
ISSN: 2321-2152
IJMECE
International Journal of modern
electronics and communication engineering
E-Mail
editor.ijmece@gmail.com
editor@ijmece.com
www.ijmece.com

IJMECE

ISSN2321-2152

www.ijmece .com

Vol 12, Issue.2 May 2024

A PRACTICAL ANIMAL DETECTION AND COLLISION AVOIDANCE ON ROAD USING COMPUTER VISION TECHNIQUE

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Abstract:

One serious problem that all the developed nations are facing today is death and injuries due to road accidents. The collision of an animal with the vehicle on the highway is one such big issue which leads to such road accidents. In this paper, a simple and a low-cost approach for automatic animal detection on highways for preventing animal-vehicle collision using computer vision techniques are proposed. A method for finding the distance of the animal in real-world units from the camera mounted vehicle is also proposed. The proposed system is trained on more than 2200 images consisting of positive and negatives images and tested on various video clips of animals on highways with varying vehicle speed. As per the two-second rule, our proposed method can alert the driver when the vehicle speed is up to 35 kmph. Beyond this speed, though the animal gets correctly, the driver doesn't get enough time to prevent a collision. An overall accuracy of almost 82.5% is achieved regarding detection using our proposed method.

I INTRODUCTION

Today's automobile design primarily depends on safety measures, security tools and comfort mechanism. The approach has facilitated the development of several intelligent vehicles that rely on modern tools and technology for their performance. The safety of an automobile is the highest priority according to a recent report [1]. The report commissioned by World Health Organization in its Global Status Study on Road Safety 2013, revealed that the leading cause of death for young people (15-29 age) globally is due to road traffic collisions. Even though various countries have initiated and taken steps to reduce road traffic collisions and accidents, the total number of crashes and traffic accidents remain as high as 1.24 million per year [2]. Road traffic accidents and injuries are expected to rise by almost 65% by the end of 2020 [3]. Due to road accidents, every year 1 out of 20,000 persons lose their life and 12 out of 70,000 individuals face serious injuries in India [4].

India is also known for the maximum number of road accidents in the world [5]. According to the data given by National Crime Records Bureau (NCRB), India, there was almost 118,239 people who lost their life due to road accidents in the year 2008 [6]. A major percentage of these road crashes and accidents involved car and other vehicles. Road accidents are increasing due to the increase in a number of vehicles day by day and also the due to the absence of any intelligent highway safety and alert system. According to data given in a study [7], the number of people who lost their lives in India due to road accidents was almost 0.11 million deaths in 2006, which was approximately 10% of the total road accident deaths in the world. According to the accident research study conducted by JP Research India Pvt. Ltd. for the Ahmedabad-Gandhinagar region (cities of India), for the duration February 2014 to January 2015, total 206 road traffic accidents were recorded and these were influenced by three main factors i.e. human, vehicle, infrastructure or a combination of them [8]. The number in figure 1 is a percentage of the total number of accidents surveyed. According to the record, human factor influence on road traffic accidents was 92%, vehicle 9% and infrastructure 45%. Out of total 45% (91 accidents) infrastructure influenced traffic accidents, 6% (12 accidents) were due to animals on the road whereas out of total 92% (171) human factor influenced traffic accidents, 14% (24) were due to driver inattention and absence of any timely alert system for preventing the collision . Similar types of surveys were conducted for the Mumbai-Pune expressway, and Coimbatore by JP Research India Pvt. Ltd. and the conclusions hinted at a significant percentage of road accidents resulting due to an object (animal) on the road, driver inattention, and absence of an intelligent highway safety alert system.

II LITERATURE SURVEY

Applications built on detection of animals play a very vital role in providing solutions to various real-life problems . The base for most of the applications is the detection of animals in the video or image. A recent study shown that human beings have to take the final call while driving whether they can control their car to prevent collision with a response time of 150ms or no. The issue with the above approach is that human eyes get exhausted quickly and need rest, which is why this method is not that effective. Some scientific researchers have proposed a method that requires the animals to take a pose towards the camera for the trigger, including face detection. The problem with this technique is that face detection requires animals to see into the camera which is, not necessarily captured by the road travel video. Animals can arrive from a scene from various directions and in different sizes, poses, and color. Animals can be detected using the knowledge of their motion. The fundamental assumption here is that the default location is static and can simply be subtracted. All blobs, which stay after the operation are measured as the region of interest. Although this technique performs well in controlled areas, e.g. underwater videos, it does not work universally, especially road or highway side videos. Researchers used threshold segmentation approach for getting the targeted animal's details from the background. Recent researches also revealed that it 's hard to decide the threshold value as the background changes often. A method applicable to moving backgrounds (e.g., due to camera motion) is presented in subsequent studies and. The authors also state that other moving objects apart from the object of interest may be falsely detected as an animal. Researchers in tried to discover an animal's presence in the scene (image) affecting the power spectrum of the picture. This method of animal detection was also considered not appropriate since quicker results with this approach would involve massive amount of image processing in a short period Researchers in also used the face detector technique initiated by Viola and Jones for a particular animal type. After the animal face is identified, the researchers track it over time. The problem with this technique is that face detection requires animals to see into the camera not necessarily captured by the road travel video. Animals can arrive from a scene from various directions and in different sizes, poses, and colors. Another method for animal detection and tracking that uses texture descriptor based on SIFT and matching it against a predefined library of animal textures is proposed in The problem with this method is that it is restricted to videos having single animal only and very minimal background clutter.

In Saudi Arabia, the number of collisions between the camel and a vehicle was estimated to reach more than a hundred each year [Authors in implemented a deployable Camel Vehicle Accident Avoidance System (CVAAS) and exploited two technologies GPS and GPRS to detect the camel position and then transmit that position to the CVAAS server consequently. The CVAAS server checks the camel position and decides to warn the drivers through activating the warning system if the camel is in the danger zone. Authors in do mention that cost of deploying such CVAAS on a great scale is too much. Also, the system suffers from many false negatives due to dependency on many parameters like a width of the dangerous zone, variation in camel speed and delay in receiving SMS message. Authors in designed a system, which uses web cameras which are placed in the detecting areas from where the animal can cross their boundary. The videos are sent to the processing unit and then uses image mining algorithm, which identifies the change in set reference background. If there is a change in the newly acquired image, then authors are applying content-based retrieval algorithm (CBIR) to identify the animal. The proposed method in based on CBIR algorithm suffers from many issues like unsatisfactory querying performance- CBIR systems use distance functions to calculate the dissimilarity between a search image and database images, low-quality recovery results. This approach is very slow and response times in the range of minutes may take place if the database is enormous. To find the accurate location of fishes in the marine, researchers aimed a technique using LIDAR (light detection and ranging). Some of the above-specified methods have been discussed in also.

III EXISTING SYSTEM

Road accidents are increasing due to the increase in a number of vehicles day by day and also the due to the absence of any intelligent highway safety and alert system. According to data given in a study [7], the number of people who lost their lives in India due to road accidents was almost 0.11 million deaths in 2006, which was approximately 10% of the total road accident deaths in the world.

IV OBJECTIVE

Intelligent highway safety and driver assistance systems are very helpful to reduce the number of accidents that are happening due to vehicle-animal collisions. On Indian roads, two types of animals – the cow and the dog are found more often than other animals on the road. The primary focus of the proposed work is for detection of animals on roads which can have the potential application of preventing an animal-vehicle collision on highways. Specific objectives of the research work are:

- To develop a low-cost automatic animal detection system in context to Indian roads.
  - Finding the approximate distance of animal from the vehicle in which camera is mounted.
  - To develop an alert system once the animal gets detected on the road which may help the driver in applying brakes or taking other necessary action for avoiding collision between vehicle and animal.

V PROPOSED SYSTEM

The video is taken from a forward-facing optical sensor (camera) in which a moving animal is present apart from other stationary and non-stationary objects. This video is stored in the computer and converted into different frames. Then we are doing pre-processing steps to enhance the image. For feature extraction and learning of the system, we are using a combination of HOG and boosted cascade classifier for animal detection. All the image processing techniques are implemented in OpenCV software. Once the animal gets detected in the video, the next step is to find the distance of the animal from the testing vehicle and then alert the driver so that he can apply the brakes or perform any other necessary action which is displayed on command prompt as a message. Depending on the distance of the animal from the camera mounted vehicle, three kinds of messages (indication) are given to the driver i.e. animal very near, if animal is very near to the vehicle, animal little far, if the animal is little far from the vehicle and very far, if the animal is very far and at a safe distance from the vehicle.

VI IMPLEMENTATION

Dataset:

Our Deep Learning application uses Neural Networks for object recognition. This requires an image dataset of the objects to train the classifier. In this project we have used COCO (Common Objects in Context) 2014 Database with 80 different object classes which have 83K training images, 41K Testing images. The dataset used is the labeled dataset which is useful to train the model. Some of the objects among 80 classes are as follows:

Animal: cat, cow, dog, horse, sheep etc

Data Preparation:

The COCO dataset was downloaded from cocodataset.orG

Data Labeling:

The images are labeled by using Label Img software. For some images the annotations file is downloaded with the dataset itself. Annotation file contains parameters object class, unique object_id, x_coordinate for centre, y_coordinate for centre, width and height for each image.

Train-Test Split:

After collecting and annotating the dataset, we randomly shuffle the data to select 80% of the data on which we train the model. The remaining 20% of the data, unseen by the model, is used for the testing of the model.

Model training:

The main idea behind making object detection or object classification model is Transfer Learning which means using an efficient pre-trained model. Here we have using three models: Object Detection API provided by Tensorflow (uses SSD mobilenet v1), MULTIBOX and YOLO. By default Object Detection API by Tensor is used since it was found to be most efficient.

Real Time Video Processing: The frames are captured at the rate of - frames per second with preview size of

640 x 680. The stable output is generated for the real-time input.

Animal Detection:

Bounding boxes are generated which predicts the certainty called as confidence score. This score lets us know that the bounding box consists of some object. For every bounding box, the cell predicts a class of that object which gives a distribution of probability among all the available classes in the given model. The confidence score along with the probability just calculated, gives us the final score which lets the user know how likely it is that the bounding box contains some specific object. Minimum detection confidence to track a decision: For Tensor flow Object Detection API: 0.6f For MULTIBOX: 0.1f For YOLO: 0.25f Bounding boxes whose score is more than the threshold is given as an output along with the respective class name. Finally, the generated text output is converted into audio by using Text To Speech API.

Distance Calculation:

In this module we are going to calculate the distance between rear camera and detected animal in the video using OpenCV. Based on the distance measured if the detected, animal is near to vehicle application will play an alarm to alert driver.

VII CONCLUSION

a large scale study of animal detection with deep learning where 8 state of the art detectors were compared in a wide range of configurations. A particular focus of the study was to evaluate their generalization ability when training and test scenarios do not match. It was shown that none of the detectors can generalize well enough to provide usable models for deployment, with missed detections on previously unseen backgrounds being the main issue. Attempts to increase recall using tracking and multimodal pooling proved ineffective. Synthetic data generation using segmentation masks to extract animals from images of natural habitats and inserting them in target scenes was shown to be an effective solution. An almost fully automated way to achieve this was demonstrated by the competitiveness of coarse unsupervised masks with precise manual ones in terms of the performance of detectors trained on the corresponding synthetic images. RETINA and YOLO were shown to be competitive with larger models while being sufficiently lightweight for multi-camera mobile deployment

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