

Automatic Detection of Bike-riders without Helmet using Surveillance Videos in Real-time

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Abstract - Now-a-days two wheelers is the most preferred mode of transport. It is highly desirable for bike riders to use helmet. In this paper, we propose an approach for automatic detection of bike-riders without helmet using surveillance videos in real time. The proposed approach first detects bike riders from surveillance video. Then it determines whether bike-rider is using a helmet or not using a visual feature. Later convolutional neural network (CNN) is used to select motorcyclists among the moving objects. Again, we apply CNN on upper one fourth portions for further recognition of motorcyclists driving without a helmet. The performance of the proposed approach is evaluated on two datasets. The experiments on the real-time videos successfully detect 96.66% bike-riders without helmet with a low false alarm rate of 0.5%. Hence the bike riders without helmet are detected.

keywords - Image Classification, OpenCV, Kera model, Convolutional neural network, region proposal networks (RPN), Histogram of Oriented Gradients (HOG).

I. INTRODUCTION

Two-wheeler is a very general mode of transportation in almost every country. However, there is risk involved because of less protection. The death rate increases every year. A report of transport ministry states that a minimum of 28 bike riders die each day because of not wearing helmet. To reduce the risk, it is necessary that the bike riders wear helmet, as the government has made it a law to ride bike with helmet & have manual strategies to catch the violator's two-wheeler rider safety in mind. But most people try to avoid wearing helmet while riding a two wheeler. The police will not be able to monitor all the two-wheeler riders who are not wearing helmet and now a day's accidents even result as the bike riders try to escape from the police also the police will not remember all the face of two-wheeler riders as they try to escape.

To avoid this kind of situations current video surveillance based methods are passive and require significant human assistance; such systems are infeasible due to participation of humans, whose efficiency decrease over a period of time. Automation of this process is highly required for reliable & robust monitoring of these violations along with it. Also, several countries are employing systems involving surveillance camera places. So, detecting violators using the proposed infrastructure is also cost-effective. As the human monitoring is not very effective, For video surveillance there is some machine learning techniques to capture two-wheeler riders without helmet. The main aim of this paper is to automatically detect the bike riders without helmet using object detection and image processing to identify the bike riders and the helmet.

In this model frames are extracted from the videos and converted to grayscale image, using template matching method (cross correlation analysis) bike riders are detected in the frame. After that, head portion is taken to identify the rider using helmet or not. Trained CNN models are used to detect helmet on bike rider's head.

II. RELATED WORK

An automatic analysis of a video stream is made to make alerts when an "unusual" incident happens [1]. Such calculations may use as a consideration mechanism, which with proper identification and bogus alarm rate, will permit a solitary administrator to adequately "watch" the number of cameras. An ongoing monocular vision-based rear vehicle and cruiser recognition and the following technique are introduced for Lane Change Assistant (LCA) [2]. To achieve vigor and precision this work identifies and tracks numerous vehicles and bikes by consolidating various signals. A vision-based motorbike observing system is used to identify and track motorbike [3]. The technique utilizes visual length, width and pixel proportion to recognize the type of motorbike. Since the motorbike riders need to wear their helmets, helmet detection or search process required whether helmet or motorbikes exists or not. A visual reconnaissance in unique scenes attempt to recognize, distinguish and track an object from image sequences [4]. The point of visual surveillance is to make the entire observation naturally. The histogram of oriented gradients (HOG) descriptor is applied to extract the characteristics of the image. The support vector machine (SVM) classifier is employed in two stages. In the first stage, the object is divided into two-wheeler vehicles and pedestrians. In the second stage, the two-wheeled vehicles are classified as motorcycles and bicycles. The vertical movement of scene is calculated using the Gabor filter. If the vertical movement is pedaling, the vehicle is classified as a bicycle [6]. Other types of vehicles, such as cars, vans and buses, travel on public roads. HOG descriptors are used for motorcycle detection. For helmet and non-helmet classification, the ROI (i.e. head region) is passed through a CNN [5]. Here non-helmet riders are recognized using video surveillance. Background subtraction [9] is done to eliminate the pedestrians and other entities. Trained model is used to classify the objects. Optical character Recognition using tesseract is used to detect the license plate of the bike. They present framework for automatic detection of motorcyclists driving without helmet surveillance videos. In proposed approach they adaptive

background subtraction on video frames to get moving objects. Again apply on CNN on upper one fourth parts for further recognition of motorcyclists driving without helmet.[7] These moving objects then given to CNN classifier as input which classifies into two classes, namely motorcyclists and non-motorcyclists are discarded and passed only objects predicted as motorcyclists for next step where we determine whether the motorcyclists wearing a helmet or not again using another CNN classifier [8]. We assume that the head is located in the upper part of the incoming images and thus located head in top one fourth parts of images. The located head of the motorcyclist is given as input to second CNN which is trained to classify with helmet vs. without-helmets. Later, Haar cascade detector can be used for the extraction of license plate numbers. A system is designed [10] which the motorcyclist's license plate and a short video clip of violating motorcyclist are automatically uploaded to an automated ticketing systems through which police operates issues a notice to the violators of helmet.

III. PROPOSED METHODOLOGY

The input of the proposed system is either a recorded video or video stream through web cam. It is processed in two phases as: Detection of Bike-riders and specifically Detection of Bike-riders without helmet.

Phase-I: Detection of Bike-riders: This phase includes identification of bike rider in a frame. All the frames are read and converted into grayscale, so that the filters can be applied on it. Template matching methods compare area of images against another using normalized correlation method. Sample frame used to recognize same object in source frame. The matching procedure moves templates to all possible locations in source frame & the template matches the frame in that location.

Fig. 1 shows the block diagram of the phase 1 of the proposed system. In the proposed system, first we apply adaptive background subtraction to detect the moving objects. These moving objects are then given to a CNN classifier as input which then classifies them into two classes, namely, motorcyclists and non-motorcyclists. After this, objects other than motorcyclists are discarded.

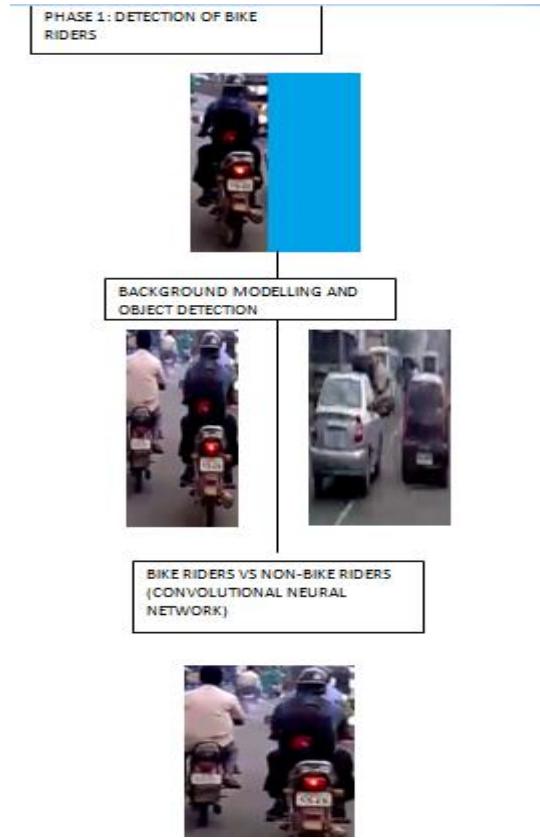


Fig. 1. Stages of phase I with initial preprocessing

Phase-II: Detection of Bike-riders Without Helmet After bike riders are identified in previous phase, the next step is to identify if bike ride is wearing helmet or not.

- Feature Extraction: Identified around head portion of bike rider is used to identify if bike-rider is wearing helmet or not.
- Object detection, a challenging computer vision task method is inherited in this project. Convolutional Neural Network, or R-CNN, model is one of the state-of-the-art approaches for object recognition tasks. It provides a library that allows developing and training R-CNN Keras models for the identification of objects such as the helmet, biking.

Fig. 2 shows the block diagram of the phase 2 of the proposed system. Objects predicted as motorcyclist for next step where we determine whether the motorcyclist is wearing a helmet or not again using another CNN classifier. We assume that the head is located in the upper part of the incoming images and thus locate the head into top one fourth parts of images. The located head of the motorcyclist is then given as input to second CNN which is trained to classify with helmet vs. without-helmet.

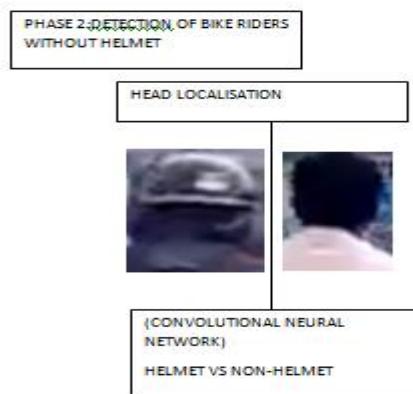


Fig. 2. Stages of phase II to detect drivers without helmet

A. Convolutional Neural Network for Object Classification

In object detection an RCNN is used to focus on regions since determining the location of multiple objects is essential to this type of model. An image is split into a lot of different boxes (regions) to check if any of them have signs of an object. The algorithm uses region proposal networks (RPN) which *ranks* the specific regions that most likely have an object. It learns high-level features from the spatial data like image. The recent widespread success of convolutional neural networks is in its ability to extract inter-dependant information from the images i.e. localization of the pixels which are highly sensitive to other pixels. The convolutional neural network training consist of convolution layers, relu layers maxpooling layers, fully connected layers and a loss function (e.g. SVM/Softmax) on the last (fully-connected) layer. In the primary layers we get the edge information of the images similar to some of the handcrafted algorithms but, In the final layers, we start getting texture and ridge information which helps us in getting sensitive information useful for classification.

B. Recognition of Motorcyclists from Moving Objects

To find bounding boxes of different objects, we used Gaussian background subtraction which uses a method to model each background pixel by a mixture of K Gaussian distributions ($K = 3$ to 5). The probable background colours are the ones which stay longer and are more static. On these varying pixels, we draw a rectangular bounding box. After obtaining all the objects of motorcyclists and non-motorcyclists, a CNN model is built using these images to separate the motorcyclists from other moving objects. Fig. 2 show the feature maps of the sample motorcycles. These feature maps illustrate that the CNN learns the common hidden structures among the motorcyclist in the training set and thus able to distinguish between a motorcyclist and other objects.

IV. EXPERIMENTAL EVALUATION

The experiments are conducted on a machine running Ubuntu 16.04 that uses Python-3.6 along the libraries such as OpenCV-3.3.0 for computer vision and image processing, Tensorflow-1.4.1 backend for building CNN, scikit-learn-0.19.1 for machine learning and numpy-1.14.0 for multi-dimensional arrays, mathematical functions and linear algebra. The experiments are performed on a 64 bit Ubuntu 16.04 Operating System. The specifications of the system are 4 GB RAM, 4 Intel PENTIUM Quad core processors and no GPU.

4.1 Datasets Used

The performance of the proposed approach is evaluated on two video datasets containing sparse traffic and dense traffic as shown in fig.3.



Fig.3. Real time video captured and the motion frames collection

4.2 Experimental Setup

To evaluate the proposed technique, various experiments were conducted on surveillance video sequences which contain pedestrian and vehicles other than motorbikes, under challenging backgrounds. We capture videos with different scenes under a fixed view point and run our detection algorithm. Evidently, the proposed technique is used to detect whether the person is wearing a helmet or not, since it is one of the important safety measure.

Here, we have labeled data into wearing helmet or not manually. The accuracy can be given by, $\text{Acc} = \frac{T}{T+F}$, where T represents the number of correct classification results and F represents the number of False classification results.

From the Fig.4 and Fig.5 it is obvious that the motorbikes and helmet along with the person has been detected. The exact positioning of the camera helps to reduce the errors. The motorbikes have been extracted from other vehicles and people who are wearing helmet are projected with bounding boxes and shown as the outcome.

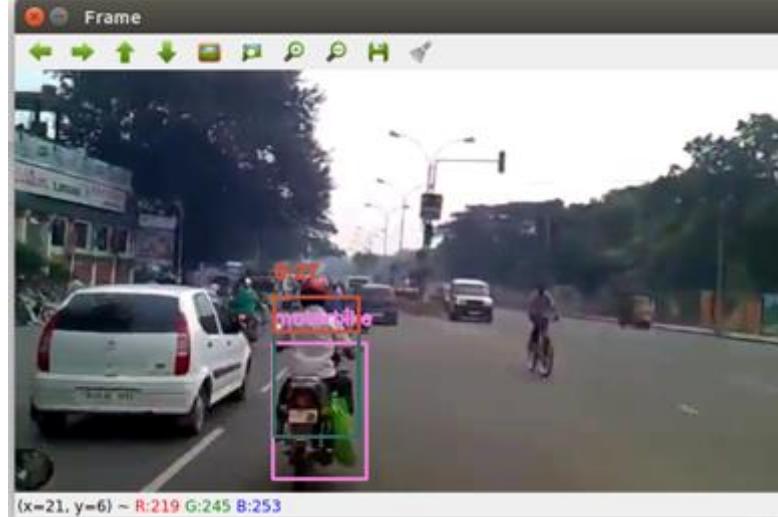


Fig .4. CNN Image capture detection of bikes



Fig .5. CNN Image capture detection of bikes and helmet analysis

Table 1. Performance (%) Of The Classification Of Motorcyclist Vs Non-Motorcyclist Using CNN

DataSet:Feature	Fold1	Fold2	Fold3	Fold4	Fold5	Avg.(%)
Helmet_1:CNN	98.99	96.54	96.77	98.43	99.48	98.042
Helmet_1:HOG	93.32	80.33	87.98	79.34	93.22	86.838
Helmet_2:CNN	99.23	82.79	98.28	96.68	97.76	94.948
Helmet_2:HOG	87.52	93.07	92.79	75.63	69.94	83.79

Results of Histogram of Oriented Gradients (HOG) based classifier is compared with the CNN classifier performance and is found to have high accuracy percentage. The 5-fold cross validation is used to conduct experiments with a view to making the efficiency of the proposed solution equally validated. Table I presents the findings of the experiments for the 'Motorcyclist' vs. 'Non-motorcyclist' classification using the proposed CNN and the current approach used for comparison for both data sets.

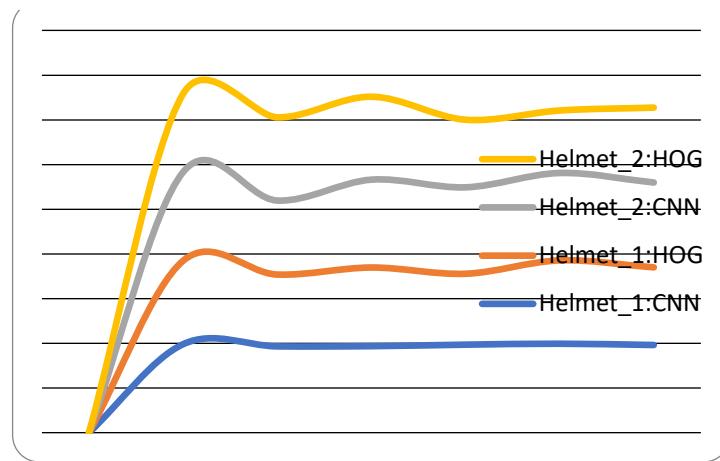


Fig .6. Average performance comparison ‘Helmet’ vs. ‘Non-Helmet’ analysis between CNN and existing HOG method

Table 1 also shows the performance comparison of ‘Helmet’ vs. ‘Non-Helmet’ using CNN and the existing strategy utilized for comparison for both the datasets. For assessment we consider only HOG-SVM as its overall performance is the highest among all the other methods. Experiments show that the accuracy is 98.04% with a low false alarm rate less than 0.5% on Helmet_1 dataset and 94.31% with a low false alarm rate less than 0.5% on Helmet_2 dataset. The proposed strategy utilizing CNN beats the classification execution of the existing HOG-SVM with an edge of 3.46% on Helmet_1 dataset and 0.056% on Helmet_2 dataset as outlined in Fig.6.

V. CONCLUSION

The proposed framework for automatic detection of motorcyclists driving without helmets makes use of adaptive background subtraction which is invariant to various challenges such as illumination, poor quality of video, etc. The use of the deep learning for automatic learning of discriminative representations for classification tasks improves the detection rate and reduces the false alarms resulting into more reliable system. The experiments on real videos successfully detect \approx 92.87% violators with a low false alarm rate of \approx 0.50% on two real video datasets and thus show the efficiency of the proposed approach.

REFERENCES

- [1] Adam, E. Rivlin, I. Shimshoni, and D. Reinitz, “Robust real-time unusual event detection using multiple fixed-location monitors,” IEEE Transactions on Pattern Analysis and Machine Intelligence.
- [2] W. Liu, P. Fu, C. Yuan, “Real-time on road vehicle and motorcycle detection using a single camera,” in Procs. IEEE Int. Conf. on Industrial Technology (ICIT).
- [3] 3. C. -C. Chiu, M. -Y. Ku, and H. “Motorcycle detection and tracking system with occlusion segmentation,” in Int. Workshop on Image Analysis for Multimedia Interactive Services, Santorini.
- [4] 4. W. Hu, T. Tan, L. Wang, and S. Maybank, “A survey on visual surveillance of object motion and behaviors,” IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews
- [5] K. Dahiya, D. Singh, and C. K. Mohan, “Automatic detection of bikeriders without helmet using surveillance videos in real-time,” in Proc. Int. Joint Conf. Neural Networks (IJCNN), Vancouver, Canada, 24–29 July 2016, pp. 3046–3051.
- [6] W. Hu, T. Tan, L. Wang, and S. Maybank, “A survey on visual surveillance of object motion and behaviors,” IEEE Trans. Systems, Man, and Cybernetics, Part C: Applications and Reviews, vol. 34, no. 3, pp. 334–352, 2004.
- [7] C.-C. Chiu, M.-Y. Ku, and H.-T. Chen, “Motorcycle detection and tracking system with occlusion segmentation,” in Proc. Int. Workshop on Image Analysis for Multimedia Interactive Services, Santorini, Greece, 6–8 June 2007, pp. 32–32.
- [8] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in Proc. Advances in Neural Information Processing Systems (NIPS), Lake Tahoe, Nevada, United States, 3–6 December 2012, pp. 1097–1105.
- [9] Saranya.S,“Review on Image Segmentation Techniques to Detect Outliers in Blood Samples”, International Journal of Engineering Trends and Technology (IJETT), ISSN 2231-5381, Volume 53, No.2, November 2017.
- [10] D. Jeff, J. Yangqing, V. Oriol, H. Judy, Z. Ning, T. Eric, and D. Trevor, “DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition,” Int. Conf. on Machine Learning (ICML), vol. 32, no. 1, pp. 647–655, 2014.