Word count – 7250 **TRB Paper Number:** #10-3933

Traffic Monitoring of Motorcycles during Special Events Using Video Detection

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August 1, 2009

ABSTRACT
Because of a recent federal initiative, states are now required (as of June 2008) to collect and submit motorcycle VMT data to the FHWA. These data are needed to obtain better counts of motorcycles to evaluate their impact on crashes and traffic flow. However, there is concern about the quality of data submitted. Many states have identified problems with using automatic traffic recorders to account for motorcycle traffic. Existing sensors exhibit difficulties in counting motorcycles that travel side by side or close behind each other, they have difficulty in distinguishing larger motorcycles from passenger vehicles, and magnetic counters in particular do not sense motorcycles that do not pass over or travel close enough to the sensor. Alternatively, some states conduct manual classification counts, but these efforts are labor intensive and lead to sparse data. A further complication is that classification counts are frequently conducted during the week and therefore do not capture weekend motorcycle traffic numbers. This paper evaluates a video based traffic monitoring system developed at Clemson University that is capable of classifying vehicles including motorcycles. The processor uses vehicle tracking rather than virtual detection as a means to collect vehicle count, speed, and classification data. Motorcycles are classified using an algorithm that calculates a vehicle's length, width, and height through a series of frames. The system is evaluated using traffic data containing more than 2000 motorcycles collected at two locations in Myrtle Beach, South Carolina during a motorcycle rally. The difference between actual and system motorcycle counts ranged from 0.6% to just over 6% depending on direction and location. The difference for all vehicles ranged from 0.25% to 3.6%. The system successfully classifies motorcycles traveling in close pairs and in small groups, while it experiences difficulty in cases of severe occlusion.

INTRODUCTION

There has been a recent initiative to obtain better counts of motorcycles to evaluate their impact on crashes and traffic flow *(1)*. Historically, the effort to improve motorcycle detection focused on traffic signal actuation. Counting motorcycles was a low priority or virtually ignored. As a result, there has been little effort by industry to address the issue of classifying motorcycles. Thus, most commercially available systems are unable to accurately capture motorcycle traffic. The main reasons why motorcycles are difficult to count is their light axle weight, low metal mass, and single wheel track. The problem is further exacerbated when motorcyclists ride in groups. The design of most traffic monitoring equipment assumes that vehicles travel in single file and use the entire lane. This is not always true for motorcycles. Rather, it is common for motorcyclists to ride closely spaced in pairs or staggered formations. These formations will confuse most traffic monitoring devices.

Data from the NHTSA's Fatality Analysis Reporting System (FARS) indicate disturbing trends in motorcycle safety. In 2006, motorcycle rider fatalities increased for the ninth consecutive year. In that period, fatalities more than doubled, significantly outpacing increases in motorcycle registrations *(2)*. In order to assess motorcycle safety it is necessary to know the number of crashes as well as the corresponding exposure to determine a fatality rate. One of the key indicators of exposure is motorcycle vehicle miles traveled (VMT) obtained from volume counts and segment lengths. In recognition of the need for accurate motorcycle VMT data, the Federal Highway Administration (FHWA) now requires mandatory reporting of motorcycle travel as part of the Highway Performance Monitoring System (HPMS). However, a report published in September 2008 that was prepared by the Highway Performance Monitoring System (HPMS) indicated the quality of reported travel data for motorcycles is questionable due to the inability and inconsistency of current traffic monitoring equipment to detect and classify motorcycles accurately *(1)*.

In this paper, we evaluate a vision-based tracking system that can count and classify vehicles including motorcycles. To evaluate the system in the presence of high motorcycle traffic traveling in a variety of formations, video data was collected during a motorcycle rally in Myrtle Beach, South Carolina in May, 2008. A review of literature indicates that this may be the first such attempt to collect motorcycle count data at a major motorcycle rally in an automated fashion. Manual data collection of motorcycle data has been historically collected at several rallies including Sturgis, South Dakota. Automated counts have been conducted at several rallies but only to get total vehicle volumes. For example, Sturgis has been using automated counters to collect vehicle volume data during all motorcycle rallies since 1990 *(3)*.

TRAFFIC DATA COLLECTION AND MOTORCYCLES

The 2001 edition of the *Traffic Monitoring Guide* (TMG) promoted increased traffic monitoring by vehicle class *(4)*. It recommended that a vehicle classification counting program should include both extensive, geographically distributed, short duration counts and a smaller set of permanent, continuous counters. However, the emphasis in the TMG was on monitoring truck movements and the special considerations that apply to monitoring motorcycles were not covered. A supplement was added in 2008 to address this deficiency. The supplement includes suggested guidelines for using permanent counters to determine how typical motorcycle travel varies by day of the week and season of the year. The supplement indicates that these counters "are the backbone of the vehicle classification program and should be maintained to a high degree of accuracy" *(5)*. As with traditional traffic volume counting, continuous classifiers must be supplemented by classification coverage counts. Factors are developed from the permanent counters to adjust coverage counts based on day of week, month of year, etc.

Coverage counts are usually monitored during weekdays while a large portion of motorcycle travel may take place on weekends. To better estimate the annual average travel by motorcycles on the roads, the TMG Supplement recommends that States develop a process that factors short duration motorcycle counts, as well as the other vehicle classes. Without adjustment, short duration classification counts yield biased estimates *(5)*.

Sufficient locations must be monitored to meet HPMS requirements. Motorcycle travel is reported under the HPMS summary travel as a proportion of total travel by roadway functional class.

Detection Devices

Axle, visual, and presence sensors are most frequently used for collecting vehicle class volume information and each use a different mechanism for classifying vehicles. Within each of these three broad categories is a number of sensors with different capabilities, levels of accuracy, performance capabilities within different operating environments, and output characteristics. Virtually all sensors have problems with motorcycles traveling in groups in various formations. For detailed evaluations of different sensors, see *(6,7,8)*. A brief summary of selected sensors is provided here. Video detection of motorcycles is covered later.

Loop detectors

A number of studies have shown that loop detectors are amongst the most reliable traffic monitoring devices. However, motorcycles are somewhat elusive to loop detectors because of their low metal mass and narrow footprint. Adjusting detector sensitivity to improve motorcycle detection may lead to crosstalk with trucks in nearby lanes. Further, loop detectors must be installed in pairs; otherwise variable vehicle speeds will affect classification data.

Road Tubes

Road tubes are relatively inexpensive and provide short, sharp signals but may have a problem with groups of motorcycles. A single tube is not sufficient for collecting classification data.

Side Looking Radar

Side looking radar provides length-based classification but usually can only classify long vehicles. They do not work with stopped vehicles and thus perform poorly in oversaturated conditions.

Small Footprint Sensors

Sensors that cover a small area such as magnetometers have problems detecting motorcycles or groups of motorcycles. Motorcyclists may actually seek to avoid even the smallest of objects that they notice in the roadway. Further, magnetometers are typically placed in the center of a lane. Motorcyclists tend to drive closer to lane lines to avoid oil buildup that is most common in the center of a lane.

Axle Sensors

For axle sensors which are staggered, a motorcycle will usually hit one sensor but not both; the system will likely record this as a vehicle with a missing axle detection and therefore classify it as a passenger car by default.

Problems with Length Based Classification

Most traffic monitoring sensors use length-based classification either by measuring the length of the vehicle or the axle spacing. Some axle sensors can use vehicle weight to classify vehicles. Vehicle length classification can give erroneous results because some cars are not much longer than the average motorcycle. Recent vehicle trends have made this even more commonplace as European “city cars” such as the Smartcar Foretwo gain popularity in the United States. Further, the average motorcycle size is larger than ever before. And custom choppers with extended front forks can reach lengths that exceed some subcompacts. Because a motorcycle’s wheel base is not much shorter than its length, the average motorcycle wheelbase is within 10 inches of many subcompacts. Thus axle counters are especially prone to length-base classification errors.

PREVIOUS WORK ON MOTORCYCLE VIDEO DETECTION

Most commercial video-based vehicle detection systems use length-based classification measuring presence using virtual detection. Some systems that use tracking can do more robust classification. While there has been significant recent work on video detection using tracking, very little work has been done that specifically addresses motorcycle video detection.

Duan et al. present a real-time on-road lane change assistant that can identify motorcycles. Vehicle classification is done through a series of steps. The first step is hypothesis generation that aims to find the bounded boxes of candidate vehicles in an image for further processing. The system uses a knowledge-based approach to generate hypotheses of vehicle and motorcycle locations using prior knowledge, In general, the information used to detect vehicles during the daytime includes symmetry, color, shadow, geometric features. In this work, the output of the hypothesis step is a set of regions of interest which are then further analyzed in the hypothesis verification step. Verification is done using Support Vector Machines (SVMs). The images used for off-line training were taken of different daytime scenes. A field test on different road functional classes provided motorcycle detection rates of over 90%. No mention was made of extending this system to traffic monitoring *(9).*

Chiu et al. proposes a vision-based motorcycle monitoring system to detect and track motorcycles for data collection purposes. The system proposes an occlusion detection and segmentation method. The method uses the visual length, visual width, and pixel ratio to detect classes of motorcycle occlusions and segment the motorcycle from each occlusive class. A helmet detection algorithm verifies motorcycles. One drawback of the system is that it assumes all riders wear motorcycle helmets, which is not the case in the U.S. Experiments obtained by using complex road scenes are reported. The system provided a recognition rate of 95% for a field study that included 42 motorcycles *(10*).

CLEMSON ALGORITHM OVERVIEW

The block diagram in Figure 1 gives an overview of the algorithm. For each input image frame a foreground mask is computed using the method of background subtraction. Feature points are tracked in the image using the Kanade-Lucas-Tomasi feature tracker, and a subset of these feature points (which we call stable features) is identified using calibration parameters and the foreground mask *(11)*. Grouping of the stable features yields vehicle detections which are classified based on estimated dimensions. Tracking of vehicles is achieved by correspondence and matching between detections over multiple frames. Note that except for vehicle classification, the rest of the algorithm presented here is similar to our previous work *(12)* which contains a more detailed description of all the processing steps.

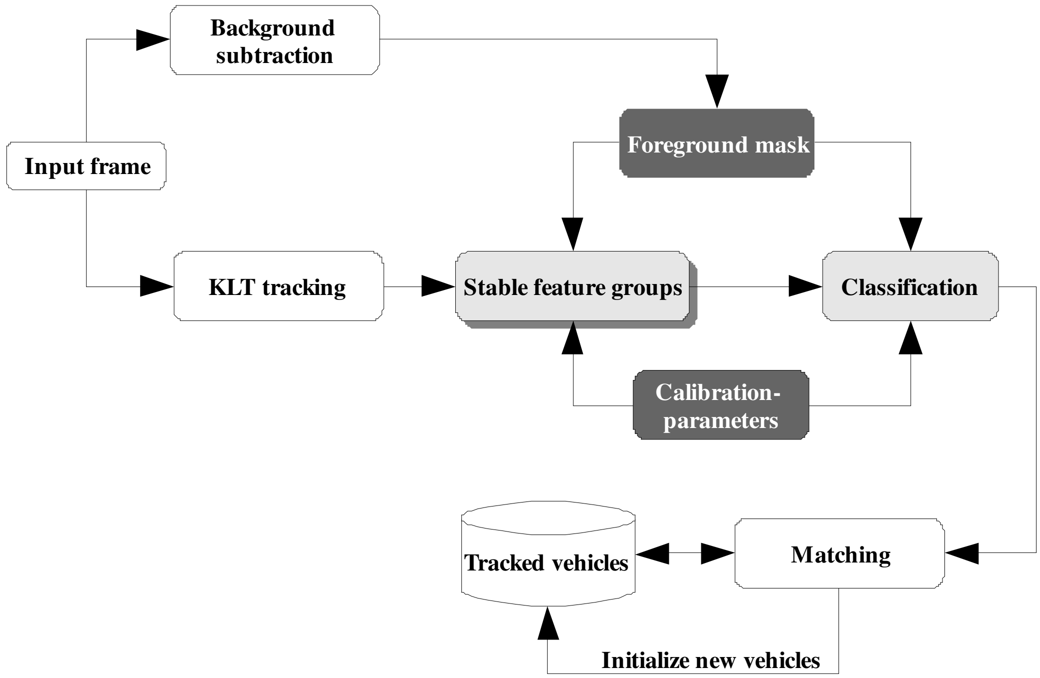

FIGURE 1 Algorithm Block Diagram

Calibration

The algorithm makes extensive use of calibration parameters which are used for mapping between the road and the image coordinate systems. Unlike simple plane-to-plane mapping, the calibration parameters yield a perspective projection matrix which relates the pixel-height of vehicles measured in the image to real world units such as feet or meters. The six-click calibration procedure can be performed easily by defining edges of the road and a line corresponding to a known length measured along the length of the road. As shown in Figure 2, a detection zone is automatically computed using the known width of the road and the three lines just mentioned.

Background subtraction

Before vehicles can be detected, the algorithm needs an image of the scene without any moving objects present in it (background image). This image can be easily generated by averaging consecutive frames of the video. Typically in free-flowing traffic, 5 to 10 seconds of video is sufficient to generate a usable background image. When the new input frame is read from the camera, the current estimate of the background image is subtracted from the input image followed by a thresholding operation on the difference image to yield a foreground mask. To handle lighting changes, at the end of processing each input image the foreground mask is used to adaptively update the background image (pixels labeled as background adapt at a faster rate to the new values compared to the pixels in the foreground).

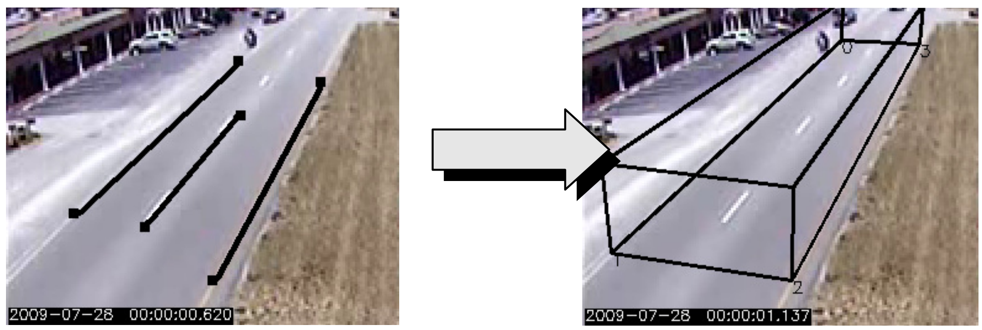

FIGURE 2 "Six-click" calibration procedure using lane lines

Identification and grouping of stable features

Feature points are selected and tracked as described in (11) using the OpenCV implementation *(13,14)*. To minimize the false detections caused by spillovers and shadows we select a subset of the tracked features which we refer to as *stable features*. Stable features are the feature points which are close to the base of a vehicle and which lie on the front or the back side of vehicles (front side for the vehicles approaching the camera and back side for the vehicles receding from the camera). Stable features are identified using their estimated height and local slope (in world coordinates) by projecting them on the base of the corresponding blob in the foreground mask. The test for selecting stable features is described thoroughly in *(12).* Once the stable features are identified they are grouped together by lane using region growing. Since we use the road coordinates for the stable features (rather than image coordinates), their top-view projection results in clusters of feature points corresponding to vehicles in the scene (all the stable features corresponding to the front or the back side of a vehicle will be projected very close to each other). Groups having an insufficient number of stable features (less than five stable features in our case) are discarded to suppress spurious detections.

Classification

FIGURE 3 Measuring the width (middle) and length (right) of tracked vehicles (left)

Once a vehicle is tracked for a certain minimum number of frames (five frames in our experiments), it is classified in each subsequent frame. Figure 3 shows an SUV in the slow lane and two motorcycles in the fast lane. The image in the middle and the one on the right show the process of measuring widths and lengths, respectively, of detected vehicles (the motorcycle in the back has not been tracked for a sufficient number of frames as a result its width and length are not measured in this frame). The gray rectangles indicate the locations of the front-center of vehicles estimated by the algorithm. Pixel-width and pixel-length are measured for each vehicle in the foreground mask as shown in the figure. The orientations of the lines along which the dimensions are measured are readily computed using the calibration parameters. The same calibration parameters are also used to convert the image measurements into world units (e.g. feet). The conversion to world units is important because although pixel measurements would vary with the location of vehicles in the image, the corresponding measurements in world units would be same regardless of vehicle location (assuming perfect camera calibration). A vehicle is assigned a class (motorcycle, passenger car, single unit truck or multi-unit trailer) based on the proximity of the vehicle's measured dimensions with the average dimensions of each class. In practice, factors such as noise in the image and calibration errors may yield different measurements over consecutive frames. A decision about a vehicle's classification is made in each frame by a voting mechanism using its classification in all previous frames.

Figure 3 also illustrates a limitation of other approaches of vehicle tracking which rely only on tracking blobs in the foreground mask. Such simple approaches would fail to identify the SUV and the motorcycle in the front as two separate objects and would instead group them into a single object. In contrast, the approach based on feature tracking correctly identifies them as two separate vehicles.

Correspondence and matching

Vehicles in the current frame are detected and classified as described above. Existing vehicles (initialized and tracked before current frame) are then matched with the new detections based on their proximity in road coordinates. New detections which are not matched with any of the existing vehicles are initialized as new vehicles to be tracked. Any vehicle for which a detection match is not found is flagged as missing, and its location is estimated using the velocity of features corresponding to it. A vehicle is discarded as a false detection if it is flagged as missing consecutively for a certain number of frames (five frames in our experiments).

FIELD EVALUATION AND EXPERIMENTAL RESULTS

The algorithm was tested and evaluated using video data collected during Myrtle Beach Bike Week in May, 2008. Video was collected at two sites.

Site 1: U.S. 17 in Garden City

The initial site was U.S. 17 Business south of Myrtle Beach in Garden City, South Carolina. The video data for this site was collected on May 17, 2008 for 45 minutes beginning at 1:00 PM. This is a 4 lane divided highway at this location. The camera was mounted at a height of 29 feet above the roadway pavement in the median. The camera was pointed along the median so that data for both travel directions could be collected simultaneously with one camera. The frame rate was 30 frames per second at a resolution of 640 x 480. The algorithm was set to process downsampled 320 x 240 images at 15 frames per second.

Ground truth counts were obtained by manually observing the video and recording traffic data in 5 minute intervals. Because the focus of this evaluation was on the ability of the system to count motorcycles, vehicles were either classified as motorcycles or non-motorcycles which includes passenger cars (PC) and heavy vehicles (HV). During the 45 minute period, 2667 vehicles traveled the 4-lane highway of which nearly 1500 were motorcycles. The recorded video was processed in real-time in July, 2009. The initial attempt to process the video with the algorithm indicated that the system was only able to correctly identify less than 80% of the motorcycles. A closer look at the processed video revealed that misclassified or miscounted motorcycles were mainly due to motorcycles traveling in pairs, tight formation, or were partially occluded.

To address these problems, some adjustments were made to calibration parameters and the detection zones and modifications were made to the tracking threshold. The tracking threshold ignores any objects that are not tracked for a certain number of frames. The initial threshold was found to be too conservative. These changes resulted in significant improvement when the video was reprocessed. For aggregate totals, the system was over 99% accurate for both motorcycles and non-motorcycles. This number is somewhat misleading because motorcycles were over-counted in the departing direction and under-counted in the approaching direction. Nevertheless, the percent differences were within +/- 5% depending on vehicle type and direction of travel. A summary of the results for the Garden City site is shown in Table 1. Additional results are illustrated in Figures 4, 5, and 6. Figure 4 shows a graph of cumulative motorcycle volumes versus time. The manual and processed motorcycle volumes show little variation regardless of time interval. The graph in Figure 5 shows that the percent difference between manual and processed motorcycles volume were less than 10% for all nine 5-minute intervals and exceed 5% in two of nine intervals. Figure 6 shows a graph of actual versus modeled volumes (sum of both directions). Using regression, models were developed that fit the data very well. Ideally, the slope of the regression line should be close to 1. This was nearly the case. The results of the regressions are shown in Table 2. The R^2 value was greater than .999 in all cases indicating that there was very little unexplained error in the models.

While the model performed well, the authors believe that the results would have been improved even further if the camera focused on only one side rather than both sides at the same time. This would improve the resolution of the detection area and much of the detection area would be seen by the center of the lens where there is the least amount of lens distortion. Excessive lens distortion can hinder the calculation of length, width, and height.

The video was further analyzed to verify the results on a vehicle-by-vehicle basis to determine the cause of miscounted vehicles. Figure 7 shows some images of vehicles being correctly classified even when motorcycles are riding in formation. The system creates colored boxes around vehicles, where the color indicates classification: blue for motorcycles, green for non-motorcycles and yellow for a pair of motorcycles riding side by side. Figure 8 (a) shows an example of a vehicle that was not counted due to occlusion. The algorithm usually identifies occluded vehicles that are traveling at the same speed by tracking and taking measurements for each frame. As the perspective view changes, even partially occluded vehicles can be identified. Problems occur if the speeds of the vehicles vary slightly and one or more of the vehicles remains "similarly occluded" throughout the detection zone and is not distinguishable by the algorithm. Further, if the base of the occluded vehicle remains occluded throughout the detection zone, the processor may not find any stable features to track.

Fairly significant over-counting of motorcycles occurred in the departing direction when two motorcycles riding side by side were counted as 3 motorcycles as shown in Figure 8b. Unlike the case of vehicles approaching the camera where both motorcycles enter the start of the detection zone simultaneously, in case of vehicles departing from the camera, the way the detection zone is setup it expands beyond the image boundary. As a result, when two motorcycles travelling side by side enter the image, one the motorcycles-the one away from the camera is detected first. When the other motorcycle closer to the camera fully enters the image, it gets detected. Because the first motorcycle is already fully in view during the detection of the second motorcycle, the combined width of the detection results in a side by side detection. So for two motorcycles side by side, the algorithm will sometimes mistakenly count three motorcycles.

Another reason for over-counting is when a car is sometimes detected as a pair of motorcycles. This may occur when the car's intensity is close to that of the road causing a fragmented foreground mask (foreground image of the car has a gap in the middle). The processor will count the two sides of the car as two motorcycles.

Table 1 Summary results of the Garden City Site

	Approaching	Departing	Total
MC Actual Counts	805	684	1489
MC System Counts	784	714	1498
MC Percent of Difference	-2.61	4.38	0.6
PC and HV Actual Counts	580	598	1178
PC and HV System Counts	593	582	1175
PC and HV Percent of Difference	2.24	-2.67	-0.25
Total Actual Counts	1385	1282	2667
Total System Counts	1377	1296	2673
Total Percent of Difference	-0.57	1.09	0.22

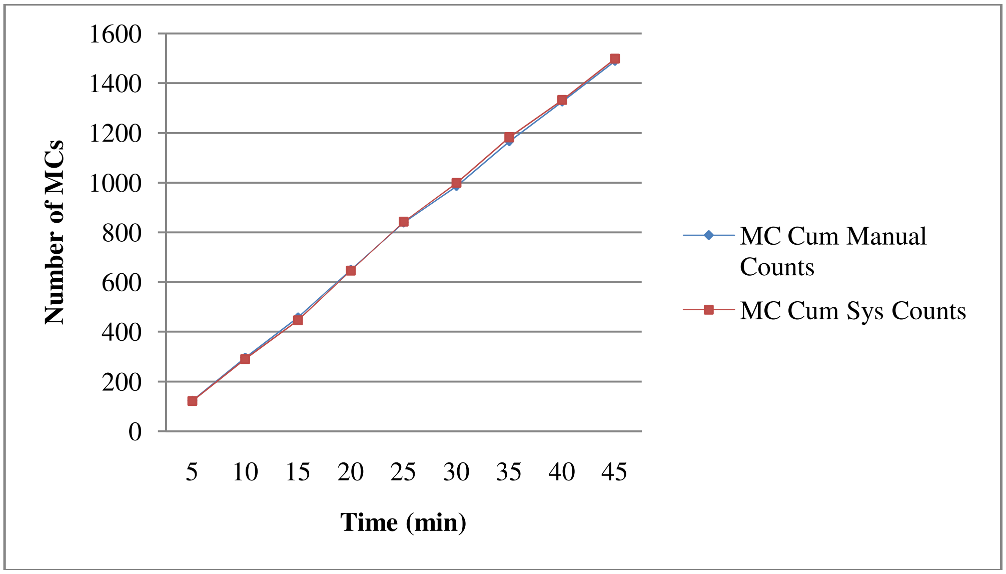

FIGURE 4 Graph of motorcycle cumulative counts vs time (both directions)

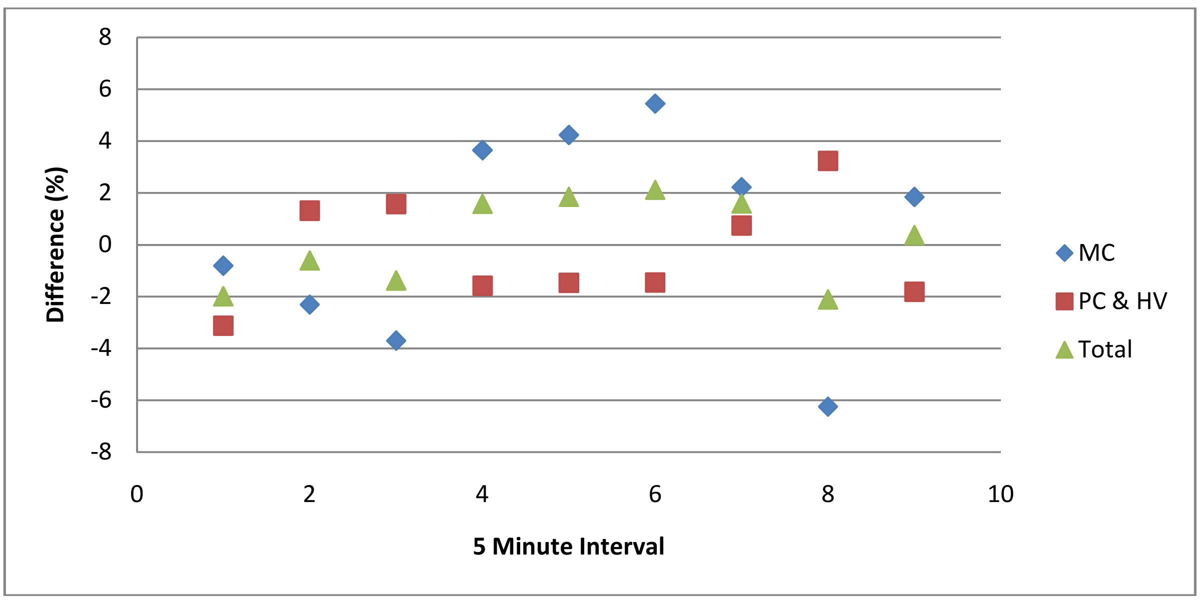

FIGURE 5 Percent difference between actual and system counts (both directions)

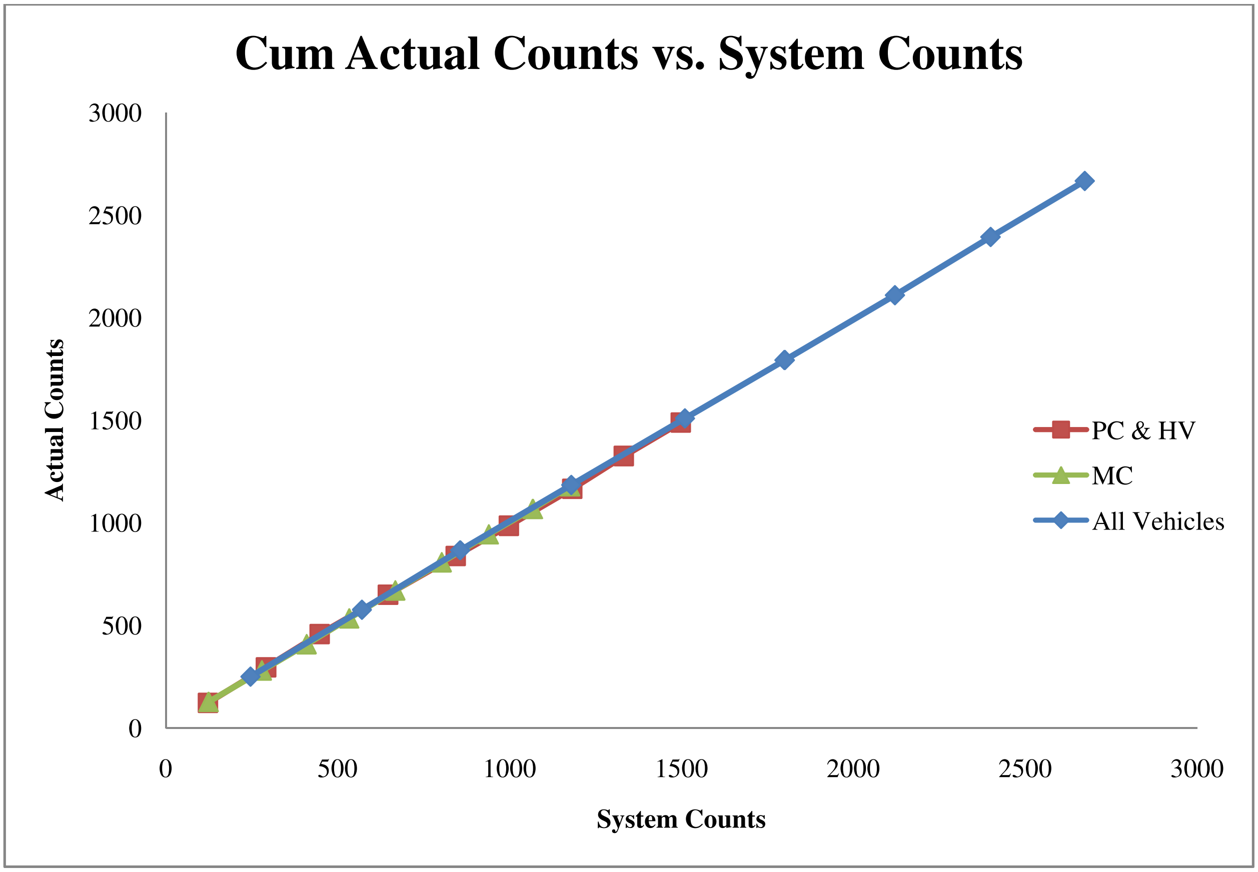

FIGURE 6 Manual counts vs system counts (both directions)

TABLE 2 Linear Regression Analysis Results

	PC & HV	MC	All Vehicles
Slope	1.0009	0.9861	0.9925
R-Sq	**1.0000**	**0.9998**	**1.0000**

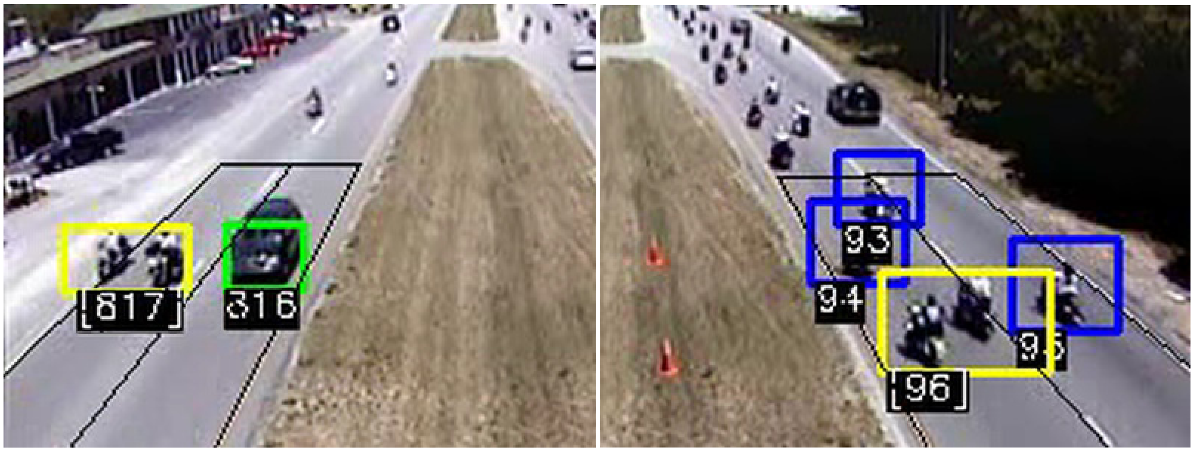

FIGURE 7 Examples of correctly classified vehicles

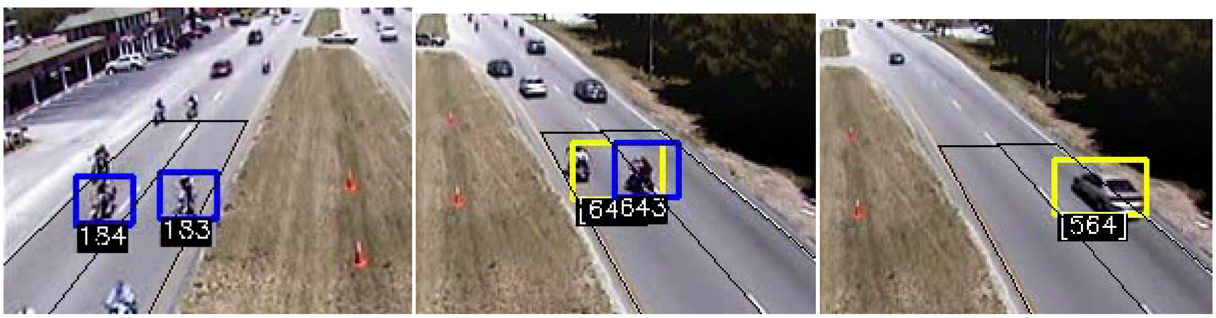

FIGURE 8 Examples of miscounted or incorrectly classified vehicles

Site 2: Ocean Blvd, Myrtle Beach

The second site was on Ocean Blvd in Myrtle Beach. Ocean Blvd is lined with beachfront hotels and is a popular cruising venue during Bike Week. Normally two-way, Ocean Blvd operates only in the southbound direction during much of Bike Week to facilitate emergency access and minimize traffic conflicts. Data was collected for 45 minutes beginning at 4:00 in the afternoon on the Saturday, May 17, 2008. The camera was mounted at 23 feet above the pavement.

As for Site 1, control counts for site 2 were done manually in 5 minute intervals. During the 45 minute period, more than 1000 vehicles including 726 motorcycles were counted. The results shown in Table 3 reveal that the aggregate manual counts for the 45 minute period were in relative agreement with the algorithms processed totals. Figure 9 shows a graph of motorcycle counts and time for each 5 minute interval. The graph shows that the processor undercounted motorcycles for some intervals and over counted for others. The undercounting was due in part to occlusion problems but also due to camera problems. The camera's automatic adjustment due to varying light conditions caused some difficulties. Sunlight reflected off of vehicles with large light colored roofs leading to some of the miscounting errors. Several vehicles were missed when the camera would "recover" after the light colored vehicle would pass. There were other types of errors as well. Figure 10 (a) shows a 3-wheeled motorcycle being classified as a pair of motorcycles. This is because it has similar features as a motorcycle but is much wider. Figure 10 (b) shows a missed motorcycle due to occlusion.

TABLE 3 Summary results of the for the Myrtle Beach Site

	Actual Counts	System Result	Dif (Percents)
MC	726	681	-6.19
PC and HV	333	321	-3.60
Total	1059	1002	-5.38

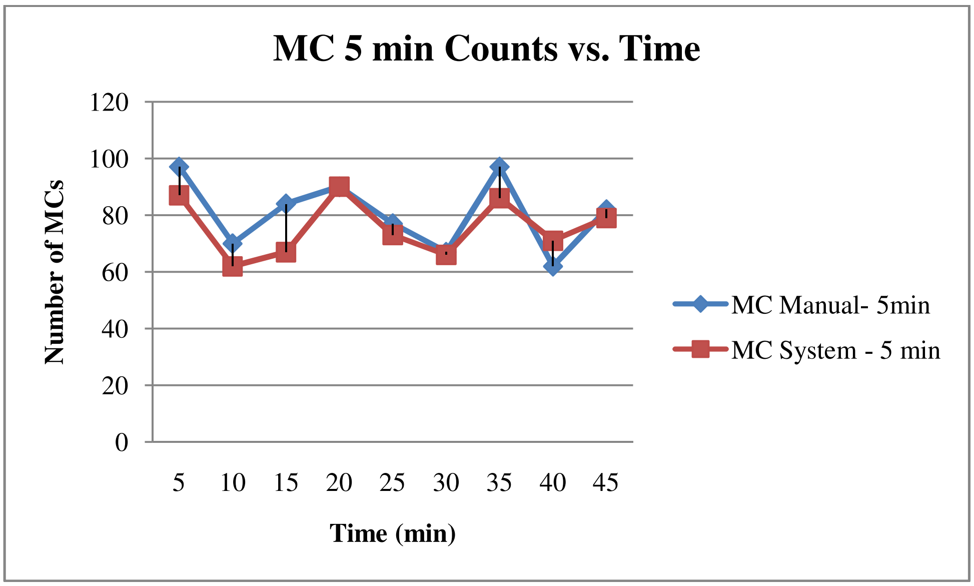

FIGURE 9 Graph of motorcycle counts vs time for each 5 minute interval

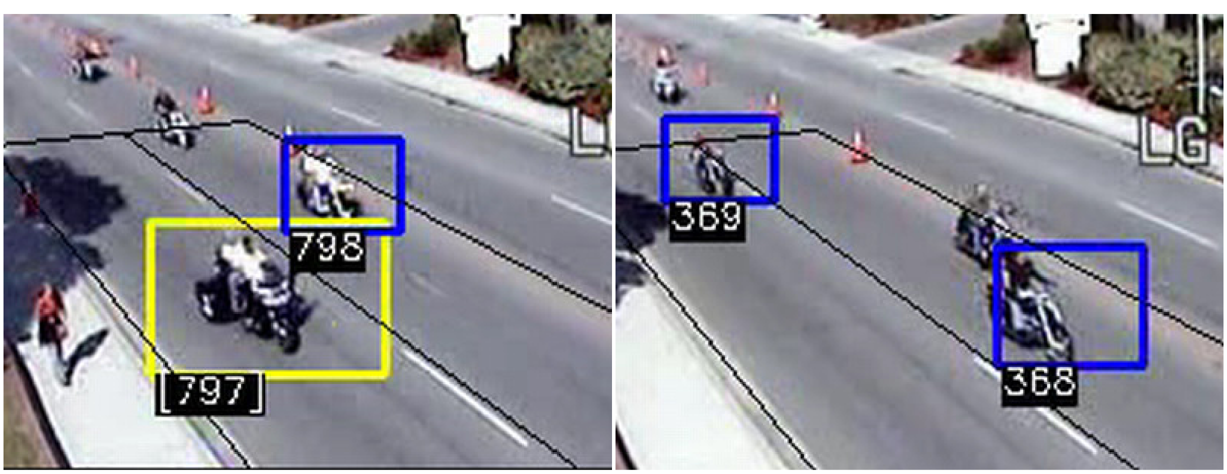

FIGURE 10 Examples of miscounted motorcycles for site 2

CONCLUSION

We have presented an analysis of an automated vehicle classification sensor that is capable of classifying motorcycles. To our knowledge, it is the first such analysis involving a large data set with thousands of motorcycles. The system was evaluated using traffic data collected at two locations in Myrtle Beach, South Carolina during a motorcycle rally. The field studies show that the system can collect total volume data to within 4% of actual and motorcycle volumes approximately 6% of actual. The system successfully classifies motorcycles in formations, such as close pairs or small groups. It is worth noting that the algorithm processes the video data in real time, thus increasing the variety of transportation applications for which it could be used.

There are situations where the algorithm fails, particularly when there is severe occlusion from a neighboring vehicle. Future work will be aimed at improving the robustness of the system in these situations, as well as extending the work to handle motorcycles at nighttime and in low ambient lighting conditions. Furthermore, we plan to augment the algorithm by incorporating pattern-based and shape-based descriptors to better differentiate motorcycles in difficult and ambiguous situations.

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