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A Novel Approach to Automatic Road-Accident Detection using Machine Vision Techniques

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ABSTRACT: In this paper, a novel approach for automatic road accident detection is proposed. The approach is based on detecting damaged vehicles from footage received from surveillance cameras installed in roads and highways which would indicate the occurrence of a road accident. Detection of damaged cars falls under the category of object detection in the field of machine vision and has not been achieved so far. In this paper, a new supervised learning method comprising of three different stages which are combined into a single framework in a serial manner which successfully detects damaged cars from static images is proposed. The three stages use five support vector machines trained with Histogram of gradients (HOG) and Gray level co-occurrence matrix (GLCM) features. Since damaged car detection has not been attempted, two datasets of damaged cars - Damaged Cars Dataset-1 (DCD-1) and Damaged Cars Dataset-2 (DCD-2) – was compiled for public release. Experiments were conducted on DCD-1 and DCD-2 which differ based on the distance at which the image is captured and the quality of the images. The accuracy of the system is 81.83% for DCD-1 captured at approximately 2 meters with good quality and 64.37% for DCD-2 captured at approximately 20 meters with poor quality.

KEYWORDS: Feature extraction; Image denoising; Machine vision; object detection; Supervised learning; Support vector machines

I.INTRODUCTION

A novel approach using image processing and machine learning tools to detect damaged cars from static images, which can be used to detect a road accident automatically is proposed. Detection or recognition of damaged cars falls under the category of object detection. Object detection or recognition using Machine Vision is achieved in two stages [1]. The first stage is feature extraction in which features common to instances from the object category are extracted from the corresponding images. The second stage includes training of a learning model like Support Vector Machines [2], Neural Networks [3] and AdaBoost [4] with the extracted features [1]. Principles used in most object detections do not work for detecting damaged instances of an object category since the damaged instances do not have the commonly extracted characteristics like shape, edges, Histogram of Gradients in common. In this paper, a supervised learning method that detects damaged cars by making use of two facts – the state-of-the-art

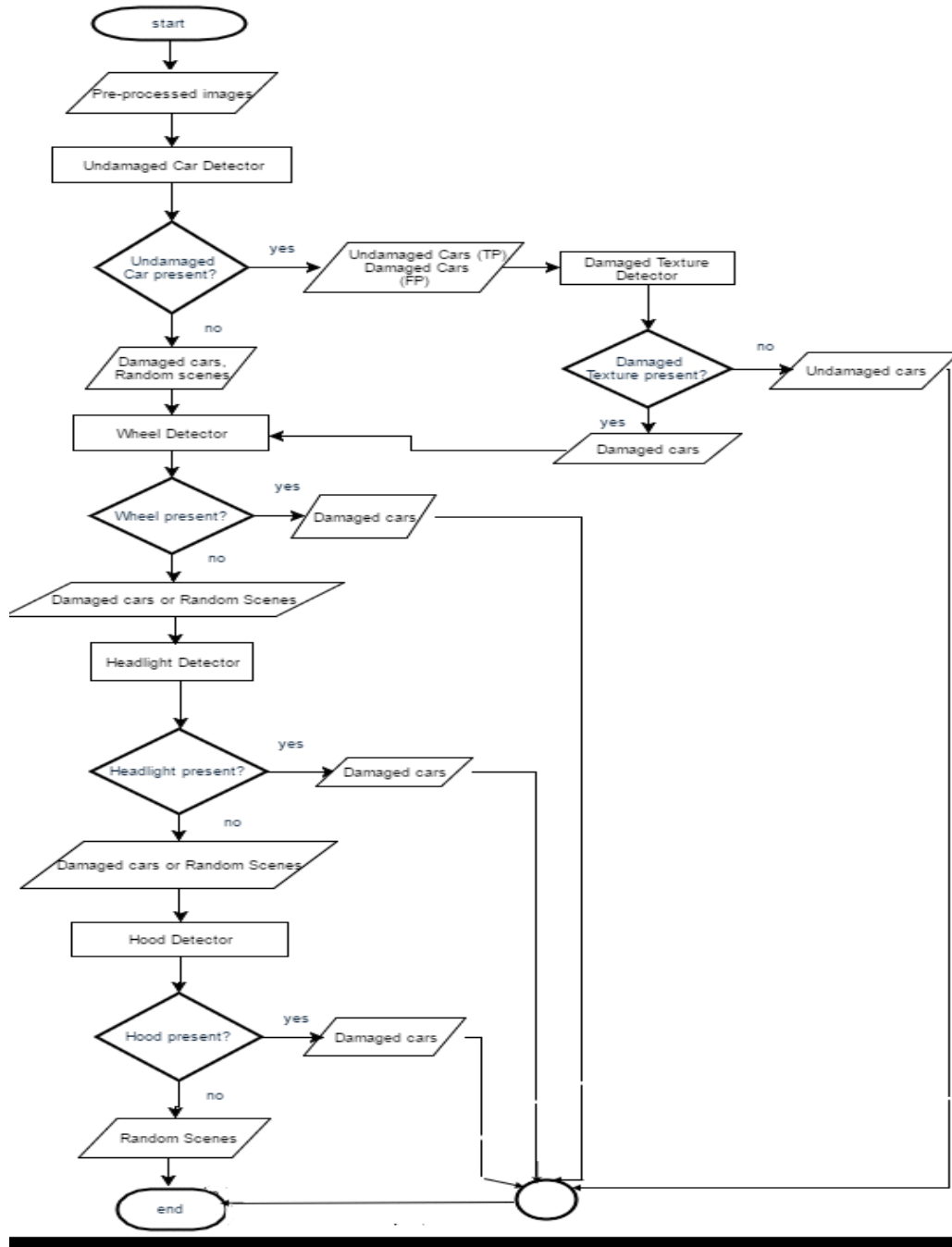
vehicle detection classifiers will not detect a damaged car and most damaged cars still have one or more car parts intact, is proposed. The experimental results obtained show that the proposed approach gives promising results when tested on two different datasets of damaged cars which differ based on the quality, distance of the camera from the object and number of objects in an image. The two datasets were compiled for the sake of the project from various sources. The proposed method can be extended to other vehicles as a part of future work. The work done includes three contributions. The first contribution includes proposing a novel approach to automatic road accident detection. The second contribution includes a supervised learning method that detects damaged cars from static images, a class of object that has not been detected so far using the techniques of machine vision. The third contribution includes the release of two public datasets of damaged cars- Damaged Cars Dataset-1 (DCD-1) and Damaged Cars Dataset-2 (DCD-2). This paper is organized as follows. Section II describes related work. The proposed method is explained in Section III. The experimental results and analysis for two different datasets are presented in Section IV. Section V presents Conclusions.

II.RELATED WORK

The Global status report on road safety 2015 [5] shows that the total number of deaths caused due to road accidents is at 1.25 million a year. One of the main reasons for fatalities from these accidents is a delay in reporting the accidents to near-by emergency health centres and delay in an ambulance reaching the accident location. Such a delay can be reduced if there is automatic detection and reporting of the accidents to emergency help centres. Most of the prevalent state-of-the-art methods use sensor technology to detect road accidents. In [6],[7] the use of sensors present inside the vehicle including accelerometers, GSM and GPS modules is made to detect unusual movements and angles of the car to indicate an accident. In [8] the use of sensors like magneto resistive sensors is made outside the vehicle, installed on the roads. In [9], MMA621010EG is a proven special car accident sensor which is integrated XY-axis accelerometer and built-in serial peripheral interface SPI bus. The variations from this sensor is detected and through the GPS software fitted in the vehicle communication is made with the satellite. The latitude and longitude values are sent to the centralized server for contacting the emergency service. The drawback with using sensor technology is that the sensors can get damaged in the accident. One way to overcome this drawback is by making use of the surveillance cameras installed in traffic junctions and highways. The static images or video footage from these cameras can be used in detecting the presence of a damaged vehicle which in turn indicates the occurrence of an accident. A new approach based on vision based object detection is presented in this paper which detects the presence of a damaged car from static images. As seen in [10][11] detection of damaged buildings and roads involves working with images of the object prior and post damage. This however cannot be applied to damaged car detection for the purpose of accident detection.

III.PROPOSED METHOD

The proposed method is a supervised learning one which works as a binary classifier distinguishing between images containing a damaged car as class 1 and images not containing it as class 0. Instances of damaged cars do not have anything in common due to loss of shape, edges and intensity gradients. Hence using the usual vision-based object detection methods where HOG, Haar, Gabor and SURF features are used to train SVM, AdaBoost and neural networks [12] will not achieve detection. However, a feature that most damaged cars do have in common is the presence of at least one car part. Our classifier is based on this fact. But training a classifier that detects car parts alone will not achieve successful detection of damaged cars since cars without any damage also show the presence of car parts. Hence there is a need to differentiate between cars that are damaged and cars that are not in addition to the step involving detection of car parts. When the state-of-the-art classifiers developed so far [12] for detection of vehicles and cars in specific were tested, results showed that they failed to detect most damaged cars. This is the second fact that forms the basis of the method developed in this project. The input images can be divided



into three types - images of damaged cars (type 1), images of undamaged cars (type 2) and images of all other objects and scenes (type 3). The classifier built should now work as a binary classifier which distinguishes between images containing a damaged car (type 1) as class 1 and images not containing it (type 2 and type 3) as class 0. The realization of the system is done in three different stages which are combined into a single framework in a serial

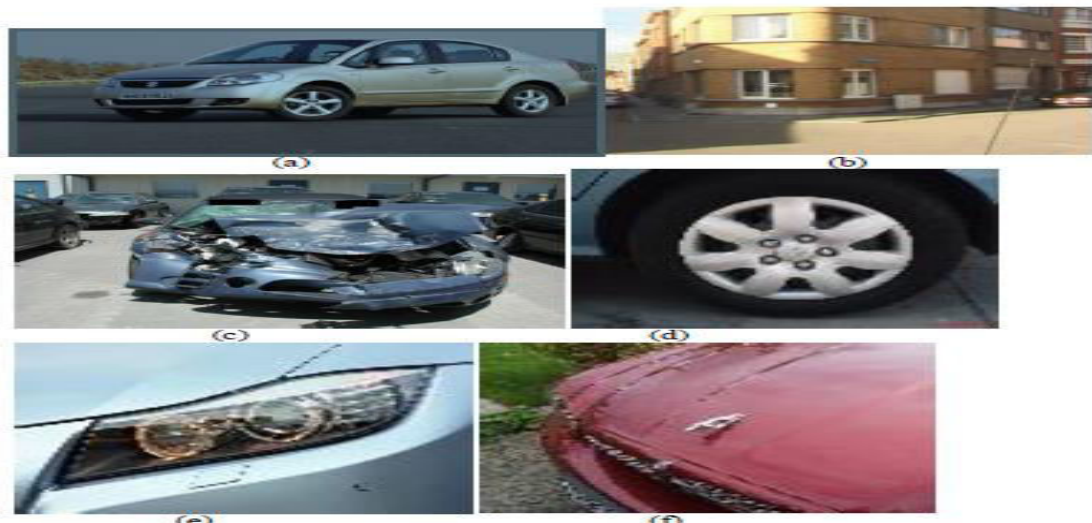
manner as shown in Fig. 1. Prior to the first stage is the preprocessing of images. The first stage is the vision based detection of undamaged cars using a SVM trained with HOG [26]. The SVM works as a binary classifier detecting the presence of a car without any damage and thus separates type 2 (class 1) from type 1 and type 3 (class 0). Since damaged cars are very close in appearance to undamaged cars results showed stage 1 misclassifies a considerable number of damaged cars as class 1, that is, as undamaged cars. Hence in order to improve the performance of stage 1, a binary classifier that detects the presence of damaged texture from all images classified as undamaged cars in the previous stage was introduced, this is stage 2. It reduces the number of false positives from stage 1. The detection of damaged texture at this stage is done by training a SVM with GLCM features. The third stage is now used to separate type 1 from type 3 by using a car parts detector which consists of three separate binary classifiers, each detecting the presence of one car part. Each of the binary classifiers at this stage is a SVM trained with HOG features of the corresponding car part. The three car parts considered are wheel, headlight and hood. The method does not work in the cases where the car is damaged to an extent where it has none of the car parts considered, this serves as the limitation of the proposed method. It can be overcome in the future by increasing the number of car parts detected.

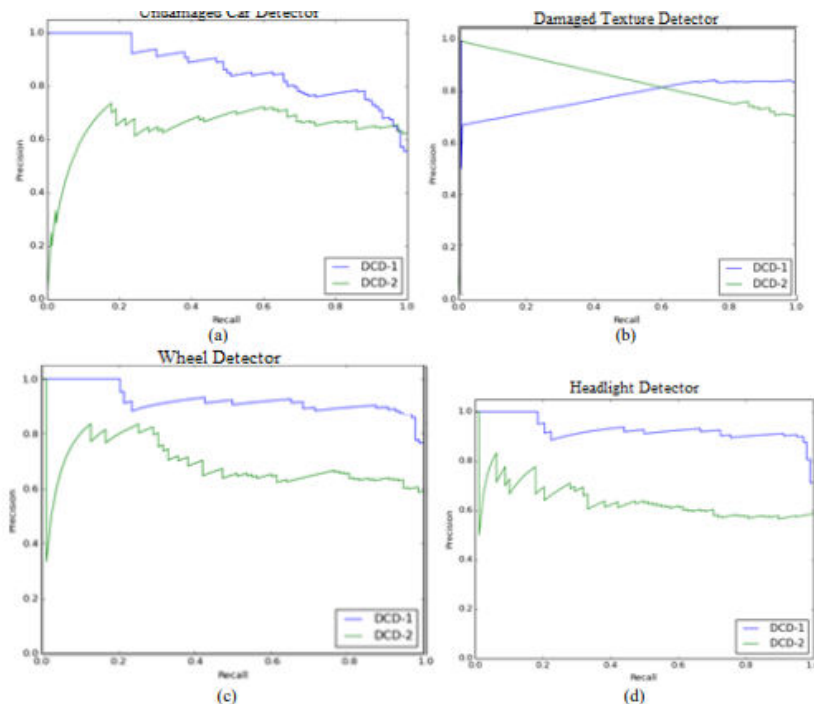
Pre-processing This is the first step that is carried in order to enhance the image and remove distortions like noise from the image. Denoising was achieved by using a Median filter [13]. The images are then resized to 256×256 for the next stage and converted to .JPEG format. **B. Undamaged Car Detector** Histogram of (HOG) features extracted from the training dataset is used to train a Support Vector Machine (SVM) which is a binary classifier based on supervised learning is employed in the first stage. HOG is a feature descriptor introduced by Dalal et al.[14]. It is global feature and not a collection of many local features, that is, the object is described by one feature vector and not many feature vectors representing different parts of the object. The training images are resized to 256×256 and converted to gray scale. The HOG descriptor is then extracted from these 256×256 images, where 4×4, 8×8 or 16×16 pixels per cell are considered known as the cell size and from each cell the gradient vector at each pixel is calculated and put into a histogram with 8 bins. The histogram has 20 degrees in each bin and ranges from 0 to 180 degrees in total. Each gradient vector's magnitude is put into the histogram of bins and each value is split between the two closest bins. The reason behind the histogram is quantization and to reduce the number of values. Apart from this, it also generalizes the values in a cell. The next step is normalizing the histograms to make them invariant to changes in illumination. When any vector is divided by its magnitude, it is said to be normalized. A gradient vector of a pixel in invariant to addition, subtractions and multiplications and hence the histograms can be normalized. This is taken one step further and instead of normalizing the histograms individually, the cells are grouped into blocks of 1×1, 2×2 or 4×4 cells known as the block size and all the histograms in the block are normalized together. The reason behind this type of block normalization is that since changes in contrast occur in smaller regions of the image than compared to the entire image, normalizing in smaller blocks is more effective. After extracting the HOG feature vectors, they are used to train an SVM model [15]. SVM is a binary linear classifier used for supervised learning. The SVM divides the training data into two classes by constructing a maximum margin hyperplane such that this plane or surface has the maximum distance from the closest points in each training set called support vectors. In order to get the optimal parameters for the SVM used to classify undamaged cars, a Grid Search [16] is performed which takes all the combinations of the parameters and finds the optimal set using cross-validation [16]. The parameters that are involved in Grid Search include the type of kernel (linear or RBF), value of C and Gamma. **C. Damaged Texture Detector** This is the second stage which improves the performance of the first stage by reducing the number of false positives from the first stage since the undamaged car detector detects a few damaged cars as undamaged cars due to their similarity. This module is implemented by training a SVM with texture features. Two types of texture features, Local Binary Patterns (LBP) and Grey Level Co-occurrence Matrix (GLCM) were extracted and it was seen that GLCM had a better performance.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

In this section, the experimental datasets used, the setting of various parameters, experimental results and analysis are discussed. **A. Experimental Datasets** The dataset used for each of the three stages is discussed in this section. Two different data sets have been used for testing of the overall system. The undamaged car detector uses 250

images of undamaged cars from [20] as the positive training data set, an example is shown in Fig. 2(a). From this data set only the portion of the images containing cars has been extracted using an object marker utility to extract the region of interest. 250 images of random scenes, that is, an image without the presence of a car, was taken from [21][22] as the negative training data set, an example is shown in Fig. 2(b). It was noticed that the performance at this step in regard to classifying damaged cars as negative cars was not satisfactory and hence 125 images of random scenes along with 125 images containing damaged cars only was added to the negative training data set from [23], an example is shown in Fig. 2(c) and available at [27] This improved the detection accuracy and the ability of the system to classify damaged cars as negative cars. Images of damaged cars were taken from the CIREN database [23]. The positive and the negative training data was resized to 256x256 and converted to grey scale. Damaged texture detector uses 250 images of damaged cars from [23] made available at [28], as positive training data and 250 images consisting of undamaged cars from [20] and random scenes from [21][22] (that have not been used in the previous stage) as negative training data. The positive images are cropped to contain only the damaged parts using an object marker utility.





V.CONCLUSION AND FUTURE WORK

A new approach to accident detection by detecting damaged cars from footage captured from surveillance cameras has been presented in this paper. Detection of damaged cars using the techniques of Machine Vision was achieved successfully. The detection was done based on the fact that an undamaged car detector will not detect damaged cars and that most damaged cars have car parts in tact. The method developed used a total of five SVM classifiers trained with HOG and GLCM features. Since damaged car detection has not been attempted before two datasets of damaged cars were compiled for the sake of the project and released for public use. The system implemented was tested on these two different datasets DCD1 and DCD-2, which differ based on the distance of the camera from the damaged car, the quality of the images and the number of objects in the images. The accuracy of the system is 81.83% for DCD-1 and 64.37% for DCD2. However, the system does not detect damaged cars that are damaged to an extent where none of the car parts being considered are present. This is the major limitation of the project. The future work includes extending the working of the system to detect all types of damaged vehicles as it currently successfully detects only damaged cars. The working of the system can also be extended to detection in nighttime conditions.

REFERENCES

- [1] X. Wen, L. Shao, W. Fang, and Y. Xue, —Efficient feature selection and classification for vehicle detection, IEEE Trans. Circuits Syst. Video Technol., vol. 25, no. 3, pp. 508-517, Mar. 2015.
- [2] Yichuan Tang. Deep learning using linear support vector machines. In Workshop on Representation Learning, ICML, 2013, Atlanta, USA, 2013.
- [3] M. Egmont-Petersen, D. de Ridder, and H. Handels, —Image processing with neural networks- A review, Pattern recognition, vol. 35, no. 10, pp. 2279-2301, Oct. 2002.
- [4] P.A. Viola and M.J. Jones, —Rapid object detection using a boosted cascade of simple features, in Proc. CVPR, 2001, no. 1, pp. 511–518.
- [5] "Global status report on road safety 2015", World Health Organization, 2016. [Online]. Available: http://www.who.int/violence_injury_prevention/road_safety_status/2015/en/. Accessed: 22- Mar- 2016



- [6] V. Goud, "Vehicle accident automatic detection and remote alarm device," International Journal of Reconfigurable and Embedded Systems (IJRES), vol. 1, no. 2, Jul. 2012.
- [7] B. Prachi, D. Kasturi and C. Priyanka, —Intelligent accident-detection and ambulance-rescue system,|| PULSE, vol. 450, no. 16, pp. 2, Jun. 2014.
- [8] G. Liang, "Automatic traffic accident detection based on the Internet of Things and Support Vector Machine", International Journal of Smart Home (IJSH), vol. 9, no. 4, pp. 97-106, Apr. 2015.
- [9] C.Vidya Lakshmi, J.R.Balakrishnan, —Automatic Accident Detection via Embedded GSM message interface with Sensor Technology,|| International Journal of Scientific and Research Publications, vol. 2, no. 4, Apr 2012.
- [10] X. Tong, Z. Hong, S. Liu, X. Zhang, H. Xie, Z. Li, S. Yang, W. Wang and F. Bao, —Building-damage detection using pre-and post-seismic high-resolution satellite stereo imagery: a case study of the May 2008 Wenchuan earthquake,|| ISPRS Journal of Photogrammetry and Remote Sensing, vol. 68, pp.13-27, Mar. 2012



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