SWWS: A Smart Wildlife Warning Sign System

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Abstract

Every year in the US, millions of animals are run over by vehicles making wildlife vehicle collisions a real danger to both animals and human. In addition, road networks become abiotic barriers to wildlife migration between regions creating ripple effects on ecosystems. In this paper, a smart wildlife warning sign system (SWWS) is demonstrated, utilizing the technologies of Internet of Things, image recognition, data processing and visualization. This smart sign system is intended to prevent roadkill by warning drivers to slow down once sensors are triggered and simultaneously capture animal images via infrared camera. Data collection is conducted through local neural network model identification of wildlife images and saved along with metadata based on animal activity occurrence. Wildlife activity data can be exported wirelessly to cloud database to assist ecologists and government road agencies to investigate and analyze the wildlife activity and migration patterns over time.

Introduction

Along America's highways, roads cross through the habitat of many native wildlife species. When these paths intersect with animal migration, collisions can occur. This presents a real danger to human safety as well as wildlife survival (Huijser et al. 2008). According to the crash analysis report of the Oregon Department of Transportation, there are about 1,250 large animal involved collisions reported in the year of 2014 (ODOT 2014).

There are a variety of limitations with commonly applied roadway warning signs: poor visibility during night and bad weather, short reaction time for drivers and a lack of ability in providing dynamic data. Furthermore, the infrastructure built to prevent roadkill such as animal overpasses and wire-fencing can be expensive and ineffective if the construction is based on inadequate outdated information. Current wildlife activity data used for these solutions is collected from human sightings or radio collars, with miscount error prone to occur due to the labor-intensive work involved.

Thus, an innovative smart wildlife warning sign system is designed to achieve three key functional goals: (1) Warn the drivers of animal presence through flashing LED light matrix when sensor is triggered; (2) Take animal images, record, and transmit metadata wirelessly; (3) Generate seasonal animal activity map, identify activity hot spots, and predict migration patterns over time for wildlife populations

Architecture and Prototype

The hardware system involves infrared and microwave radar sensor array, LED light matrix, No-InfraRed camera, Raspberry Pi, wireless transmission module, and solar offline power generator. Prototype is built and shown in Figure 1. This smart system utilizes a passive infrared sensor alongside microwave radar depth detection for consistent and accurate recognition of animal presence. In addition, sensor detection is paired with the NoIR camera for night and daytime image capture capabilities acting as a trap-camera subsystem. Once animal presence has been detected, the warning LED light matrix blinks and simultaneously captures wildlife in the camera field of vision. The smart warning sign system packages all these components together in a compact and modular arrangement allowing for flexible adjustments depending on field conditions.

Figure 1: Prototype Pictured from Front side and Back side

As soon as both the PIR sensors and the microwave radar sensor detect an animal disturbance in the environment, the LED Matrix facing the road begins to flash indicating the driver the animal presence. The NoIR camera facing away from the road simultaneously takes a picture of the animal sighted. This image is sent to an onboard pre-trained machine learning model loaded onto the Raspberry Pi for live predictions on the wildlife species captured. The identified species as well as metadata such as location and time are saved into a data log file to be sent via wireless Ad-Hoc to a remote server for further process. Data is organized by location, time, and species to generate a bubble choropleth map of animal activities over time.

A deep Convolutional Neural Network (CNN) VGG16 architecture is used to optimize training efficiency in terms of times and accuracy (Zisserman 2015). The training study is conducted through the US Department of Fish and Wildlife Image library using Python-based TensorFlow and Keras. Over 5000 images of 6 different wildlife species (Black-Tailed Deer, Mule Deer, Rocky Mountain elk, Roosevelt Elk, Coyote, and Cougar) were used for model training based on the frequency of roadkill collisions. These images were then randomly shuffled and distributed into sets for training/validation/testing in an 80%/20%/10% blend. To ensure testing model accuracy, 10 new images of each of the 6 species were extracted from the chosen image library. Besides a baseline model with no image processing techniques applied, different image filters and blurs techniques such as the Gaussian Blur, Median filter (Huang et al. 1979), and Laplacian filter were tested and compared to improve the accuracy and training efficiency (Shapiro and Stockman 2001). Each of the methods implements unique modifications to the image via background blending, overall noise reduction, and gradients respectively.

Experimental Results

Image Training and Model Selection. In this study, Gaussian Blur, Median filter and Laplacian filter are compared against the baseline model without any image sharpening techniques. The accuracy comparison among baseline and filtered models indicates that the Laplacian is the most accurate model at a 95% prediction accuracy. Laplacian filter will be used for future image processing for this project.

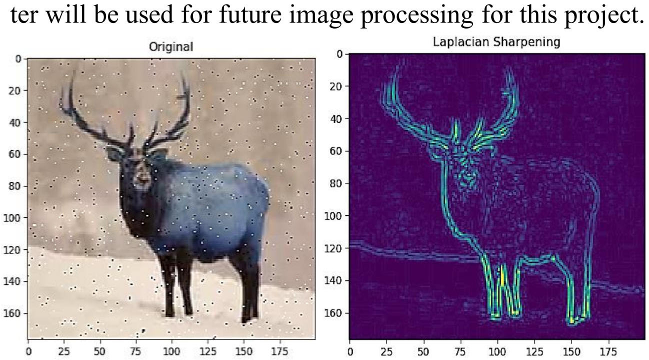

Figure 2: Resultant Laplacian Filter Image

Migration Pattern Generation. Due to inadequate in-field testing data, an existing database (Rodriguez 2008) is used to demonstrate the longstanding application of this system to monitor animal activities and predict migration patterns for ecologists and government infrastructure planning. In the case study, 3 species of animals: Black-tailed deer, Roosevelt elk and Coyote, are tracked across 6 locations in Oregon: Bend, Ontario, Roseburg, Medford, La Grande and John Day, during 4 seasons of 2008 with number of occurrences sighted. Each species has a unique heat color code. Darker color shade and bigger bubble indicate dense activity while light shade and a smaller bubble show lighter activity at a location. Utilizing Folium in Python, the interactive maps are generated so that users can click on each bubble to access information like location, species, and occurrences. A clear wildlife activity pattern in 2008 is demonstrated in Figure 3.

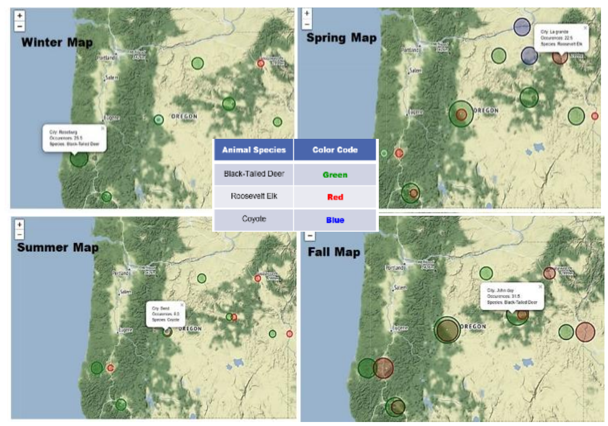

Figure 3: Wildlife Activity Bubble Map

Conclusions and Future Work

This paper demonstrates a working prototype with the integration of IoT technology to minimize roadkill accidents. In addition, machine learning methods used can assist wildlife conservation by identifying animal species, monitoring animal activity, and predicting animal migration patterns over time. Through comparison of three different computer vision techniques, the highest accuracy of 95% can be achieved through application of a Laplacian filter on the final test set.

Future work focuses in-field testing and machine learning model accuracy. A wider variety of animal species will be used to grow the identification capacity. Furthermore, wireless capabilities will be improved by utilizing an app-based system and connecting to the vehicle cloud for live traffic feed information on the go.

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