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Highway IDEA Program

Using Image Pattern Recognition Algorithms for Processing Video Log Images to Enhance Roadway Infrastructure Data Collection

Final Report for Highway IDEA Project 121

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IDEA Program Final Report

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EXECUTIVE SUMMARY

Collecting roadway infrastructure data, including traffic signs, such as stop signs, speed limit signs, and other information signs, along with designated locations (mileposts and longitude/latitude coordinates), is essential for state departments of transportation (DOT) to submit Highway Performance Monitoring System (HPMS) data annually and for state and local transportation agencies to plan, design, construct, operate, and manage their transportation systems. Traffic signs are vital for roadway safety, and inventorying them is necessary for compliance with the Manual on Uniform Traffic Control Devices (MUTCD) (*1*). However, the data collection process is time-consuming and costly. Current software reviews one image at a time, so extracting sign information from the millions of images is still time-consuming and hinders the effective data collection. To remedy the problem of reviewing images frame by frame, there is a need to develop algorithms that can batch-process video log images and support an intelligent sign inventory and management system. Although some algorithms reported in literature have been developed for automatically detecting and recognizing some particular signs (e.g. stop signs and speed limit signs), they are not suitable for a comprehensive sign inventory because the algorithms are not generalized, and they are unable to recognize more than 670 types of traffic signs on U.S roadways, a technically challenging job. Figure 1 shows an example in which a speed limit sign (25 mph) in a video log image (the first picture) was detected and recognized by color segmentation (the second picture) and pattern recognition (the third picture).

In this research project, two innovative, modularized algorithms, sign detection and sign recognition, are developed. They form a solid foundation for developing an intelligent sign inventory and management system. A two-step sign inventory data collection process is proposed to seamlessly incorporate these two algorithms for batch processing millions of video log images, which can save great amounts of time and significant costs. The generalized sign detection algorithm, the first step in the intelligent sign inventory and management system, is developed using the shape, color, location, and other features of a traffic sign defined in the MUTCD standard. Sign shapes are detected using the polygon approximation approach; sign colors are processed with the Statistical Color Model (SCM) by using an Artificial Neural Network (ANN); the Probabilistic Distribution Function (PDF) of sign locations is obtained from the training video log images in which the sign locations are manually tagged. The generalized sign recognition algorithm, the second step in the intelligent sign inventory and management system, is developed based on the multi-feature fusion. The features include Haar features, sign color, sign shape, and sign PDF. Haar features encode the sign texture information using an Adaboost algorithm to generate strong classifiers with a boosting training approach.

Preliminary tests show promising results. The traffic sign detection algorithm is tested on two sets of video log images provided by the Louisiana Department of Transportation and Development (LADOTD) and the City of Nashville. The tests on LADOTD video log images (37,640 video log images, covering 75.17 miles (120.27 km)) show that 86% of manual, frame-by-frame review efforts could potentially be saved by using the generalized sign detection algorithm. And, the tests on Nashville video log images (1,105 video log images, covering 4 miles (6.4km)) show that 60.3% of manual, frame-by-frame review efforts could be saved. The developed sign recognition algorithm can be used to automatically extract the detailed sign attributes. Due to the limitation of the training data set, the proposed algorithm is only tested on recognizing speed limit signs using the video log images collected in Georgia on Interstate I-75 from Macon to Atlanta (5,387 video log images covering 80 miles (128km)). The preliminary results show that the algorithms could successfully recognize 28 out of 31 speed limit signs, a 90% recognition rate. With the sign attributes automatically extracted, the effort of manually typing the data into database can be further reduced. Results demonstrate that the developed automatic sign detection and recognition algorithms are promising and have the potential to save time and cost for transportation agencies by enhancing their traffic sign inventory process.

It is highly possible to fully automate the sign inventory process by incorporating the proposed algorithms for developing an intelligent sign inventory and management system. The algorithms will be further tested and implemented by transportation agencies, including the Georgia Department of Transportation (GDOT), the Ohio Department of Transportation (ODOT), the Connecticut Department of Transportation (ConnDOT), the Oklahoma Department of Transportation (ODOT), the City of Nashville, etc. The research results have been migrated to the next level with the incoming support of the US DOT Research and Innovative Technology Administration (RITA) program, which will test the proposed algorithms on a larger number of video log images and under the real-world environmental conditions in which sign dimension, color, text fonts, etc. may not follow the exact MUTCD standard, and the varying lighting and illumination conditions may change the sign appearances.

(a) Raw image containing speed limit sign

(b) Processed binary image after color segmentation

(c) Extracted speed limit digits

FIGURE 1 Traffic sign data inventory using image processing algorithms.

1. IDEA PRODUCT

The product of this IDEA concept exploration research project includes the generalized algorithms developed to automatically detect and recognize more than 670 different types of traffic signs specified in the Manual on Uniform Traffic Control Devices (MUTCD) (*1*) by using video log images that are widely available. Instead of manually reviewing millions of images frame by frame, the developed algorithms provide new capabilities for automating the traffic sign inventory by means of batch processing. The potential impact of the developed algorithms on transportation practices lies in its capability to significantly reduce the time and cost spent by state departments of transportation (DOT) for acquiring traffic sign inventory data using video log images. Preliminary tests show that 86% of manual frame-by-frame image review efforts could be potentially saved by using the developed sign detection algorithm. Based on the preliminary tests on speed limit sign recognition, the algorithm successfully recognized 28 out of a total of 31 speed limit signs, a 90% recognition rate. Tests show that the developed detection and recognition algorithms are promising for developing an intelligent sign inventory and management system. The large-scale tests using the video log images provided by state DOTs and local transportation agencies for interstate, state, county, and city roads are needed for further refining and implementing these algorithms. It will also allow the developed algorithms to be tested under real-world environmental conditions in which sign dimension, color, text fonts, etc. might not follow the exact MUTCD standard and lighting conditions might change the sign appearance.

The developed algorithms provide an automatic way to enhance the traffic sign data collection process by saving time and cost, improving the safety during data collection, enhancing data quality control and quality assurance (QC/QA), and making it feasible for frequent updates of traffic sign inventory data. The algorithms maximize the utilization of video log images that are already available. Most importantly, the proposed algorithms have established a solid foundation for developing an intelligent transportation infrastructure inventory and management system.

2. CONCEPT AND INNOVATION

Traffic signs are important for roadway safety, and their inventory is necessary for compliance with the MUTCD standard. However, sign inventory data collection is time-consuming and costly. Current software reviews one image at a time, so extracting sign information from the millions of images is still time-consuming and hinders effective data collection. The concept of this IDEA exploration research project is to maximize the utilization of video log images that are widely available in transportation agencies and to develop an automatic batch process to extract traffic signs from these video log images.

Although many image-processing-based sign detection and recognition algorithms have been developed in literature, they cannot be used for comprehensive sign inventory. Developing such algorithms for sign inventory is technically challenging because the algorithms need to be able to detect and recognize all types of signs specified in the MUTCD standard instead of just focusing on particular signs (e.g. stop sign or regulatory signs) usually used for vehicle navigation. Automatically detecting and recognizing more than 670 different types of signs specified in the MUTCD standard is a major technical challenge. First, individual sign features, including sign shapes, colors, and textures that can be used to distinctly differentiate signs from their backgrounds need to be studied. Second, methods that can integrate different features for effective sign detection and recognition need to be developed. Third, false negative (FN) and false positive (FP) rates need to be minimized while improving correct detection and recognition rates. Finally, the proposed algorithms need to be seamlessly incorporated into the new automatic sign inventory operation processes. Two innovative modularized algorithms, sign detection and sign recognition, are developed to support the development of an intelligent sign inventory and management system with a two-step process. The generalized sign detection algorithm, the first step in the intelligent sign inventory and management system, is developed using the sign shape, color, location, and other sign features of more than 670 types of traffic signs defined in the MUTCD standard. Among them, sign shapes are detected using the polygon approximation approach. Sign colors are processed with the Statistical Color Model (SCM) by using an Artificial Neural Network (ANN). The generalized sign recognition algorithm, the second step in the intelligent sign inventory and management system, is developed based on the multi-feature fusion. These features include Haar features, sign color, sign shape, and sign location Probabilistic Distribution Function (PDF). Haar features encode the sign texture information using the Adaboost algorithm to generate strong classifiers and a boosting training approach.

3. INVESTIGATION

This section is organized into four sub-sections. The first sub-section reviews the state-of-the-practice of roadway infrastructure data inventory process; the second sub-section reviews the state-of-the-art of traffic sign detection and recognition algorithms; the third sub-section presents the developed generalized sign detection algorithm; and the last sub-section presents the developed generalized sign recognition algorithm.

3.1 REVIEW OF CURRENT ROADWAY INFRASTRUCTURE DATA INVENTORY PROCESS

Collecting roadway infrastructure data, including roadway geometric properties (number of lanes, travel lane, and shoulder width), traffic signs (stop signs, speed limit signs, etc.) with their designated locations (mileposts and longitude/latitude coordinates) is essential for supporting state DOTs to plan, design, construct, operate, and manage their transportation systems; it is also required for the annual Highway Performance Monitoring System (HPMS) submission to the Federal Highway Administration (FHWA). Category 1, 2, and 3 roadway data collection methods presented below represent the current roadway data collection practice. The fourth category is the prospective data collection practice to be developed through this research.

- Category 1: Pencil and paper field data collection.
- Category 2: Electronic field data collection using a laptop computer or Personal Digital Assistant (PDA).
- Category 3: Taking video log images in the field and then manually extracting roadway infrastructure data by visually identifying and measuring each roadway feature from the video log images on the computer screen.
- Category 4: Automatically extracting roadway infrastructure data from video log images using pattern recognition and image processing algorithms.

Many DOTs still use pencil and paper, the Category 1 data collection practice, to collect roadway data. This collection process is very time consuming, and the collected data is error-prone because of the data re-typing and transfer processes. The Category 1 data collection practice can be streamlined using the Category 2 data collection practice. Electronic devices, such as laptop computers and PDAs, are used in field for the roadway data collection. In addition, some agencies have applied advanced Information Technology (IT) to enhance data collection productivity. For example, some agencies have developed field data collection processes using Global Positioning System (GPS) and Geographic Information System (GIS) (*2*), and speech recognition (*3*) to further enhance the electronic field data collection process. The errors associated with the manual data transfer process are significantly reduced in Category 2. Data quality and the overall inventory productivity are also improved over Category 1. However, both Categories 1 and 2 require data collectors work in hazardous roadway conditions for long periods of time during field data collection.

With the advances in information and sensor technologies, collecting video log images of roadways has become a common practice. For example, 25-ft. interval video log images can be collected easily using a vehicle driving at a speed of 70 miles per hour. Also, the image resolutions continuously increase while the costs of collecting video log images continuously decrease. Consequently, many state DOTs have video log images taken of their roadways for roadway data inventory and, often, for the main purpose of using the images for visualization to enable engineers to view and explore roadway conditions in the office. The challenges are how to effectively manage the huge amounts of image data and how to effectively extract quantitative information from these images. Category 3 describes the most recent development and practices performed by state DOTs in response to these challenges. The technician plays video log images on a computer screen to manually identify each roadway feature from each video log image and measure the features one image at a time. The longitude/latitude coordinates of each roadway feature are computed by using geometric optics along with the GPS data. Data collectors' exposure to the hazardous roadway conditions is dramatically reduced because the data collection is performed in office. Data accuracy is improved using this operation. However, this method is still very time-consuming and costly.

For the Category 3 data collection process, the video log images are displayed on a computer screen frame by frame, and the various roadway features, such as the number of lanes, travel lane width, and shoulder width, and the type and location of signs, are manually extracted and measured. It takes approximately 30 seconds to measure one feature on one image using up-to-date software. The total efforts and costs required for taking the video log images and extracting the roadway infrastructure data from the images could render this roadway data collection process less attractive than the traditional manual field data collection process. Instead, as categorized in Category 4, developing a system to automatically extract roadway infrastructure data from video log images could save millions of dollars and, more importantly, could expedite the data-acquisition process. This would, also, make the use of video-logging more appealing.

This research is motivated by the need to effectively extract useful, quantitative roadway infrastructure information from video log images. This proposed research study is intended to develop and refine algorithms and applications that can automatically extract traffic sign data from video log images. Before the proposed algorithms are presented, the following section first reviews image processing and pattern recognition algorithms for traffic sign detection and recognition reported in literature.

3.2 REVIEW OF SIGN DETECTION AND RECOGNITION ALGORITHMS

This section presents a literature review of image processing and pattern recognition algorithms for image-based sign data extraction. The challenges for developing the generalized sign detection and recognition algorithms are also discussed, as is the innovation of the developed algorithm.

Detection and recognition of traffic signs from video log images is the core of a successful intelligent sign inventory and management system. The effectiveness of these algorithms determines the workload that can be saved in comparison with the manual field data collection and semi-automatic data collection processes.

For the past two decades, image processing techniques have been widely used for transportation infrastructure data analysis, especially in the area of automatic traffic sign data collection, pavement cracking, etc. Most of the algorithms developed for traffic sign detection and recognition used distinct image features, such as color, shape, edge, texture, etc. Some algorithms use only color features (*4*) or shape features (*5-7*), while other algorithms combine these two features (*8-11*). Other features, such as geometrical, physical and text/symbol features, are also used for traffic sign detection (*12*). To extract the features of traffic signs, methods like the Support Vector Machine (SVM) and the Neural Network (NN) are used (*6*, *11*). Some algorithms are designed to handle traffic signs with specific shapes, such as rectangles and triangles (*11*, *13*). Other algorithms have been developed to detect and recognize specific sign types, such as stop and speed limit signs (*14-16*). Because roadway conditions are complicated and dynamic, many algorithms have been developed to detect and recognize traffic signs under unfavorable conditions (*17*, *18*). Besides sign detection and recognition, images and videos are also being used for cycle failure detection (*19*), pavement crack analysis (*20*, *21*), and traffic surveillance (*22*).

Through the review of the algorithms that have been developed for sign detection and recognition, it can be found that most of the algorithms were designed to detect and recognize some specific signs. For example, some algorithms only deal with traffic signs with the rectangle or triangle shapes (*11*, *13*), while other algorithms only detect or recognize speed limit or stop signs (*14-16*). The sign-specific algorithms are not suitable for an intelligent sign inventory and management system because they are unable to detect and recognize more than 670 types of signs. It is also not practical to develop a separate algorithm for each of these signs. Thus, our research focuses on the development of an intelligent sign inventory and management system using image processing and pattern recognition, a much bigger challenge than a driver navigation assistance system for the following reasons:

1. The algorithms need to process more than 670 types of signs. Both sign detection and recognition algorithms need to be generalized to process all traffic signs;
2. Generalized sign features are more difficult to extract, since we need to extract the common features of more than 670 types of signs;
3. The algorithms must be thoroughly tested with a huge number of real-world images that are collected by different transportation agencies with different image resolutions and camera configurations;
4. Additional algorithms need to be developed to detect/recognize the locations, conditions, dimensions, and pole materials of signs for sign maintenance.

3.3 PROPOSED SIGN DETECTION ALGORITHMS

This section presents the sign detection algorithms and the experimental results. Sign detection aims at eliminating those images containing no sign while keeping the images containing signs. A low FN rate and a low FP rate are desirable to assure the reliability and productivity of the detection algorithms. Since there are more than 670 types of traffic signs, a generalized sign detection algorithm is required.

3.3.1 A Generalized MUTCD Sign Detection Algorithm

A sign detection algorithm is developed for identifying images containing signs. As specified in the MUTCD standard, there are more than 670 types of standard traffic signs on US roadways. To detect all these signs, a generalized sign detection algorithm is needed. Unlike the past work on detecting a specific sign, the common features of all traffic signs need to be identified. Based on a study of the MUTCD standard, sign shape, color, location PDF, and other sign features are selected.

FN and FP rates are two critical performance indicators of the sign detection algorithm. The intelligent sign inventory and management system requires a low FN rate so that no or very few signs are missed by the algorithm; it also requires a low FP rate so that the images containing no sign are filtered out to minimize the manual review efforts.

3.3.2 Sign Feature Extraction

Feature extraction is important for sign detection. Traffic signs have a dominant color, shape, texture, or other attribute, that makes them distinct from the background. According to the MUTCD standard, traffic signs have ten MUTCD colors (black, blue, brown, green, orange, red, white, yellow, fluorescent yellow-green (FYG) and fluorescent pink) and six shapes (triangle, rectangle, pentagon, octagon, circle, and cross). For video log images, which are collected by state DOTs using a survey vehicle, the traffic signs demonstrate obvious non-uniform location distribution on the image plane. For example, a traffic sign doesn’t appear on the left bottom and right bottom parts of an image. Also, there are other sign features, such as size, width-to-height (W/H) ratio, distortion angle, etc. that can be used. This section will show how these features are extracted.

3.3.2.1 Sign Color Feature Extraction

Color is a very important feature of a traffic sign because it usually receives more attention from the drivers. However, the actual sign color may vary because of different lighting, camera settings, and other imaging conditions. For example, the red color for the same stop sign has different Red, Blue and Green (RGB) values under different lighting conditions. As a result, sign colors in video log images have much broader color distribution than the MUTCD color specifications. Therefore, it is difficult to use any deterministic segmentation method to recognize the original MUTCD color class. A sophisticated model should be developed to describe the actual sign color distributions so that it can be segmented in a more reliable and accurate way.

In the algorithm, SCM, developed in our lab, is used for sign color processing (*23*). SCM is based on the specifications of the MUTCD. It can successfully process the colors of sign background and legend, thereby providing reliable results for image segmentation and sign color feature analysis. SCM has good ability for general MUTCD sign color processing because it is based on the statistical colors that were collected from the real-world video log images and trained by ANN with Function Link Network (FLN) structure. The proposed SCM is briefly introduced below.

The SCM color model uses a given input pixel value that has the probability of A to be a MUTCD color X and a probability of B to be a MUTCD color Y. The MUTCD SCM was first built statistically using labeled traffic sign color samples. The dataset for the experiment is excerpted from the LADOTD video log images. From 45,151 video log images captured under various outdoor lighting conditions in Louisiana, 3,023 images were identified as having a total of 5,052 traffic signs of 62 different types. All of the traffic signs were manually color labeled according to one of the 10 MUTCD colors. Finally, a total of 413,724 distinct samples and each reference count were used to build the ground-truth probability.

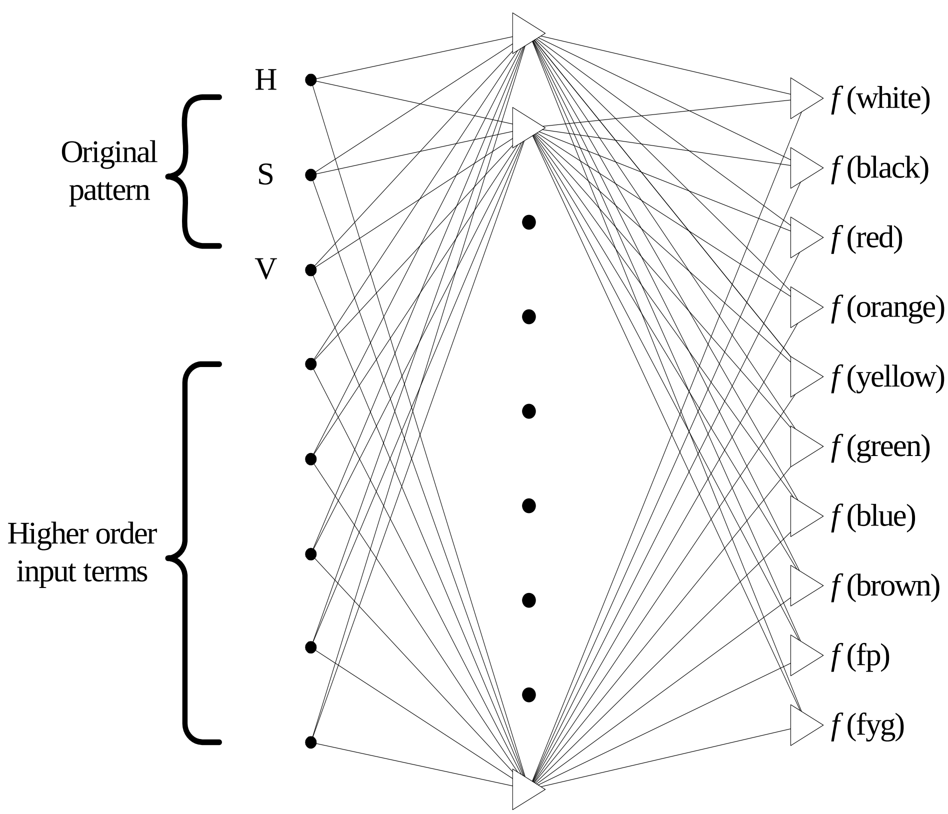


FIGURE 2 Hybrid functional link network for MUTCD SCM training (*23*).

An ANN is used to train the MUTCD SCM approximation function. An FLN architecture is used, as shown in Figure 2, in which inputs are expanded with high-order polynomials and trigonometric series. Details of non-linear input construction are found in Pao's work (*24*). One advantage for using the FLN structure is that one single layer can analogously replace multilayer networks by using expanded inputs to model the nonlinearity of an unknown system. Instead of using RGB color space, HSV (Hue, Saturation and Value) color space is used in the algorithm to represent a color. The output of FLN is a set of probabilities that the input HSV value will be one of the MUTCD colors. For instance, if an input sample RGB (196, 6, 15) is manually labeled as the MUTCD color red, then the actual inputs to the FLN are the transformed HSV values (253, 240, 101) with the expanded inputs, and they are trained to produce 10 real output values filled with the group-truth probabilities of the tagged MUTCD color samples. The testing results with the proposed SCM color model are presented in the experimental section, where two image data sets are used to validate the color model.

With the trained SCM from the practical color samples, every sign image is then decomposed into the ten MUTCD colors and the colors of the sign background and legend will be analyzed for traffic sign detection. A traffic sign on a US roadway complies with the MUTCD color standard for both background and legend color. Usually, the background and legend of a traffic sign has some defined area ratio according to the MUTCD standard, which can be represented by the color segmentation with the background and legend colors. Table 1 illustrates the color distribution rules for detecting a traffic sign, which mean only the candidates that pass these color distribution rules are accepted as traffic signs. These rules are trained with the proposed algorithm, and all the color thresholds (or ratios) have been adjusted for accurate and reliable detection.

TABLE 1 Color Distribution Rules for Traffic Sign Detection

Background	% (>)	Legend	% (>)	Other color (<)
White	50%	Black	7%	20%
	50%	Green	7%	50%
	50%	Blue	7%	20%
	50%	Red	7%	50%
	50%	Yellow	10%	50%
Green	40%	White	7%	20%
	40%	Blue	7%	20%
	50%	Red	7%	20%
Blue	40%	White	5%	50%
Red	50%	White	5%	50%
Yellow	50%	Black	10%	20%
	50%	Green	7%	20%
	50%	Red	7%	20%
Orange	50%	Black	7%	70%
FYG	40%	White	10%	20%

3.3.2.2 Sign Shape Feature Extraction

Sign shape is another important feature for traffic sign detection. The polygon approximation based algorithm is used for shape detection. In this algorithm, the boundary region of a traffic sign is identified first, and then the features within the boundary region is analyzed to determine if it is a candidate of a traffic sign. The use of a polygon approximation algorithm is based on the fact that 99.4% of traffic sign types are convex, and 99.8% of those convex traffic signs have a limited number of vertices based on the sign types specified in the MUTCD. For example, a stop sign has a hexagonal convex boundary with eight vertices. Besides, even non-convex traffic signs (for example, the shield type) that typically appear within the information class of traffic signs have a rectangular boundary with a green background. As a result of such commonalities, the following assumptions can be made for traffic sign detection: (1) a traffic sign is convex and (2) a traffic sign has a limited number of vertices. These assumptions lead to the conclusions that a traffic sign boundary becomes a polygon because a traffic sign is a two-dimensional planar object and that the boundary shape is also a plane figure with a limited number of vertices. The non-convex exceptions are rare. One example of such an exception is the X-shaped sign (with MUTCD code W10-1) that occurs at rail crossings. However, a proprietary algorithm can be developed to detect such special objects and separate them from their backgrounds. This section briefly describes each step for the proposed shape feature extraction algorithm.

STEP 1: Image preparation and binarization

Polygon approximation needs a binary input image in which the line process for boundary detection is distinguished from others. To do this, several preprocessing steps are applied. First, from a given image, a Gaussian up-and-down sampling method is applied to smooth the fractional noises, such as those of JPEG lossy compression. It was found that LADOTD video log images are heavily compressed to reduce the total size of millions of images. To reduce noise, a 5x5 zero-mean Gaussian filter is used in the practice. Since Gaussian functions are rotationally symmetric, the filter operates equally in all directions.

Second, for polygon approximation, the input image should be binarized so the boundaries of a traffic sign are emphasized. For this, two methods are employed: Canny edge detection and thresholding method. The Canny edge detector (*25*) is the first derivative of a Gaussian and closely approximates the operator that optimizes (*26*) the product of signal-to-noise ratio and localization. This has been used widely in civil engineering, such as for crack identification in bridges (*27*) and concrete damage analysis (*28*, *29*). The Canny algorithm contains a number of adjustable parameters that affect computation time and edge candidates. Based on the experiments with large numbers of traffic sign samples, two hysteresis thresholds of the Canny algorithms are determined through practice: (1) the aperture size of the Sobel operator is set as 7, which provides the first derivative of Gaussian edges; (2) the upper threshold is set as 50 and the lower one to 0 to force the edges to merge.

Although the Canny edge detector performs well in extracting a line segment, the images taken of traffic signs vary significantly because the environments surrounding signs vary by location and time. Consequently, the threshold technique needs to additionally be used. Thresholding is a method to convert a gray scale image into a binary image so that objects of interest are separated from the background. For thresholding to be effective in object-background separation, the object and its background must have sufficient contrast. However, because millions of outdoor images are to be handled under various lighting conditions, finding an optimal threshold value is not feasible. To overcome this problem, the threshold value is changed incrementally from 10 to 255 in 11 steps to achieve binarization.

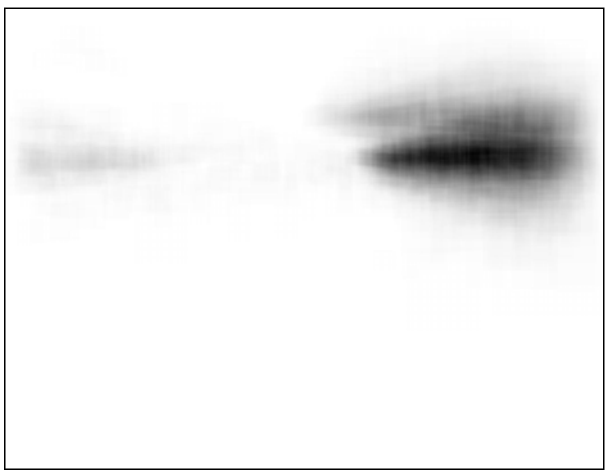
STEP 2: Nested contour chain detection for polygon approximation

The Douglas-Peucker (DP) algorithm (*30*) is used as a primary polygon detection algorithm; specifically, the computational speed enhancement (*31*) version is used for polygon approximation. The DP algorithm can approximate one or more curves with the desired precision. The output binarized images from thresholding and Canny edge detection are fed into the polygon approximation algorithm to retrieve contours. Then, a convex contour with a specified number of vertices is detected using a recursive algorithm. All retrieved contours are stored in a list chain in which they are arranged according to their spatial associations (find the nested spatial relationships facts associated with the polygon). This is essential because the detected contours are from the Canny edge detection result and are also from 11 thresholded images. Therefore, many contours found from multiple images could be spatially overlapped. Within the overlapped polygons, if they are traffic sign candidates, only the most external contours in the nested groups are used.

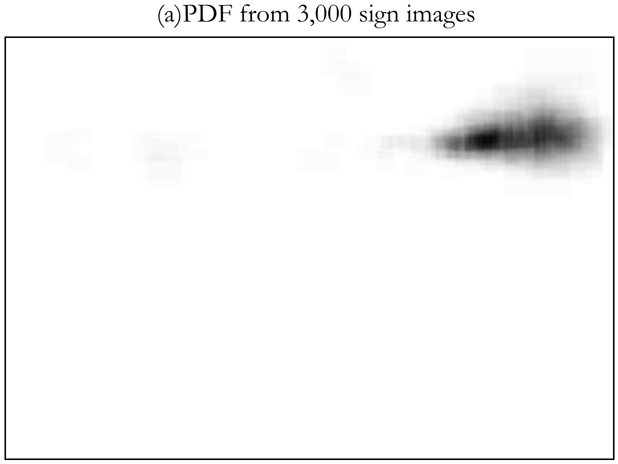
3.3.2.3 Sign Location Feature Extraction

Traffic signs in video log images typically sit in several specific regions, such as the top-right area, because, in a practical survey, the survey vehicle travels along the roadway with the camera fixed on the vehicle, resulting in the locations of traffic signs exhibiting certain distribution patterns. Based on the statistical analyses on the actual locations of traffic signs on images, the sign location PDF is developed.

A traffic sign is typically on the right side of the roadway. The survey vehicle follows the roadway so that the location of a typical is not uniformly distributed (non-uniform image sign location distribution) on the image plane. Therefore, in some areas of the images, a sign will be unlikely to occur, such as the bottom-left. The analyses of a large number of video log images provided by different highway agencies such as LADOTD and the City of Nashville shows that the non-uniform image sign location distribution can be used as a feature for sign detection. The main objective of the sign location PDF is to model the spatial distribution pattern of traffic signs on an image. In such a model, a location, which corresponds to a pixel location in the image, has a probability score ranging from zero to one; the high probability means that it is very likely that a traffic sign will appear in that location.



(a)PDF from 3,000 sign images



(b) PDF from 1,000 sign images

FIGURE 3 Sign location distribution from a) 3,000 and b) 1,000 images. The darker of a location (or pixel), the higher of probability of a traffic sign.

To develop a location PDF, the traffic signs on the images are manually tagged first and used as the training sets. From the locations of these tagged signs, a distribution map can be generated from which a sign location PDF is formed by normalization. If the training signs are insufficient, interpolation can be used so that the probability for each pixel on the image can be assigned. Figure 3 shows two sign location distribution maps that were generated using different numbers of traffic signs from video log images provided by LADOTD and the City of Nashville respectively. The first one is obtained from 3,000 images containing signs, while the second one is obtained from 1,000 images. The sign location map shows that the sign locations in the images are non-uniformly distributed. Both figures demonstrate the dominant, non-uniform location distributions, and in some areas, such as the bottom left and bottom right, traffic signs never appear. With such an image sign location distribution model, some FP cases can be removed in both traffic sign detection and recognition processes.

With the above developed sign location PDF model, a sign candidate can be rejected with high confidence if it is located in the areas with a very low probability, such as at the left corner of the image. Also, a high probability can add scores to the final recognition results.

3.3.2.4 Other Sign Feature Extraction

Besides the above three features, some other sign features are also used, such as the sign size, the W/H ratio of a sign, distortion angle, and sign color area ratio. For example, a sign candidate will be rejected if its size is too small or too large, or the W/H ratio is abnormal according to the MUTCD standard. Distortion angle can also be used to accept or reject a sign candidate because most of the traffic signs have very regular shapes, such as a rectangle, pentagon, octagon, etc. As a result, those candidates with very irregular shapes, reflected by the distortion angle, are rejected.

3.3.3 Sign Detection from Multiple Features

Based on the above extracted features, the final decision rule is made for reliable sign detection. The decision rule is described in Figure 4. The input video log image is first processed with the shape analysis algorithm so that all the polygon-like sign candidates are detected. Then, each detected polygon candidate will be further processed by analyzing its other features, such as the location PDF, sign color profile, sign W/H ratio, sign area ratio, and sign angle distortion, which will contribute to the final decision.

The detailed decision rules can be found in the paper (*23*). With the defined decision rules, a video log image can be identified as containing signs or containing no sign. Note that all the features are defined for the generalized traffic signs rather than one or two specific signs. For example, the shape detection part can detect all the possible shapes that are included in the MUTCD standard. The sign color profile features are also defined for all possible sign color distributions. Therefore, the detection algorithm is a generalized one that can handle all MUTCD traffic signs.

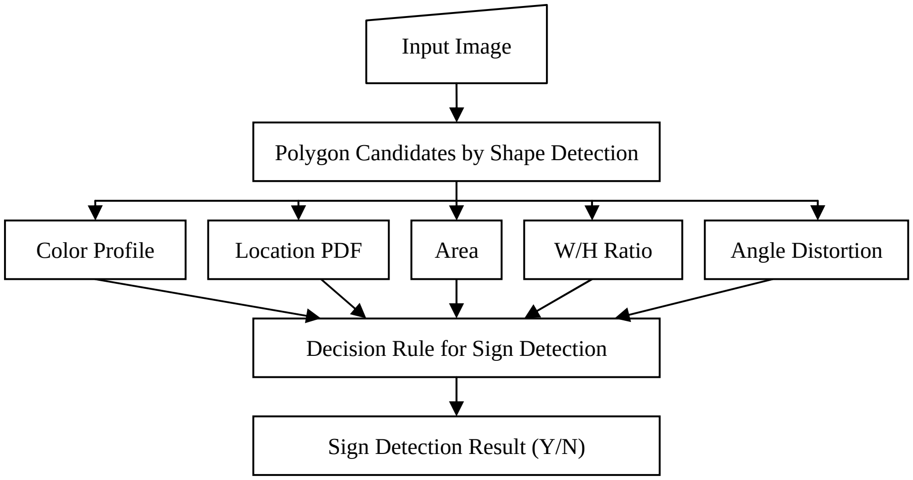


FIGURE 4 Sign detection from multiple features.

3.3.4 Experimental Results

This subsection presents the experimental results. Firstly, the proposed SCM color model is tested. The video log images used for this test are provided by LADOTD and the City of Nashville. These two image sets have different acquisition situations and cover different roadway functional classes. Secondly, the proposed generalized sign detection algorithm is tested. In this test, 37,640 images provided by LADOTD are used; they were taken in rural and urban areas. Finally, the detection algorithm is further tested by using 1,105 video log images provided by the City of Nashville; these were taken on city streets where the backgrounds are complicated by many sign-like objects that make sign detection more challenging.

3.3.4.1 Experimental Results for Testing SCM

The proposed SCM is tested with image data sets provided by LADOTD and the City of Nashville. There 37, 000 video log images from LADOTD and 27,000 images from the City of Nashville. Testing results show that the overall root mean square (RMS) error on 413,724 training samples is 0.057198 and 19,422 bit failures out of 3,309,792 (413,724 x 8 color outputs) input bits, a performance that achieves 99.5% correct matches. To quantitatively evaluate the test result of the color model, two factors, FP and FN, are used.

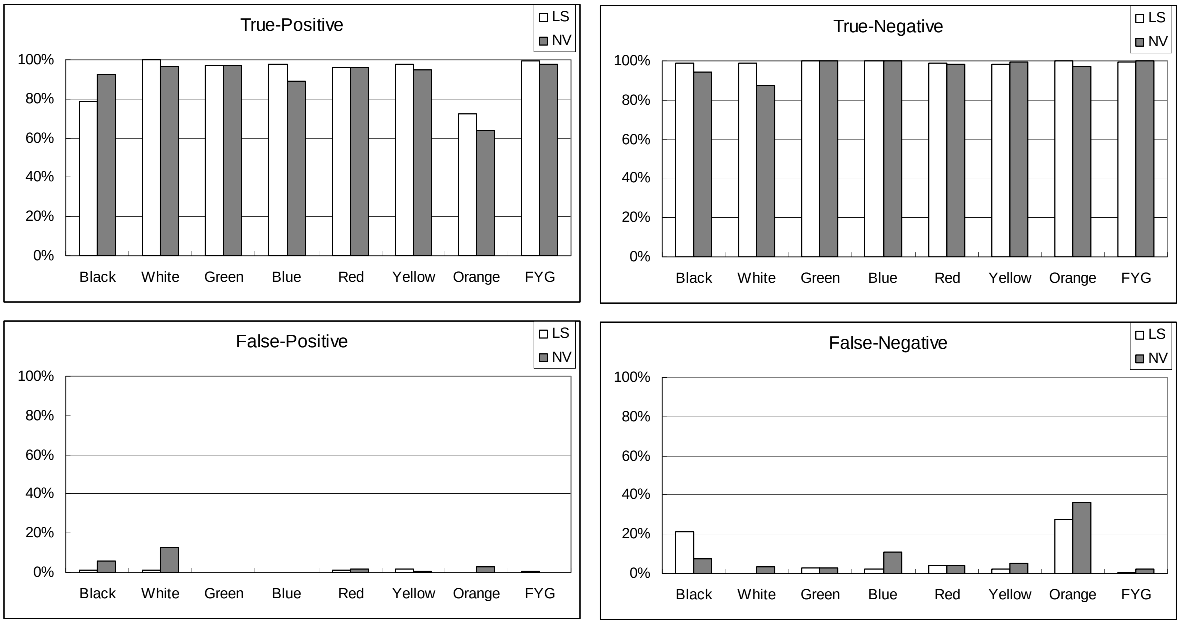
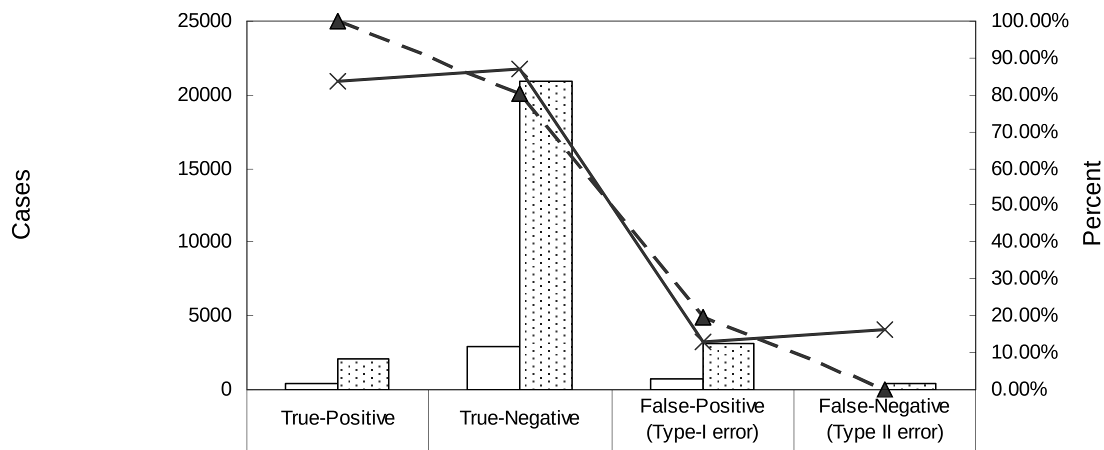


FIGURE 5 MUTCD SCM performance evaluation results for LADOTD set (LS) and Nashville set (NV). FYG in the X axis represents Fluorescent Yellow-Green color.

To validate the performance of the color model built from LADOTD images, a different image data set collected and provided by the City of Nashville was tested; the set consists of 1,926,652 pixels and evenly covers eight distinct colors. The white bar in Figure 5 shows the results of the LADOTD data set; the gray bar is for Nashville data set. Results demonstrate that the proposed SCM model has very good performance with low FP rate and FN rate errors. Compared with other published works (*14*), our model registered 25,000 red color samples by predicting the correct values with 1.2% FP rate and 3.5% FN rate errors, whereas the red color model proposed in (*14*) produced an 11.8 % FP rate error and a 5.5% FN rate error. Comparing the two test sets from LADOTD and Nashville, although built from LADOTD images, our model demonstrates a robust performance when applied to a data set with different lighting conditions, varying contrasts, and different camera parameters.

3.3.4.2 Detection Results with LADOTD Video Log Images

This section critically assesses the performance of the proposed algorithm through testing the actual video log images provided by LADOTD. LADOTD collected the video log images of 35,000 miles (56,000 km) of directional roadways at an interval of 0.002 mile (3.21 meter). There are 17.5 million front-view images. The image resolution is 1300 × 1060 pixels in JPEG format. The tested roadways are located in Jefferson Parish, Louisiana, and cover a portion of New Orleans. To evaluate the proposed algorithms, three categories of roadway settings (interstate, non-interstate urban and non-interstate rural) with different functional classes are chosen; 37,640 video log images, covering 75.17 miles (120.27 km) of directional roadways are used. In this test, the sign location PDF feature is not applied.



	True-Positive	True-Negative	False-Positive (Type-I error)	False-Negative (Type II error)
Site (count)	446	2956	730	0
Image (count)	2115	20969	3097	413
Site (%)	100.00%	80.19%	19.87%	0.00%
image (%)	83.67%	87.13%	12.86%	16.34%

FIGURE 6 Traffic sign detection results of LADOTD video log images.

The productivity and reliability of the algorithm is evaluated by comparing the computed outputs with the manual review results. Image-based and site-based evaluations are performed for the purpose of evaluating productivity and reliability, respectively. Image-based comparison is to compare the outputs (acquired from the computed and manual review) image by image. If the two are the same for an image (a sign is detected both by the algorithm and by a manual review, or no sign is detected), the result of this image is identified as "True"; otherwise, it is identified as "False." To implement the computed outputs, it is required to differentiate between the "True" and "False" cases. One of the four evaluation factors (TP, FP, TN, and FN) is assigned to each image to evaluate the performance of the algorithm. If the algorithm outputs are reliable, agencies need to only review the images in which signs are positively detected by the algorithm, which are TP and FP images. This will save much effort for agencies by skipping the images that don't contain any sign because, based on our experimental study on the actual video log images, more than 80% of images do not contain a sign. Apparently, the number of FP images directly affects the productivity because, in reality, there are no signs in them, but agencies still need to review them because the algorithm cannot correctly label them as no-sign images. In Figure 6, the dot-filled bars show the sum of images for these four factors. The solid line shows their percentages. There are a total of 2,528 (2,115 + 413) images with signs in them obtained by manual review, which is the ground-truth. In the meantime, 2,115 (83.67%) images are correctly detected by the algorithm, while 413 (16.34%) images are not detected. Meanwhile, among the 24,066 images with no sign in them, 20,969 (80.19%) images are correctly detected by the algorithm, while another 3,097 (19.87%) images are mistakenly detected as positives. Based on the above discussion, if the algorithm outputs are reliable, agencies need to only review 5,212 (2,115 + 3,097) out of total 37,640 images, which is approximately 14%. In other words, 86% of the workload in manual review can be saved.

One important feature of video log images is that they are spatially continuous, which leads to a "site" detection in our algorithm. With a small image capturing interval (0.002 mile or 3.21 meters) for LADOTD, the same sign can appear in several consecutive images. A sign may not be detected by the algorithm in some images due to its small size or temporary blockage by moving objects; however, it won't be missed in a traffic sign inventory if it can be detected from one of the consecutive images containing the same sign. To facilitate the evaluation, a site is defined to be a cluster of consecutive images with a sign or no sign in them. All consecutive images are clustered as sites based on the algorithm outputs and marked as positive (with sign) and negative (without sign) to conduct the site-based evaluation. Similar to the image-based evaluation, each site can be classified as one of the four factors mentioned previously. Among these four factors, the FN determines the reliability of the algorithm outputs because it means the algorithm fails to detect signs from consecutive images (a site image cluster) containing the same sign. In other words, as long as the algorithm can detect one occurrence of the same sign in a site image cluster, it is not a problem that the sign in other images of the same site image cluster is not detected because the sign will not be missed. In Figure 6, the blank bars indicate the sum of sites for these four factors. The dotted line shows their percentages. There are 446 sites with signs in them. By comparison with the manual review, all 446 sites are all correctly identified as true, which means no sign is missed. Table 2 also details the results for each roadway category. As expected, rural areas, which typically have fewer complex objects, show slightly lower false-positive percentages. The above site-based evaluation has demonstrated that the proposed algorithm can reliably detect signs because no sign is missed. Based on the image-based evaluation, it also demonstrates that 86% of manual image review efforts can be saved.

TABLE 2 Results of Experimental Study in Site (MC for major collect and MA for minor arterial)

Category	RouteID	Mile	Site	TP (%)	TN (%)	FP (%)	FN (%)
Interstate	450-15	9.52	515	112(100%)	293(73%)	110(27%)	0(0%)
Urban\ Pri Art	006-02	3.47	203	39(100%)	121(74%)	43(26%)	0(0%)
	006-30	6.29	339	30(100%)	257(83%)	52(17%)	0(0%)
Urban\ Min Art	063-04	8.29	409	47(100%)	284(78%)	78(22%)	0(0%)
	282-01	2.00	137	10(100%)	66(52%)	61(48%)	0(0%)
Urban\ Collect	826-13	4.20	225	27(100%)	179(90%)	19(10%)	0(0%)
	249-01	9.00	517	40(100%)	386(81%)	91(19%)	0(0%)
Urban\ Local	826-05	5.10	298	20(100%)	248(89%)	30(11%)	0(0%)
	826-08	0.74	43	8(100%)	29(83%)	6(17%)	0(0%)
	826-10	0.86	49	5(100%)	35(80%)	9(20%)	0(0%)
	826-54	0.64	36	4(100%)	30(94%)	2(6%)	0(0%)
	826-20	0.60	40	6(100%)	24(71%)	10(29%)	0(0%)
Rural*MC*	249-90	9.61	532	48(100%)	393(81%)	91(19%)	0(0%)
Rural*MA*	429-02	0.86	395	19(100%)	344(91%)	32(9%)	0(0%)
Rural\ Local	826-06	2.99	174	14(100%)	90(56%)	70(44%)	0(0%)
	826-12	0.40	22	2(100%)	19(95%)	1(5%)	0(0%)
	826-39	0.29	17	2(100%)	13(87%)	2(13%)	0(0%)
	826-55	0.41	23	0(100%)	19(83%)	4(17%)	0(0%)
	826-56	0.32	20	3(100%)	15(88%)	2(12%)	0(0%)
	826-57	0.32	21	1(100%)	18(90%)	2(10%)	0(0%)
	826-58	0.24	14	0(100%)	12(86%)	2(14%)	0(0%)
	826-59	0.29	20	1(100%)	18(95%)	1(5%)	0(0%)
	826-60	0.30	13	1(100%)	11(92%)	1(8%)	0(0%)
	826-61	0.38	20	3(100%)	15(88%)	2(12%)	0(0%)
	826-62	1.13	50	4(100%)	37(80%)	9(20%)	0(0%)
Total			4132	446(100%)	2956(80%)	730(20%)	0(0%)

3.3.4.3 Detection Results with Nashville Video Log Images

The algorithm was further tested with the Nashville dataset. There are a total of 1,105 video log images with acquisition interval between two consecutive images being 20ft (or 6m). Therefore, these images cover approximately a distance of 4 miles (6.4km). The testing site for these video log images is on a urban (or city) street area, where the image backgrounds are very complicated with a lot of sign-like shapes and objects, e.g. the advertisement panel, the windows on the wall, and other signs on the street. Among these images, 183 images have traffic signs, accounting for 16.6% of the total images. The sign features, including sign color, shape, location PDF, sign area, and sign distortion angle, are used for traffic sign detection. The results are presented in Table 3.

TABLE 3 Sign Detection Results from Nashville Video Log Images

Section#	**TP**	**TP %**	**TN**	**TN %**	**FP**	**FP %**	**FN**	**FN %**
1	17	100	57	79.167	15	20.833	0	0
2	26	100	12	80	3	20	0	0
3	5	100	14	33.333	28	66.667	0	0
4	4	100	35	89.744	4	10.256	0	0
5	5	100	13	33.333	26	66.667	0	0
6	9	100	26	100	0	0	0	0
7	2	100	53	94.643	3	5.357	0	0
8	2	100	5	100	0	0	0	0
9	3	100	9	60	6	40	0	0
10	1	100	0	100	0	0	0	0
11	12	100	12	70.588	5	29.412	0	0
12	15	100	42	70	18	30	0	0
13	9	100	9	25	27	75	0	0
14	2	100	0	100	0	0	0	0
15	3	100	4	50	4	50	0	0
16	18	100	21	53.846	18	46.154	0	0
17	2	100	0	100	0	0	0	0
18	13	100	24	64.865	13	35.135	0	0
19	11	100	24	100	0	0	0	0
20	24	100	306	78.061	86	21.939	0	0
Total	183	100	666	72.2	256	27.8	0	0

The results show that the algorithm can achieve a zero FN rate while keeping the FP rate as low as 27.8%. Therefore, with the proposed algorithm, more than 72.2% of the images containing no signs can be disregarded because they do not need manual review. These results further demonstrate that the proposed sign detection algorithm is very reliable even in the complicated environments. Based on the above discussion, if the algorithm outputs are reliable, agencies need to only review 439(256 +183) out of total 1, 105 images, which is approximately 39.7%. In other words, 60.3% of the workload in manual review can be saved with the proposed algorithm even in a very complicated roadway conditions, such as on a unban street.

3.3.5 Summary

This chapter presents the developed generalized sign detection algorithm, which is crucial for an intelligent sign inventory and management system. Sign detection is used for filtering out the images containing no sign and keeping the remaining images. Based on the MUTCD standard, several features, such as sign color, sign shape, sign location PDF, and other sign features are chosen for sign detection. An SCM color model is developed to process the MUTCD color for video log images. Then, sign shapes are analyzed by a polygon detection algorithm. Based on the statistical analysis on the sign location distribution in video log images, a location PDF model is developed to extract the non-uniform sign location features for video log images. Other features, like sign area, sign width-to-height ratio, and sign distortion angles are also used. These features are generalized from video log images and the MUTCD standard, which provides reliable sign detection. The proposed algorithm has been tested on two different video log image sets provided by LADOTD and the City of Nashville. The results with LADOTD video log images show that the algorithm could achieve a zero site-based FN rate, so there is not any sign that could be missed by the algorithm. In addition, the image-based TP and FP cases account for 14% of the total images, which means that 86% of the workload for manual review of images is saved. The results with the City of Nashville show that the algorithm can achieve 27.8% FP rate while keeping zero FN rate, and 60.3% of the workload for manual reviewing images are saved. The preliminary results from both LADOTD and the City of Nashville demonstrate that the algorithm can greatly help users save time and improve efficiency, which could also enhance roadway infrastructure data collection for an intelligent sign inventory and management system.

3.4 PROPOSED SIGN RECOGNITION ALGORITHM

Sign recognition aims at identifying sign type, MUTCD code, and other sign attributes. A successful sign recognition algorithm can extract sign's information correctly and automatically input it into the sign inventory database, to minimize the manual review and sign attributes input.

3.4.1 A Generalized Sign Recognition Algorithm

As specified in MUTCD, there are more than 670 types of traffic signs on U.S roadways. An intelligent sign inventory and management system requires an algorithm to recognize all of them. It is not feasible to develop sign-specific algorithms, as proposed in the existing literatures. Instead, a generalized sign recognition algorithm is required to process more than 670 types of traffic signs. The main purpose for a generalized sign recognition algorithm is that each type of traffic sign can be recognized using the same framework.

In order to develop a generalized sign recognition algorithm, sign features need to be extracted in a generalized way. In the proposed sign recognition algorithm, the following sign features are used: sign color, shape, location, Haar features, and other features like height-width ratio, area, angles. Each feature can be extracted in the same way for all types of traffic signs. For example, the SCM color model can be used to extract the ten MUTCD colors for all types of traffic signs. Once the features are extracted, they can be trained to recognize different types of traffic signs by using sign-specific training data. As a result, different types of traffic signs can be recognized by using different training sets and different training parameters for recognition. Since the features of sign color, shape, location, etc., are discussed in the sign detection chapter, this chapter only focuses on the Haar feature extraction and training with the Adaboost Cascade algorithm.

3.4.2 Feature Extraction and Training for Sign Recognition

3.4.2.1 Sign Feature Extraction

Since sign features, such as color, shape, location PDF, and other features have been discussed in the previous chapter, the Haar feature extraction is the focus of this section; Harr features are used to represent the sign texture or content for sign recognition.

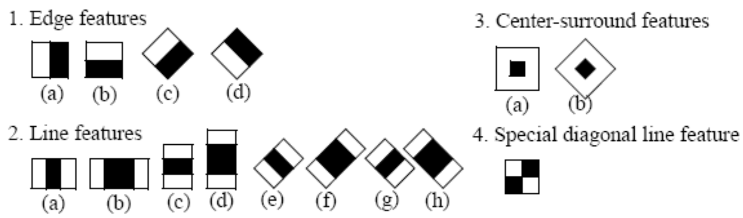


FIGURE 7 Feature prototypes of simple Haar-like and center-surround features. Black areas have negative weights and white areas have positive weights.

Haar features are used as the basic image features to represent objects. The basic idea of Haar features comes from the Haar wavelet transformation. The Haar features-based Adaboost algorithm was used originally for face detection and has proven to be very effective (*32*). Figure 7 shows the different types of Haar features, including the edge features, line features, center-surround features, and the special diagonal line features. For a 24×24 sub-window, approximately 120,000 Haar features can be extracted, a number larger than the actual pixel numbers of the sub-window. Since so many Haar features are used in the object recognition step, it has very strong representative ability.

The computation of a single Haar feature is straightforward. As shown in Figure 7, a Haar feature for each type is the difference between the white areas and the black areas. Since there are many Haar features even for a small sub-window of 24×24 (in pixel), the computation complexity is rather high. To solve this problem, Viola and Jones (*32*) proposed the integral image for feature extraction. An integral image is the sum of the pixels, which is above or to the left the corresponding location, which is given in the following formula (*32*):

$$ii(x, y) = \sum_{x' < x} \sum_{y' < y} i(x', y')$$

where $ii(x, y)$ is the integral image at location (x, y) and $i(x', y')$ is the original image. By using the integral image, the Haar features can be quickly computed. For example, in Figure 8, the sum of the pixel at the rectangle B can be computed by using the two integral images at the positions 1 and 2, and C from the integral images from 1 and 3. D is also computed with four positions of 1, 2, 3, and 4. Since the Haar feature is defined by the difference of a pixel sum of a set of rectangles, all the Haar features can be quickly computed from the integral images.

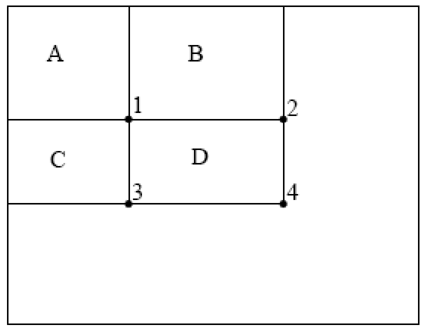


FIGURE 8 Integral images for Haar feature computation.

3.4.2.2 Sign Feature Training

There are a huge number of Haar features even for a small image 24×24 sub-window--about 120,000 Haar features (*32*). For the practice, not all the extracted Haar features are used because some of the features may not be good enough for sign detection and recognition. Instead, the distinct, representative features need to be selected to identify a true traffic sign from a false one. This selection process is called training. The well-known Adaboost Cascade algorithm is one of the most successful and effective training methods. Details for the training steps with Adaboost algorithm can be found in (*32*).

To perform the training, sufficient positive and negative samples are needed, from which the selected Haar features can correctly classify them. For example, Viola and Jones (*32*) used 9,832 positive and 10,000 negative samples to perform training. Sufficient and comparable positive images (with the specified sign type) and negative images (without specified sign type) should be prepared for the training to achieve good FN and FP rates. In practice, negative samples (without specified sign type) can be generated randomly from the non-sign video log images by extracting sub-images from random locations with random sizes. Before training, all the positive and negative samples are normalized to have the same size (e.g., 24×30 for speed limit sign).

An insufficient number of positive samples might lead to an FP. Details of the training sample preparation and processing are presented in the experiment test section in this chapter. Besides Haar features, other features are also used to improve the recognition rate, which are presented below.

3.4.3 Sign Recognition from Multi-Features

We can use the features extracted from images to recognize sign types. The Haar features, sign shape, sign color, and sign location PDF, are used for sign recognition, as shown in Figure 9. From Figure 9, each feature can be used to reject or accept a sign candidate. Sometimes, a true traffic sign cannot satisfy all the features at the same time.

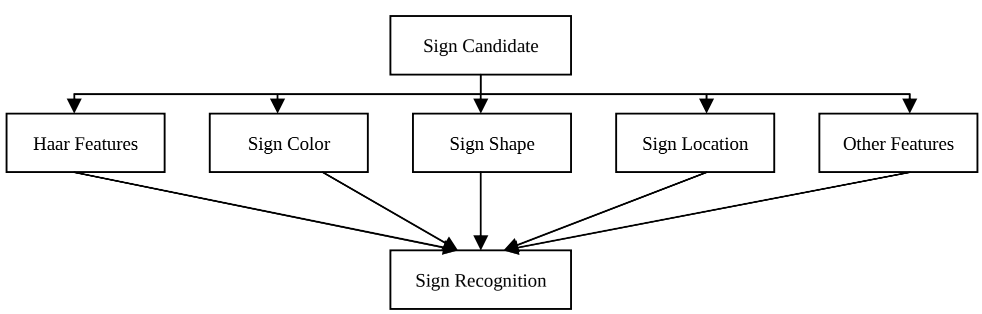


FIGURE 9 Sign recognition from multi-features.

The designed rules should remove the FP candidates while keeping the true positive ones. All the rules finally form a decision function as follows:

$$F(Haar, Color, Shape, Location, other) = \begin{cases} 1 & \text{if true sign} \\ 0 & \text{if false sign} \end{cases}$$

The following are the decision rules used to distinguish a true sign candidate from a false sign candidate:

RULE 1: candidate should be detected by Haar features;

RULE 2: candidate should pass the sign location validation;

RULE 3: candidate should pass either color OR shape validation.

RULE 4: candidate should pass all the width-to-height ratio, area, and angle validations.

Using the rules, sign type can be recognized. Examining the above features, it can be seen that the proposed algorithm provides a generalized methodology and framework for sign recognition because the sign features are generalized. Therefore, different types of signs can be recognized using the same framework. For example, under the same framework, a stop sign and a speed limit sign can be recognized with the following difference:

1) Prepare different training images (stop signs or speed limit signs) for Haar feature extraction. However, the training steps are the same.

2) Specify the shape to detect, e.g. a rectangle for a speed limit sign or an octagon for a stop sign. Both shapes can be automatically extracted using the same polygon-based shape detector.

3) Define different color ratio thresholds. For stop signs, the ratio threshold needs to be trained for a red background and a white legend. For speed limit signs, the threshold for a white background and a black legend need to be trained. However, the same SCM color model is applied to extract their color features.

As a result, by preparing different training image sets, training different thresholds, and adjusting different parameters, the proposed sign recognition algorithm can be applied to recognize different types of signs. The methods used, such as color analysis, shape extraction, and the training procedures, are the same for training different sign types. Therefore, the proposed algorithm is a generalized sign recognition algorithm. The following section uses the speed limit sign to demonstrate the capability of the developed algorithm.

3.4.4 Experimental Results

This section uses speed limit sign recognition to demonstrate the capability of the proposed algorithm. Two sub-sections are included. In the first sub-section, five tests are performed to show that it is difficult to produce a low FP and low FN using only the Haar features extracted from Adaboost Cascade method when there is limited number of positive samples (e.g. images containing signs). Besides Haar features, other features are incorporated, including color, shape, location, and sign height-to-width ratio, to further reduce FPs. In the second sub-section, the proposed algorithm using these features and models for recognizing speed limit signs is briefly introduced. The experimental tests using the real-world video log images to recognize speed limit signs are also performed to validate the proposed algorithm.

3.4.4.1 Feature Training and Models Used

Five tests with different numbers of negative and positive samples were performed using only the Haar features extracted from the Adaboost Cascade method to extract speed limit signs. The positive and negative samples first need to be prepared to train the Cascade network for performing Haar feature- based sign recognition. All the positive samples were generated from two sources: 1) manually tagging the video log images provided by state DOTs; 2) searching sign images from websites. All the negative samples were generated by our program with random sizes and from random locations of the non-sign video log images. Before training, both the positive and negative samples are normalized to have the same image resolution, 24×30 pixels. This size is based on the width-to-height ratio of an actual speed limit sign. Different numbers of positive and negative samples were used to perform four training tests. Then, four trained Cascade networks were used to test the data set with 1,000-images; the results are in Table 4.

The first column in Table 4 shows five tests. The second and third columns are positive and negative sample numbers. The fourth column is the stage of the trained network (see more details in (*32*)). The FP and FN rates are shown in the fifth and sixth columns. The last column shows the number of test images. The same 1,000 test images were used for all five tests. Table 4 shows that the proposed algorithm can achieve low FN rates, which means that no sign or only very few signs will be missed. However, the algorithm has a high FP rate, which means that many non-sign objects are falsely identified as signs. A comparison of Test 1 and Test 2 shows that they have the same positive samples, yet different FN samples. By adding more negative samples, both the FP rate (FPR) (from 98% to 59%) and the FN rate (FNR) (from 3.4% to 2.2%) can be decreased. However, when the negative sample (from 1,500 to 6,000 negative samples) are continuously increased, as shown in Test 3, FPR and FNR do not decrease continuously; instead, they increase. This indicates that low FPR and FN cannot be achieved by simply increasing negative samples. In Test 4, after increasing the positive samples, we can see both FPR and FNR are decreasing, which achieves the best FPR and FNR results for the above four tests. However, the FPR is still as high as 42%. Test 5 further demonstrates that fewer positive samples (100 positive samples) lead to even worse FPR and FNR. Therefore, more positive samples must be added to further enhance the algorithm's performance because, in the original Adaboost Cascade method for face detection, Viola and Jones (*32*) used 9,832 positive and 10,000 negative samples to get good detection results. However, it would be difficult to collect more than 6,000 positive samples, especially for some types of signs. Therefore, besides using the Adaboost Cascade method, the proposed sign recognition algorithm incorporates other features, including color, shape, location, and height-to-width ratio, to further reduce FPs. Figure 9 illustrates the multiple-feature fusion using the proposed sign recognition algorithm. By incorporating multiple sign features, much better recognition performance can be achieved. Besides Haar features, the following are the additional features and models used for the subsequent experimental test of speed limit sign recognition:

a) The SCM color model is developed from 45,151 video log images captured under various outdoor lighting conditions in Louisiana, producing 3,023 images. A total of 413,724 distinct samples and each reference count were used to build the SCM color model. For speed limit signs, two distinct color ratios are 0.5 for white and 0.07 for black. Details can be found from the paper (*23*).
b) The image sign location PDF model is developed using 3,000 video log images that contain signs provided by LADOTD.
c) The polygon-based shape analysis is performed to extract a speed limit sign's boundary. A speed limit sign has 4 vertices.
d) A speed limit sign has a height-to-width ratio between 1.05 and 1.35. A typical sign distortion angle is 10 degrees, and the minimal sign size for recognition is 24×30 pixels.

The following presents the proposed generalized sign recognition algorithm using multiple features with the actual images. The trained Cascade network from Test 4 in Table 4 is still used for the tests discussed in the following section.

TABLE 4 Recognition Results of Speed Limit Sign with Different Positive and Negative Samples

Test	PS #	NS #	Stage#	FPR (%)	FNR (%)	Test Images #
Test-1	191	300	8	98%	3.4 %	1,000
Test-2	191	1,500	8	59%	2.2%	1,000
Test-3	191	6,000	8	77%	3.7%	1,000
Test-4	293	6,000	8	42%	1.8%	1,000
Test-5	100	6,000	8	100%	5.7%	1,000

3.4.4.2 Tests Using Video Log Images

The proposed sign recognition algorithm was tested with the actual video log image data collected on I-75 from Macon to Atlanta, Georgia. There are 5,387 video log images covering 80 miles (128km) of urban and rural areas. In this test, the video log images were collected with the survey vehicle. The vehicle is equipped with cameras, two Global Position System (GPS) receivers, a Distance Measurement Instrument (DMI), a laser ranger, etc. The video log images were taken using a front-view camera. The image acquisition interval between two images is 24 meters with the interval pulse generated by a DMI device. The driving speed is about 70 miles per hour (70 MPH). All images have a resolution of 2448×2048 (pixels) in JPEG format. For the 24-m acquisition interval, a traffic sign appears about four times in consecutive images. For sign inventory, it is not necessary to recognize the same sign in all the consecutive images. Instead, if the sign in one of the consecutive images can be recognized, it won't be missed by the algorithm. This "site-based" concept is same as the one introduced in the previous chapter of sign detection.

TABLE 5 Recognition of Speed Limit Signs Appearing on I-75 from Macon to Atlanta

Site #	Image#	TP	FP	TN	FN	Image Rec Rate (%)	Site Rec Rate (%)
1	4	3	0	0	1	75	100
2	5	5	0	0	0	100	100
3	6	4	0	0	2	66.7	100
4	7	6	0	0	1	85.7	100
5	4	0	0	0	4	0	0
6	4	2	4	0	2	50	100
7	5	2	0	0	3	40	100
8	4	2	0	0	2	50	100
9	5	3	0	0	2	60	100
10	4	2	0	0	2	50	100
11	3	0	0	0	3	0	0.0
12	3	3	0	0	0	100	100
13	4	3	0	0	1	75	100
14	4	1	0	0	3	25	100
15	5	3	0	0	2	60	100
16	3	2	0	0	1	66.7	100
17	5	3	0	0	2	60	100
18	5	3	0	0	2	60	100
19	5	3	0	0	2	60	100
20	4	3	0	0	1	75	100
21	4	2	0	0	2	50	100
22	4	3	0	0	1	75	100
23	4	2	0	0	2	50	100
24	5	0	0	0	5	0	0.0
25	6	1	1	0	5	16.7	100
26	5	3	0	0	2	60	100
27	4	3	0	0	1	75	100
28	4	2	0	0	2	50	100

29	3	2	0	0	1	66.7	100
30	4	4	0	0	0	100	100
31	4	2	0	0	2	50	100
Total	136	72	5	0	64	52.9	90

From these 5,387 video images, there were 136 images containing 31 different speed limit signs from both the rural and urban areas. The ground truth for the speed limit signs was established by manually reviewing all the video log images and tagging the images containing speed limit signs. The recognition results with the proposed algorithm were then compared to the ground truth data. Table 5 shows the recognition results automatically generated by the proposed sign recognition algorithm.

In Table 5, the first column is the "site" number; 31 sites mean 31 different speed limit signs. The second column is the number of consecutive images for each speed limit sign. The third column is the successfully detected images, and the fourth is the FP for all the images in each site. The fifth and the sixth columns are for the true negative and FNs. The seventh column is the image-based recognition rate for each site. The last column is the site-based recognition rate.

In the results, 28 out of 31 speed limit signs were successfully recognized with the proposed algorithm, a recognition rate of 90%. The results show that the algorithm is very promising for sign recognition. Besides, the algorithm only generated 5 FPs from the 136 video log images, which demonstrates that the algorithm is effective in removing FP using multi-feature fusion. By analyzing the signs that were not recognized by the proposed algorithm, it can be seen that these signs have the following conditions that make recognition difficult: a) blocked sign; 2) too small; 3) too-complex background; and 4) extreme lighting conditions, which greatly affect the sign color, sign shape features, and Haar features.

With the proposed algorithm, the information of sign type, MUTCD codes, sign color, etc. can be automatically stored into a database to save manual input efforts. Users need only to manually enter the information for the remaining 3 speed limit signs into a database. As a result, the recognition algorithm can cut workload and enhance sign data collection efficiency.

3.4.5 Summary

Image detection and recognition algorithms are crucial for developing an intelligent sign inventory and management system that uses video log images. The technical challenge is to detect and recognize more than 670 different types of signs specified in the MUTCD. This chapter develops a generalized image recognition algorithm that can recognize different types of signs based on shape, color, location PDF, and Haar features extracted from the Adaboost Cascade method. With the algorithm, traffic sign attributes, such as sign type and MUTCD code, can be extracted automatically, which can further reduce manual workload for sign inventory and management system. The proposed algorithm was tested with the actual video log images collected on Interstate I-75 from Macon to Atlanta, Georgia, a distance of 80 miles (128km), in both rural and urban areas. Speed limit signs are used to validate the proposed algorithm. Our results show that the algorithm can recognize 28 of 31 speed limit signs for a 90% recognition rate. Among the images with signs, the algorithm has only 5 FPs. The results show that the algorithm can effectively remove FNs with multi-feature fusion. These preliminary results show significant promise for development of an intelligent sign inventory and management system. With sufficient image training data sets, the proposed algorithm can be applied to other sign types.

4. CONCLUSIONS AND RECOMMENDATIONS

Collecting roadway infrastructure data, including traffic signs (stop signs, speed limit signs, etc.), with the designated locations (mileposts and x, y coordinates) is essential for state DOTs to submit HPMS data annually and for state and local transportation agencies to plan, design, construct, operate, and manage their transportation systems. Traffic signs are also important for roadway safety; therefore, the inventory of sign data is a necessity for compliance with the MUTCD standard.

However, sign inventory data collection is time-consuming and costly. Current software reviews one image at a time, so extracting sign types from millions of images is time consuming and hinders effective sign inventory data processing. There is a need to develop algorithms that can batch-process more than ten million video log images instead of reviewing them frame by frame and support an intelligent inventory system. Although algorithms have previously been developed for automatically detecting and recognizing particular signs (e.g. stop and speed limit signs), they do not work for a comprehensive sign inventory because sign-inventory algorithms must be capable of recognizing more than 670 types of traffic signs on U.S roadways. It is technically challenging to develop the generalized algorithms that are capable of detecting and recognizing more than 670 types of signs. In this research project, two innovative modularized algorithms, sign detection and sign recognition, are developed for sign inventory data collection. They form the foundation for developing an intelligent sign inventory and management system. A two-step sign inventory data collection process is proposed to seamlessly incorporate these two algorithms so that millions of video log images can be batch processed, which can save time and cost for transportation agencies.

The generalized sign detection algorithm, the first step of the intelligent sign inventory and management system, is developed using the sign shape, color, location, and other features defined in the MUTCD standard. During the sign detection phase, the goal is to remove all the images containing no sign, while keeping the images containing signs so that users don't need to review tens of millions of images manually. In order to achieve this goal, a desirably low FN rate should be guaranteed so that no traffic signs will be missed. Also, the FP rate needs to be kept as low as possible, since it reflected the extra percentage of images that still need manual review. Sign shapes are detected using the polygon approximation approach. Sign colors are processed with the SCM by using an ANN. The trained colors for SCM were selected manually from the video log images and then trained by a hybrid Neural Network. The SCM model was tested using two different data sets and has demonstrated a promising result. The PDF of sign locations is trained from the manually tagged sign locations on the images. The final sign detection algorithm from the multiple features was tested on two data sets. One is from the video log images provided by LADOTD, where there are more than 37,640 video log images. The developed algorithm could achieve zero FN rates and 19% FP (site-based) rates for the LADOTD data set and could save 86% of the workload for the manual review (because the TP and FP images account for approximately 14% of the total images). The algorithm was also tested on the Nashville video log images covering a street with many sign-like objects, such as advertisements, windows, etc., which makes the detection more challenging. The results show that the algorithm could still achieve 27.8% FP rate while keeping a zero FN rate. And, it can save 60.3% of the workload for manual review even in very complicated roadway conditions, such as in an urban street area, where many sign-like shapes and objects make the detection much more difficult.

Sign recognition follows sign detection in an intelligent sign inventory and management system. The generalized sign recognition algorithm, the second step of an intelligent sign inventory and management system, is developed to automatically identify and extract correct sign type and MUTCD code from the images containing signs, which are identified in the sign detection phase. This can reduce the manual data entry effort. In this instance, a multi-feature fusion algorithm is proposed for sign recognition. The basic features used in the algorithm include Haar features, sign color, sign shape, and sign PDF, based on the fact that a sign can be recognized from its shape, color, texture, and location in the image. Haar features encode the sign texture information and are used in the Ada-Boost algorithm, which consists of the training and testing parts. In the training part, the sign images were selected and normalized and the weak classifiers were selected by the boosting training approach. A final strong classifier is then generated based on a cascade structure. In this part, two different data sets are used to test the proposed recognition algorithm. One data set was collected with our developed survey vehicle along Interstate I-75 from Atlanta to Macon, Georgia, which covers 80 miles (128km) of interstate highways. The proposed recognition algorithm was used to recognize the speed limit sign along the roadway. The results show that the algorithm could successfully recognize 28 out of a total of 31 speed limit signs, with 90% recognition rate, which is promising. With results from the recognition algorithm, the sign attributes can be automatically input into the sign inventory database. Therefore, it can greatly save manual effort and improve sign data collection efficiency.

In summary, the proposed algorithms have demonstrated its promising capabilities in saving time and effort on transportation agencies' sign inventory data collection. The following are recommendations for future research:

1) Perform more large-scale tests on the proposed algorithms using the images collected under real-world environments in which sign dimension, color, text fonts, etc. may not exactly follow the MUTCD standard, and the varying lighting and illumination conditions may change sign appearances. The large-scale image data tests provided by both state DOTs and local transportation agencies for interstate, state, county, and city roads can be used to further refine the developed algorithms for final implementation.
2) Based on the developed sign detection and recognition algorithms, other sign feature data, including sign geometric attributes (*33*) , such as sign-to-camera distance, height, GPS coordinates, tilt angle, etc., sign condition changes (*34*), such as missing, tilted, and block signs, can be automatically collected.
3) Software, which seamlessly incorporating sign detection and recognition algorithms, needs to be developed to effectively perform traffic sign inventory.
4) GIS technology can be incorporated into an intelligent sign inventory and management system.
5) Although image processing algorithms have been developed to automatically extract traffic signs (*14-16*, *23*) and other roadway features such as traffic geometry (*33*, *35*) and roadway horizontal curvature (*36-38*), and automatically detect deficient video log images (*39*), video log image data acquisition has yet to be designed to support the automatic feature extraction. There is a need to study the impact of different sensor configurations on automatic feature extraction. It will help to promote the integration of hardware and software in support of automatic roadway data collection.
6) The proposed algorithms can be extended to collect other roadway assets, such as roadway geometry (pavement width, shoulder widths), guardrails, pavement marks, etc. from video log images.

5. PLANS FOR IMPLEMENTATION

With the support of the IDEA concept exploration research project, two generalized algorithms, sign detection and sign recognition, are developed to automatically detect and recognize more than 670 different types of signs specified in the MUTCD standard by using video log images that are widely available. The preliminary tests demonstrate these developed algorithms are promising and provide new capabilities to significantly reduce the cost and time spent by state DOTs for acquiring traffic sign inventory data using video images.

With the incoming support of the US DOT RITA program and GDOT, the IDEA concept exploration research outcomes, including the developed sign detection and recognition algorithms, will be migrated to a large-scale, national demonstration for further implementation of the developed algorithms. It will, also, allow the developed algorithms tested under real-world environmental conditions in which sign dimension, color, text fonts, etc. may not follow the MUTCD standard exactly, and the varying lighting and illumination conditions may change sign appearances. The large-scale image data tests provided by both state DOTs and local transportation agencies for interstate, state, county, and city roads will be used to further refine the developed algorithms for final implementation.

Based on the developed sign detection and recognition algorithms, other sign feature data, including sign geometric attributes (*33*), such as sign-to-camera distance, sign height, GPS coordinates, sign tilt angle, etc., sign condition changes (*34*), such as missing, tilted, and blocked signs can also be extended. Some of the work has been accepted for publication in journals (*33*, *34*). As a result, a complete sign inventory and management system can be developed in which sign data and feature can be reviewed, queried, and evaluated more effectively to support sign management and maintenance.

Based on the developed algorithm, software will be developed to effectively perform traffic sign inventory. GIS technology can also be incorporated in the intelligent sign inventory and management system. Many transportation agencies, including GDOT, the Ohio Department of Transportation, the Connecticut Department of Transportation, the Oklahoma Department of Transportation, and the City of Nashville have committed to providing video log images in support of the national demonstration project.

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