Automatic detection of motorcyclists without helmet

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***Abstract*—Motorcycle accidents have been rapidly growing throughout the years in many countries. Due to various social and economic factors, this type of vehicle is becoming increasingly popular. The helmet is the main safety equipment of motorcyclists, but many drivers do not use it. If an motorcyclist is without helmet an accident can be fatal. This paper aims to explain and illustrate an automatic method for motorcycles detection and classification on public roads and a system for automatic detection of motorcyclists without helmet. For this, a hybrid descriptor for features extraction is proposed based in Local Binary Pattern, Histograms of Oriented Gradients and the Hough Transform descriptors. Traffic images captured by cameras were used. The best result obtained from classification was an accuracy rate of 0.9767, and the best result obtained from helmet detection was an accuracy rate of 0.9423.**

Keywords—motorcycle detection; vehicle classification; helmet detection; hybrid descriptor;

I. INTRODUCTION

Motorcycles are widely used as a mean of transportation in many countries. The major advantages are their low prices and low operation cost in comparison with other vehicles. In the last decade, it was observed an increase in the number of motorcycle accidents. According to National Traffic Department (DENATRAN), in March 2013, Brazil had a fleet of $20.281.986$ motorcycles and scooters [1]. In 2011, according the National Department of Transport Infrastructure (DNIT), Brazil had a total of $34,635$ motorcycles involved in accidents [2], according with DNIT in $1,011$ accidents the motorcyclist was without helmet.

The main safety equipment of motorcyclist is the helmet. Although helmet use is mandatory in many countries, many motorcyclists do not use it or use incorrectly. The Department of Transportation in USA said that, in 2011, only 66% of motorcyclists used the helmet according to the law [3].

The Centers for Disease Control and Prevention in USA presented a report in 2012 where the findings indicated that, on average, 12% of fatally injured motorcyclists were not wearing helmets in states with universal helmet laws. In states that adopt partial helmet law (only required specific groups, usually young riders, to wear helmet) the number increased to 64%. Finally, the number is 79% in states without a helmet law [4]. Additionally, according to the same report, in 2010, economic costs saved from helmet use by society in states with a universal helmet law were, on average, $725 [1] per registered motorcycle, nearly four times greater than in states without such a law ($198).

[1]United States Dollar

Due to the large number of vehicles that exist, researches in intelligent traffic systems became popular, including vehicles detection, recognition, tracking and counting, and traffic parameters estimation. Motorcycles segmentation on public roads images can be seen as the first step to develop any research in traffic estimation as speed computation, motorcyclist helmet use, vehicle tracking and occlusion processing.

A. Contributions

This paper presents two main contributions: a new automatic method to detect motorcyclists without helmet on public roads; and a new hybrid descriptor based on geometric, shape and texture features. The aim of this study was to propose and develop a system for automatic detection of motorcyclist without helmet. For this approach, we created a strategy divided into two parts: motorcycle and helmet detection.

B. Related work

Over the past years many works were carried out in traffic analysis on public roads, including vehicle detection and classification, and helmet detection [5], [6], [7], [8], [9]. Background and foreground image computation algotrithms are necessary to segment the moving objects and classify them. Next, some related works to helmet detection are shown.

Wen et al. [10] suggested a circle arc detection method based upon the Hough transform. They applied it to detect helmet on the surveillance system of the Automatic Teller Machine. The weakness of this work is that they only use geometric features to verify if any safety helmet exists in the set. Geometric features are not enough to find helmet. The people head can be mistaken with a helmet.

In [11] it was proposed a computer vision system aiming to detect and segment motorcycles partly occluded by another vehicle. A helmet detection system is used, and the helmet presence determines that there is a motorcycle. In order to detect the helmet presence, the edges are computed on the possible helmet region. The Canny edge detector [12] is used. The quantity of edge points which are similar to a circle define a helmet region. The method needs so much information (helmet radius, camera angle, camera height, etc) that must be provided by user.

Chiverton [9] described and tested a system for the automatic classification and tracking of motorcycle riders with and without helmets. The system uses support vector machines trained on histograms. The histograms are derived from head region of motorcycle riders using both static photographs and individual image frames from video data. A high accuracy rate was obtained but the number of test images is insufficient.

Motorcycle segmentation on public roads can be seen as the first step to develop any research in traffic estimation. Next, some relevant works about vehicle segmentation are shown.

A segmentation and classification vehicle system was proposed in [13]. It also computes the approximated speed of the vehicle. Three-dimensional models are created based on vehicle size. The size depends on the vehicle class: car, bus, pedestrian, etc. The generated models are compared to the computed models to classify the vehicles. The main drawback of this paper is that a single model is used for both bicycles and motorcycles.

Leelasantitham et al. [5] proposed a technique that detects moving vehicles using image tracking methods. The classification of vehicles is based on traffic engineering knowledge. The vehicles are separated into five groups, first: bicycle, motorcycle and motor tricycle; second: passenger car, pickup, van and passenger pickup; third: six-wheel truck and mini bus; fourth: ten-wheel truck and big bus; fifth: eighteen-wheel truck and trailer. The weakness of this work is that the attributes extraction procedure only uses 3 types of information: vehicle position, length and width.

In another paper [14] Zengqiang et al. implemented a system that identifies vehicles even if part of it is occluded. The system can track the detected vehicle even if the occlusion continues to occur. In order to do this, a vehicle segmentation algorithm, which is based on feature points on contour, is presented.

Takahashi et al. [15] introduced a computer vision system for bicycle, pedestrian and motorcycle detection. The system detects moving objects (horizontal motion) and pedaling movement (vertical motion) using the Gabor filtering. The HOG descriptor is computed and the SVM classifier classifies the objects into two classes: two-wheel vehicle and pedestrian. At the end, the vertical motion is computed and the two-wheel vehicle are classified into *motorbike* and *bicycle*.

Sonoda et al. [16] proposed a system to detect moving objects. The system aims to detect moving objects at an intersection (like vehicles and pedestrians), and to warn the driver. They used the Mixture of Gaussians to detect the moving objects and the Lucas-Kanade Traker algorithm for pedestrian tracking.

Chen et al. [8] presented a system for vehicle detection, tracking and classification. The system separate them into four categories: car, van, bus and motorcycle (including bicycles). A new background Gaussian Mixture Model (GMM) was proposed. A Kalman filter tracks a vehicle to enable classification by majority voting over several consecutive frames. The SVM as classifier and HOG (Histogram of Oriented Gradients) descriptor features was used. The results were not similar when the weather conditions have changed.

C. Technique overview

This work deals with the problem of detecting helmet use by motorcyclists on public roads. The problem can be splitted in two steps. The first step consists of segment and classify the vehicle images. This step aims to determine the moving objects in the scene. In this phase the user specifies a line (defined Cross Line - CL) to detect the vehicles (see Figure 2(a)). After this, the system classifies them into *motorcycle* and *non-motorcycle*. The vehicles are classified into two classes because it is only necessary to know if the vehicle is a motorcycle or not. The second step consists of the helmet detection procedure. A Region of Interest (RoI) was used aiming to improve the computational cost and the accuracy. The helmet detection is made using a hybrid descriptor to extract image features, and the support vector machine classifier is used to classifier an image in *helmet* or *non-helmet*. The diagram of the proposed system is shown in Figure 1.

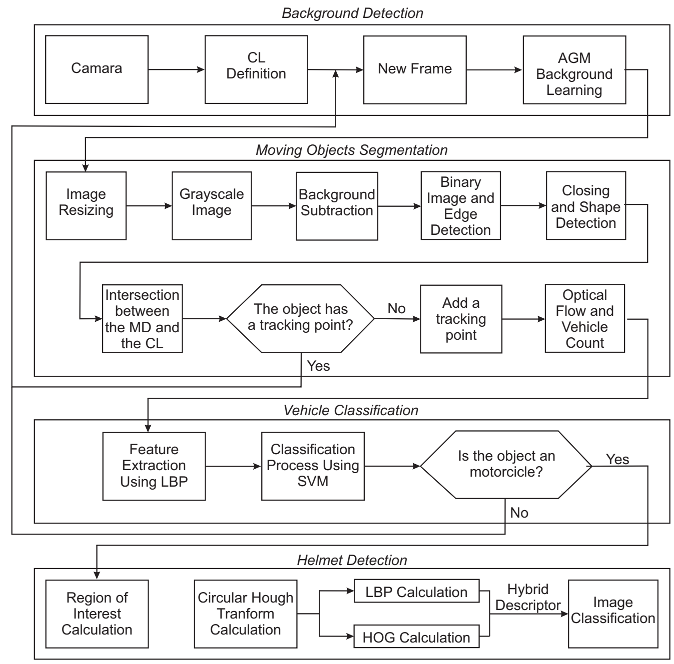


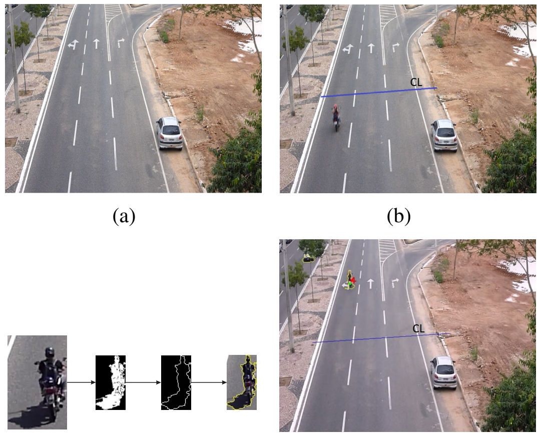
Fig. 1. Flow chart of the method.

II. SEGMENTATION AND CLASSIFICATION OF VEHICLES

A. Vehicle segmentation

In order to segment the vehicles, two steps are necessary: background detection and moving objects segmentation. Figure 2 shown the steps of vehicle classification.

1) Background Detection: The main objective of this step is the determination of an image that will be used to detect moving objects. We used a video camera to capture the traffic images. The frames were captured and used to create an image which represents the scenario background. In environments where the static objects change during the time (parked vehicles along the roads, changing position of the shadow over the course hours, etc), the algorithms to calculate adaptive backgrounds are necessary. In this way, we update the image background using the Adaptive Mixture of Gaussians (AMG) [17]. Figure 2(a) show an example of background image.



(a) (b)

(c) (d)

Fig. 2. Steps of the vehicle segmentation. Figure 2(a) shows the background image. Figure 2(b) shows an example of CL determination. Figure 2(c) shows the steps of moving object ssegmentation. Figure 2(d) is the result of all processing including the vehicle count.

2) Moving Object Segmentation: Concerning the problem of motorcycle detection on public roads, the segmentation of moving objects in scene allows that only objects of interest in the image are evaluated. This causes a reduction in processing time due to the fact that the classification algorithm works only in a small area of the image. It also reduces the probability of false-positive outputs in classifiers.

In our moving object segmentation approach, it is necessary to define a line (CL) (see Figure 2(b)) that must be marked by the user. This line is defined once, when the algorithm starts. The CL must cross the road. When a vehicle cross this line the process for moving object segmentation is started and the image frame is captured. The image frame is resized to reduce the computational cost. The motion detection is made using the AMG algorithm [17]. Using only the grayscale information, the subtraction between the current frame and the background image is made. After this, to create a binary image is used the Otsu algorithm [18]. The Sobel algorithm [19] is used to edge detection. One morphological closing operation is applied to remove the image noises. The next step is the shape detection, for this the algorithm proposed in [20] is used. This process is shown in Figure 2(c).

A tracking algorithm is necessary to ensure that each vehicle can be counted only once. For each detected object (vehicle), the intersection point between the Main Diagonal (MD) of the object and the CL is computed. This point is marked as the tracking point of the object. Aiming to reduce the computational processing, only detected objects previously not marked are analyzed. The next step consists in compute the optic flow of the detected object using [21]. The optic flow procedure is necessary to do not detect the same vehicle many times, this way, in the next frame the object is not processed because it already has a tracking point. The optical flow is computed only for the tracking points, this decrease the computational processing. At last the vehicle detected is counted. The Figure 2(d) shows the result of the all processing.

B. Vehicle classification

In pattern recognize works is necessary extract image features at first. After this, classifiers are used to recognize an image. This way, we use descriptors to extract image features. The descriptor returns a set of values as result. This set is called "feature vector" of the image object. The feature vector is used by the classifier to separate the two classes of the problem.

1) Feature Extraction: In feature extraction procedure, the Local Binary Pattern (LBP) descriptor was used. The LBP has a good performance in many applications, including texture classification, image recovery and surface inspection [22], [23], [24]. The original LBP [25] labels the image pixels in 3×3 neighborhood. Each pixel is compared with the central pixel and the result is the binary number. The LBP was used with a 3×3 window, this means that the image is divided in nine windows, a histogram of 256 labels partitions is computed for each window. The neighborhood was 3×3 size for the label computation. The labels are marked from 0 to 255 because we use a grayscale image with 256 gray levels. This histogram can be used like a texture descriptor. Each partition histogram encodes local primitives. The local primitives include different types of edges, curves, stains, plain areas, etc. Figure 3 shows the LBP computation.

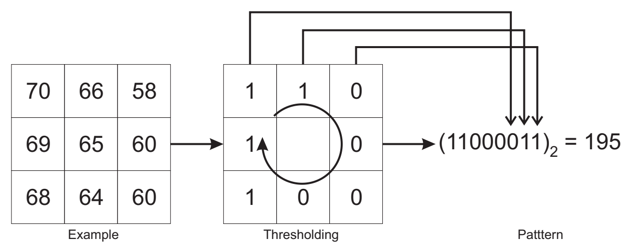


Fig. 3. Example of Local Binary Pattern.

2) Classification process: The main goal of any classifier is to use the object's features to identify which class it belongs to. The feature vectors that are contained in the same region of decision have similar characteristics. To classify the objects we use the SVM classifier [26]. The vehicle classification consists of differentiating the segmented objects into two classes *motorcycle* e *non-motorcycle*. In this work, the objects are classified only into two groups just because it is enough to know that each object corresponds to a motorcycle or not.

III. Helmet detection

The helmet detection process is divided in three main steps: Region of Interest (RoI) determination, feature extraction and image classification.

A. Region of interest

The RoI determination is an important step in our problem. It is used to search the helmet, the motorcycle head must be in the RoI. Using an RoI we decrease the computational cost and decrease the search area. In our database, in all images the head region are in the RoI. We use the top of the image ($1/5$ of the image height), Figure 4 shows an example of RoI.

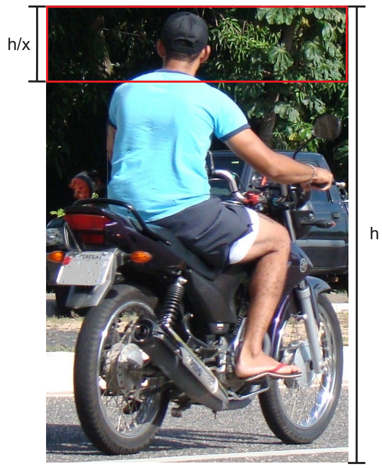


Fig. 4. Region of Interest example. The red contour is the ROI of this image. Were h is the height and $x = 5$.

B. Feature extraction

For the feature extraction we use a hybrid descriptor, this descriptor was made combining Circular Hough Transform (CHT), LBP and HOG descriptors.

1) Circular Hough Transform: Hough Transform is a technique that may be used to find geometric shapes in images (circles, lines, ellipses). It is used a voting process to detect circles in images. The votes are attributed to points of possible circles existing in an image. The votes are accumulated in an accumulation vector of votes. When a maximum value is obtained in the vote accumulator, the detection of a possible circle is obtained. The main parameters of CHT are: the minimum and maximum radius (this limited the size of the found circles), and the amount of circles, this parameter returns circles with more votes in the accumulator.

2) Histogram of Oriented Gradients: The HOG algorithm [27] is a feature descriptor that calculates an image histogram of oriented gradients. The final descriptor is an one-dimensional array of histograms extracted from the image. The algorithm is based on the local object shape and appearance, which in an image can be represented by intensity gradients or edge directions. The feature extraction can be done without an edge position foreknowledge. Two parameters are necessary to run the HOG descriptor: number of windows and the amount of histograms by window.

3) Hybrid descriptor: Before we compute the hybrid descriptor a set of preprocessing are made. Firstly, we compute the grayscale image using the euclidian distance between the red and green bands of the RGB space. A media filter with 5×5 pixels neighborhood is applied to reduce the noises. After, a threshold is compute using the Otsu function [18], this threshold is applied and get an binary image. The Sobel [19] operator is applied to get the image edge. The next step is to use morphological operators aims eliminates small regions and other noises.

After the preprocess, we use the CHT. The CHT computes the 10 best image circles (circles with more points). The CHT was applied with a minimum and a maximin radius of *RoI height* and *(RoI height/5)*, this values was choice because they returns the bests results. After this, we compute the LBP and the HOG descriptor by the square circumscribed in each circle. The LBP was used which a window of 3×3 corresponding to 9 histograms. The neighborhood used was 3×3 for the computing of the label, the labels are of 0 to 255. A grayscale image was used for the processing. The HOG descriptor has been set up with a 9 histograms by 9 partitions window. This way, a vector of 81 features is generated. Here, it was also used a large variation of histogram and partition sizes to conclude which one is the best. The two features vector resultant (LBP and HOG) are combined in one vector, generating the hybrid descriptor based on shape(CHT), texture(LBP) and gradients(HOG).

C. Image classification

The selected classifiers cover the three different classification families described by [28]: probabilistic, geometric and tree-based. For the probabilistic family we tested the Naive Bayes classifier with two ways of estimating the prior probabilities, by assuming a Gaussian distribution of the data and by employing the Parzen Window approach. For the geometric family, two Support Vector Machines (SVMs) were tested, as implemented in libSVM[29]. For the tree-based family, the Random Forest algorithm was chosen [30].

1) Naive Bayes: Bayesian classifiers are statistical classifiers. They can predict class membership probabilities, such as the probability that a given sample belongs to a particular class. Bayesian classifier is based on Bayes' theorem. Naive Bayesian classifiers assume that the effect of an attribute value on a given class is independent of the values of the other attributes. This assumption is called class conditional independence. It is made to simplify the computation involved and, in this sense, is considered “naive”.

2) Random Forest: [30] proposed random forests, which add an additional layer of randomness to bagging. In addition to constructing each tree using a different bootstrap sample of the data, random forests change how the classification or regression trees are constructed. In standard trees, each node is split using the best split among all variables. In a random forest, each node is split using the best among a subset of predictors randomly chosen at that node. This somewhat counterintuitive strategy turns out to perform very well compared to many other classifiers, including discriminant analysis, support vector machines and neural networks, and is robust against overfitting [30]. In addition, it is very user-friendly in the sense that it has only two parameters (the number of variables in the random subset at each node and the number of trees in the forest), and is usually not very sensitive to their values.

3) Support Vector Machine: SVM makes a mapping of input space into a space of high dimensionality. Thereafter, the hyperplane for optimal separation is computed. The optimal hyperplane is chosen in order to maximize the separation distance between the classes [31]. Consider an training sample $\{(\mathbf{x}_i, d_i)\}_{i=1}^{N}$, where $\mathbf{x}_i$ is the input vector for the i-th element and d_i is the corresponding output. By default, the class represented by $d_i = +1$ e $d_i = -1$ are linearly separable.

In non-linearly separable classes it is not possible to create a separation hyperplane without classification errors. Therefore, the aim is to find an optimal separation hyperplane that minimizes the probability of classification errors. In order to use SVM in pattern recognition it is necessary to convert a nonlinearly separable function into a linearly separable. This is done by increasing the dimensionality of the problem. This way, it is possible to ensure a larger generalization space. The function that increases the dimensionality of the input space is called Kernel Function [31].

IV. Results and discussion

The videos used for tests were obtained from a CCD video camera on public roads during the day and night, captured at 25 frames per second with an image size of 1280×720 pixels, and they have 114 minutes long. All the algorithms were implemented using the MATLAB® tool and the OPENCV library.

A. Vehicle segmentation

The segmentation of moving objects returns a total of 3245 images (2576 *non-motorcycle* and 669 *motorcycle*). These images are used by the classification procedure. The Figure 5 shows examples of images generated in this step.

Fig. 5. Example of images generated in the segmentation of moving objects step. The images was captured during the day and night.

B. Vehicle classification

We use the K-fold cross-validation statistic method with $K = 10$ to generate the results. In 10-fold cross-validation, the original sample is randomly partitioned into 10 equal size subsamples. Of the 10 subsamples, a single subsample is retained as the validation data for testing the model, and the remaining 9 subsamples are used as training data. The cross-validation process is then repeated 10 times (the folds), with each of the 10 subsamples used exactly once as the validation data. The 10 results from the folds then can be averaged to produce a single estimation. The advantage of this method over repeated random sub-sampling is that all observations are used for both training and validation, and each observation is used for validation exactly once. In stratified 10-fold cross-validation, the folds are selected so that the mean response value is approximately equal in all the folds.

TABLE I. Evaluation of the classifiers Neural Multilayer Perceptron (MLP), Radial Basis Function Network (RBFN) and SVM, and the descriptors LBP, HOG, Haar Wavelet.

	S	SP	PPV	NPV	A
LBP+MLP	0.1001	0.8998	0.2062	0.7938	0.7350
LBP+RBFN	0.9417	0.9615	0.8642	0.9845	0.9574
LBP+SVM	0.9372	0.9864	0.9471	0.9837	**0.9762**
HOG+MLP	0.9402	0.9798	0.9236	0.9844	0.9716
HOG+RBFN	0.9013	0.9639	0.8664	0.9741	0.9510
HOG+SVM	0.8445	0.9751	0.8983	0.9602	0.9482
Haar Wavelet+MLP	0.8834	0.9732	0.8954	0.9698	0.9547
Haar Wavelet+RBFN	0.8998	0.9786	0.9163	0.9741	0.9624
Haar Wavelet+SVM	0.7922	0.9565	0.8255	0.9466	0.9226

We have a total of 2576 *non-motorcycle* images and 669 *motorcycle* images. The classification detected correctly 2541 *non-motorcycle* (True Negative - TN) and 627 (True Positive - TP). The classifier wrong in 77 occasions, 35 images of *motorcycle* were classified like *non-motorcycle* (False Negative - FN) and 42 images of *non-motorcycle* were classified like *motorcycle* (False Positive - FP). In order to evaluate the algorithm performance, we used sensitivity (S), specificity (SP), positive predictive value (PPV), negative predictive value (NPV) and accuracy (A) as [32], Table I show these values. We compare our result (LBP + SVM) with other methods of vehicle classification. Many authors use others classifiers and descriptors [13], [33], [15], [34], [8]. We take the most common algorithms like Radial Basis Function Network (RBFN) and Multilayer Perceptron as classifier and Histogram of Oriented Gradients (HOG) and Haar Wavelet as image descriptor (see Table I).

In order to illustrate the performance of the classifier, the Receiver Operating Characteristic (ROC), also known as ROC curve, was used. The ROC curves in Figure 6 show the comparative results. It was observed that the best Area Under Curve (AUC) from our approach is 0.9951 close of 1 (the ideal result).

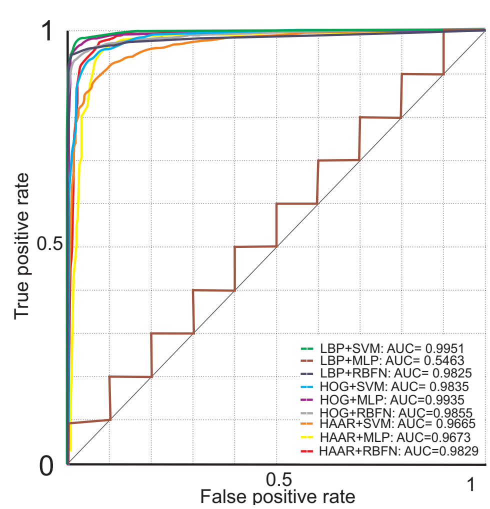


Fig. 6. ROC curve for the results, where *AUC* is the area under curve.

C. Helmet detection

In helmet detection step we just use 471 motorcycle images. This was needed because several images has very low resolution and is not possible to detect the helmet. To classify the images we use the same strategy of the vehicle classification: 10-fold cross validation.

Naive Bayes classifier was performed using estimator classes. Numeric estimator precision values are chosen based on analysis of the training data. In Random Forest classifier the maximum depth of the trees was unlimited and the number of trees to be generated was 80. SVM classifier was performed using linear kernel function. The better results were obtained from these functions in comparing to radial basis functions and tangent sigmoid. The weight to use for the classes was 2000, and the cost parameter was 1.

Table II shows the results of classification step. The best result was obtained using the Random Forest classifier with an accuracy rate of 0.9423. The worst result was obtained using the SVM classifier (accuracy of 0.8913).

TABLE II. RESULTS FOR NAIVE BAYES, RANDOM TREE AND SVM CLASSIFIERS.

	S	SP	PPV	NPV	A
Naive Bayes	0.9478	0.7794	0.9603	0.7260	0.9224
Random Forest	0.9791	0.7353	0.9542	0.8621	**0.9423**
SVM	0.9765	0.4117	0.9034	0.7567	0.8913

The ROC curve of Random Forest classifier has the largest area. This situation reflects the results presented in Table II.

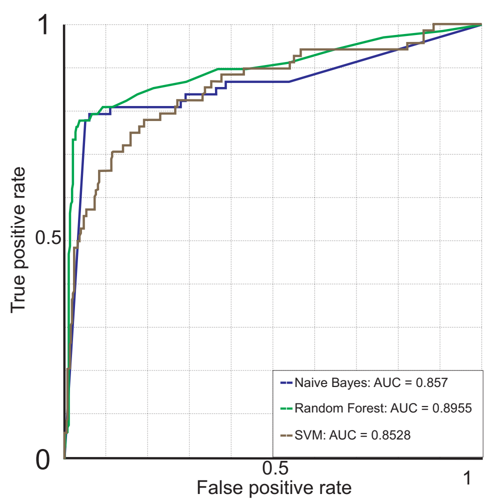


Fig. 7. ROC curve for all classifiers in helmet detection step.

Comparing our result with Chiverton's prosed system [9]. It was obtained a overall accuracy of 0.85 in helmet classification step.

V. CONCLUSION AND FUTURE WORKS

The results presented in Section IV-B are very satisfactory for the problem of vehicle classification. It was obtained 0.9767% accuracy rate. The results show that LBP descriptor proved to be more robust for the problem than HOG and Haar Wavelet descriptors. The LBP descriptor describes the local texture structure by pattern joint distribution. The texture patterns in motorcycles contribute to good performance of the classifier using the LBP features. SVM classifier presented good results. The main advantage of the SVM is the performance in the training phase. The SVM, as described in [31], are, usually, faster in the training process than Multilayer Perceptron (MLP) and Radial Basis Function Network (RBFN).

In helmet detection step the Random Forest algorithm obtained the best result. It was obtained 0.9380 accuracy rate. The combination between CHT, HOG and LBP return a good satisfactory result in helmet detection. This can be explained by the combining information edge(HOG), texture(LBP) and geometric(CHT) information to build the feature vector.

The results presented here are promising, but they can be improved. The main step to improve the results is capture images with a better resolution, several images was not used in helmet detection because of low resolution. One of the future works is the licence plate recognize, for this is necessary a high resolution image to recognize the numbers and letters of the licence plate. It is necessary too testing other descriptors like SURF, SIFT, FOURIER, Haar Wavelet to helmet detection.

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