Abstract—To manage ever increasing traffic volume on modern highways, transportation agencies have introduced special managed lanes where only vehicles with a certain occupancy level are allowed. This encourages highway users to ride together, thus, in theory, more efficiently transporting people through the highway system. In order to be effective, however, adherence to the vehicle occupancy rules has to be enforced. Recent studies have shown that the traditional approach of dispatching traffic law enforcement officers to perform roadside visual inspections is not only expensive and dangerous, but also ineffective for managed lane enforcement. In this paper, we describe an image-based machine learning approach for automatic or semi-automatic vehicle occupancy detection. Our method localizes windshield regions by constructing an elastic deformation model from sets of uniquely defined landmark points along the front windshield. From the localized windshield region, the method calculates image-level feature representations, which are then applied to a trained classifier for classifying the vehicle into violator and non-violator classes.

I. INTRODUCTION

Traffic congestion on busy commuter highway brings not only inconvenience and frustration, but also substantial financial cost and time loss to commuters. Our society as a whole also suffers from its consequences in the form of pollution, reduced productivity, and unnecessary emission of greenhouse gasses. With the cost of traffic congestion increasing at the same rate as the frustration levels of commuters nationwide, government officials and members of the transportation industry are seeking new strategies for addressing the problem. One mechanism to reduce the congestion on busy highway corridors is the introduction of managed lanes, i.e., High Occupancy Vehicle (HOV) and High Occupancy Tolling (HOT) lanes. HOV lanes impose limits on the number of occupants in a vehicle to travel on those lanes while HOT lanes employ variable pricing depending on the number of occupants in a vehicle to bring transportation supply and demand into balance. Due to those limits imposed on the use of the lanes, HOV/HOT lanes are often congestion free or much less congested than other commuter lanes, and thus commuters have the benefit of getting to their destination in a timely manner. Furthermore, other users of the highway systems also benefit since, presumably, the high occupancy vehicle passengers would otherwise be driving a vehicle themselves.

One challenge associated with efficiently operating managed lanes is violation enforcement. Even though lack of rigorous enforcement may be tolerable for HOV lanes, strict enforcement is essential for HOT 2.0+ lanes (i.e., more than 2 travelers in a vehicle) given its need for revenue and dependence on pricing to manage traffic flow. Violation rates during peak hours can exceed 50%, while successful manual enforcement rates are typically less than 10% [1]. Persistent violation problems can result in significant loss of revenue and ineffective congestion reduction. Traditionally, enforcement is performed by traffic law enforcement officers that make traffic stops in response to roadside visual inspections. However, on-site monitoring and enforcement by law enforcement officers face many challenges such as difficulty of determining vehicle occupancy, safety concerns, and disrupting traffic, not to mention the personnel cost. Study in [2] showed that personnel costs for enforcing just ten mainline HOV lanes in California alone could exceed $400,000 back in 1990.

An alternative approach that has been implemented in a number of facilities across the United States is to install transponder-based HOV/HOT facilities [3]. However, because the enforcement for transponder violation is still performed by visual inspection, it suffers from the same challenges such as difficulty in identifying vehicle occupancy, which in turn makes it difficult to match a signal of a violator to a real violator.

To comply with the mandated standard of having advanced or “smart” air bags in front seats of all new vehicles sold in the United States, manufacturers have developed in-vehicle technologies for occupancy detection such as technologies based on weight sensors, electromagnetic field based capacity sensors, and ultrasonic sensors [4]. However, none of the technologies has been proven to be robust against “tricks” or undesired objects (bags, animals, etc.) in the cabin [5].

Image-based roadside occupancy detection technologies have been developed and tested since the early 90s, especially for automated or semi-automated verification systems [5-11]. For example, Alves [7] disclosed a roadside imaging unit, in which images captured at roadside were processed for the locations of the faces of occupants. Facial images with only one area of high enough confidence, and in a reasonable location relative to the vehicle, are taken to indicate a probable HOV violator. The method developed by Fan et al. [8] is based on seat pattern recognition to determine whether a front seat in a motor vehicle is occupied. It took advantage of the observation that an unoccupied seat of a motor vehicle exhibits features which are distinguishable from a human occupied seat. In [9], the passengers are
detected by combining the results of different types of classifiers, searching for different features that characterize the presence of people (faces, safety belt, etc.). A cascade of boosted classifiers is implemented for fast feature detection. In [10], multi-spectral information extracted from pixels identified as human tissue from driver's face is used to determine a pixel classification threshold, which is then used to facilitate a classification of pixels of the remainder of the multi-spectral image. Once pixels in the remainder of the image have been classified, a determination can be made whether the vehicle contains additional human occupants other than the driver. These object-recognition-based occupancy detection methods rely on image content or material assumptions, i.e., objects within the captured image including faces, seats, seat belts, and so on that are visible to the camera and extract their corresponding spatial or spectral features for violation detection. Various imaging systems proposed in the past included video, microwave, ultrawideband radar, single-band near infrared (NIR), and multi-band NIR. Studies in [3] have shown that NIR is the most promising roadside detection technology with the ability to address many challenges in vehicle occupancy detection such as windshield penetration and environmental conditions with good imaging resolution and fast image acquisition. Even though roadside detection systems can be expensive, study in [12] showed that it is the most feasible near-term solution and the cost can be offset by savings in catching more HOV/HOT violations. Unfortunately as discussed in [2], no proven technologies are currently available that offer the potential to fully automate the enforcement of occupancy restrictions.

In this paper, we focus on developing a solution for front seat vehicle occupancy detection for use as part of an automatic or semi-automatic HOV/HOT lane enforcement system. Rear seat occupancy detection can proceed using similar methods, but will not be described here. Our camera based imaging system captures front seat still images in NIR band (wavelength > 750nm) through the front windshield of an approaching vehicle. A deformable part model (DPM) [13] is used to localize windshield regions of captured images. Subsequently, a machine learning based classifier was developed to detect front seat occupancy using global image representations of the windshield regions. The rest of this paper is organized as follows: in Section II, we briefly describe the details of the deformable part model for windshield localization and the global Fisher Vector (FV) image descriptors [14] for classification. Evaluation of the methods using real world road images is presented in Section III. In Section IV, we discuss the advantages and disadvantages of the proposed approach and present the conclusions.

II. METHOD

In this section, we will describe the data acquisition system followed by a brief introduction of DPM [13] for windshield segmentation and FV representation [14] to classify captured images into violator vs. non-violators.

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![Image 1](image1.png)

Fig. 1: Illustration of a gantry mounted acquisition setup.

![Image 2](image2.png)

Fig. 2: Examples of captured images.

![Image 3](image3.png)

Fig. 3: Examples of the cabin from front windshield (left and middle rows: without passengers and right row: with passengers).

A. Image Acquisition System

As studies in [3] show, NIR is the most promising roadside detection technology with the ability to address many technical challenges for occupancy detection. Although multi-band solutions have been developed and tested [15-17], the cost of multi-band cameras alone can be quite high. Hence, we assembled a single-band NIR imaging system including illuminators, cameras, and controlling and processing units. The imaging system was setup to capture images of approaching cars driving at normal speed (30–80 mph). The imaging system can be mounted on overhead gantries or roadside poles. The distance from camera to cars is 60-feet on average and the horizontal field of view of the camera is approximately 12-feet at the distance (typical width of highway lanes in United States). An example of the acquisition geometry is illustrated in Fig. 1. Visible light from the illuminator is filtered out by a long pass filter (>750nm) to reduce its visual impact on drivers.
Images were captured using single-band cameras triggered by either ground loops or laser break beam triggers. Fig. 2 shows examples of captured images (small black rectangles were inserted to hide travelers’ identity). Note that there can be large variations in image intensity and image content due to variations in windshield transmission, windshield angle with respect to illuminator, illuminator conditions, weather conditions (e.g., sunny, cloudy, and rainy days), other cars and objects on the road or roadside, and other environmental factors. The appearance of the front seat occupants can also have a wide variety such as facial poses, body posture, occlusions from windshield visors and hats, and other natural variations in human facial appearances as shown in Fig. 3 (right row). Even empty passenger seats can have large variations due to tone level and texture changes or objects present as shown in Fig. 3 (left and middle rows). Because of these real-world variations, accurate occupancy detection via traditional object detection approaches (e.g., face, seat belt detection etc.) can be challenging. We developed a machine learning approach that localizes the windshields and classifies them into violators vs. non-violators without specifically identifying objects or human faces in captured images.

**B. Windshield Localization via DPM**

Although our machine-learning based classifier can detect violations by using a global image feature representation of the entire image, there are many advantages to focus on a region of interest (ROI) around the windshield. In addition to substantial computational cost and time savings, localized ROI’s around windshields can potentially produce less false positives. Moreover, defined ROI regions enable us to incorporate certain geometric constrains in the process, e.g., front passenger-seats/passengers can only appear on a certain side of a windshield and can often be found at a range of pixels away from the driver etc.. Even for our machine-learning based approach, by isolating windshields for further processing, the classifier focuses on the most relevant differentiating characteristics between violators and non-violators (i.e., human vs. car seat or other features around the front passenger-seat) and not on extraneous features outside of windshields to achieve better classification accuracy with potentially fewer training samples. Hence, accurate windshield localization is a crucial step. In this paper, we construct a DPM [13] for windshield localization by defining a unique set of landmark points around front windshields.

Zhu et al. [13] developed a face detection method based on a mixture of trees with a set of parts $V$ to capture topological changes due to viewpoint changes. Each tree $T_m = (V_m, E_m)$is a linearly-parameterized tree-structured model, where $m$ indicates the mixture, $V_m$ is the set of parts in $V$ with every feature part is considered as a node (part) in the tree, and $E_m$ is the set of edges between parts. For a particular configuration of parts $L = \{l_i; i \in V\}$for a given image $I$, a score function defined in [13] is shown by,

$$ S(I, L, m) = \text{App}_m(I, L) + \text{Shape}_m(L) + \alpha_m, \tag{1} $$

where $\text{App}_m$ is defined as

$$ \text{App}_m(I, L) = \sum_{i \in V_m} w_i^m \cdot \phi (l_i, l_i), \tag{2} $$

that sums the appearance evidence for placing the $i$th template, with weight $w_i^m$ tuned for mixture $m$, at location $l_i$, where $\phi (l_i, l_i)$ is the histogram of gradients (HoG) features extracted at the pixel location $l_i$. $\text{Shape}_m$ in (1) scores the spatial arrangement $L$ of the set of parts as

$$ \text{Shape}_m(L) = \sum_{l \in E_m} a_i^m \cdot dx^2 + b_i^m \cdot dx + c_i^m \cdot dy^2 + d_i^m \cdot dy \tag{3} $$

where $dx$ and $dy$ represent the spatial displacement in $x$ and $y$ between parts $i$ and $j$, respectively. Each term in (3) can be considered as constrains between a pair of parts with $\{a_i^m, b_i^m, c_i^m, d_i^m\}$ denoted to the rest location and rigidity of each pair. This model can be viewed as a linear classifier with parameters of $w_i^m$ and $\{a_i^m, b_i^m, c_i^m, d_i^m\}$ that can be learned using a latent SVM formulation as shown in [18]. The task is then to find the best configuration of parts by maximizing $S(I, L, m)$ over $L$ and $m$ for a given test image $I$ using dynamic programming.

In our work, the DPM is constructed for identifying front windshield regions. We introduced a unique set of landmark points around the windshield (e.g., 13 red dots shown in Fig. 4). It is important to note that our set of landmark points included the 2 side view mirrors, which we found are essential in reducing false positives in our windshield localization. The trapezoid shape of windshields alone is not sufficient to uniquely identify windshields due to similar shapes that can often be observed from miscellaneous objects in the scene such as the trapezoid shape of car roof tops, sunroofs, road marks, or the front hood from cars. The 13 landmark points are manually labeled in a set of training images. The labeling follows the same linear sequence such as starting from the middle point on the hood of a car. Negative samples can be regions/images other than the windshields in the same scene or images without cars. The training is similar to what is presented in [13], which allows us to construct the DPM by learning the appearance, i.e., $\text{App}_m$ in (2), and the relationship between parts, i.e., $\text{Shape}_m$ in (3). In (2), each $l_i$ corresponds to one of the 13 landmark points and $\phi (l_i, l_i)$is extracted using 7x7 windows with 8
angular bins. Equation (1) is maximized over the 13 landmark points for a given $I$ using dynamic programming to find the best configuration of parts, i.e., $w_i$ and $[a_i, b_i, c_i, d_i]$ in (3). By applying the trained model, a list of candidate windshields are identified within an incoming image and the region with the highest score can then be selected as the windshield as shown in Fig. 5, where the left and right figures show feature windows at each landmark points and the candidate windshield region with the highest score, respectively. Because of the fixed acquisition geometry at each scene, we have $m = 1$, i.e., the mixture has only one component (multiple components can be introduced to account for different appearances of the front windshields between small trucks and passenger cars). The process was performed at multiple image scales (e.g., 2 scales at 1x and 0.5x). In our experiment, the captured images have 2352x1728 pixels and windshields are around 750x300 pixels depending on the types of cars. After windshield region is identified, the passenger side is cropped out and sent to a trained classifier for violation detection.

C. Fisher Vector Representation for Image Classification

In image classification, FV has become a standard for aggregating local descriptors into an image level representation [19], which can then be passed to a classifier.

Suppose $X = \{x_i; t = 1...T\}$ denotes the set of $T$ local descriptors extracted from a given image. Assuming the generation process of local descriptors can be modeled by a probabilistic model $p(X|\theta)$, where $\theta$ denotes its parameters, as shown in [20], $X$ can then be represented by the gradient vector:

$$G_\theta^X = \frac{1}{T} \nabla \log p(X|\theta). \quad (4)$$

The gradient of the log likelihood describes the contribution of the parameters to the generation process. Its dimensionality only depends on the number of parameters $\theta$. A natural kernel on these gradients is the “Fisher kernel” as described by [20]:

$$K(X, Y) = G_\theta^X F_\theta^{-1} G_\theta^Y, \quad (5)$$

where $F_\theta$ is the Fisher information matrix of $p(X|\theta)$ defined by calculating the expectation $E_{x,p}$ over $\log p(X|\theta)$ as,

$$F_\theta = E_{x,p} \left[\nabla_\theta \log p(X|\theta) \nabla_\theta \log p(X|\theta)^T\right]. \quad (6)$$

Because $F_\theta^{-1}$ is symmetric and positive semi definite, it has a Cholesky decomposition $F_\theta^{-1} = L_\theta L_\theta^T$ and (5) can be rewritten as a dot product between normalized vectors

$$g_\theta^X = L_\theta G_\theta^X, \quad (8)$$

where $g_\theta^X$ is referred to as the FV of $X$.

We assume our probabilistic model $p(X|\theta)$ is a Gaussian Mixture Model (GMM) written as $p(x|\theta) = \sum_{i=1}^{N} w_i p_i(x)$ with $\theta = \{w_i, \mu_i, \sigma_i, i = 1...N\}$, where $w_i, \mu_i$, and $\sigma_i$ are the mixture weight, mean vector and variance matrix of Gaussian $p_i$, respectively. In what follows, we only consider the gradient with respect to the mean parameters. Let $g_\theta^X$ denotes the $d$-dimensional gradient with respect to the mean $\mu$ of Gaussian $i$. Let $\alpha_i(t)$ be the assignment of the descriptor $x_t$ to the $i$th Gaussian:

$$\alpha_i(t) = \frac{w_i p_i(x_t|\theta)}{\sum_{j=1}^{N} w_j p_j(x_t|\theta)}. \quad (9)$$

Assuming that $\alpha$‘s are generated independently by $p(X|\theta)$, we will have the mathematical derivations of (8) as:

$$g_\theta^X = \frac{1}{T \sum_i w_i} \sum_{t=1}^{T} \alpha_i(t) \frac{\partial \log p_i(X_i)}{\partial \mu_i} \quad (10)$$

where the division between vectors should be understood as a term-by-term operation. The final vector $g_\theta^X$ is the concatenation of the $g_i^X$ vectors for $i = \{1...N\}$ and is a $N \times d$ dimensional vector.

In our work, we use HoG as the local image descriptors. Each one is a 4x4 window with 8 angular bins. We then apply Principal Component Analysis (PCA) on the HoG descriptors to reduce the dimensionality from 128 to $d = 64$ based on our experience. A study in [19] indicated that the positive impact of this PCA step in improving the final classification performance may come from two reasons:

1) Decorrelated data can be fitted more accurately by a GMM with diagonal covariance matrices;

2) The GMM estimation is noisy for the less energetic components.

The local descriptors are then aggregated using the FV aggregation approach presented above to form an image level representation. Our experiment led us to choose $N = 256$. Once the image level representations are obtained for positives and negatives, i.e., w/o passenger(s) and w/ passenger(s) in the front passenger seat, respectively, using (10), we learn a linear SVM classifier with stochastic gradient descent techniques shown in [21-22].

III. EVALUATION

The performance of our approach was evaluated using two datasets, the 1st with a roadside pole mounted camera and the 2nd with a gantry mounted camera. The DPM for windshield localization discussed in Sect. II.B was trained by randomly select 20 positive (Fig. 3) and 90 negative images from the 1st dataset. Because of the amount of work of manually label 13 landmark points for each positive sample, we only selected 20 images. The 90 negative samples were selected to represent the range of variations we might encounter in the scene in the absence of a vehicle. Our experiment showed that the limit number of samples and the imbalance of positives and negatives did not prevent us from constructing a robust DPM for windshield localization.

By applying the trained DPM model to incoming images, a list of candidate windshield areas is identified in each image. Each candidate area has a classification score calculated by (1). Although we can always pick the region with the highest score, the score itself is not sufficient to eliminate false-positives. Hence, what is needed is a suitable threshold of the scores. Next, we describe an approach to determin the threshold by calculating an error rate between the localized windshield region from the automatic method and a manual approach.
The manual approach had one human operator label 4 corners of a windshield (excluding the rear view mirrors) in a set of images. The smallest polygon is constructed based on the 4 corners. Similarly, the smallest polygon is constructed using 4 corner points taken from the identified 13 landmark points (excluding the rear view mirrors) by applying the trained DPM. As to the region-representation based metric used in the Pascal VOC (visual object classes) challenge [23], we define an error rate as

\[
E = \frac{\text{Auto} \cup \text{Manual} - \text{Auto} \cap \text{Manual}}{\text{Auto} \cup \text{Manual}}, \quad (11)
\]

where “Auto” and “Manual” correspond to the polygons constructed from the automatic and manual windshield localization processes, respectively. A Measurement System Analysis (MSA) commonly used in Design for Lean Six Sigma (DfLSS) practice was conducted to estimate the human measurement error (i.e., repeatability and reproducibility) of the manual process for windshield localization. In our experiment, we asked two operators, twice for each, to label windshields in ten randomly selected images. The ground truth was assumed to be the average of the four sets of corner measurements. An error rate (11) for each labeled windshield was then calculated where “Auto” and “Manual” denotes to the polygons constructed from the ground truth and each repeat from the two operators, respectively. The total human measurement error rate is about 0.04, which is the lower bound of the error rate when we can claim that the automatic windshield localization “Auto” is the same as “Manual”. We evaluated 1153 images, from which the 20 images used in training the DPM were randomly selected. The windshield regions were identified using both the trained DPM and the aforementioned manual labelling process by one human operator. The error rate between the two approaches using (11) ranged from 0.05 to 0.65 for 1153 images. Two examples with an error rate exceeds 0.4 are demonstrated in Figs. 6. Note that these types of vehicles (i.e., trucks and buses) and the corresponding windshield/rear view mirror configurations were not included in the training set. Hence, the large error is not unexpected and we are confident that the performance on these types of vehicles could be improved with training. Also, we’d like to point out that these types of vehicles are out of scope for most HOV/HOT enforcement applications.

From Fig. 7, we can see that when the score is low, the error rate tends to be high. From the 1153 windshields, we generated a Receiver Operating Characteristic (ROC) curve shown in Fig. 8 for different classification scores, which we used to determine a threshold of the classification score for localizing a windshield region. The value we chose was -0.6 where the curve starts to bend down. The method was tested with two data sets, one with 39K images and one with a total of 93277 images including substantial environmental changes (day/night, sunny/cloudy, etc.). For in-scope types of vehicles (i.e., passenger cars), the approach has greater than 99.9% accuracy with 99% yield for windshield localization for both datasets. The accuracy was calculated based on human visual inspection of every localized windshield. The failed cases can be attributed to cars driving between lanes (i.e., missing one rear view mirror in the scene) and out-of-scope types of vehicles.

From the identified front windshield regions, image-level feature representations discussed in Sect.IIC were calculated from the passenger sides only (equal partition of the windshield regions) to reduce computational cost. In one experiment, 143 positives (w/o passenger at the passenger side) and 143 negatives (w/ passenger at the passenger side) from the morning of the 1st day of the 1st dataset were used to train a linear SVM classifier with SGD. The classifier is then applied to 39K images collected over 5 consecutive days. Our automatic front seat passenger detection gave an accuracy of 97.6% with 100% yield (i.e., every image was evaluated). For the second dataset obtained from the gantry mounted camera, we didn’t retrain the DPM for windshield localization and we were still able to achieve greater than 99.9% accuracy for windshield localization. The initial results using the violation classifier trained from the 1st dataset gave 87.5% accuracy for 3 consecutive days. However, the accuracy degraded substantially when strong glare was observed, which was not present in the 1st dataset. We retained the classifier with images obtained from the 2nd dataset using 300 positives and 240 negatives (randomly selected from the first three days). Table 1 summarizes the
classification performance over 9 days, where the precision and recall are defined by:

\[
\text{Precision} = \frac{\text{True Positives}}{\text{True Positive} + \text{False Positives}}, \quad (12)
\]

and

\[
\text{Recall} = \frac{\text{True Positives}}{\text{True Positive} + \text{False Negatives}}, \quad (13)
\]

respectively. In (12) and (13), positives and negatives refer to vehicles without and with front-seat passengers, respectively. As we can see from Table 1, the accuracy of our approach is in the range of 93–96% and is robust against some environmental changes (e.g., day/night, sunny, cloudy, snowy, vehicle types, vehicle speed, and different windshield penetrations) for classifying passengers vs. no-passengers from the cropped windshield regions.

Table 1: Classification performance for 9 days (93277 images).

<table>
<thead>
<tr>
<th>Total</th>
<th>Accuracy(%)</th>
<th>Precision/ Recall (%)</th>
<th>% of Passenger cars</th>
<th>Day of week</th>
</tr>
</thead>
<tbody>
<tr>
<td>14759</td>
<td>93.5</td>
<td>99.3/91.3</td>
<td>30.4</td>
<td>Fri.</td>
</tr>
<tr>
<td>9091</td>
<td>94.7</td>
<td>98.6/90.8</td>
<td>49.3</td>
<td>Sat. (holiday)</td>
</tr>
<tr>
<td>14598</td>
<td>94.0</td>
<td>99.4/93.0</td>
<td>25.9</td>
<td>Tue.</td>
</tr>
<tr>
<td>15121</td>
<td>94.0</td>
<td>99.5/92.6</td>
<td>23.5</td>
<td>Wed.</td>
</tr>
<tr>
<td>12746</td>
<td>93.0</td>
<td>99.2/91.8</td>
<td>23.1</td>
<td>Thur.</td>
</tr>
<tr>
<td>11425</td>
<td>94.8</td>
<td>97.2/95.1</td>
<td>32.5</td>
<td>Fri.</td>
</tr>
<tr>
<td>10516</td>
<td>93.0</td>
<td>98.4/88.5</td>
<td>46.2</td>
<td>Sat.</td>
</tr>
<tr>
<td>8308</td>
<td>96.0</td>
<td>98.7/94.1</td>
<td>44.9</td>
<td>Sun.</td>
</tr>
<tr>
<td>14786</td>
<td>94.1</td>
<td>99.6/92.7</td>
<td>23.1</td>
<td>Tue.</td>
</tr>
</tbody>
</table>

IV. CONCLUSION

In this paper, we presented a machine learning approach for automatic or semi-automatic front seat vehicle occupancy detection. Road tests show that the approach has high detection accuracy without sacrificing yield. It is noted that even though the approach can be fully automatic, it can also be incorporated into a human reviewing process to reduce workload for human operators. One of the drawbacks of the approach is the workload of labeling ground truth of a set of images for training the DPM and image classifier. However, our study shows that the number of images required for training is reasonably small and the approach is robust against some environmental changes such as day/night and sunny/cloudy. In addition to vehicle occupancy detection for HOV/HOT enforcement, data analysis across a single day or multiple days can also reveal valuable traffic information. For example, we observed significant increase in high occupancy vehicles during weekends, holidays and certain periods of the day. The information can be used as prior knowledge in designing new HOV/HOT lanes as well as developing an effective enforcement strategy. The performance of the classifier can be further improved by incorporating additional information present in a front windshield region such as the presence of a driver.

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