IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received September 27, 2016, accepted November 8, 2016, date of publication December 21, 2016, date of current version February 25, 2017.

Digital Object Identifier 10.1109/ACCESS.2016.2642981

A Practical Animal Detection and Collision Avoidance System 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 km/h. Beyond this speed, though the animal gets detected correctly, the driver does not get enough time to prevent a collision. An overall accuracy of almost 82.5% is achieved regarding detection using our proposed method.

INDEX TERMS Cascade classifier, computer vision, histogram of oriented gradient, haar, image processing, intelligent vehicle system, OpenCV, road injuries.

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

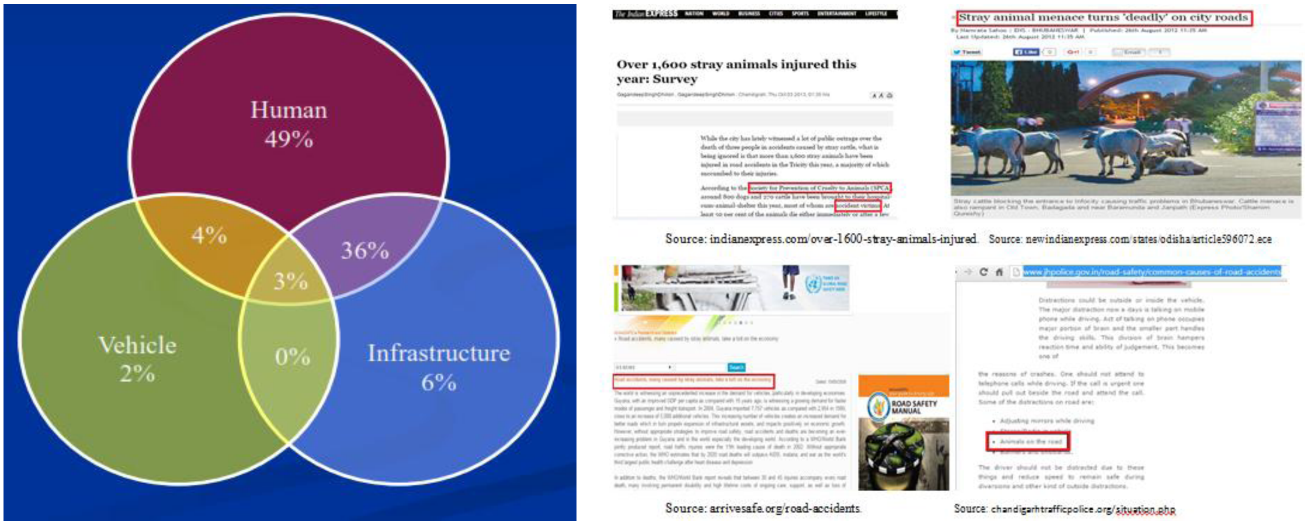


FIGURE 1. **Influences on road traffic accidents [8].**

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. EVIDENCES OF AN ANIMAL-VEHICLE COLLISION

According to the report given by the Society for Prevention of Cruelty to Animals (SPCA), around 270 cattle had been brought to their hospital-cum-animal-shelter in the year 2013, most of whom were accident victims [27]. Below are some of the snapshot of the images with the sources which suggest that there are many challenges that the drivers are facing because of animals on the road.

III. LITERATURE SURVEY

Applications built on detection of animals play a very vital role in providing solutions to various real-life problems [9]. The base for most of the applications is the detection of animals in the video or image.

A recent study [10] 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 [11] 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 [12] 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 [13] used threshold segmentation approach for getting the targeted animal's details from the background. Recent researches [14] 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 [15], [16]. The authors also state that other moving objects apart from the object of interest may be falsely detected as an animal.

Researchers in [17] 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 [18]. Researchers in [19] 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 [20]. 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 [21]. Authors in [21] 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 [21] 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 [22] 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 [22] 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 [23] aimed a technique using LIDAR (light detection and ranging). Some of the above-specified methods have been discussed in [24] and [25] also.

IV. RESEARCH GAP AND CHALLENGES

- Though various practical solutions for automatic lane detection and pedestrian detection on highways are available still research related to automatic animal detection on highways is going on.
- Animal detection in wildlife (forest) videos or underwater videos (controlled areas) have been tried in past but the challenges are much more when detecting animals on highways (uncontrolled areas) as both animal as well as a camera mounted vehicle is moving apart from other obstacles on the road which are also moving or stationary. There is no issue of speed (vehicle speed as well as animal speed) and detecting distance of animal from the vehicle in wildlife videos which is crucial and critical in animal detection on highways.
- The biggest challenge in detecting animals compared to pedestrians or other objects is that animals come in various size, shape, pose, color and their behavior is also not entirely predictable. Though the basic shape and size of a human being are pretty average and standard, the same is not true for animals.
- Although various methods and approaches have been used and are still in progress to detect, solve and reduce the number of animal-vehicle collisions, the absence of any practical systems related to an animal-vehicle collision on highways has delayed any substantial development in the scenario [24].

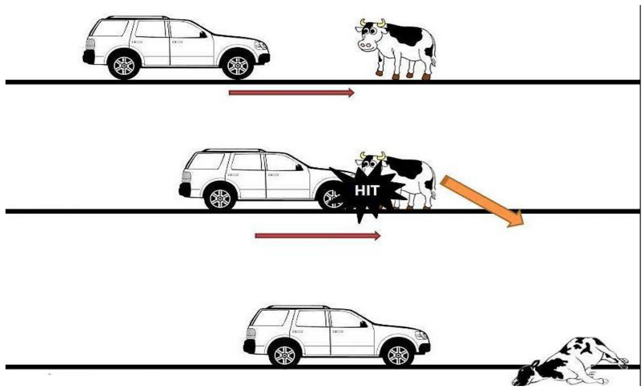


FIGURE 2. Case 1 scenario [26].

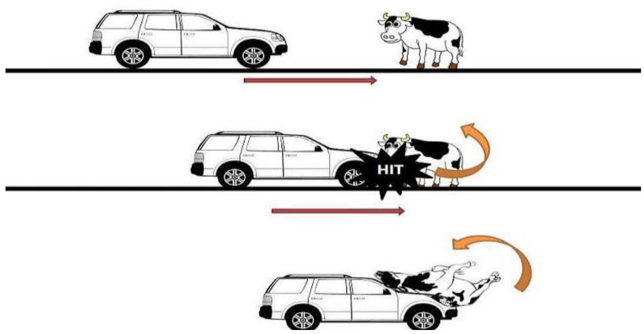


FIGURE 3. Case 2 scenario [26].

V. DIFFERENT SCENARIOS AND CONSEQUENCES OF ANIMAL-VEHICLE COLLISION ON HIGHWAY

Animal-vehicle collision can be classified using two ways [26]:

1) Direct collision
2) Indirect collision

Direct collision: It happens when the vehicle directly hits the animal. Following cases and outcome may occur depending on the speed of the vehicle and the speed of the incoming or outgoing animal.

Case 1: Vehicle hits the animal and animal gets thrown to the side. This scenario may be less critical, but damages will be there. Figure 2 shows the case 1 scenario.

Case 2: Vehicle hits the animal, and the animal jumps/gets raised in the air and again gets back or falls back on the windshield. This is quite critical and dangerous scenario and can cause the death of the animal or even the driver of the vehicle. Figure 3 shows the case 2 scenarios.

Case 3: Vehicle hits the animal and runs over the animal. In this case, a particular injury will occur to the animal. It may also happen that because of the impact of a collision, the vehicle may get overturn which can cause injury to the driver. Figure 4 shows the case 3 scenarios.

Indirect collision: In this case, an accident occurs because of animal only but not directly. The driver of one vehicle finds an animal on the highway and tries to change the direction or

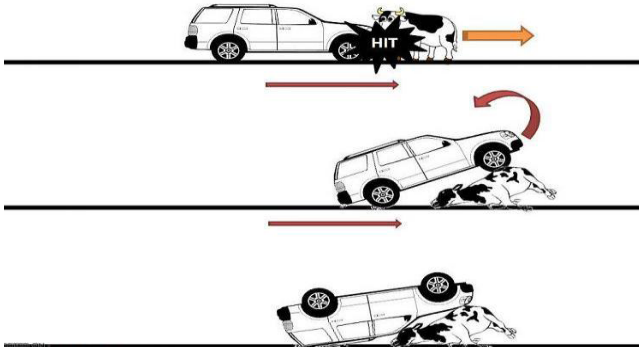


FIGURE 4. Case 3 scenario [26].

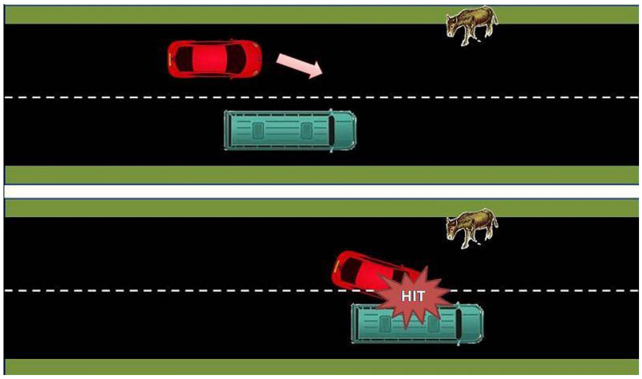


FIGURE 5. Indirect collision scenario [26].

the lane and collides with the vehicle which is running on the other lane. Figure 5 shows the indirect collision scenario.

In all the cases as discussed above, if the driver has some automatic animal detection system in the vehicle, then it is possible to some extent to prevent injuries and collisions between vehicle and animal.

VI. OBJECTIVES AND SCOPE OF WORK

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.

VII. SPECIFIC REASONS FOR ANIMAL (COW) DETECTION

According to the surveys and report given by the Society for Prevention of Cruelty to Animals (SPCA) *and* [27]–[31], the number of accidents on Indian roads has increased due to increase in a number of vehicles day by day and also due to the presence of animals on the road (mainly two animal's dog and cow). The collision of an animal with the vehicle on the highway is one such big issue apart from other problems such as over speed, abrupt lane change, and drunk-drive and others which lead to such road accidents and injuries. The associated number of fatalities and injuries are substantial too.

Specific reasons behind developing automatic cow detection system in place of any other animal are:

- India is mainly an agriculture based country where 70% of people depend on agriculture, and 98% of them depend on cow based agriculture.
- The cow is a sacred animal in India and nobody wants to hit a cow.
- Cow milk is the most useful and compatible with human mother's milk than any other animal or so.
- According to some surveys, cow's milk and cow dung have many medicinal benefits.
- Cows, as well as dogs, are found quite often than other animals on the Indian roads.
- As cow is a large (heavy) sized animal, the collision between a cow and vehicle will be very much severe. The collision between a small (less weight) sized animal like dog and car won't be that much severe.

The speed with which the vehicle is coming and hitting the animal also plays a critical role in deciding the impact of the collision.

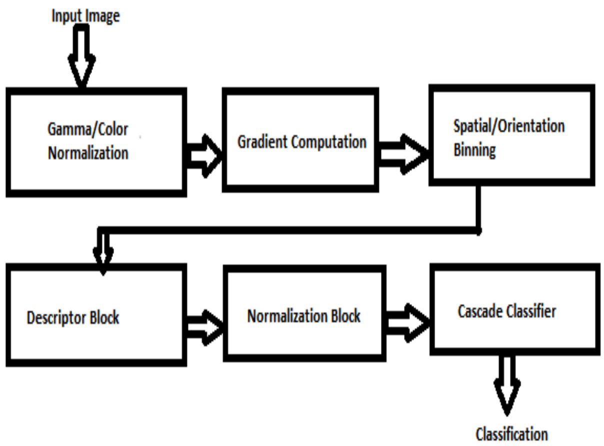
VIII. BRIEF OVERVIEW AND ADVANTAGES OF HOG AND CASCADE CLASSIFIER

A histogram of oriented gradients (HOG) is used in computer vision applications for detecting objects in a video or image, which by definition is a feature descriptor [32]. Figure 6(a) and 6(b) shows the block diagram and block normalization scheme of HOG.

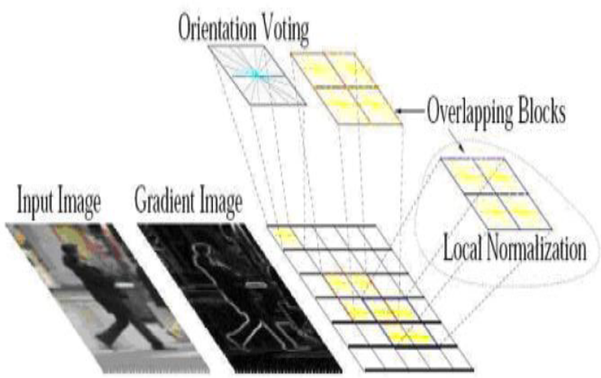
As shown in figure 6(a), first the input image is given to color normalization block. Color normalization is used for object recognition on color images when it is important to remove all intensity values from the picture while preserving color values. After color normalization, the second step of calculation is the computation of the gradient values. The most common method is to apply the 1D centered point discrete derivative mask in both the horizontal and vertical directions. Specifically, this method requires filtering the grey scale image with the following filter kernels:

$$D_X = [-1 \quad 0 \quad 1] \quad \text{and} \quad D_Y = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}$$

So, given an image I, we obtain the x and y derivatives using a convolution operation: $I_X = I^*D_X$ and $I_Y = I^*D_Y$.



(a)



(b)

FIGURE 6. **(a) HOG algorithm [32]. (b) Block normalization scheme of HOG [32].**

The magnitude of the gradient is given by $|G| = \sqrt{I_X^2 + I_Y^2}$, and orientation of the gradient is given by $\theta = \arctan\left(I_Y/I_X\right)$.

The next step of calculation involves creating the cell histograms. Each pixel within the cell casts a weighted vote for an orientation-based histogram channel based on the values found in the gradient computation. The cells themselves are rectangular, and the histogram channels are evenly spread over 0 to 180 degrees or 0 to 360 degrees, depending on whether the gradient is "unsigned" or "signed". As for the vote weight, pixel contribution can be the gradient magnitude itself, or the square root or square of the gradient magnitude.

To account for changes in illumination and contrast, the gradient strengths must be locally normalized, which requires grouping the cells together into larger, spatially-connected blocks which are the next step. The HOG descriptor is then the vector of the components of the normalized cell histograms from all of the block regions. These blocks typically overlap, meaning that each cell contributes more than once to the final descriptor.

Two main block geometries exist: rectangular R-HOG blocks and circular C-HOG blocks. R-HOG blocks are square grids, represented by three parameters: the number of cells per block, the number of pixels per cell, and the number of channels per cell histogram. There are different methods for block normalization. Let v be the non-normalized vector containing all histograms in a given block, $||v_k||$ be its k-norm for $k = 1, 2$ and e be some small constant (whose value will not influence the results). Then the normalization factor can be one of the following:

$$\text{L2-norm: } f = \frac{v}{\sqrt{\|v\|_2^2 + e^2}}$$

$$\text{L1-norm: } f = \frac{v}{\|v\|_1 + e}$$

$$\text{L1-sqrt: } f = \sqrt{\frac{v}{\|v\|_1 + e}}$$

Finally, the image goes to cascade classifier for classification of the object. HOG descriptor is mainly suitable for animal detection in video or images due to some key advantages compared to other descriptors. First, it operates on local cells, so it is invariant to geometric and photometric transformations. Secondly, coarse (spatial) sampling, fine orientation sampling, and strong local photometric normalization allow different body movement of animals to be overlooked if they maintain a roughly upright position.

Cascading is a concatenation of various classifiers (group based learning). The technique involves taking all the data collected from the output of the first classifier as a supplementary data for the next classifier in the group [33]. The key advantages of boosted cascade classifiers over monolithic classifiers are that it is a fast learner and requires low computation time. Cascading also eliminates candidates (false positives) early on, so later stages don't bother about them.

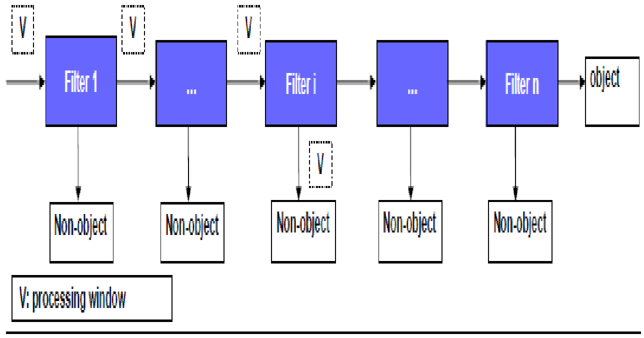


FIGURE 7. **Boosted cascade classifier [33].**

As shown in figure 7, each filter rejects non-object windows and let object windows pass to the next layer of the cascade. A window is considered as an object if and only of all layers of the cascade classifies it as object [33]. The filter i of the cascade is designed to

- Reject the possibly large number of non-object windows
- To allow possible large number of object windows for quick evaluation

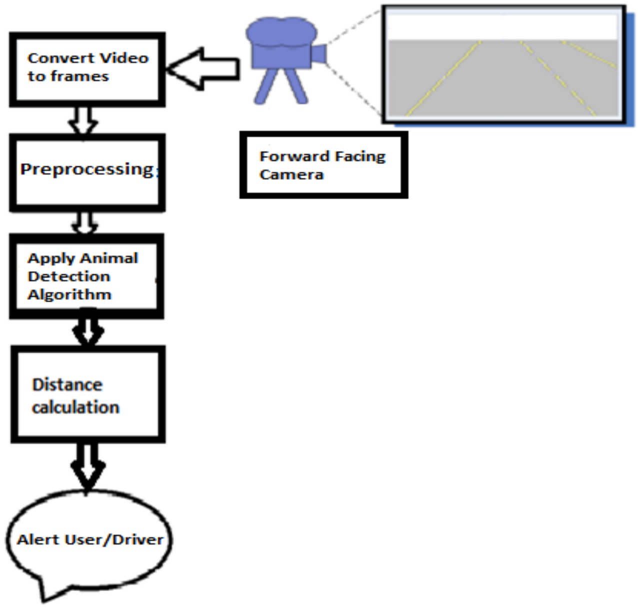


FIGURE 8. Architecture of animal detection and collision avoidance system.

IX. RESEARCH METHODOLOGY

As shown in figure 8, 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.

X. PROCEDURE FOR TRAINING AND TESTING

India has more than 20 varieties of cow found in different states of India such as Gir, Sahiwal, Red Sindhi, Sahiwal, Kankrej, Dandi, and others. We have collected and added all the varieties of a cow in the database for training the system. Following is the proposed procedure for training and testing of the data for animal detection:

- Collect all positive and negative images in the data folder (figure 9(a) and 9(b))
- Generate Annotation
- Create sample i.e. generate .vec file

(a)

(b)

FIGURE 9. (a) Positive samples. (b) Negative samples.

- Train data and generating XML file. Table 1 shows the parameters used /set during training of the system
- Testing

The average time it took to generate a cascade on Intel(R) Core(TM) i5-2430M CPU 2.40GHz, 4GB RAM was almost 14 hours.

TABLE 1. Parameters set up during training of the system.

Parameters	Value/Type
numPos (number of positive samples)	700
numNeg (number of negative samples)	1500
numStages (number of stages in cascade)	20
stageType (type of stage in cascade)	BOOST
featureType (feature type for extraction)	HOG
sampleWidth (width)	70 pixels
sampleHeight (height)	40 pixels
boostType (type of boosting)	GAB (Gentle AdaBoost)
minHitRate (minimum hit rate of the classifier)	0.995
minFalseAlarmRate (minimum false alarm rate of the classifier)	0.5

XI. DISTANCE CALCULATION OF THE DETECTED ANIMAL

As shown in figure 10, the video is taken and converted into frames (image of size $640 * 480$). Following is the procedure for calculating the distance of the detected animal from the camera-mounted vehicle:

- Image resolution is 640×480
- X range is 0 to 640
- Y range is 0 to 480

Let the right bottom coordinate of the detected cow be (x, y). Then the distance of cow from the lower edge (car/camera) is 480 – y.

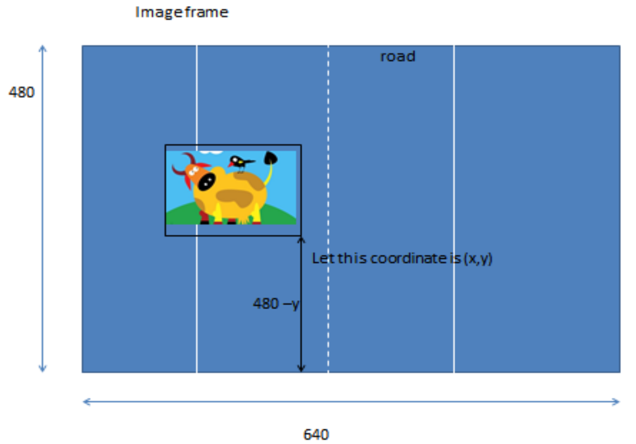


FIGURE 10. Distance calculation.

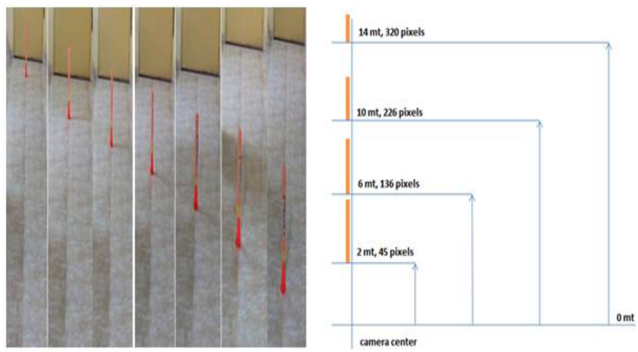


FIGURE 11. The same object kept at different positions (depth) from the camera centre.

Note: The above method of distance calculation works well with the flat ground surface. Suffers a bit if the ground surface is not perfectly flat.

XII. CONVERSION FROM PIXELS TO METERS

There is some relationship between the depth of the object in pixel and depth in real world units (meters) from the camera mounted vehicle once the object (animal) gets detected in the frame. As the depth of the object in meters from the camera mounted vehicle increases (size of the object decreases), the depth in pixels also increases and vice versa [34]. This hinted us to find a relationship between the depth of the object in pixels and meters. Once the camera position in the car and height of the camera from the ground was fixed (camera calibration done), we took different images of the same object kept at various depths from the camera centre (figure 11). The depth of the object from the camera centre in meters was known to us.

We then noted the corresponding depth of the object in pixels. Table 2 represents the relation between pixels and meters. Graph of depth in meters versus depth in pixels was plotted in Excel (figure 12) and the best fitting second order polynomial equation is

$$y = 0.0323x^2 + 22.208x + 1.3132 \quad (1)$$

where y is the depth in pixels and x is depth in meters.

TABLE 2. Relationship between pixels and meters.

Depth (mt)	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Depth (pixel)	23	45	69	91	114	136	159	180	206	226	245	274	295	320

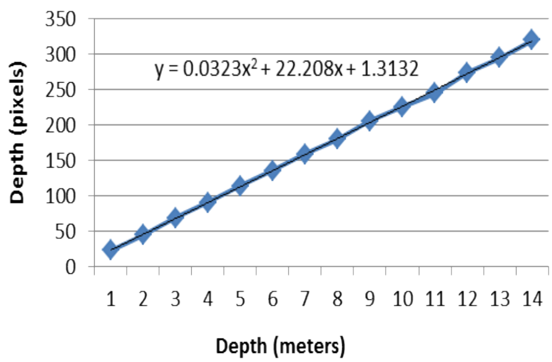


FIGURE 12. Graph of depth (meters) versus depth (pixels).

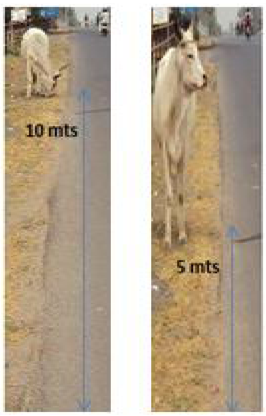


FIGURE 13. Testing images (depth in meters was already known).

XIII. TESTING OF ACTUAL DISTANCE VERSUS CALCULATED DISTANCE

As shown in figure 13, we took two images of a cow in which we knew the depth of the cow in meters from the camera-mounted vehicle. We then calculated the depth using the technique as mentioned earlier. Table 3 shows the results of actual depth and calculated depth. The error is very less (less than 2 percent).

XIV. EXPERIMENTS AND RESULT ANALYSIS

We are using HOG descriptors which are feature descriptors and are used in computer vision and image processing for the purpose of object detection [32]. For object classification, we are using boosted cascade classifiers. A good source for the animal images is the KTH dataset [35] and NEC dataset [36] that included pictures of cows and other animals. Some more animal images have been clicked (during different weather conditions i.e. morning, afternoon and evening) for creating a robust database of almost 2200 images consisting of positive images in which the target animal is present and negative images in which there is no target animal for feature extraction and for training the classifier. After the classifier is trained and the detection system is built, we tested the same on various videos.

TABLE 3. Actual depth versus calculated depth.

Parameters	Observation 1	Observation 2
Actual depth (meters)	10	5
Calculated depth (meters) after converting from pixels to meters	9.85	4.95
Error in Percentage (%)	1.5	1

Videos have been taken using a camera having a frame rate of 30fps mounted on the testing vehicle. Hardware used in our experiment is ASUS x53s, Intel(R) Core(TM) i5-2430M CPU 2.40GHz, 4GB RAM. Software used is Microsoft Visual Studio 10 Professional, OpenCV 2.4.3, 64 bit operating running under Windows 7.

Parameters which are necessary for checking the performance of the test/classifier are Sensitivity (True Positive Rate), Specificity (True Negative Rate) and Accuracy [37] which are given as

$$\text{Sensitivity} = \text{TP}/(\text{TP}+\text{FN}) \tag{2}$$

$$\text{Specificity} = \text{TN}/(\text{TN}+\text{FP}) \tag{3}$$

$$\text{Accuracy} = (\text{TN}+\text{TP})/(\text{TN}+\text{TP}+\text{FN}+\text{FP}) \tag{4}$$

Here in above equations, TN stands for true negative; TP stands for true positive; FN stands for false negative, and FP stands for false positive. True positive (TP) and true negative (TN) are the most relevant and correct parameters of classification. False Positive indicates that the animal is detected in the frame (video) even though the animal is absent in that particular frame at that given location. False Negative (FN) indicates that there is no animal present in the frame (video) even though the animal is present in that particular frame.

In our implemented animal detection system, we took 640 frames in which 105 frames are showing animal detected i.e. rectangular box even though there is no animal present in those frame at those places. So, false positive in this case turns out to be 105 and true negative turns out to be 535. Similarly out of 640 frames, 125 frames are showing no animal detected i.e. no rectangular box even though animals are present in that frame. So false negative turns out to be 125 and true positive turns out to be 515. Substituting the above parameter values

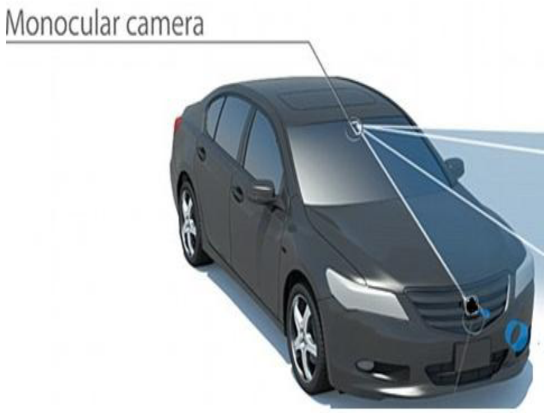


FIGURE 14. Camera mounted vehicle.

FIGURE 15. True positive case.

FIGURE 16. False positive case.

in equation (2), (3) and (4), we get sensitivity close to 80.4%, specificity close to 83.5% and accuracy of the classifier close to 82.5%.

Figure 14 shows the on-board camera with the processing and display system inside the car on the dashboard side. We performed extensive experiments and spent so many hours testing the system in different weather conditions on

FIGURE 17. False negative case.

FIGURE 18. Animal detection at 0 kmph speed (morning condition).

the road. Figure 15 shows the true positive scenario wherein in the video, animal (cow) is present and our proposed system correctly detects it and gives an indication (box). Similarly, figure 16 shows a false positive case wherein animal (cow) is detected in the video by the system even though it is absent in that particular frame at that given location. Figure 17 shows a false negative case wherein though the animal (cow) is present in the video; the system indicates absence (no box) of the animal. Figure 18 shows animal detected in the morning condition with the experimental camera mounted vehicle stationary i.e. at 0 kmph speed. Figure 19 shows animal detected in the afternoon condition with the vehicle speed at 40 kmph. Figure 20 shows animal detected in the evening state at a distance of 11 meters from the camera mounted testing vehicle with the vehicle moving at a speed of 60 kmph. Figure 21 shows multiple animals detected in one of the testing videos at a distance of 17 meters from

FIGURE 19. Animal detection at 40 kmph (afternoon state).

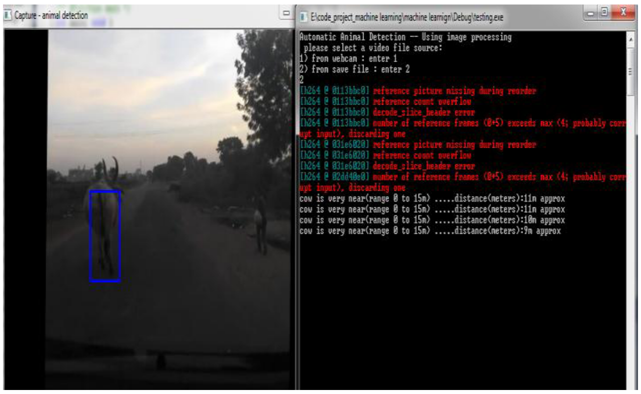


FIGURE 20. Animal detected at a distance of approximately 11 meters from the camera mounted vehicle with the speed of 60 kmph in evening time.

FIGURE 21. Multiple animals detected in one of the testing video (detecting distance of 17 meters).

the camera mounted vehicle. Training and testing on large datasets will improve the detection rate and accuracy of the classifier.

The average processing (computation) time with our proposed image processing method is 100ms (10 frames per second) which can be still be shortened using Nvidia's CUDA processor. According to the article [39], the term response time or brain reaction time of the drivers in traffic engineering literature is composed of mental processing time, movement time and mechanical response time. As per the ''two-second rule'' which is usually a rule of thumb suggests that a driver should ideally stay at least two seconds behind any object that is in front of the driver's vehicle [40]. The two-second rule is useful as it can be applied to any speed and provides a simple and common-sense way of improving road safety. So if we go with ''two-second rule'', clearly from Table 4 (speed-distance relation as well as actual time (onboard) available for the driver to responds), it indicates that when the speed of the vehicle is between 30 to 35 kmph, the driver gets some time to apply brakes and can avoid a collision. Anything above this speed, though the alert signal is available the driver won't be able to avoid a collision.

TABLE 4. Speed-distance relation.

Vehicle speed (kmph)	Approximate distance of detection from the camera mounted vehicle (meters)	Approximate time available for the response (sec)
0 (stationary)	20	Enough time to avoid collision as maximum speed of Indian cows is 3 to 3.5 kmph [38]
20	18	3.24
30	17	2.04
35	17	2.04
40	15	1.35
50	14	1.00
60	11	0.66

TABLE 5. Set of tests by cascade classifier.

Feature descriptor	TP	FP	TN	FN	Sensitivity	Specificity	Accuracy	Average processing time
HOG	515	105	535	125	80.4%	83.5%	82.5%	100ms
HAAR	502	142	498	138	78.4%	77.8%	78.1%	150ms

XV. COMPARISON OF HOG AND HAAR

Comparison of HOG with another popular feature descriptor (HAAR) is shown in Table 5. ROC (receiver operating characteristic) curve, which is a graphical plot that illustrates the performance of a classifier system as its discrimination threshold is varied, is shown in figure 22 for the hog-cascade classifier, haar-cascade classifier. The curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. Apparently, our method based on hog-cascade classifier gives good results compared to haar-cascade classifier.

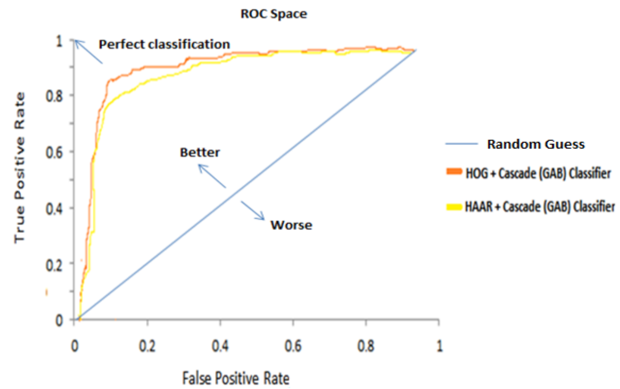


FIGURE 22. ROC curve.

XVI. ACHIEVEMENTS WITH RESPECT TO OBJECTIVES

- Algorithm developed is working properly and able to detect an animal in different conditions on roads and highways.
- Estimation of animal distance from the testing vehicle is done. Maximum detecting distance of the animal from the camera mounted vehicle was found to be 20 meters.
- Speed analysis (different speeds like 20, 30, 35, 40, 50, 60 kmph) is implemented and tested.
- Alert signal to the driver is available.

XVII. CONCLUSION

An efficient automatic animal detection and a warning system can help drivers in reducing the number of collisions occurring between the animal and the vehicle on roads and highways. In this paper, we discussed the necessity of automatic animal detection system and our algorithm for animal detection based on HOG and cascade classifier. The algorithm can detect an animal in different conditions on highways. The proposed system achieves an accuracy of almost 82.5 % regarding animal (cow) detection. Estimation of approximate animal distance from the testing vehicle is also done. Though the proposed work has been focused on automatic animal detection in context to Indian highways, it will work in other countries also. The proposed method can easily be extended for detection of other animals too after proper training and testing. The proposed system can be used with other available, efficient pedestrian and vehicle detection systems and can be offered as a complete solution (package) for preventing collisions and loss of human life on highways.

XVIII. LIMITATIONS AND FUTURE SCOPE

Though our proposed system can detect the animals (cow) on roads and highways as well as gives alert to the driver, it has some limitations too. The proposed system can detect animal up to a distance of 20 meters only when a vehicle is stationary. The system can prevent collision of the vehicle with the animal when driving at a speed in between 30 to 35 kmph. Beyond this speed, though animal gets detected time is not sufficient to prevent animal-vehicle collision.

Some means or method of increasing the detecting distance of the animal from the camera mounted vehicle needs to be done so that driver gets sufficient time for applying brakes or take any other action for preventing the collision which may be solved using high-end resolution cameras or radar. No effort has been made to detect animals during the night, which is expected to be done in our future scope of study and research

ACKNOWLEDGMENT

The authors would like to thank all who were involved directly or indirectly in the data collection, experiment conduction, and analysis stage of the project.

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