A Real Time Image Processing Bird Repellent System Using Raspberry Pi Pi

*Olouwole Arowolo, Adefemi Adekunle and Joshua Ade-Omowaye
Department of Mechatronics Engineering, Federal University Oye - Ekiti, Nigeria

{arowolo.olouwole|adefemi.dekanlue}@fuoye.edu.ng |jadem25@gmail.com

Received: 28-MAR-2020; Reviewed: 12-APR-2020; Accepted: 23-JUN-2020

http://dx.doi.org/10.46792/fuoyejet.v5i2.496

Abstract- Rice is one of the most consumed staples in Nigeria, with an average consumption rate of 32kg per person, annually (Pricewaterhouse Cooper, 2017). Consequently, demand is higher than rate of production of local rice, hence, importation becomes a necessity. Despite the Nigerian government policies implemented in 2015 as regarding production of rice and importation of rice, local rice has not met the demand in terms of quantity and quality due to low capacity of local farmers (Falayi, 2019). Lack of processing machines has also been attributed to low quantity and consumption of local rice (Fakayode, Ometosho & Ominniwa, 2010). Aside from lack of processing machines, pests such as birds are also contributors to low production of rice. These pest attacks also subsequently alter the quality such as off-odours, damaged grain, excretions, and presence of diseases from the beaks. In the South Western part of Nigeria, pests especially birds, have been identified as a major limitation on rice production and it has been reported that up to 75% of total output from entire production areas have been eaten up by them (Elliott & Bright, 2007).

Different methods of bird repelling are employed to limit the epidemic damage caused by pests. One of these methods is use of chemical repellent such as pesticides. Pesticides are chemical substances or mixture of chemical elements used for exterminating, avoiding, repelling, or mitigating pests (Kim, Kang, Lee, Kim & Han, 2005; Lushchak, Matviishyna, Husaka, Storey, & Storey, 2018). As a result of these harmful effects of pesticides to wildlife and humans, there is a growing demand for pesticide alternatives or other method of bird repelling. One of these alternatives is using a visual repellent or deterrent. The most common visual deterrent and the oldest is scarecrow. Due to the motionlessness of scarecrows, they only give short term protection because the initial intimidation they create is perceived rather than real.

Motion was incorporated in the making of scarecrows to discourage birds from associating with the scarecrow and to increase its effectiveness. Even with the motion that was incorporated, Bishop et al. (2003) concluded that, ultimately, however lifelike scarecrows are, they do not pose a significant intimidation to the birds. Therefore, to improve the effectiveness of scarecrows, it was proposed that these devices are combined with actual human activity or audio deterrents.

Audio deterrent, also known as sonic deterrents, operate by broadcasting either bird calls or ultrasonic sound waves to get rid of the surrounding area of birds. Several research works have been conducted to determine the effectiveness and efficiency of the ultrasonic deterrent system. These involve testing of commercially available ultrasonic devices on different types of animals. In a review carried out by Afflito & DeGomez (2015), on sonic pest repellents, it was reported that most of the commercially available sonic repellents were ineffective or after a short period of its use, stopped repelling pests. The majority of success using sound to combat pests involved devices were developed by professionals and researchers. This success was likely attributed to the advancement of techniques and devices that target specific species. It was concluded that sonic pest devices sold commercially for use in residential areas have not been displaying effectiveness in scientific studies (Afflito & DeGomez, 2015). Due to this, use of these devices is not recommended to treat common pest problems. Though certain number of researchers are developing sonic techniques that illustrate potential for specific pests, these technologies are yet to be commercially available.

Despite the ineffectiveness of commercially available ultrasonic devices as reported above, evidence abound of researchers who have successfully developed ultrasonic devices to repel birds. Ezeonu et al. (2012) developed an ultrasonic bird repeller and it was tested. Ultrasonic waves were generated, with varying frequency between 15 KHz and 25 KHz. The waves were amplified and broadcast at high sound pressure level from the solar powered electronic device which was fabricated locally. The ultrasonic waves created an unconducive

Keywords- Electronic pest repeller, Haar cascade classifier, ultrasonic

1 INTRODUCTION

Rice is one of the highly consumed staples in Nigeria, one of the highly consumed staples in Nigeria, with an average consumption rate of 32kg per person, annually (Pricewaterhouse Cooper, 2017). Consequently, demand is higher than rate of production of local rice, hence, importation becomes a necessity. Despite the Nigerian government policies implemented in 2015 as regarding production of rice and importation of rice, local rice has not met the demand in terms of quantity and quality due to low capacity of local farmers (Falayi, 2019). Lack of processing machines has also been attributed to low quantity and consumption of local rice (Fakayode, Ometosho & Ominniwa, 2010). Aside from lack of processing machines, pests such as birds are also contributors to low production of rice. These pest attacks also subsequently alter the quality such as off-odours, damaged grain, excretions, and presence of diseases from the beaks. In the South Western part of Nigeria, pests especially birds, have been identified as a major limitation on rice production and it has been reported that up to 75% of total output from entire production areas have been eaten up by them (Elliott & Bright, 2007).
environment for the birds and had a repulsive influence on them. This device had a small radius of action and ultrasonic wave created reactive stimulus to weaver birds and black birds but not quelea birds, as such would be limited to these birds.

Birds will always not be present; therefore, it is necessary to incorporate a detecting mechanism to avoid loss of power because of the system being on at all times. The research works reviewed always required their system to be on, this could lead to quick malfunctioning, damage or destruction of the system and noise pollution in a habituated environment. Therefore, a detecting mechanism that uses a camera could be employed. Maheswaram et al. (2016), designed and simulated a real time image processing system to scare birds from the agricultural field using MATLAB. The birds are detected and tracked using two algorithms namely background subtraction and Kalman filter using MATLAB tools. The birds are detected accurately using background subtraction algorithm but along with birds, the objects in motion in the background are also detected. To overcome the drawback of background subtraction method, Kalman filter algorithm was applied and the performance was tested. This method detected the birds accurately and tracked them with less error probability. Although, Kalman filter algorithm had better result, it would not perform satisfactorily in real-time applications because it is a predictive filter and the bird motion may not be accurately predicted. In real-time applications, time is of the essence, and the time used to predict the next position of the bird may not be enough to correctly track it.

Xinyu and Chang (2017) designed and tested an intelligent bird-repellent device based on Raspberry Pi. The system was able to detect object, although the object was not a bird, it proved that the system was able to detect object designed to be identified. The system was able also to detect the object in motion. Their method of bird scaring was motion detection which is different from bird detection model trained here. Motion detection does not involve training of any model. The algorithm for motion detection captures the first image of the video and stores it, and then compares it with subsequent images received from the camera. If there is difference between the stored image and subsequent image, it means there is motion, hence scaring tactic of the repellent system is deployed. The limitation to this is that, if any flying object passes by, system will assume it is a bird and engage scaring tactic, which could be noise pollution and wastage of energy.

Machine/ computer vision has proved to be a helpful tool in detection of objects in an image. With this system, birds can be detected, and an ultrasonic sound can be generated to dissuade birds from the destruction of rice farms.

2 MATERIALS AND METHODS
The proposed system is made up of two parts, the hardware and software components.

2.1 HARDWARE COMPONENTS
The hardware components are: Raspberry pi, Camera, Motor, Ultrasonic device/speaker, Solar panel, and battery

i. Raspberry Pi: The main hardware component is the Raspberry Pi. Raspberry Pi is a kind of microcomputer. It uses ARM 7 architecture, and its about the size of a credit card. It has powerful system and interface resources. Raspberry Pi can achieve most functions of traditional computers only by being connected to a display and a keyboard, such as word processing, image processing, etc. Furthermore, it is attractive in price and quality. Therefore, it has been widely used in advanced project development all over the world. The ARM processor receives real time video from the camera that is interfaced with ARM 7 cortex Linux based board.

ii. Camera: This is for capturing of scenes on rice fields. The camera has a 640 × 480 resolution. For better and farther detection, a camera with higher resolution can be used. For this prototype, the camera can identify bird at a linear distance of about 2m from the camera from observation. The video acquisition process consists of two steps, video streaming and frame capturing. Video streaming process involves getting the video file from the camera. The video is given as input to the image processing algorithm which recognizes and identify the birds in the video frame.

iii. Motor: This is for rotation of the camera, to increase field of view. Once the birds are detected and located in the video, the algorithm continues to track the birds till they disappear from the camera’s field of view. The location of the bird at any moment is calculated and based on its position, the motor connected to the embedded board is rotated.

iv. Ultrasonic device/speaker: The ultrasonic device is to emit ultrasonic sound to deter the birds. A speaker can be used in place of the ultrasonic device, but predator sounds will be emitted from the speaker to deter birds.

v. Solar panel and battery: The battery supplies needed power to the system and the solar panel is to charge the battery.
2.2 SOFTWARE COMPONENT

i. Python (Raspberry Pi Development Language): Python is the first programming development environment of Raspberries Pi. It is an object-oriented, literal translation type computer programming language. Python language was used in writing the code for bird detection.

ii. OpenCV (Raspberry Pi Image Processing): The full name of OpenCV is Open Source Computer Vision, which is a cross-platform library Computer Vision based on Open Source distribution (Xinyu & Chang, 2017). It can be run on the Linux operating system, Windows and Mac OS. OpenCV can implement many of the general image processing algorithm through programming languages such as python language.

OpenCV is used for training cascade classifiers for object detection. A cascade function is trained from a sample of positive and negative images (Vallez et al., 2015). This machine learning based approach is then used to detect objects in other images. For this system, video taken from the field is analysed and processed using the Haar cascade algorithm. Haar feature-based cascade classifiers is an efficient object detection method proposed by Viola and Jones (2001). Other cascade classifiers are Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG). The HOG features have been used for detecting objects such as people (whole body instead of just a person’s face) and cars. They are useful for capturing the overall shape of an object. LBP and Haar features have been used detecting faces. As stated, this study focuses on Haar feature based cascade classifier. The algorithm has four stages: Haar Feature Selection, Integral Images, AdaBoost Training and Cascading Classifiers

2.2.1 Haar Feature Selection

At the initial stage, the algorithm requires a lot of positive images (images of the object to be detected) and negative images (images without the object to be detected) to train the classifier. Thereafter, the features are obtained from it. For this, Haar features shown in Fig. 2 will be applied. They are like convolutional kernel. Every feature is a single value gotten from subtracting sum of pixels beneath the white rectangle from sum of pixels beneath the black rectangle.

![Haar Features](image)

Fig. 2: Haar Features

Each of these features are moved about in a target window which moves over the image. The value of each feature is computed. If the line feature were to be moved over a bird image with wings spread, a feature selected will seem to focus on the property that the region of the body without the wings is often darker than the region of the wings.

2.2.2 Integral Images

To calculate the features, all possible sizes and locations of each kernel are used. For each feature calculation, the addition of the pixels under white and black rectangles is calculated. A solution to this is the integral image. The integral image at location \(x, y\) comprises the sum of the pixels above and to the left of \(x, y\) inclusive:

\[
ii(x, y) = \sum_{x' \leq x, y' \leq y} i(x', y')
\]

Where \(ii(x, y)\) the integral image and \(i(x, y)\) is the initial image. Using the following pair of recurrences:

\[
s(x, y) = s(x, y - 1) + i(x, y)
\]

\[
ii(x, y) = ii(x - 1, y) + s(x, y)
\]

(Where \(s(x, y)\) is the cumulative row sum, \(s(x, -1) = 0\), and \(ii(-1, y) = 0\), the integral image can be computed in one pass over the original image. However large the image, it reduces the calculations for a given pixel to a process involving four pixels. It makes the process quick.

2.2.3 AdaBoost Training

Among all these features that were calculated, most of them are not important. Selection of the best features is achieved by AdaBoost. For this, every feature is applied on all the images for training. For every single feature, it searches for the best threshold which will classify the image to positive and negative. Due to errors or misclassifications, the features with minimum error rate is selected, which means they are the features that most accurately classify the object and non-object images. (Each image is given an equal weight in the beginning. After each classification, weights of misclassified images are increased. Then the same process is done. New error rates are calculated. Also new weights. The operation is repeated until the required accuracy or error rate is achieved or the required number of features are found).

The last classifier is a weighted sum of these weak classifiers. It is called weak because it alone cannot classify the image, but together with others forms a strong classifier. In an image, most of the object is non-object region. So, it is a better idea to have a simple method to check if a window is not an image region. If it is not, it is discarded in a single stage, and no further processing, and this aids in checking for potential object/image region. This way, more time is spent checking possible object regions.

2.2.4 Cascading Classifiers

To aid in searching for possible object regions, the concept of Cascade of Classifiers was introduced (Viola and Jones, 2001). Instead of applying many features on a window, the features are grouped into different stages of classifiers and applied one-by-one. (Normally the first few stages will contain very many fewer features).
Overview of code (The codes are boxed in stages 1 to 5)

```python
import os
import sys
import cv2
import numpy as np
import serial
import time

arduino = serial.Serial('COM5', 9600)
time.sleep(2)
print("Connection to arduino...")
bird_cascade = cv2.CascadeClassifier('bird.xml')
```

1. Necessary software packages for the Python compiling environment are imported.

2. Variable Arduino is created to establish a connection between the raspberry pi and the Arduino board. The variable bird_cascade is cascade classifier object with the path to the xml file that contains the bird features.

3. The image is acquired at this stage, resized, and converted to grayscale. Variable 'birds' is for the bird detected coordinates in the frame.

4. At this stage, the rectangle properties to enclose the birds detected in the image are specified. The centre of the frame is calculated and compared with the position of the rectangular coordinate, the difference is sent to the Arduino to rotate the motors relatively. At this stage also, the predator calls are played.

5. The processes are made visual.

### 2.3 Experimental Setup

The Cascade Trainer GUI (Graphic User Interface) made by Ahmadi (2016) was used to train cascade object classifiers. It uses OpenCV library. This trainer aids in setting up all the parameters that involves training a Cascade Object Detector function. Fig. 3 shows the User interface of the trainer.

Parameters can be adjusted in the trainer for training of different cascade functions. The feature types and number of stages were adjusted to determine what feature had the highest accuracy. The different features that can be extracted are Haar features, Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG). All these features can be extracted involve the same training parameters. Comparison will show whether bird detection will perform better with Haar, LBP, or HOG feature type.

```
for (x,y,w,h) in birds:
    cv2.rectangle(img,(x,y),(x+w,y+h),(0,255,0),5)
    roi_gray = gray[y:y+h, x:x+w]
    roi_color = img[y:y+h, x:x+w]
    arr = [y:y+h, x:x+w]
    xx = (x+(x+h))/2
    yy = (y+(y+w))/2
    center = (xx,yy)
    os.system('Predator_call.mp3')
    data = "X = {} Y = {}".format(xx, yy)
    arduino.write(data.encode(data))
```

Fig. 2: Cascade trainer GUI

Fig. 4 and Fig. 5 show horizontal and vertical positive samples, respectively. The length of width is greater than height for the horizontal samples while the length of the height is greater than the width for vertical samples. This variation was included in the data set since in real life application, the birds would be seen from different field of views or angles. The Red-billed Quelea (Quelea quelea) being the most serious bird pest in Sub-Saharan Africa (Elliott & Bright, 2007) is included in the sample. Other birds such as the pigeon (Columbidae), Scaly-Breasted Munia (Lonchura punctulata) were also added. Some other birds which are not pests of rice were included for the system to have a good enough accuracy.
All the images were converted to grayscale so that bird detector would not be overly sensitive to variations in bird colour. 430 images were used as negative images and 272 images were used as positive images. 45 bird images were used as test images. The test images are a different set of images used from the training stage. Some of the images were acquired from Caltech-UCSD Birds data set and online search engine (Google). The images were resized for uniformity. The negative images are more than the positive images to have less of false detections and the number of images over all are low due to computational power (4GB RAM, 32-bit OS).
Fig. 8 and 9 are two different videos of birds. Input video 2 has only one bird while input video 1 has more than one. Input video 1 is 40 seconds long with 1200 frames and input video 2 is 67 seconds long with 1675 frames. The videos were used to test the accuracy of the trained model since motion (birds flying) would be involved on the field (rice field). Videos are series of images (frames) displayed at a fast rate. The processing system (computer) can extract images from videos being played and process them at a quick rate to obtain information. This is what the Raspberry pi shown in fig. 10 and 11 is for. The camera mount shown in fig. 10 and 11 is where the camera is attached and the servos enable the camera to be moved both horizontally and vertically as to increase the field of view and track birds in the area until they are out of the field. The Arduino board controls the servo movements, it receives coordinates from the raspberry pi.

The setup was powered with 5V 3A source. A battery of at least 6V 4.5Ah with a 12V solar panel is sufficient for the power requirement on a field. The setup would cover an area of 25m² with a speaker rated 85dB, 1W. Predator sounds generated from this speaker, would scare birds away from rice fields.

3 RESULTS AND DISCUSSION

Fig. 11: Sample of Successful bird detection

Fig. 12: Sample of unsuccessful/partially successful bird detection

Fig. 13: Sample of unsuccessful/partially successful bird detection

Fig. 12 and 13 show sample of successful and unsuccessful bird detection. Successful bird detection is when the algorithm succeeds in detecting the actual number of birds in the test image while unsuccessful bird detection involves incorrect detection of birds in the test image. Unsuccessful bird detection is categorised into two, namely false positive (FP) and false negative (FN). False positive bird detection is detecting a bird in an image when it is not actually there while false negative detection is not detecting bird in an image with bird or birds. Successful bird detection can also be categorised into two, which are true positive (TP) and true negative (TN). True positive bird detection is accurately detecting the actual number of birds in a test image with birds while true negative bird detection is not detecting of birds in an image with no birds. FP, FN, TP and TN can be used to compute the accuracy of the cascade trained.
Fig. 13 shows the accuracy of HOG, LBP and Haar features. It was observed that Haar features had the highest accuracy of 76% while LBP and HOG had 72% and 27% respectively.

The accuracy of HOG, LBP and Haar features as cascade stages is increased is shown in fig. 16. It was seen that as number of cascade stages is increased the accuracy increased for all the features and it started declining at 20 number of stages for LBP and HOG, this is due to the fact that accuracy becomes so rigorous that many birds are overlooked that are slightly different from the birds in the training data. Although there was a slight decline in Haar features but it became steady and had the highest accuracy.

Fig. 17 shows that number of false positives decreased with increase in number of cascade stages. This was because as the number of cascade stages gets increased, the bird detector becomes more complex and more rigorous. For bird images, Haar almost consistently gave a better accuracy (fig. 16) and a lower value of false positives compared to LBP.

Because Haar features gave the highest accuracy and consistency, the cascade trained with Haar was used for the videos for bird detection. The recorded video is processed using python with OpenCV library and the birds in the video are detected and tracked.

The birds were detected in each of the video. Although some of the birds were incorrectly detected, it is better to incorrectly identify a bird in a scene than not capturing a bird at all. Some of the difficulties in finding bird in a scene are that birds overlap each other, there are various positions birds can be in (flying, standing, etc.), lighting can vary depending on the camera and time of the day, etc. Overall, it would be important for the bird repellent system to be able to detect at least one bird. It does not necessarily need to detect all the birds on the scene to effectively scare them away.
4 CONCLUSION
The Haar-like features gave the highest accuracy of 76% compared to HOG and LBP features. Haar features are best for bird detection. Bird detection algorithm is most suitable for bird repellent system than motion detection algorithm when using machine vision. Motion detection senses motion in the imaging system (video) without differentiating between birds, flying objects and other moving object while bird detection algorithm distinguishes between flying objects and birds as it has been trained to identify the features of birds.

For better accuracy, more positive and more negative images should be used to train the model so that there would be fewer false positive and false negative results. Also, deep learning platform should be used for bird identification/recognition. Low power consumption (15 W), less weight (low number of parts), environmentally friendly are some of the advantages of using the electronic bird repellent system over using conventional scarecrow of low efficiency.

REFERENCES
Aflitto, N. & DeGomez, T. (2015). Sonic Pest Repellents. College of Agriculture and Life Sciences, The University of Arizona Cooperative Extension. Retrieved from https://repository.arizona.edu
Ahmadi A. (2016). Cascade trainer GUI. Retrieved from https://amin-ahmadi.com/
Bishop, J., McKay, H, Parrott, D. & Allan, J. (2003). Review of international research literature regarding the effectiveness of auditory bird scaring techniques and potential alternatives. Retrieved from https://pdfs.semanticscholar.org/52d1/7a806a7156e45b3f50bf7e8a8e70918ac4ab.pdf?_ga=2.255559432.1883534728.1583497847-1581887134.1568980202
Clarke, T.L. (2004). An autonomous bird deterrent system (Research project). Faculty of Engineering and Surveying, University of Southern Queensland. Retrieved from https://core.ac.uk/download/pdf/11034512.pdf
Ezeonu, S.O., Amaefule, D.O. & Okonkwo, G.N. (2012). Construction and testing of ultrasonic bird repellent. Journal of Natural Sciences Research, 2(9), 8-17. Retrieved from https://www.researchgate.net/
Elliott, C. & Bright, E. (2007). Review of the bird pest problem and bird scaring in south west Nigeria (Series 8). PrOpCom. Retrieved from http://www.propcomalkafiri.org/
Fakayode, S.B., Omotosho, O.A. & Omoniwa, A.E. (2010). Economic Analysis of Rice Consumption Patterns in Nigeria. Journal of Agriculture, Science and Technology, 12(2), 135-144. Retrieved from https://www.researchgate.net/
Falayi, K. (2019). Why Nigeria has restricted food imports. British Broadcasting Corporation Africa business report. Retrieved from https://www.bbc.com/news/
Kim, J.K., Kang, C.S., Lee, J.K., Kim, Y.R. & Han, H.Y. (2005). Evaluation of Repellency: Effect of Two Natural Aroma Mosquito Repellent Compounds, Citronella and Citronellal. Entomological Research, 35(2), 117–120. http://doi.org/10.1111/j.1748-5987.2005.tb00146.x
Lushchak, V.I., Matviishyna, T. M., Husaka, V. V., Storey, J. M., & Storey, K. B. (2018). Review article: a mechanistic approach. EXCLI Journal, 17, 1101-1136. doi:10.17179/excli2018-1710
Maheswaran, S., Ramya, M., Priyadharshini, P. & Sivarani, J. P. (2016). A real time image processing system to scaring the birds from agricultural field. Indian Journal of Science and Technology, 9(30), 1-4. http://doi.org/10.17485/ijst/2016/v9i30/98999
Tiwar, D.K. & Ansari, M.A. (2016). Electronic pest repellent: A review. International Conference on Innovations in information