# Generic Sign Board Detection in Images 

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#### Abstract

Sign board detection is important for such computer vision applications as video surveillance and content based visual information retrieval. Previous researches on this topic focus mainly on application specific sign board such as car plates and traffic signs. Many special properties including special color, size, shape, and symmetry have to be used to detect these special sign boards. In this paper, we develop a system to detect generic sign board in an image or video. The only assumption we made is that the sign has to be a polygon formed by straight boundaries. Using a new set of straight line and polygon geometry analysis techniques, we can accurately locate a sign in a cluttered image efficiently. Experiments on over one hundred images clearly demonstrate the efficacy of the new algorithms.


## Categories and Subject Descriptors <br> I.4.8 [Scene Analysis]: Object recognition, Shape.

## General Terms

Algorithm, Design, Experimentation.

## Keywords

Hough transform, Image analysis, Line verification, Sign board detection.

## 1. INTRODUCTION

Sign board detection is important for such computer vision applications as video surveillance and content based visual information retrieval. Previous researches on this topic focus mainly on application specific sign board such as car plates and traffic signs [1-7]. Color segmentation, gradient analysis, and Hough transform are generally used [1-5]. Some papers also used neural network or symmetry transform [6-7]. However, these methods are all limited by some application specific conditions, such as the shape of the car plates and the color of traffic signs.

In this paper, we present a system that can detect generic signs. The signs can be any polygon, not necessarily restricted to traffic

[^0]signs or car plates. They can also be posters, name plates on doors, advertising board etc. The only assumption we made is that the sign has to be formed by straight boundaries. The system uses a gradient based Hough transform [8-10] to detect the boundary lines. We then develop a fast close circuit detection algorithm and a redundant line deletion technique to locate the sign board in the image. The algorithm is tested on over one hundred images.

## 2. PRE-PROCESSING

The pictures taken in outdoor environment are usually very cluttered. Fig. 1(a) shows such an example. So pre-processing is necessary to simplify the image before further processing. We propose three preprocessing steps for this purpose: edge detection, corner detection, and small segments deletion. For the first step, we use Canny edge detection algorithm. Figure 1 (b) shows the image after Canny edge detection.


Figure 1. Original image and edges.

After edge detection, there are usually a large number of edges in a natural image, as shown in Fig. 2 (a). The signs are assumed to have relatively straight long boundaries. Other natural objects on the background may have randomly oriented interconnecting segments or curves as shown in Fig. 2 (a). We use a corner detection algorithm [11] to detect all the corners in the edge map, and then remove the corner points to break the interconnecting long edges into small segments. Since the corners do not affect long straight lines, we can therefore remove all the short segments broken by the corner points, as shown in Fig. 2 (b). Now the number of edges are much smaller thus enable a faster processing in the following steps.

## 3. GRADIENT BASED HOUGH

## TRANSFORM

Hough transform is an often used method to detect straight lines in an image [12]. But the main disadvantage of Hough transform is the large time and memory consumption, which is an important issue we consider for this application. So we use a significantly faster gradient based Hough transform instead [13].


Figure 2. Illustration of cutting short segments.


Figure 3. Parameters d and $\theta$ in Hough.
For Hough transform, a line function passes through an edge point p is determined by an angle $\boldsymbol{\theta}$ and distance $d$ : $x \cos \theta+y \sin \theta=d$, as shown in Fig. 3. Hough transform specifies all possible angles $\boldsymbol{\theta}$ to the points, and calculates the corresponding distance $d$. By using an accumulator $A$ for all d and $\boldsymbol{\theta}$, the peaks in $A$ are the most probable lines in the image. As mentioned above, Hough transform is very time consuming. So we use gradient based Hough transform instead. Notice that points are most likely to be on the line that has the same gradient as the point itself. So each point is calculated only for one angle $\theta$ and one distance d according to the gradient of the point. Although this algorithm is sometimes not very accurate due to the gradient computation error, it is still often used because of the great amount of time it saves. For the standard Hough transform, we need to consider the range of $\boldsymbol{\theta}$ for $0^{\circ}-180^{\circ}$ and $270^{\circ}$ -
360. Suppose the angle quantization interval is $5^{\circ}$. Then there will be 270/5=54 angles for one point that we need to calculate the distance $d$. But if we use gradient information, we only need to calculate the distance once. The lines detected are shown in Fig. 4(b). The points in Fig. 4(a) are the edge points with the same gradient and distance as the lines in Fig. 4(b). They contribute to the peaks in the accumulator.

## 4. LINE VERIFICATION

After Hough transform, we get all the possible lines in the image. In order to find out the two ending points of each boundary segment, we compute the intersection points of all the lines first. Then the lines are cut into small segments by these intersections. And the corners of the signs should be among these intersections.


Figure 4. Lines detected and corresponding density points.

(a)
(b)

Figure 5. Intersection point that is occluded.


Figure 6. Lines before and after density checking.

If the segment is indeed the boundary, there should be many points with the same gradient and distance lying on that line. So we check the point's density on the segment then the segments with a density over a threshold are kept, and other segments are removed. For example, the points in Fig. 6(b) all belong to the segment in Fig. 6(a). Because of the high point density, this segment is kept as a boundary segment. Figure 6(c) shows the segments selected for lines in Fig. 4(b). The boundaries of the sign board are believed to be among these segments. Some more complicated results are shown in Fig. 7.


Figure 7. Line segment extraction results after checking point density.

### 4.1 Find Close Circuits

Now the candidate segments are found. We still need to decide which segments eventually form the boundaries of the sign. Since sign boundaries usually form a close circuit, we first detect all the close circuits among the line segments. Some of the segments may not be connected due to the noise, even though in fact they should be connected. So we first merge some intersections that are close enough. Examples of a set of closed segments are shown in Fig. 8(a).


Figure 8. Steps of finding closed circuit.

Depth-first search is a popular method to find closed circuits [14]. If we want to find out every possible closed circuits, depth-first search need to be used for every points. The method is too time consuming for our application.

We propose a fast algorithm that first only finds one closed circuit in a connected graph. Then, each path with its two ends connected to that circuit is treated as an additional part of that closed circuit.

Repeat the process until the entire closed circuit is found. Using the example in Fig. 8(a), we illustrate the algorithm as follows.

First, delete the points with only one segment connected to it, like point 9 in Fig. 8(a). "Delete" here means delete the point and all the segments that end at this point. Double check until every point is connected with more than 1 segment.

Starting from the smallest number point (1) to find the first loop starts and ends at it. Number the loop as loop No.1, as shown by the dotted segments in Fig. 8(b). Put the loop's points $(1,4,8)$ into a point set $P$. Put the path's segments (1-4, 4-8, 8-1) into a segment set S .
Then, try to find a path that starts and ends at the points in P , but the segments cannot be the ones in S . For example, path $1-5-8$ satisfies this condition. Because its two ends 1 and 8 all belong to loop No.1, the path $1-5-8$ also belong to path No.1, as shown by dotted segments in Fig. 8(c). Put the corresponding points (5) and segments (1-5, 5-8) into P and S .

Find every possible segment that can be added to the closed circuit No.1. Then start from the smallest point that is not in S. In this case, it is point (2). Again, try to find a closed loop. In the example, the loop is shown in bold dotted segments in Fig. 8(d). Because it is independent of loop No.1, number it as loop No.2. Also, put the points ( $2,3,6,7$ ) into P and segments (2-3, 3-6, 6-7, 7-2) into $S$.

For the new points in P , we can find a path (7-8) that starts and ends at the points in P. But points 7 and 8 belong to different loop (No. 1 and No.2). So we combine loop No. 2 into loop No. 1. Thus the loop No. 1 becomes Fig. 8(e). Continue until all the points are checked. The final result is shown in Fig. 8(f).


Figure 9. Examples of finding closed circuit.

The segment (7-8) seems redundant in Fig. 8. However, it should not be removed in the searching process. Because removing this type of segments may cause losing some loops, as shown by the example in Fig. 9. The dotted segments in Fig. 9(b) are the closed
loops we found. If we delete the path that ends at different loops, the path (3-9-6) will be removed, and the result would become Fig. 9 (f). That is definitely not the result we want. If those paths are kept, the result will be Fig. 9 (c). All the possible closed circuits are included in Fig. 9 (c), though there are some redundant segments. These redundant lines can be removed after the close circuit detection step. Some image results are shown by dotted segments in Fig. 10(a) \& (b).


Figure 10. Results of close circuits detection.

## 5. REMOVE REDUDANT LINES

Although the closed loops are detected, there exist some redundant segments, like segment 7-8 in Fig. 8(f). Some typical redundant segments are shown in Fig. 11. The middle line in (a), the smaller rectangle in (b), and the connecting segment in (c), are segments that should be removed. We design a fast algorithm to remove these lines.


Figure 11. Three examples of redundant segments.

The algorithm tries to color the background pixels that surround the outer most close circuit. Then the line pixels with these colored pixels around are the pixels we want. "Colored" means the value of the point is set to 2 in the following example. The searching order is from left to right, and top to bottom. We use the image in Fig. 11(a) as an example to illustrate algorithm.
2. Find the neighbors of the line points. That is to expand the lines using a $3 \times 3$ zero kernel. The result is D in Fig. 12(b).
3. In the line's neighborhood points, find the first uncolored background pixel in C. That means $C(x, y)=1$ and $\mathrm{D}(\mathrm{x}, \mathrm{y})=0$. Color it into 2 . In the example, this pixel is at point $(5,5)$, which is bracketed in Fig. 12(a)(b).
4. Color the background pixels in the neighbor area with point $(5,5)$. Scan the pixels to its right side and on the same row until we find a pixel which do not satisfy the following conditions: $C(m, n)=1 \& D(m, n)=0$. Color all these pixels into 2 . Then the same coloring procedure is used for the left, up, and down directions of pixel $(5,5)$. Then D is shown in Fig. 12(c).

(a)

(b)

1. Assume the line points are 0 , the backgrounds are 1 . Then the original image is shown as matrix C in Fig. 12(a).


## Figure 12. Illustrations of removing redundant segments.

5. Find the next non-colored pixel ( $\mathrm{x}, \mathrm{y}$ ) at the line neighbor. In addition, it should satisfy the condition that at least one of its 4neighbours is colored. Such pixel is bracketed, as shown in Fig.

12(c). If no such pixel is found, go to step 6. Otherwise, go to step 4.
6. Now, D becomes the matrix in Fig. 12(d). Check for the line pixels $(C(x, y)=0)$. If the colors of all its neighbors are the same in D , then this pixel is redundant, and need to be removed. The final result is shown in Fig. 12(e).

Thus, we can remove the redundant lines successfully. Figure 13 shows the result for Fig. 11. An image example is shown in Fig. 10(c).

This method can identify the redundant lines efficiently. The neighbors of the inner segments (Fig. 11(a,b)) are all 0 . The neighbors of the connecting segments (Fig. 11(c)) are all 2 or 0. And the neighbors of the pixels on the lines that we really want are 1 and 2 . Also, this method is very fast. Because only the neighbors of the line points are considered.


Figure 13. Results of Fig. 11 with redundant segments are removed.

## 6. EXPERIMENTS

In the experiment, we test the system on 104 images. The results are listed in Table 1. The successful rate is over $93 \%$. Some detection results are shown by dotted segments in Fig. 14. The background is quite cluttered. The signs are correctly detected. In addition, the algorithm can also detect a sign that is covered partly, as shown in Fig. 15. Of course, the covered part should not be too large.

Table 1. Performance of the system.

| Total images | Success | Fail | Success Ratio |
| :---: | :---: | :---: | :---: |
| 104 | 97 | 7 | $93.3 \%$ |

The reasons that cause the failure are listed below. It is possible that more than one of these reasons may cause a failure:

- The boundaries are too blurry. Thus it fails at the edge detection step.
- The boundaries are cut into segments thus can't create a peak in the accumulator. Then the boundary segments are removed at the pre-processing step.
- Gradient error that causes the distances of the boundary vary greatly thus cannot create a peak cell in the accumulator.


Figure 14. Some example results.


Figure 15. Signs with corners covered in the image.

## 7. CONCLUSION

In this paper, we present a method to detect sign boards in image and video. The sign can be any polygon shape, and is not limited to rectangles or triangles. In our system, gradient based Hough transform is used. After the Hough transform, we compute all the line segments candidates by checking the point density of each segment. Then using a fast closed circuit detection algorithm and an efficient redundant line deletion method, the signs can be correctly detected. Experimental results on over one hundred images demonstrate the efficacy of the algorithm. In the future study, we intend to add texture information to the system. Since texture right inside the sign boundary tend to be smooth.

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