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Automated Helmet Detection using Image Processing Algorithms

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Abstract

In the last couple of years, most deaths in motorcycle accidents were due to damage to the head of the motorcycle riders. Helmets are being utilized to minimize such damages to the head. Lately, the Government has enforced strict penalties on motorcycle riders who don't wear helmets while driving. But many violations are still being pursued. To overcome these violations, our team proposes a project to detect motorcycle riders without helmets. The proposed approach first detects bike riders from surveillance video using background subtraction and object segmentation. Then it determines whether the bike-rider is using a helmet or not, attains the number plate of the motorcycle and sends a message stating the fine to the defaulter using a mail. Image processing is used here and processes live video streams from traffic inspection recordings. We propose to use Python programming to implement this project.

Keywords: Image Processing, Faster R-CNN, YOLOv3, Pattern Recognition, Helmet Detection

I. INTRODUCTION

Motorcycle accidents are growing consistently throughout the years. Wearing helmets is critical to decrease the danger of injuries during accidents. Here we propose an approach for programmed identification of bicycle riders without helmets and who are triple riding. Using the process of image recognition in digital image processing.

Bike accidents without helmets are far more likely to result in death or brain trauma than ones where the riders' head was properly protected. In 2014, according to the Insurance Institute for Highway Safety, over 60% of deaths in bicycle crashes were people who were not wearing a helmet. Laws making helmet use compulsory are important in increasing the wearing of helmets, especially in low-income and middle-income countries where helmet-wearing rates are low, and where there are large numbers of users of motorized two-wheelers. There have been many studies that have evaluated the impact of motorcycle helmet laws on helmet-wearing rates, head injury or death. When mandatory helmet laws are enforced, helmet-wearing rates have been found to increase to 90% or higher; when such laws are repealed, wearing rates fall back to generally less than 60%.

The primary aim of our project is regarding the safety of the motorcycle riders. Drivers without helmets are detected. Other benefits include; The Motor vehicle department is able to reduce the number of accidents, real time identification and punishment of defaulters is possible, software capability to detect the violation of rules, enforcement of law and order in society.

II. METHODOLOGY

Objects on each frame are identified separately using object detection algorithm, Faster R-CNN. The first stage of the R-CNN pipeline is the generation of 'region proposals' or regions in an image that could belong to a particular object. We use the selective search algorithm. The selective search algorithm works by generating sub-segmentations of the image that could belong to one object — based on color, texture, size and shape — and iteratively combining similar regions to form objects. This gives 'object proposals' of different scales. R-CNN pipeline is agnostic to the region proposal algorithm. The selective search algorithm is used to generate 2000 category independent region proposals (usually indicated by rectangular regions or 'bounding boxes') for each individual image. These individual rectangular boxes include all the objects identified in the particular background including our region of interest i.e. the motorcycle along with their relative distances in the frame indicated.

A Faster R-CNN is an advanced version of R-CNN that employs selective search and Regional Proposal Network (RPN) for identification of particular specified objects separately rather than identifying all objects in the particular background. The R-CNN uses 2,000 proposed areas (rectangular boxes) from search selective. Then, these 2,000 areas are passed to a pre-trained CNN model. Finally, the outputs (feature maps) are passed to a SVM (Support Vector Machine) for classification. The regression between predicted bounding boxes (bboxes) and ground-truth bboxes are computed. R-CNN includes the following steps:

A. *Feature extraction from Region Proposals*

A 4096 dimensional feature vector is obtained from each of the 2000 region proposals for every image using a Convolutional Neural Network (CNN). CNN is then trained to identify the particular features. The details of training this CNN are as given below.

1) Supervised Pre-training:

CNN is first trained on the ILSVRC2012 *classification* dataset for a 1000 way image classification task with a large number of images so that the convolution layers can learn basic image features.

2) Domain-Specific Fine-Tuning:

Now, the network needs to be fine-tuned to learn:

1) The visual features of the new types of images- distorted region proposals
2) Specific target classes of the smaller dataset for the detection task.

We fine-tune the classification network to identify the classes belonging to the detection task from the region proposals. Thus by training the system motor cycle could be identified separately from all the backgrounds. On separately extracting motorcycles from the particular background the algorithm is then trained to identify presence or absence of helmet by providing data set with and without helmet. Rather than R-CNN, YOLOv3 is used for training the machine to identify motorcycles with and without helmets.

By using all the above mentioned technologies automated helmet detection can be done by the following steps:

B. *Detection of bike riders*

This phase involves detection of bike-riders in a frame.

1) Feature extraction:

Object classification requires some suitable representation of visual features. In literature, HOG, SIFT and LBP are proven to be efficient for object detection. For this purpose, we analyze following features:

- Histogram of Oriented Gradients: HOG descriptors are proven to be very efficient in object detection. These descriptors capture local shapes through gradients. We used 9 bins, 8×8 pixels per cell and 2×2 cells per block. The resulting feature vector is h, where $h \in R$ n, and n is 3780.
- Scale Invariant Feature Transform: This approach tries to capture key-points in the image. For each key point, it extracts feature vectors. Scale, rotation and illumination invariance of these descriptors provide robustness in varying conditions. Feature vectors are used to determine similarity between images.
- Local Binary Patterns: These features capture texture information in the frame. For each pixel, a binary number is assigned by thresholding the pixels in the circular neighborhood.

2) Classification:

After feature extraction, the next step is to classify them as 'bike-riders' vs. 'other' objects. Thus, this requires a binary classifier. Any binary classifier can be used here, however we choose SVM due to its robustness in classification performance even when trained from less number of feature vectors. Also, we use different kernels such as linear, sigmoid (MLP), radial basis function (RBF) to arrive at best hyper-plane.

C. *Detection of bike riders without helmet*

After the bike-riders are detected in the previous phase, the next step is to determine if the bike rider is using a helmet or not.

1) Feature extraction:

Identified region around the head of the bike-rider is used to determine if bike-rider is using the helmet or not. To achieve this, similar features as used in phase-I i.e. HOG, SIFT and LBP are used. The distribution of the HOG feature vectors show that the two classes i.e 'non-helmet' (Positive class) and 'helmet' (Negative class) fall in overlapping regions which shows the complexity of representation.

2) Classification:

The method needs to determine if the biker is violating the law i.e. not using a helmet. For this purpose, we consider two classes :

1) Bike-rider not using helmet(Positive Result)
2) Biker using helmet (Negative Result).

The support vector machine (SVM) is used to classify using extracted features from the previous step. To analyze the classification results and identify the best solution, different combinations of features and kernels are used. Results along with analysis are included in the Result section.

III. WORKING

The video is initially converted into image frames using python programs by using python library openCV. Thus each video get converted into thousands of frames. Further processing is done on this image frames.

A. *Detecting motorcycle using YOLO*

On each frames of images, an analysis is done by the YOLO algorithm for image detection. We unify the separate components of object detection into a single neural network. Our network uses features from the entire image to predict each bounding box. It also predicts all bounding boxes across all classes for an image simultaneously. This means our network reasons globally about the full image and all the objects in the image. The YOLO design enables end-to-end training and real-time speeds while maintaining high average precision. Yolo architecture is more like FCNN (fully convolutional neural network) and passes the image once through the FCNN and output is prediction. YOLO does some preprocessing on the image before any object detection mechanism.

The preprocessing includes:

- Blur: The representation of blur includes motion blur, disk blur and Gaussian blur, etc. The blur is mainly caused by the uniform linear motion of the object during this moment. This needs to be resolved.
- Rotate (Flip): Sometimes the camera has a certain tilt angle when shooting, so images will have a degree of rotation. The image should be rotated so that it can be processed easily.
- Noise: There may be a lot of noises existing in images due to some reasons such as electromagnetic interference and low illumination level, etc. They are all eliminated.
- Cropping: When the subject is obstructed by other objects, we can only photograph a part of the object. Thus, we cropped the image randomly. Both cropping width and height vary from 0 to 0.15.

Consider that we has an input frame of image; our system divides the input image into an S*S grid. If the center of an object falls into a grid cell, that grid cell is responsible for detecting that object. Each grid cell predicts B bounding boxes and confidence scores for those boxes. These confidence scores reflect how confident the model is that the box contains an object and also how accurate it thinks the box is that it predicts. If no object exists in that cell, the confidence scores should be zero. The boxes with high confidences represent an image. Thus image gets identified. The initial convolutional layers of the network extract features from the image while the fully connected layers predict the output probabilities and coordinates.

The database for detecting a motorcycle rider with or without a helmet is already what the system is trained to identify. So, when a motorcycle is present inside the image, the image gets divided to different boundary boxes and the boundary box containing the motorcycle inside it has a particular confidence score associated with it. Depending on the score the bicycle gets identified with or without a helmet on it. Thus, we have now identified the images on a frame and particularly identified the motorcycle separately by the predefined databases.

B. *Detecting helmet by RCNN*

By YOLO algorithm we have had already identified all the objects in the particular frame and has separated motorcycle from the rest of the images. Now we need to specifically identify the presence and the absence of helmet in the particular vehicle. For this we uses the Fast-RCNN. The CNN processes the entire image with several convolutional and max pooling to produce a conv feature map. For each object proposal a region of interest (RoI) pooling layer extract a fixed-length feature vector from the feature map. Each feature vector is fed into a sequence of fully connected layer that finally branch into two sibling output layers, one is the softmax layer that differentiates the helmet object from the background, the other layer outputs four real value numbers for the helmet which encodes the refined bounding-box positions of the object.

R-CNN into two separate parts: region proposal and object recognition. The region proposal will determine whether the helmet appear in an image. We specify the region proposal as helmet; we can remove the object recognition. The architecture construction of the fast R-CNN for our vehicle. Helmet identification is constructed by position regression and object position classification. Each offset corner coordinate, x or y of the left top or right bottom corner, is regressed from a convolution layer. Each convolution layer contains 15x15 possible object targets. The position regression proposes 9 layers of 15815 targets. There are 36 layers for position regression. In position classification, each possible object target is assigned to the possibility of object. Finally, helmet recognition applies non maximum suppression on removing the redundant region proposals and output the final result. We modify the fast R-CNN network which has two output layers. The 1st output layer generates a discrete probability pv (per RoI), pv indicating the likelihood of the existence of a helmet on the head of a motorcycle rider.. The pv is computed by a softmax of a fully connected layer. The second output layer generate the bounding-box regression offsets, tv = (xr, yt, xl, yb) for the helmet. Here, tv specifies a scale-invariant translation and height/width shift relative to the object proposal. Each training RoI is labeled with helmet and without helmet with aground-truth bounding box regression offset tv. Thus the presence or absence of a helmet gets detected.

C. *Detecting license plate by Faster-RCNN*

RCNN involves four key operational layers like i) Convolution, ii) ReLu (Non-linearity), ii) Maximum pooling and iv) Fully Connected layer. The process of Convolution includes the formation of the featured layer by multiplying the values in the filter with the original pixel values of the image. Inputs from the convolution layer are smoothened to reduce the sensitive nature of the filters towards noise and variations. The process of pooling mainly reduces the size of the image, or the color contrast across red, green, blue (RGB) channels.

CNN is compatible to a wide variety of complex activation functions to model signal propagation. One of the common function is the Rectified Linear Unit (ReLU), is favorable for its faster training speed. The last layers in the network are fully connected, where the neurons of preceding layers are connected to every neuron in subsequent layers. Number plates with distortion, tilt, and illumination at different angles have been considered here for giving it a realistic effect. So that all sets of motorcycles could be detected using the

RCNN network. Training of the RPN can be done in an end-to- end manner using stochastic gradient descent (SGD) for both classification and regression branches. For the entire system, we have to take care of both the RPN and Fast R-CNN modules since they share convolutional layers. Note that the input of the Fast R-CNN is actually dependent on the output of the RPN. For the exact joint training, the SGD solver should also consider the derivatives of the RoI pooling layer in the Fast R-CNN with respect to the coordinates of the proposals predicted by the RPN. The RPN can be trained end-to-end by back propagation and stochastic gradient descent (SGD). The database for the detection of number plate is pre fed to the processer from different angles and also with different patterns of letters. Thus any number plate in the image frame is detected using faster RCNN.

D. *Sending mail through SMTP*

A mail is send to concerned authority through SMTP via python program codes.

– Abbreviations and Acronyms

1) CNN: Convolutional Neural Network
2) R-CNN: Region-CNN
3) YOLO: You Only Look Once
4) RPN: Regional Proposal Network
5) SVM: Support Vector Machine
6) HOG : Histogram of Oriented Gradients
7) MLP: Multilayer Perception
8) SMTP: Simple Mail Transfer Protocol

IV. CONCLUSION

Motorcycle accidents have been growing consistently throughout the years. Because of different social and monetary elements, individuals pick motorbikes over other vehicles as it is significantly less expensive to run, less demanding to park and adaptable in rush hour gridlock. Here we propose a system to detect motorcycle riders without helmet and sending a message to the motorcycle owner if he/she is not wearing the helmet. This system can save many lives as about 400 motorcycle riders perish every day in India because of not wearing helmet. If we use helmets it could increase the chances of survival by 42 percent. It also reduces the injuries up to 70 percent. In future, the system can be expanded by detecting motorcycle riders without helmet along with those who are triple riding. The proposed system will also assist the traffic police for such violators in odd environmental conditions like hot sun, rain etc.

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