PDE Incorporated Multi-Feature Traffic Sign Detection

Chengbo Ai
Department of Civil and Environmental Engineering
Georgia Institute of Technology
210 Technology Circle
Savannah, GA 31407
Phone: (912) 660-4533
Email: chengbo.ai@gatech.edu

Yi-Chang (James) Tsai
Department of Civil and Environmental Engineering
Georgia Institute of Technology
210 Technology Circle
Savannah, GA 31407
Phone: (912) 966-6977
Email: james.tsai@ce.gatech.edu

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ABSTRACT

Traffic signs are important transportation assets that are integrally related to roadway safety. Current traffic sign inventory by transportation agencies is still a manual process that is labor intensive and time consuming. A generalized traffic sign detection algorithm with a reasonably good performance has been developed using multiple features to automatically detect signs. However, correctly detecting signs with discontinuous boundaries remains a challenge that lead to false negatives. To address the issue, a partial differential equation (PDE) method, which is a region-based active contour model, is proposed. A new energy function incorporated with a location probability distribution function (PDF) is proposed for the active contour. The contributions of this paper include the following: 1) proposes a PDE method to improve discontinuous sign detection; 2) proposes a location PDF incorporated energy function component to provide a more accurate contour initial guess; 3) the new method is integrated into existing system framework without affecting existing methods. The video-log image data from the City of Nashville are used to perform the test. Using the new method, 24 out of 26 images with a discontinuity issue are correctly detected, and 607 images from a road segment are tested to compare the performance of the enhanced system and the previous system. Results show that false negative rate has been reduced 6.8% from 21.1% while the false positive rate has increased 1.2% from 11.2% with the enhanced system. The results show that incorporating the proposed PDE method to develop an enhanced sign detection system is promising. Future research for incorporating additional distinct features into the generalized algorithm is also discussed.

1. INTRODUCTION

As one of the most important traffic control devices defined in the Manual of Unique Traffic Control Devices (MUTCD), a traffic sign's existence, location, and condition inevitably affect transportation mobility and safety, as stated in the revised MUTCD (2003). Thus, different transportation agencies, such as state departments of transportation (DOTs), are dedicating their workforce to traffic sign inventory and condition assessment. Traditionally, transportation agencies manually collect traffic sign data in the field, which is time consuming, costly, and dangerous. Some transportation agencies collect traffic sign data in the office by manually reviewing video-log images. For example, Georgia has approximately 118,000 centerline miles of roadway. According to the current data collection practice, 100 images per mile, the Georgia Department of Transportation has more than 11 million roadway video-log images. Reviewing these images one frame at a time is extremely time consuming and costly.

To reduce the cost and time of traffic sign inventory, much effort has been expended to develop algorithms for automatic traffic sign detection and recognition. These algorithms try to extract a traffic sign using distinct features that uniquely define different types of traffic signs. Some algorithms use color (Ritter, 1995) or shape (Schiekel, 1999; Gil-Jimenez, 2005; Kim, 2005; Tsai and Wu, 2002) for traffic sign detection and recognition, while others combine these two features (An, 1998; Miura, 2002; Gao, 2003; Zhu, 2006; Wu and Tsai, 2006). In addition, geometrical, physical, and text/symbol features are used for traffic sign detection (Liu, 2007; Wu and Tsai, 2005). To extract traffic sign features, methods like the Support Vector Machine (SVM) and the Neural Network (NN) are used (Gil-Jimenez, 2005; Zhu, 2006). In recent years, the Haar feature-based Ada-boost method, which was originally applied in face detection (Bahlmann, 2005; Silapachote, 2005), was developed for traffic sign detection and recognition. However, the following challenges still remain:

1. For traffic sign inventory, more than 670 types of traffic signs with different sizes, shapes, colors, and legends are specified in the MUTCD. It is a challenge to develop a generalized automatic traffic sign detection algorithm to process all of these types;
2. To make an automatic process practical, the automatic traffic sign detection algorithm should be accurate with an acceptable false negative rate that reflects reliability and a reasonable false positive rate that reflects productivity;
3. The algorithms should be robust enough to detect images that are captured under different lighting conditions, e.g. backlight and sun glare, and varying environmental conditions, e.g. foggy weather and rain showers;
4. Because there is no standard among transportation agencies, the algorithms should be adaptive enough to process images captured by different camera configurations, e.g. different camera resolution, orientation, etc.

To address these challenges in the existing automatic traffic sign detection method, a novel, generalized, multi-feature traffic sign detection algorithm is developed. The performance test shows a reasonably good result (Tsai et al, 2009; Tsai and Wang, 2008) in terms of traffic sign detection rates. A new proposed statistical color model (SCM) is first applied to determine and classify the color probability of each image. The Canny edge detection method with Sobel operator is then applied (Canny, 1986; Abdou, 1979) to extract all the edges in the segmented color images. Finally, a contour-smoothing and approximation algorithm is applied to extract all the possible polygons (Douglas, 1973).

Though the algorithm performed well in several large-scale tests, e.g. on more than 37,000 images collected by Louisiana Department of Transportation and Development (LaDOTD), challenges remain. After analyzing the false negatives in the test results, images with discontinuous sign boundaries are identified as one of the most difficult technical challenges for correctly extracting traffic signs. Figures 1(a) and 1(b) show two traffic signs that are not detected in the existing system due to the discontinuous sign boundary. In Figure 1(a), the upper left portion of the deer warning sign (W11-3) merges into the background, making the boundary indistinguishable. In Figure 1(b), the school sign shares the same boundary with the "ahead" legend (W16-9p); the shared boundary does not have a consistent intensity and does not separate the two adjacent traffic signs clearly.

(a) (b)

FIGURE 1 Two Cropped Color Segmented Images with Discontinuity Issues.

The objective of this paper is to improve the performance of contour extraction for traffic signs with discontinuous boundaries and to reduce the false negative rate without adding excessive false positives. Considering the strong capability of active contour in boundary extraction and shape description (Kass, 1988), this partial differential equation (PDE) method is introduced and incorporated in the current automatic traffic sign detection system. In this paper, a new, region-based active contour model is formulated by incorporating the location probability distribution function (PDF) information and curve length constraint. Based on the formulated energy function, the contour will evolve within the color-segmented images and, finally, locate the traffic sign boundary, even when sign boundaries are discontinuous. The location PDF information is implicitly embedded in the energy function, so the initial guess can be improved. Also, the curve length constraint, as a global iteration termination criterion, is included to prevent excessive iteration during the contour evolvement and to separate compound traffic signs.

This paper is organized into several sections. This section introduces the need for an automatic traffic sign detection system. The undetected traffic signs with discontinuous boundaries are identified, and a region-based active contour is proposed to improve the system. Section 2 presents the methodology for integrating the region-based active contour into the existing system. The formulation of a location PDF incorporated region-based active contour to enhance the initial guess is presented. Section 3 presents the test results and shows the improvement in detecting traffic signs with discontinuous sign boundaries and also shows the robustness of active contour initial region guesses. The assessment and analysis of the results is also presented. The last section presents the conclusion. Recommendations for further improvement of this PDE method, as well as the improvements for the entire detection system, are also presented.

2. METHODOLOGY

2.1 Introduction of Active Contour

Active contours, or snakes (Kass, 1988), are computer-generated curves that move within images to find object boundaries. They are often used in computer vision and image analysis to detect and locate objects and to describe their shapes. They are widely used in medical image processing, e.g. in automatically extracting MRI images of cancer. An edge-based active contour approach (Malladi, 1995; Chenyang, 1998) and a region-based active contour approach (Chan, 2001) are the two most popular formulations. With a good energy function and initial guess, the active contour method is capable of accurately extracting the boundary around the target object. There are two major challenges existing in all the active contour methods:

1. Initial guess. The active contour method requires an initial guess to accelerate the contour-evolving process and obtain the target contour accurately. This is a challenge, especially when the image has a complicated background and heavy noise, e.g. in natural-scene images;
2. Iteration termination. When performing of the active contour, the contour will stop evolving when the preset iteration number is achieved or the iteration converges with certain errors. However, the decision to terminate iteration is still a challenge and, most of the time, is handled case by case;

Due to these two major challenges, to the best knowledge of the authors, there is little research that directly applies active contour methods to traffic sign detection or other natural scene object extraction problems. Quan and Mohr (1990) apply a geodesic active contour directly to the collected raw image and get some preliminary results in traffic sign detection. Paulo (2008) presents an active contour-based method with a selected dataset to extract the legend and icon from a traffic sign. Several methods are proposed based on geodesic active contour and optical flow analysis in sequential images with static backgrounds to deal with the application of vehicle extraction, pedestrian extraction, and tracking, etc (Andrade, 2005; Coifman, 1998). In this paper, the initial guess and the iteration termination challenges are dealt with by using the newly proposed hybrid energy function.

To detect a traffic sign with discontinuous boundaries, the region-based, active contour model is selected. The region-based active contour is first proposed by Chan and Vese (2001). It is considered as the “active contour without edge.” Similar to the edge-based active contour, the problem is considered as an energy-minimization problem. The difference is that instead of using an energy function with an edge-sensitive element $|\nabla I|$, the region-based active contour energy function incorporates the regional information inside the contour and the information outside the contour, which is much more robust than the noise and local perturbation. Compared with the edge-based active contour, the region-based contour performs much better when the input image has a pattern that includes two different intensities throughout the image, especially the images with heavy noise. The color-segmented images by SCM provide a preferable input for the region-based active contour, which shows that the foreground traffic sign region has a higher intensity while the background region has a lower one.

2.2 Active contour incorporated traffic sign detection algorithm framework

In this paper, the newly proposed active contour algorithm is designed as an enhancement of the existing system. The existing system consists of three major procedures, including color segmentation, polygon detection, and polygon validation. As mentioned in the previous section, the enhancement algorithm, using active contour, is applied in the polygon detection procedure to extract the previously omitted contours. An enhanced traffic sign detection algorithm framework is formulated by incorporating the active contour algorithm in parallel into the existing polygon detection procedure.

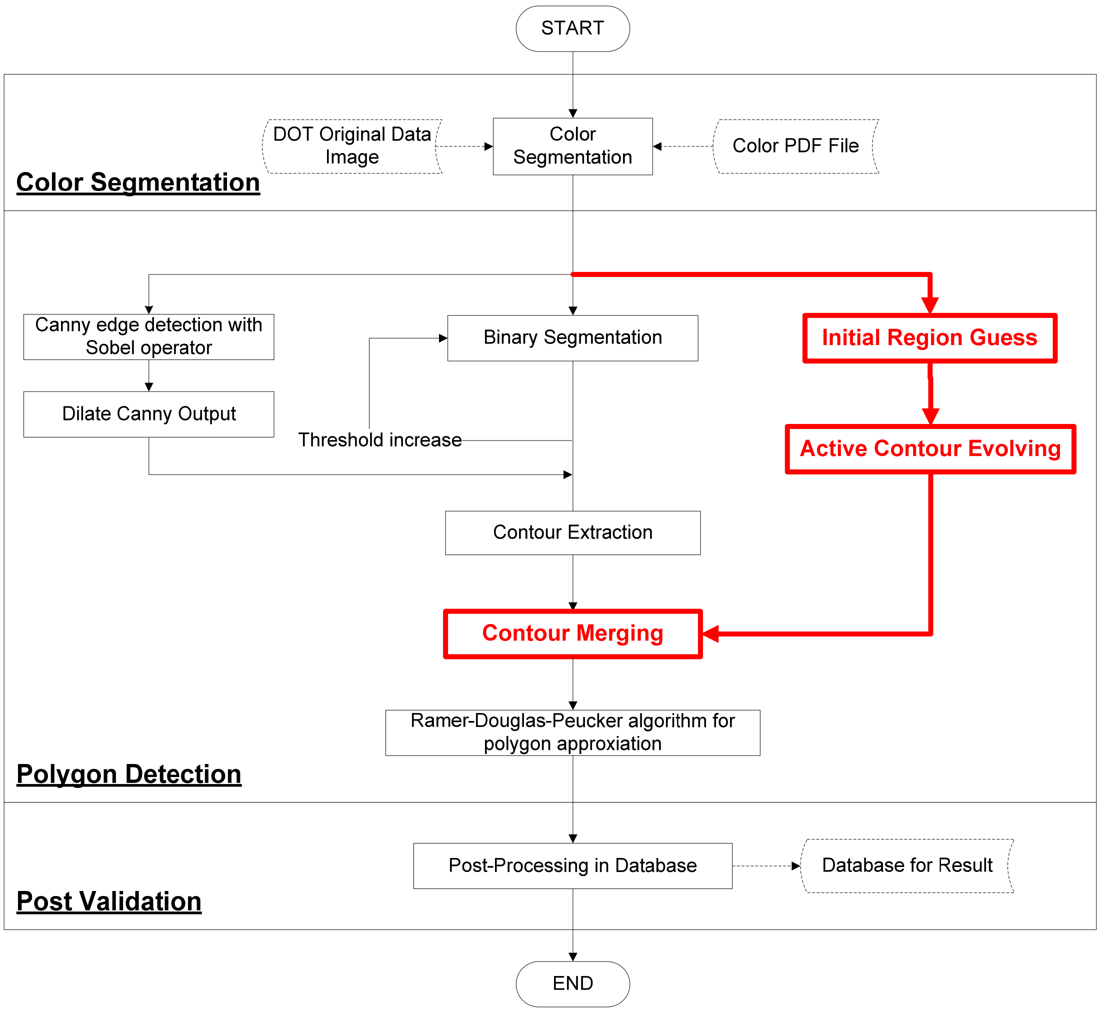


FIGURE 2 Framework of Current Detection System and Enhanced Detection System.

In the existing algorithm for polygon detection, the Canny edge detection and multi-step binarization methods are applied to the color segmented image inputs to extract the contours, as shown in Figure 2. In the enhanced algorithm, the active contour algorithm is appended, as shown in Figure 2 (in bold), to the existing algorithm. Color segmented images are separately input through three different contour extraction paths. For the two paths in the existing system, edges are first detected, and then the contours are retrieved using interpolation of the edge points. For the active contour path, according to the formulated energy function, the contours are directly extracted. All the contours obtained from the existing branches and active contour branch are merged into the same data storage as a pool of all the contours, i.e. sequences of contour point vectors. Finally, the polygon approximation continues with all of those contours and formulates the polygons.

The design of the parallel structure in the enhanced system maintains the strength of the existing system and further utilizes the capability of active contour. Thus, the contours of the undetected traffic signs with discontinuous boundaries can be extracted and detected as traffic signs. The parallel algorithm design also maintains the capability of processing large numbers of images without intermediate inputs, which makes the system ready for practice use.

2.3 Formulation of Region-Based Active Contour

Under the new formulation of the enhanced system, a new energy function is needed for the region-based active contour, which can be used to trace discontinuous boundaries but not add excessive contours that do not belong to the traffic sign. Based on these considerations, the new region-based active contour is formulated with a hybrid energy function consisting of three sub-energy components: location PDF energy, color segmented image energy, and global curve length. These sub-energy components are designed to force the active contour to trace the traffic sign boundary locally and to improve the initial guess and global termination in the general active contour method.

- Energy 1: Location PDF energy. The location PDF (Tsai et al, 2009) energy serves as an implicit, initial region guess of the active contour. It is formulated within the location PDF bitmap image. As shown in Figure 3, a location PDF bitmap generated from 1000 video-log images collected by the City of Nashville is used. The dotted squares indicate several random initial guesses, and the arrows indicate the contours' evolving directions. This energy controls the global evolvement of the contour moving towards the high-likelihood area of traffic sign's occurrence, defined by the location PDF.

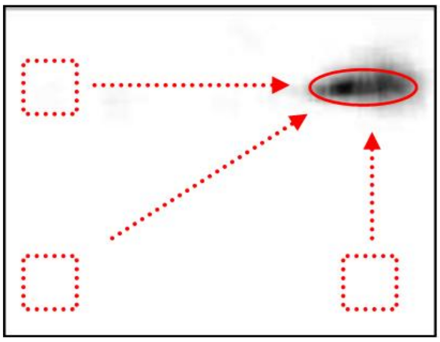


FIGURE 3 Contour Evolvement Forced by Location PDF Energy.

- Energy 2: Color segmented image energy. This energy serves as the basic region-based active contour energy. It is formulated over the color-segmented image input. As shown in Figure 4(a), after the global evolvement controlled by Energy 1, most of the time the contours have already been located at the upper right area of the images, where they will be most likely to occur. The circle indicates the contour developed following Energy 1. This energy controls the local evolvement of the contour along the traffic sign boundary. The energy will pull the contour towards the traffic sign boundary from the outside when the curve is out of the traffic sign region, and the energy will push the contour towards the traffic sign boundary from the inside when the curve is across or within the traffic sign region. Specially, shown in Figure 4(b), when there are two traffic signs sharing certain parts of the boundary, this energy will trace the gap of the boundary between the traffic signs and, from outside, pushes the curve to separate the two signs.

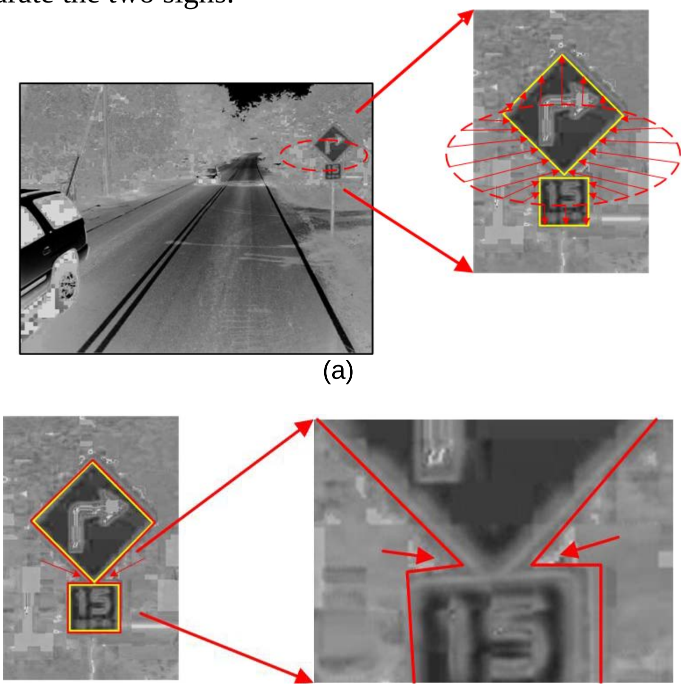


FIGURE 4 Contour Evolvement Forced by Color Segmented Image Energy.

- Energy 3: global curve length energy. The global curve length serves as a global iteration termination criterion. When the curve length is too long, this component becomes a dominant energy of the total energy, which prevents the contour from continuously evolving and blowing up, especially when the iteration number is set as a large one. Also, this energy could help to separate one big curve into several smaller ones when processing the compound traffic signs sharing the same boundary;

Each of the energy components is shown as below in Equation (1):

$$E = \lambda \cdot \left[\int_{R_{PDF}} (I_{PDF} - u_{PDF})^2 dA + \int_{R_{PDF}^c} (I_{PDF} - v_{PDF})^2 dA \right] + (1-\lambda) \cdot \left[\int_{R_{Original}} (I_{Original} - u_{Original})^2 dA + \int_{R_{Original}^c} (I_{Original} - v_{Original})^2 dA \right] + \mu \mid c \mid \quad \ldots\ldots\ldots\ldots\ldots\ldots \ (1)$$

where
$I_{Original}$ is the color segmented video-log images,
I_{PDF} is the location PDF bitmap;
λ is a scaling parameter to balance the two sub components, e.g. 0.15;
u and v are the average intensity inside of the contour and outside of the contour respectively. The suffix indicates the value is from the color segmented video-log image or the location PDF bitmap.

This approach can be implemented using the level set method; the energy function can be rewritten using Heaviside function H as

$$\begin{aligned} &E\left(u_{Original}, v_{Original}, u_{PDF}, v_{PDF}, \phi\right) \\ &= \lambda \cdot \left[\int_{R_{PDF}} \mid I_{PDF} - u_{PDF} \mid^2 H(\phi) dA + \int_{R_{PDF}^c} \mid I_{PDF} - v_{PDF} \mid^2 H(\phi) dA \right] \\ &+ (1-\lambda) \cdot \left[\int_{R_{Original}} \mid I_{Original} - u_{Original} \mid^2 H(\phi) dA + \int_{R_{Original}^c} \mid I_{Original} - v_{Original} \mid^2 H(\phi) dA \right] \\ &+ \mu \int_R \mid \nabla (H(\phi)) \mid \end{aligned} \quad \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

where
φ is the level set function;
H is the Heaviside function.
To minimize the energy function E with respect to $u_{Original}$, u_{PDF}, $v_{Original}$, v_{PDF} and φ, we need to solve the equations (3) and (4):

$$u_X = \frac{\int_{R_X} I_X H(\phi) dA}{\int_{R_X} H(\phi) dA} \quad v_X = \frac{\int_{R_X} I_X (1 - H(\phi)) dA}{\int_{R_X} (1 - H(\phi)) dA} \quad X = Original, PDF \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (3)$$

$$\begin{aligned} \frac{\partial \phi}{\partial t} &= \delta_\varepsilon(\phi)[-(1-\lambda) \mid I_{PDF} - u_{PDF} \mid^2 + (1-\lambda) \mid I_{PDF} - v_{PDF} \mid^2 \\ &- \lambda \mid I_{Original} - u_{Original} \mid^2 + \lambda \mid I_{Original} - v_{Original} \mid^2] + \mu div\left(\frac{\nabla \phi}{|\nabla \phi|}\right) = 0 \end{aligned} \quad \ldots\ldots\ldots\ldots\ldots\ldots \ (4)$$

where
$\delta_\varepsilon = H'_\varepsilon$, that H_ε is a C^1-approximation of H. These equations can then be implemented using standard finite difference (Ames 1977).

The feature of the location PDF provides extra information of the potential traffic sign occurrence location in the image plane, which can be used to guide the evolvement of the active contour. By formulating a hybrid energy function with the global information from the location PDF and the local information from the color-segmented video-log image, the moving trajectory of the contour evolvement follows the behavior even when the initial guess region is randomly selected:

- If the preset initial guess happens to be at the region with higher probability to find a traffic sign, the location PDF energy, defined above as Energy 1, component has less effect on the total energy, so the dominant component of the energy is shifted to the color segmented image energy, defined above as Energy 2. The contour will evolve locally to trace the traffic sign region's boundary, which behaves like the basic region-based active contour;
- If the preset initial guess happens to be at the region with a lower probability of finding a traffic sign, the location PDF related energy has a dominant decision that directs the contour moving towards the higher probability area, and the color segmented related energy will not affect the total energy much until the contour arrives at the region with high probability to find a traffic sign;
- Eventually, the global curve length energy, defined above as Energy 3, will contour the overall contour length and terminate the evolvement. According to the observation of a large set of video-log images, it is noticed that the coverage of a traffic sign in a video-log image is no more than ¼ of the image. Therefore a preferred length can be defined, e.g. 1200 pixels.

3. TESTS AND RESULTS

In this paper, three test results are presented. First, the robustness of the initial guesses is tested with different initial region guesses. Second, a number of undetected traffic signs with discontinuous boundaries are tested. Finally, a general performance test is performed after incorporating the region based active contour into the existing system. For the robustness test with different initial region guesses, 10 images are tested with 4 initial guesses each. For the performance test in processing traffic signs with discontinuous boundaries, a selected set of 26 images containing traffic signs that have discontinuous boundaries is prepared and tested. For the general performance test, 607 video-log images from a complete segment provided by the City of Nashville, with a resolution of 1300*1030, are used. In the 607 images, there are 474 negative images that do not contain traffic signs and 133 positive images that contain traffic signs with different sizes, colors, shapes, and conditions. In the 133 positive images, 7 images with discontinuity issues are from the 26 images used in the previous test.

3.1 Robustness test of different initial region guesses

In this test, 10 selected images are processed by the enhanced system. Each image is tested four times with different initial guess regions, i.e. four corners of the image. The initial guess region is set up as a 30*30 square pixels. A location PDF bitmap image generated from 1000 video-log images provided by the City of Nashville is used as another input. Figure 5 shows the bitmap pattern of the location PDF. The dark area indicates a high probability of traffic sign occurrence, while the bright area indicates the opposite. As mentioned in the energy formulation, the location PDF is derived using the actual sign location in the roadway video-log images. The four squares indicate four initial guesses for the designed region based active contour.

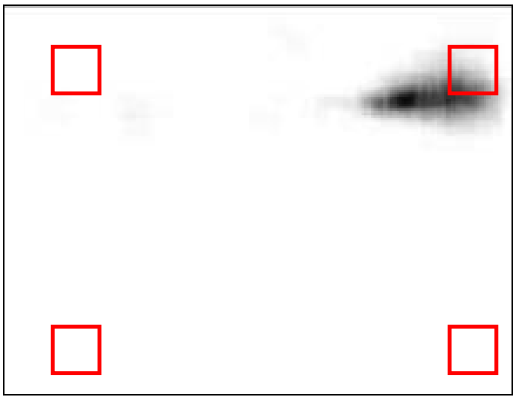


FIGURE 5 Location PDF Bitmap Image and Four Initial Guesses.

The results show that by following the energy decreasing direction proposed in Section 2, the contours converge to the same area, i.e. top-right of the image, and extract the traffic sign correctly, regardless of the different initial guesses. Figure 6 shows an example of the contour converging to the same location with different initial guess regions. It is observed that after the iterations, the initial guess contour region, which is the square, either on the upper left or on the bottom left, converges to the traffic sign region and finally traces the traffic sign boundary correctly.

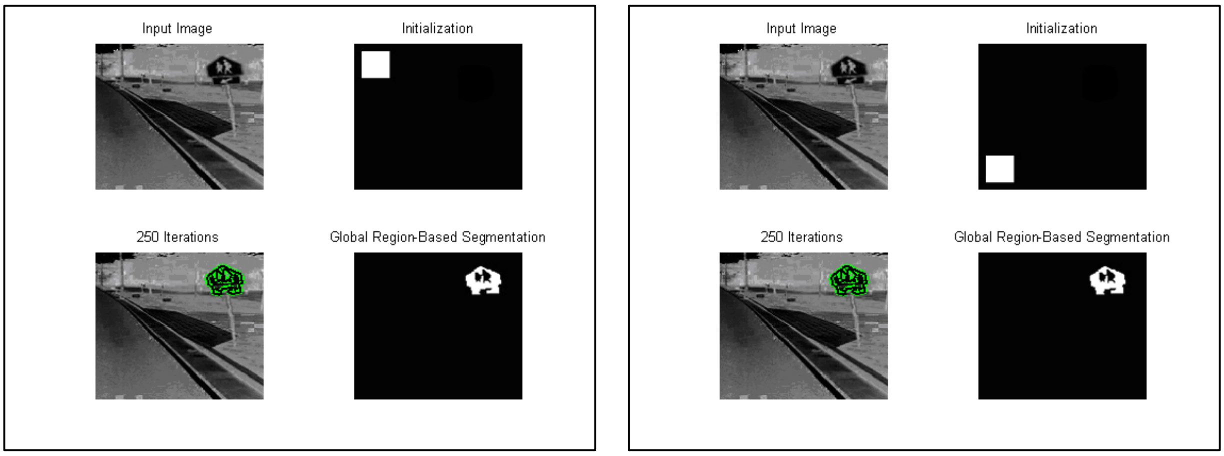


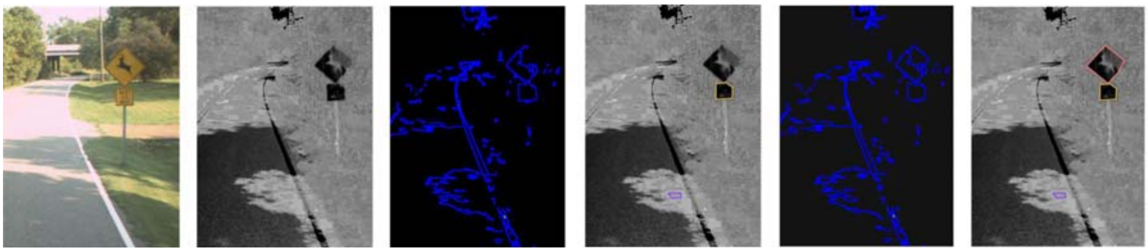
FIGURE 6 Result in Testing Robustness of Different Initial Guess Regions.

3.2 Discontinuity image detection

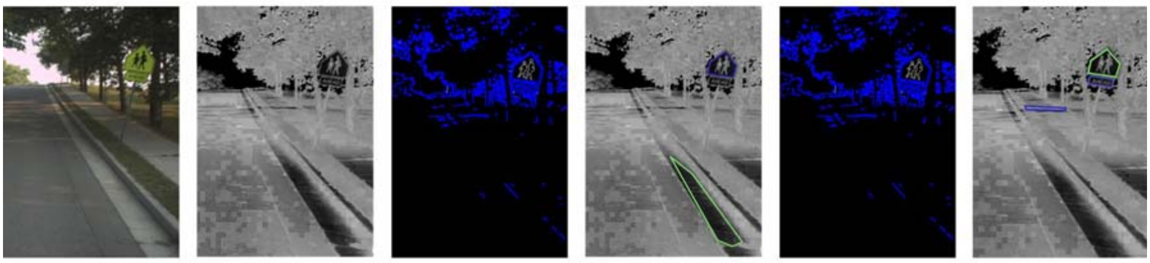
In this test, 26 selected images with discontinuity issues are tested. The 26 images are first processed by the existing system, and the results show that the existing system cannot correctly detect them, which causes false negatives. The enhanced system is applied. Of the images with traffic signs that have discontinuous boundaries, 24 out of 26 are correctly detected by the enhanced system. Figure 7 shows some of the results. It can be observed that the following discontinuity cases are successfully detected:

- Broken traffic signs due to the shadows or light glaring, shown in Figure 7(a). After color segmentation, the image is decomposed in different colors, shown in 7(a)-2, however, the upper right region of the deer sign (W11-3) is decomposed as a different color from the rest of the sign, which breaks the traffic sign region into two pieces, as well as the boundary. In 7(a)-3, it is shown that with the color segmentation results, the boundary of the deer sign is not completely extracted, which produces an undetected case shown in 7(a)-4. After applying the proposed active contour algorithm, the boundary is completely extracted with the shape of the diamond, shown in 7(a)-5, which helps to correctly detect this traffic sign, as shown in 7(a)-6;

- Compound traffic signs sharing the same boundary, as shown in Figure 7(b). After color segmentation ,the image is decomposed in different colors shown in 7(b)-2; however, there are two traffic sign in this image sharing the same boundary and the boundary does not clearly separate the two traffic signs which have an inconsistent intensity along the boundary. In 7(b)-3, it is show that due to the inconsistency intensity along the in-common boundary, the contours extracted do not close the boundary of both of the traffic sign; instead, only the upper school sign's contour is closed, while the lower "ahead" sign (W16-9p) has a non-close contour. Thus, as shown in 7(b)-4, only the school sign can be extracted, but the "ahead" sign is undetected. After applying the proposed active contour algorithm, the boundary is completely extracted for both of the traffic signs, shown in 7(b)-5; finally, both of the signs can be correctly detected shown in 7(b)-6.



(a)-1 (a)-2 (a)-3 (a)-4 (a)-5 (a)-6



(b)-1 (b)-2 (b)-3 (b)-4 (b)-5 (b)-6

FIGURE 7 Result Comparison of Images with Discontinuity Issues.

(From left to right, original image, color segmented image, extracted contour with existing algorithm, polygon detection result with existing algorithm, extracted contour with enhance algorithm, polygon detection result with enhanced algorithm)

The results show the enhanced system performs well in detecting traffic signs that have discontinuity issues. However, there are still some cases for which the enhanced system has challenges to handle. Figure 8 shows the 2 unhandled cases. In Figure 8(a), the original image has a similar foreground and background in the color space, which causes undistinguished color segmentation. When the region-based active contour is applied in that area, the contour region will blow up, as shown. An improvement in color segmentation might be needed for such cases.

Figure 8(b) shows that the region-based active contour basically locates the traffic sign boundary, except the upper portion. Instead of following the actual boundary, the contour kicks into part of the legend area. This occurs because, after the color segmentation, the upper portion of the boundary is decomposed as a different color from the rest of the boundary. Better color segmentation or a relaxed polygon approximation might resolve this issue.

(a) (b)

FIGURE 8 Undetected Images with Discontinuous Boundaries.

3.3 General performance and comparison

In this test, the 607 selected video-log images are separately processed from a complete road segment by the existing system and the enhanced system. The results are compared with the manually extracted ground truth, including both the Yes/No tag on each image and the exact traffic sign location. Table 1 shows the results.

TABLE 1 Overall Performance Comparison Table of 607 Images from City of Nashville

	True Positive	True Negative	False Positive	False Negative
Existing system	78.9% (105/133)*	88.8% (421/474)	11.2% (53/474)	21.1% (28/133)
Enhanced system	85.7% (114/133)	87.1% (413/474)	12.9% (61/474)	14.3% (19/133)

*Case Rate (Correct #/Total Case #)

The results show that the enhanced system demonstrates a superior performance over the existing system by providing a false negative rate of 14.3%, which is 6.8% lower than the previous one. Also, the false positive rate in the enhanced system is 12.9%, which is only 1.7% higher than the rate by the existing system. The results show that by improving the contour extraction using region-based active contour and incorporating this method into the existing system, the overall false negative rate produced by discontinuity issues are minimized without adding excessive false positives. All of the three experimental results have demonstrated that the enhanced system maintains the detection capability of the existing system and satisfactorily handles the discontinuity issues with the color-segmented image input. By incorporating the location PDF information, the new, proposed region-based active contour demonstrates robustness for different initial guess regions. In summary, the enhanced algorithm provides a promising sign detection capability.

4. CONCLUSTIONS AND RECOMMENDATIONS

In this paper, a new region-based active contour model is presented to enhance the existing automatic traffic sign detection system by improving contour extraction performance when the input color segmented images contain traffic signs with discontinuous boundary. The major contributions of this paper are as follows:

- Traffic signs with discontinuous boundaries can be detected by the new region-based active contour method. The test result shows that 24 out of 26 traffic signs with discontinuous boundaries that could not be detected previously are correctly detected;
- The location PDF information is implicitly embedded in the new region-based active contour energy function and demonstrates robustness in the contour initial guesses. The test results show that all of the contours converge to the traffic sign region regardless of different initial guesses.
- The new, region-based active contour algorithm is incorporated into the current traffic sign detection system. The enhanced system demonstrates a promising performance in traffic sign detection. The test results show that an overall 14.3% false negative rate is achieved by using the enhanced system compared with the 21.1% false negative rate by using the existing system. Also, the overall 14.3% false positive rate is achieved compared with a 12.9% false positive rate, which is only 1.7% more than the existing system.

In future work, the following studies on the PDE method, i.e. active contour, are recommended:

1. A complete performance test with a larger number of images is recommended so that an more comprehensive assessment of the whole system performance can be conducted;
2. Other robust initial region guesses can be explored and applied to the system, such as multiple initial guess regions, etc. Also, other global iteration termination criteria can be applied instead of the curve length used in this paper's enhancement, e.g. the area of the contour region, etc.
3. An enhanced color model is recommended for color segmentation, especially when the images contain the foreground traffic sign color and the background color that are visually undistinguishable;
4. A reliable polygon validation method is recommended to further reduce the extracted candidate traffic sign regions after polygon detection using other traffic sign features, e.g. validation of the legend shapes, etc., so that the false positive rate can be further reduced;
5. Multiple sensing technologies are recommended for incorporation into the system, so that some invisible features can be utilized, such as depth information by using LiDAR (Light Detection and Ranging), etc.

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