Tree-Based Vehicle Color Classification Using Spatial Features on Publicly Available Continuous Data

Lisa M. Brown, Ankur Datta, Sharathchandra Pankanti
IBM T.J. Watson Research Center
Yorktown Heights, NY 10598
lisabr@us.ibm.com

Abstract

Several recent investigations attempt to classify vehicles into a small number (5-7) of colors. A significant complication arises, however; a large proportion of vehicles (>50%) are various shades of gray: white, black, silver, gray, and variations such as gun metal and pearly white. Distinguishing such shades of gray in vehicle body color from lighting changes is an unsolved problem. Furthermore, previous studies have evaluated their performance on private datasets precluding a comparison of methodologies. In this paper, we release a public dataset with ground truth color classification for future evaluations and comparisons based on the publicly available i-LIDS data [9]. We describe a method to perform vehicle color classification into 7 frequently occurring colors including dark red, dark blue and light silver, using pose dependent vehicle detection, vehicle alignment, and vehicle body part masks. We introduce new features for tree-based vehicle color classification based on the reliability of color information and the relative color of various vehicle parts.

1. Introduction

As more digital video surveillance solutions are deployed, the need for accurate object characteristic measurements has become critical. Yet the ability for video analytics to extract useful attributes is limited.
For example, although color is extremely useful and one of the first attributes to be used by people to describe vehicles, the ability to accurately characterize vehicle color has been extremely challenging. Although, there are many publications describing research in this area [1-8], commercial systems provide only a rudimentary ability to search for vehicles based on color and there are no industrial publications describing their accuracy.

There are many challenges to the problem of vehicle color classification. First of all, the vehicle has to be found and segmented from the image. Second, the body of the car or a part of it such as the "hood", needs to be segmented from the rest of the car. Thirdly, the pixels of the body of the car are used to determine the actual color of the car. Unfortunately, the color of these pixels may not actually represent the color of the vehicle due to lighting, reflections (specular and non-specular) and shadows effects. Similarly, the time of day, the weather, and the settings of the camera such automatic white balance can all affect the observed color. Finally, as shown in Fig. 1, the colors of vehicle are not uniformly distributed. A majority of vehicles are either various shades of gray or very dark or very pale, such as dark navy or silver with a slight color cast.

Figure 1. The color of some vehicles is very difficult to characterize. Top row: silver or white? Bottom row: black or navy?

According to the 2011 DuPont Automotive Color Popularity Report [10] regarding the choice of colors in American cars, white is the top choice with 20% and silver and black are tied for second with 17% each. In addition, gray takes another 12%. Clearly an important task in vehicle color classification is to distinguish different shades of gray since more than half of all cars do not contain a hue.

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Method	Colors	Accuracy	Pose	Cameras	Reso-lution	Contin-uous Samples	#train/ #test samples	Preprocess	Segment	Features	Classifier
Dule 2010	Black, Gray, White, Red, Blue, Green, Yellow	83.5%	Front	N/S	N/S	No	180/100 train/test for each color	No	Given car, hood relative to license plate	16 color space histograms	K-NN, artificial NN, SVM
Hsieh 2012	Black, Silver, White, Red,Blue, Green, Yellow	94.02%	Front	1	N/S	No	16648 total	Color correction [Reinhard] in train/test	Fore ground detection & window removal	28 polar bins from LAB, 6 RGB bins	Multiple SVMs in tree structure
Yang 2011	Black, Silver, White, Red,Blue, Green, Yellow	89%	Any view, front & rear shown	N/S	N/S	No	319 total	Gauss filter	Fore ground detection & homogenous region detection	Hue angle, saturation weighted hue sum, average intensity	Empirical cut-offs

Table 1. Comparison of recent methods in vehicle color classification [N/S = not specified]

Figure 2. Distribution of vehicle colors in the U.S.
Gray: white, silver, black, gray (20+ 17+17+12) =66%

Furthermore, the research conducted to date has been performed on in-house datasets making it difficult to evaluate and compare results across different approaches. In this paper, we introduce a publicly available dataset with ground truth annotation for vehicle color classification. We hope that the release of this dataset will encourage research in this task and provide a forum for comparison. We believe an important challenge for research in this area is an underestimation of the difficulty of the problem. Making a dataset available will provide useful training data for color classification systems and a verifiable benchmark for progress.

2. Related Work

Vehicle color classification methods can be categorized into four steps. The first step is based on image preprocessing and may include such processes as gamma correction, intensity normalization, color correction and noise filtering. The second step provides a segmentation of the vehicle or part of the vehicle for color analysis. This may be based on vehicle detection, license plate detection, and/or background subtraction. It also includes finding regions of the vehicle with a certain spatial relationship (i.e. to the license plate, or w.r.t. to the object segmentation) or specific properties such as color smoothness.

The third step is the selection of image features including the choice of color space (or color spaces). Typical features include histograms, statistical properties such as the mean, majority, co-occurrence or correlogram.

The last step is a classification method (such as support vector machines, neural network, nearest neighbor etc.) and the associated similarity metric (or distance measure) such as Bhattacharya distance, L1, L2, color distance etc.

Table 1 compares three of the most recent methods including the reported accuracy, dataset attributes, and algorithm choices. Each of these works use in-house data, does not give the image resolution, and does not specify the number of cameras used. They each use 7 colors, but the data is not collected continuously and therefore does not represent the real-world distribution. The resulting accuracies reported reflect this bias. The division between training and testing is also unclear.

All the methods rely on either background subtraction or assume the vehicle window is given. This will not be sufficient in practice where cars may be too close together, and shadows and occlusions are prevalent.

Yang et al. [7] claim to deal with any pose, but the method they describe relies on finding smooth regions. We believe this method will break down in many instances where both specular and non-specular reflections occur and body trim and shadows are common.

Hsieh et al. [6] perform color correction on both training and testing data and have developed a promising approach using a tree-based classifier. Our method is based on a similar scheme in which we train separate classifiers for different distinctions in order to optimize performance.

3. Public Vehicle Dataset

To facilitate research in vehicle color classification, we have annotated the publicly available i-LIDS dataset (UK) [9]. This annotation can be downloaded from [14]. We use two high resolution (720x576) clips from scenario 3:

2010-01-01-123030_720x576_PVTRN301b

2010-01-01-123030_720x576_PVTRN301a

The i-LIDS dataset includes many other clips of the same camera at different times of the day and under different weather conditions. It also includes clips from other cameras. This will be useful for extending the dataset as research in the area progresses.

We believe an important value of this dataset is the availability of the original video. This will make it possible to test a broader set of research questions concerning vehicle classification. For example, it will be possible to evaluate different methods for vehicle extraction/segmentation and color correction. It will also enable the use of multiple frames to improve color classification accuracy. Other vehicle attributes such as model or headlight type could also be explored.

Tables 2 and 3 show the statistics of the dataset and the distribution of colors that were found in the dataset. Every vehicle that passed along the road on the bottom right hand side of the video was annotated. In addition to the color, we also specified if the vehicle was not a car or if it contained multiple colors. An example frame from the video is shown in Figure 3.

Determining the number and specific distinct color categories was very challenging. In an effort to determine as many categories as possible, we had the user specify two levels of information. First, the user specified the color as one of 7 categories: black, white, silver, blue, green, yellow, and red. After specifying the color, the user then specified the color saturation and brightness by specifying one of 6 categories: light, medium, dark, pale light, pale medium, pale dark. The "pale" categories were needed to label vehicles which were difficult to categorize. In practice there were two types of instances that required the "pale" category: cars which were either dark blue or black and cars which were light silver or white. If the user had difficulty deciding which category, these vehicles were labeled pale dark blue and pale light silver respectively. Examples are shown in Figure 1 and the distribution of pale samples for each color class is shown in Figure 4.

Total	#Frames	Non-Car	Multi-colored	Visible Color	Ambiguous color
506	89K	18	25	378	85

Table 2. i-LIDS video ground truth distribution.

Figure 3. Example frame from i-LIDS dataset [9]. Each vehicle that traverses the road on the right is annotated as it passes along the bottom right. Notice the difficulty in discerning the color of each vehicle.

To gain some insight into how challenging these examples were, we took 12 examples of pale dark blue and pale light silver and had 5 different users label them either dark blue or black for the pale dark blue examples and either light silver or white for the pale light silver examples. Figure 5 shows the histogram of label frequency for pale dark blue alongisde the histogram for pale light silver. In only 1/12 of these examples, users were able to agree upon the label for these vehicles. However, in another 5/12, users were unable to consistently label the vehicle.

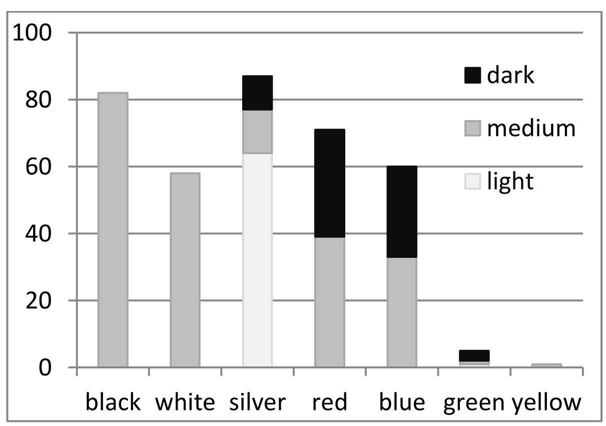

Table 3. Color Distribution of Ground Truth Data

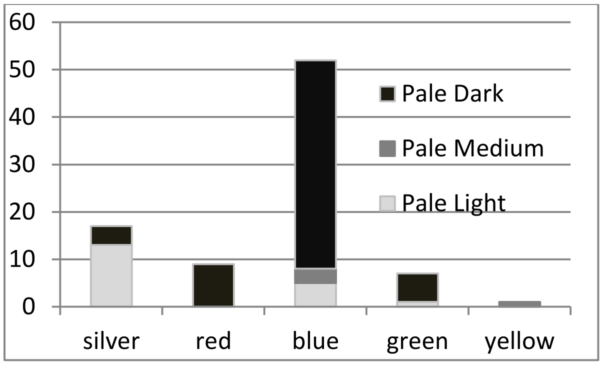

Figure 4. Histogram of vehicles with uncertain color categorization – i.e. between the specified color and either white, silver or black.

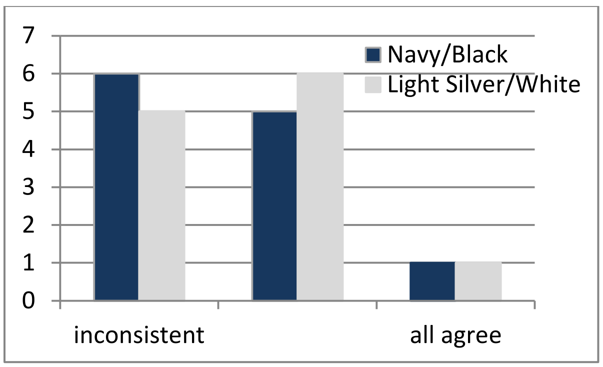

Figure 5. Histogram of the number of users who agree on the color of a vehicle from the "pale dark blue" and "pale light silver" collection. There were 5 users. The histogram shows that for many of the examples in the collection the users were inconsistent about the color label they associated with the given vehicle sample. Inconsistent is 3/5 agree and all agree is 5/5 agree. For some examples (the middle bar) 4/5 agree.

4. Method

In order to deploy vehicle color classification for different cameras, for vehicles at different poses, we utilize pose-dependent vehicle detection developed by Behjat et al.[12]. Vehicle detection can be applied in many situations where standard foreground detection may fail – particularly in crowded scenarios, partial occlusions and fast lighting changes. This system uses 12 different vehicle detectors to detect vehicles whose poses vary every 30 degrees. The method is very general and has been shown to be both fast and accurate. Once detected, the pose is known and can be used to apply the proper vehicle body segmentation and pose-dependent color classifier.

For each vehicle that is detected, the pose is given within 30 degrees. We then apply the entropy minimization method of Huang [13] to refine the alignment between all vehicles of this pose. This method works particularly well for vehicles. Furthermore, the model for each pose can be built off-line, and the alignment for a new detection can be efficiently applied at run-time.

Alignment allows us to find relative body parts of cards such as the hood, the windshield, and the side of the car using various car body part masks. Examples of the alignment and car body part extraction are shown in Fig 6.

Our approach is a tree-bases classification similar in spirit to that used by Hsieh[6]. At each node of the tree, the system uses a sub-classifier with features optimal for the specific decision. The tree of sub-classifiers, their specialized features, and its layout are shown in Fig. 7.

Once the body part is extracted, we measure each feature for every pixel in the given region. We first separate cars with color from cars without color. To do this, we measure the amount of color information in each body part using the color strength metric developed by Brown [11]. The color strength metric takes into account the reliability of the color information at each pixel based on the saturation and hue. This has been shown to accurately predict the error in the hue measurement. We use three features based on the color strength (CS) metric:

$$ave(CS) = \sum_{i=1}^{N} CS_i$$
$$\max(CS) = \max_i CS_i$$
$$CS\ weighted\ Hue = \frac{\sum_{i=1}^{N} CS_i Hue_i}{\sum_{i=1}^{N} CS_i}$$

For these measures, we use only pixels i in the hood of the car. N is the number of pixels in the hood region.

If a car is classified as chromatic, it is then sub-classified based on its hue. For this classifier the *CS weighted Hue* metric is used. If the car is achromatic, we then classify the vehicle as light or dark. For this classifier we use the normalized intensity. We normalize the intensity based on the road color.

For each color, we further sub-classify based on brightness, since this is a useful categorization given the distribution of vehicle colors seen in practice. We use both the normalized intensity and the average color strength.

Finally, we classify light achromatic cars into light silver and white given the large number of cars found in these categorizations. This is a very challenging differentiation, and we found the most useful cues to be the variance in the intensity, the difference between the hood and the side of the car, and the difference between the hood and the windshield.

We tested both k-nearest neighbor (NN) classification (k=3) and least squares (LS). These methods were selected since we did not have sufficient training data for more complex machine learning. Also, since we built several sub-classifications and we use a small number of features, they were both practical and efficient.

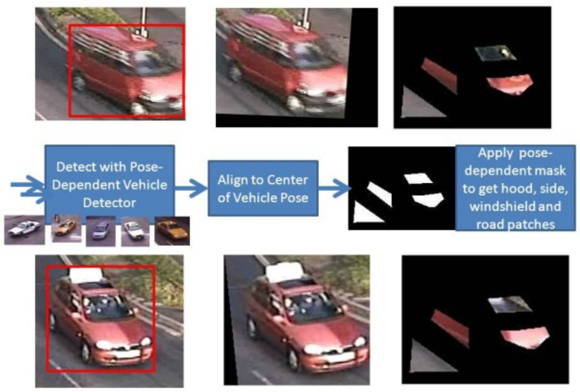

Figure 6. The flow chart of the method is shown in the center. Examples of pose-dependent detection are shown above and below on the left. Examples of these detections after alignment are shown in the center. Examples of the extracted vehicle body parts and the road are shown on the right.

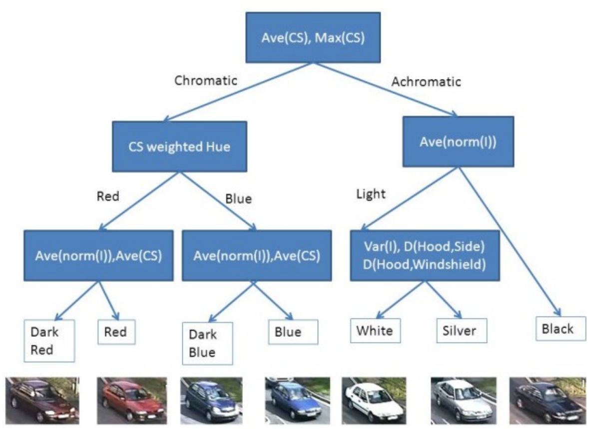

Figure 7. Tree-based classifier for vehicle color classification into 7 categories and the associated features used at each decision point.

5. Results of Vehicle Color Classification

The results of our system are shown in Table 4. Least squares classification was superior to nearest neighbor. The chart also shows the advantage of using the color strength metrics. The methods were tested using cross validation since our dataset is small. The data was divided into 20 parts. The results are averaged over 20 tests, each using 19 parts for training and the remaining part for testing.

The total accuracy is based on the relative amount of data in each color category and is therefore realistic for real-time performance where this distribution is realized. Since our data was constructed from continuous sampling, we believe this is an important aspect of the system and should in practice be the metric used. For LS classification including the color strength metrics, we obtained 91% accuracy including differentiating cars that are red from dark red, blue from dark blue and white from light silver. These are each difficult categorizations with some noise in the ground truth data. We expect our accuracy is at least partially limited by the accuracy of the ground truth data. In some cases, the system performance is possibly improving upon the ground truth.

Sub-Classifier	NN - No CS	LS - No CS	NN	LS
Chromatic vs. Achromatic	81%	99%	93%	100%
Hue (Red vs. Blue)	80%	99%	58%	99%
Dark vs. Light Red	70%	77%	90%	93%
Dark vs. Light Blue	68%	73%	75%	82%
Light vs. Dark	99%	99%	100%	100%
White vs. Light Silver	86%	86%	76%	83%
Total Accuracy	73%	83%	76%	91%

Table 4. Results of each sub-classifier using a Nearest Neighbor (NN) classifier and Least Squares (LS) classifier with and without color strength (CS) features.

6. Conclusions

We have introduced a new public dataset for vehicle color classification. The dataset is based on publicly available high resolution video from the larger i-LIDS dataset. This will enable research in the area to use video information when needed, and to extend the dataset in many ways: more cameras, different times of day, variations in lighting, vehicle tracks, background subtraction information, etc. Most importantly, it will provide a benchmark for comparative work.

The annotation provided is based on continuous sampling. In this way, the data is more representative of the underlying color distribution. We have also provided a benchmark system for vehicle classification on this dataset. This classification uses the underlying distribution to categorize vehicles into the most useful classes in practice. We have found that the following 7 categories were useful for this dataset: white, light silver, red, dark red, blue, dark blue, and black. Although green and yellow are typically used by investigators, we did not find sufficient data for these categories. We believe these categories are useful and easy to implement and will only improve the accuracy.

Previous work in this area has been focused on primary color distinctions (typically using color histograms) and some initial work on distinguishing gray from white or black cars. In this work, we developed vehicle color classification based on the *a priori* distribution of vehicle color using new spatial features comparing the intensity and color of the different parts of the car. We also show the advantage of using the color strength metric, a measure of color reliability. We are able to classify vehicles into new relevant color classes: dark red, dark blue and light silver.

In future work, we would like to extend the dataset to more cameras, times of day, and different poses. We also intend to use a multi-shot approach in which more than one frame is used to improve accuracy.

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