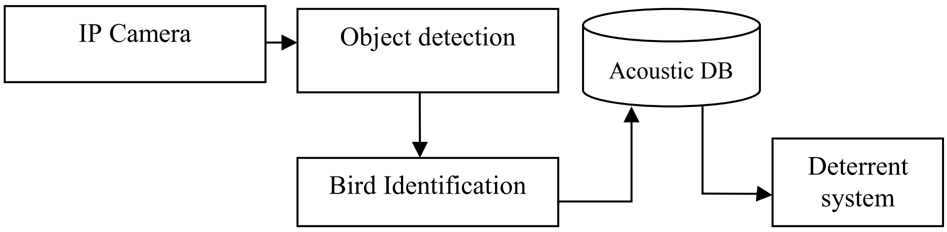

Fig.1. Overall system architecture

The entire system deals with the designing part of the Bird deterrent system as shown in Fig.1.The image captured from the IP Camera is verified from the database for the species related to the bird and the corresponding deterrent noise of the bird is chosen from the database and raised in order to fly away from the bird.

3.1 Motion detection

One of the traditional motion detection algorithms used for tracking objects 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. The main goal was to be able to track birds. Background subtraction would not be a good solution for outdoor video footage. The lighting in the scene would cause the background image to be potentially inaccurate of what the current background is. Motion detection can also be influenced by background subtraction method as specified in equation 1. The absolute value of this difference then becomes a difference image that can be used to find blobs which are objects in the scene.

$$d_{i,j}(x,y) = \begin{cases} 1, if\left|f(x,y,t_{i,}) - f(x,y,t_j)\right| > T \\ x, otherwise \end{cases} \tag{1}$$

This method can be further improved by adding up the accumulative differences. An Accumulative Difference Image is built by comparing this reference image with every subsequent image in the sequence. A counter for each pixel location in the accumulative images is incremented every time a difference occurs at that pixel location between the reference and an image in the sequence. Absolute, Positive, and Negative ADIs are considered often as shown in equations 2,3, and 4.

$$A_k(x,y) = \begin{cases} A_{k-1}(x,y) + 1, if[R(x,y) - f(x,y,k)] > T \\ A_{k-1}(x,y), otherwise \end{cases} \tag{2}$$

$$P_k(x,y) = \begin{cases} P_{k-1}(x,y) + 1, if[R(x,y) - f(x,y,k)] > T \\ P_{k-1}(x,y), otherwise \end{cases} \tag{3}$$

$$N_k(x,y) = \begin{cases} N_{k-1}(x,y) + 1, if[R(x,y) - f(x,y,k)] < T \\ N_{k-1}(x,y), otherwise \end{cases} \tag{4}$$

3.2 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 compares the image over the search area that is tried to locate object 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. Then the minimum distortion or maximum correlation position (depending on the implementation) is taken to represent the instance of the template into the image under examination. There are various ways of calculating the degree of dissimilarity or similarity like Sum of Absolute Differences (SAD) and the Sum of Square Differences (SSD). The Normalized Cross Correlation (NCC) is by far one of the most widely used correlation measures. In the paper they compared various image processing techniques for bird recognition. One of the techniques was template matching and they were able to in some cases get high accuracies. Template subsampling is done by means of Normalized Cross Correlation with the image under examination by searching for the maximum of the NCC function:

$$NCC(x,y) = \frac{\sum_{j=1}^{N}\sum_{i=1}^{M} I(x+i,y+j).T(i,j)}{\sqrt{\sum_{j=1}^{N}\sum_{i=1}^{M} I(x+i,y+j)^2}.\sqrt{\sum_{j=1}^{N}\sum_{i=1}^{M}(i,j)^2}} \tag{5}$$

where x and y are the coordinates, i and j are integers, I and T denote the image and the template array matrix, and the original image is of dimensions MxN. In any comparison, there may be n number of matches for an image , hence the points with a normalized cross correlation above a certain threshold are considered matches. Another way the NCC can be calculated in a way more tailored to the image that is discussed in and is as follows:

$$\rho(x,y) = \frac{\varphi(x,y)}{\sigma_1\sigma_T} \tag{6}$$

where the numerator φ(x, y) represents the cross correlation between the template and the current sub-window of position (x, y) in the input image. It can be calculated as following:

$$\varphi(x,y) = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}[I(x+i,y+j) - \bar{I}]\,[T(i,j) - \bar{T}] \tag{7}$$

And the terms σ_1 and σ_T represent standard deviation of the current sub-window of the input image and the template.

$$\sigma_1 = \sum_{j=1}^{n}\sum_{i=1}^{n}\left[I(x+i,y+j) - \overline{I(x,y)}\right]^2 \tag{8}$$

$$\sigma_T = \sum_{j=1}^{N}\sum_{i=1}^{N}[T(i,j) - \bar{T}]^2 \tag{9}$$

where$\overline{I(x,y)}$ and $\bar{T}$ represent the mean of the current sub-window of the input image and the template as follows:

$$\overline{I(x,y)} = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n} I(x+i,y+j) \tag{10}$$

$$\bar{T} = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n} T\,(i,j) \quad (11)$$

The standard deviation and mean of the current sub-window allow the NCC to be less affected by the lighting conditions in the image. The value of the NCC is between -1 and 1. Template matching is normally carried out in the spatial domain, while it is much faster in the Fourier Domain. Below are the main steps in implementing the algorithm for each image that needs to be analyzed.

I. Load the original image and template.

II. The next steps are then done independently on each color space (the first one run for red, the second run for green, and –the third run for blue).

a. Calculate the Fast Fourier Transform (FFT) of both the image and template

b. Pad the image on all the sides with zeroes so that the center of the template falls on the very first pixel of the main image when kept on the top-left corner

i. Calculate the size of the template.

ii. Pad rows of zeroes on the top and bottom of main image. The number of rows is equal to the size of template in y-direction divided by 2.

c. Now, move the mask over the entire image and simultaneously multiply both the padded image and the template and store it in an array.

d. Normalize NCC values such that they lie in the range from 0 (template and image are not similar at all) to 1 using mean compensation.

e. Reveal the array where the NCC values are being stored.

III. Combine R, G, and B pieces by averaging the NCC results.

IV. Find the positions where the value is above the selected threshold. These co-ordinates are the potential desired objects to be located.

V. Combine coordinate points that are clustered near each other

VI. Repeat previous steps with scaled (resized) template.

When the number of templates used for comparison is raised it may produce a better result, but that may not bring a solution for real-time processing.

When the number of templates used for matching the increases the processing time also increases. Ideally the template is also scaled and rotated about each coordinate point in the image making template matching highly computationally intensive. Accuracy could be increased to a higher percentage by increasing the templates whereas it greatly slows down the system because of the extra computations needed for each additional template. In frames with multiple bird images the algorithm as able to find at least one bird image. So this may provide a higher Acceptance rate on presence of obstacle. A lot of the false positives were caused by branches, water backgrounds, and some birds occlude other birds. For this project high false positive is not as damaging as false negatives. It is more fatal to not catch a bird attacking produce then the smart scarecrow indicating there is a bird when there isn't one. The false positives decrease with increase in threshold which also decreases the accuracy. Therefore a lower threshold is optimal for this project because the accuracy of the system is more important than how many false positives are detected. When the number of templates increases the accuracy may increase but there will not be any change with the false positives. In order reduce the risk of identification templates that could be added to the collection are an average of birds that are facing straight (are centered) and templates with birds with their wings open.

Bird Detection Using the Viola-Jones Algorithm

Research is streamlined to application of face detection techniques that could possibly be applied to bird detection. A popular face recognition algorithm that has competitive detection rates in real-time, is the Viola-Jones algorithm [7], The Viola-Jones algorithm has shown to be successful especially in face detection. Although the training for the object classifier is slow, the actual detecting is fast which is why there have been some web browser implementations like [8] and mobile implementations like [9]. This method is also used for finding human body parts in a scene [10] and not just faces. The Viola-Jones algorithm can be trained for almost any object as long as there is enough similar positive images that can be used for training the classifier. The classifier learns via machine learning from labeled data. Images with the desired object labeled are called positive data. Ideally the training data should be large as thousands of images. The labeled data is encouraged to have many variations across the desired object to detect such as variations in the pose of the object, the illumination in the image, etc. Images not containing the desired object are also needed and are considered negative images. Then the AdaBoost algorithm is used. A set of weak classifiers are made and then iteratively combines classifiers. Image features are extracted using AdaBoost that are “rectangle filters” similar to Haar wavelets. The integral image is also used by AdaBoost. The integral image computes a value at each pixel (x, y) that is the sum of the pixel values above and to the left of (x, y), inclusive. This can quickly be computed in one pass through the image. These classifiers are then cascaded for even higher accuracies. Usually the higher cascade level (higher feature classifier) will have a lower false positive rate.

4. Results and Discussion

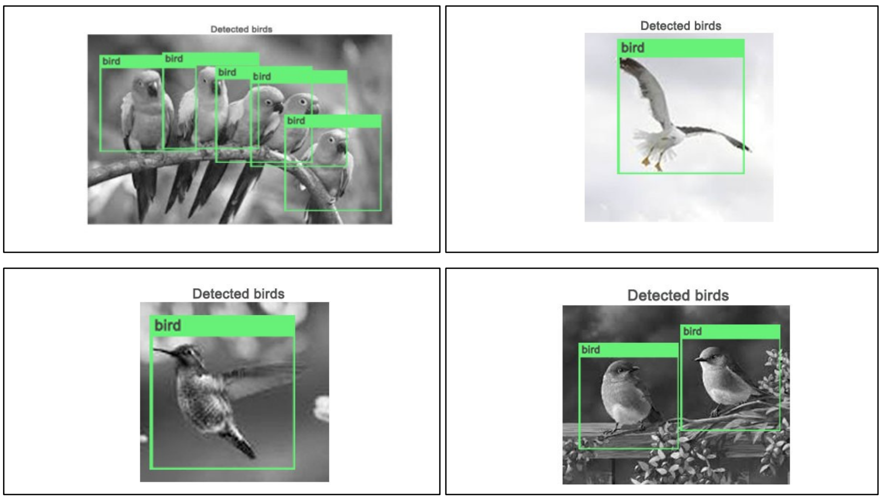

Fig.2. Examples of successful bird detection

Runtime for training the detector varies depending on the parameter settings. Varying values of certain parameters increases complexity and more time on the run time. The bird detector that produced an accuracy of 87% took 4 hours to train. The average run time for the actual detection of birds is similar to results in the Motion Detection section, 0.1950 seconds. Fig. 2. gives the sample images of detected bird. Overall an accuracy of 87% with the average number of false positives below 3 is quite useful in real world applications as in Table 1. Some drawbacks may be in finding the scenes of birds due to their overlapping positions, lighting can vary depending on the camera and time of the day, etc., overall it would be important for a scarecrow to be able to detect at least one bird. In this case the accuracy is more important than the number of false positives because there is a bigger penalty in not capturing a bird than incorrectly guessing a bird is in the scene.

Table 1. Accuracy and FP for FAR

FAR	Accuracy	False positive
0.1	0.71	0.86
0.2	0.72	1
0.3	0.68	1.03
0.4	0.73	0.87
0.5	0.86	1.94
0.6	0.86	11.41
0.7	0.64	39.12
0.75	0.48	94.05

Using an algorithm as a bird deterrent is cheaper than the traditional scarecrow, and will deter birds at a rate of 87% (if one bird of many is selected this is still for a real world implementation so in a way the accuracy is actually higher) which is higher than what netting (30%) and scarecrows (0% long term) can accomplish. The motion detection algorithm that had the highest accuracy was the absolute ADI with a k value of 10. It was able to able to find objects in a scene at a rate of 100%.

Table 2. Accuracy and False Positive for TPR

TPR	Accuracy	False Positive
0.825	0.12	0.11
0.845	0.15	0.18
0.865	0.29	0.48
0.885	0.37	0.4
0.9	0.37	0.71
0.945	0.61	1.33
0.965	0.71	2.6
0.985	0.82	5.87
0.995	0.86	11.41
0.999	0.79	16.47

The discussions and findings are shown in Table 2.Template matching at a threshold of 0.7 (with scaling the templates to four different sizes) achieved the highest accuracy (for template matching specifically) of 59% with a false positive rate per frame of 4.65. Padding the image with white borders instead of black borders lowered the false positive rate per frame to 3.67.The template matching technique would not be suitable for the smart scarecrow system because of the fact that it cannot be run in real time the absolute ADI and the Viola-Jones algorithm.

Conclusion

The surrounding of most runways is characterized by an enormous bio-diversity. Lot of birds are flying around the runways and most probably to strike with aviation. Bird Conservation is Mandatory in wild life preservation. Here a perfect system for Bird conservation and Bird Strike Prevention is proposed. The system is being implemented using Viola Jones method for bird detection and Neural networks for bird classification .In this system, Bird presence is identified , Bird species identification is made and based on the database creation for Bird Deterrent noise is done. The motion detection algorithm used is Kalman filter. Template matching is used for object recognition. After the template matching the bird detection is done using Viola-Jones algorithm. One of the advantages of the system is after detection of the Bird and identifying its species classification is performed to create deterrent noise from the trained database suitable for that particular bird. Future work includes preparing bird repellent system.

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