■ 論 文 ■

New Method for Vehicle Detection Using Hough Transform

HOUGH 변환을 이용한 차량 검지 기술 개발을 위한 모형

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목 차

요 약

차량대수, 속도, 대기행렬길이, 정체 및 유고 검지 등의 실시간 교통 정보를 얻기 위하여 현재 영상처리기술(Image Processing technique)이 기존의 루프검지기(Loop Detector)가 갖는 여러 단점들을 보완하는 효과적인 대체검지기로 널리 인식되고있다. 그러나 현재 사용되는 대부분의 영상검지기는 아주 작은 영역에서의 흑백 강도값(gray level)를 사용하며, 따라서 검지기의 정확도는 취급하는 영상의 화질에 크게 영향을 받을 뿐만 아니라 3차원 실제 공간이 2차원 영상평면으로 표출되므로 생기는 透視射影(perspective projection)문제에 효과적으로 대처할 수 없다. 이런 문제 때문에 현재 영상검지기는 가능한 한 높게 그리고 도로면에 수직으로 카메라를 설치하여 가능한 한 평면화 된 2차원의 영상을 얻어 처리한다. 그러나 이는 한대의 검지기가 포함할 수 있는 영역이 매우 작을 뿐만 아니라, 가능한 한 카메라를 높게 설치해야 하므로 현실적으로 많은 어려움이 따른다.

본 연구에서는 카메라의 설치 위치 또는 각도에 따라 인식율의 정확도에 큰 차이를 보이는 기존의 알고리즘에서 탈피하여, 낮은 위치에 설치할 때 나타나는 透視射影 문제 및 물체 영상의 일부가 가려져 다음 물체의 인식이 곤란한 문제 등을 해결하기 위한 새로운 방법을 제시하였다. 본 연구에서 제시된 방법은 차량의 검지뿐만 아니라, 차량의 위치, 3차원 공간에서의 차량의 관계 등에 관한 정보를 얻을 수 있으며, 사용된 알고리즘은 3차원 공간에서의 물체 인식에 우수한 확장된 Hough Transform에 기초하고 있다.

Ⅰ. Introduction

Traffic data information is essential in the transportation engineering, management and planning areas. Although a wide range of data collection systems exist, there is increasing research on image processing for automatic traffic data collection in Europe, Japan, and the USA, because of the fact that, potentially, image processing is more powerful and flexible than methods currently available, such as buried magnetic loops.

Until recently, many image processing systems have been developed for collecting traffic parameters. Systems for collecting microscopic data, such as traffic counts, speed measurement, and vehicle tracking, are TRIP (Dickinson and Waterfall, 1984a, 1984b ; Ashworth *et al.*, 1986), TULIP (Rourke and Bell, 1988), VDDAS (Dods, 1984), CCATS (Versavel *et al.*, 1989) and Autoscope (Michalopoulos, 1991). For macroscopic traffic parameters, such as congestion monitoring or incident detection, there are IMPACTS (Hoose, 1990), TITAN (Blosseville *et al.*, 1989), FAST_Q (Rourke and Bell, 1991). Hoose (1991) has described many of the image processing systems in traffic engineering.

Even though there is growing interest about image processing, detection algorithms are still unreliable in the certain circumstances, and need to be developed further. most of the current image processing systems for vehicle detection process a small subset (tens or hundreds) of the pixels in the digital image in order to achieve high speed processing, and are based on the frame differencing methods. frame differencing methods, Background frame differencing and Inter frame differencing, are also based on image segmentation by the subtraction of two time different frames((see Hoose, 1991). By taking the absolute difference between two frames, on a pixel-by-pixel basis, the regions of the scene in which a change has occurred are heightened and contextual information can then be used to identify those areas that correspond to vehicles. All of these methods have problems in dealing with physical constraints of the image, such as illumination, contrast, types of vehicles, occlusion and perspective.

This paper propose a new method to detect vehicles, finding straight lines of the vehicles by Hough Transform which is based on edge information. Radford(1989) has used the Hough Transform method to detect vehicles outside of the Laboratory. His method was to detect arc/circle features which are presented by vehicle wheels and wheel-arches using Hough Transform. However, this method is restricted to only side views of vehicle. Also, his method cannot deal with occlusion. The application of the new algorithm proposed in this research will be used for vehicle and vacancy detection in a car park.

Ⅱ. Hough Transform

The Hough Transform is a useful tool for establishing meaningful groups of feature points. It was first proposed as a method for detecting and identifying straight lines by Hough and has been extended to other types of curves, including cycles, parabolas, ellipses and generalized shapes (Ballard, 1981 ; Duda and Hart, 1972 ; Hunt *et al.*, 1990). It has, recently, been applied for shape description and recognition of three-dimensional objects (Wahl, 1988; Tsui and Chan, 1989; Nitzan, 1988) and vehicle detection (Radford, 1989; Kim, 1994). One of the major reasons for applying the Hough Transform for 3-dimensional object recognition is that straight lines and other simple shapes occur in most natural and man-made scenes.

The basic concept of the Hough Transform is a mathematical mapping from the object space into a parameter space. The peaks on the Hough domain, are parameter combinations which are consistent with edge data, and the structural array of peaks expresses the presence of the shape with corresponding parameters.

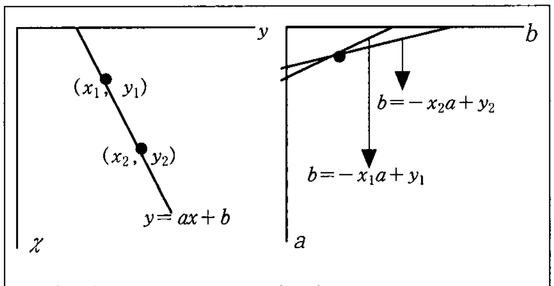
A set of image points (x, y) which lie on a straight line can be defined by a relation,

$$f(x, y) = y - ax - b = 0 \tag{1}$$

where a and b are two parameters, namely the slope and intercept respectively, which characterize the line. Eq.(1) maps each value of parameter combination (a, b) to a set of image points. The mapping of image points to parameter space is given by

$$g(a, b) = b - xa - y = 0 \tag{2}$$

Points which are collinear in image space all intersect at a common point in parameter space and the co-ordinates of this parameter point characterizes the straight line connecting the image points 〈Figure 1〉. The Hough Transform identifies these points of intersection in parameter space.



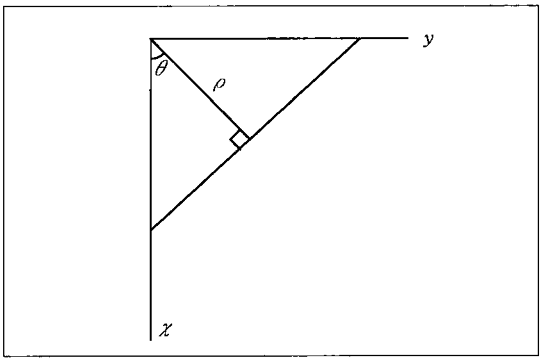
(1-1) Image plane (1-2) Parameter space

〈Figure 1〉 Basis of the Hough Transform for line detection

A problem with using the form of Eq. (1) and Eq. (2) to represent a line is that the value of a tends to infinity as the line approaches the vertical. To solve this problem, Duda and Hart (1972) proposed an alternative representation based on the length and angle of the normal to the line from the origin of the feature space. The equation of a straight line is given by

$$\rho = x\cos\theta + y\sin\theta \tag{3}$$

where ρ is the perpendicular distance from the origin to the line, and θ is the angle the perpendicular makes with the x-axis 〈Figure 2〉.

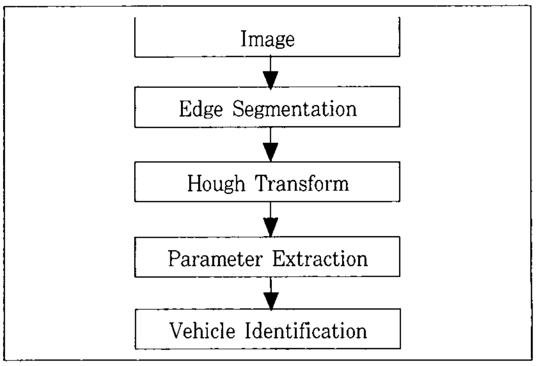


〈Figure 2〉 Normal representation of a line for Hough Transform

One of the main characteristics of the Hough Transform is that it consists of a series of fairly simple calculations carried out independently on every feature in an image. As a result, the implementation of the Hough Transform needs much computing time. In this research, a new algorithm, which is proposed by Franc(1993) for its implementation on parallel architecture, SIMPATI II, to save computing time, is used.

Ⅲ. Vehicle Detection Using Hough Transform

The Procedure of this research to detect a vehicle in the image is as follows:



〈Figure 2〉 Procedure Flow for Vehicle Identification

1. Edge Segmentation

An edge, which is the boundary between two regions with relatively distinct gray level properties, is very important to both biological and computer vision systems. The edges of objects within an image characterize significant attributes which can be utilized in feature extraction, and provide strong visual clues that can help the recognition process.

The basic idea of most edge detection methods is the computation of local derivatives. The magnitude of the first derivative can be used to detect the presence of the edge, while the sign of the second derivative can be used to determine whether an edge pixel lies on the background or object side of an edge.

For a function $f(\chi, y)$, the gradient of $f(\ )$ is defined as the vector

$$\nabla f(x,y) = \begin{bmatrix} \partial f/\partial x \\ \partial f/\partial y \end{bmatrix} \tag{4}$$

The magnitude of this vector and gradient direction, α, can be expressed respectively as

$$|\nabla f(x,y)| = \sqrt{(\partial f/\partial x)^2 + (\partial f/\partial y)^2} \tag{5}$$

$$\alpha(x,y) = \tan^{-1}\left(\frac{(\partial f/\partial y)}{(\partial f/\partial x)}\right) \tag{6}$$

where the angle α is measured with respect to the χ axis. For computation, the Eq. (4) can be approximated by

$$|\nabla f(\mathrm{x},\mathrm{y})| \cong |\nabla_x f(x,y)| + |\nabla_y f(x,y)| \tag{7}$$

There are many different types of differential operators, such as the *Roberts, Prewitt, Kirsch,* and *Sobel operators.* (Faugeras, 1983), of which the Sobel edge operator is the most popular operator since it possesses noise immunity (Pal and Pal, 1993). The Sobel operator has the advantages of providing both a differencing and a smoothing effect (Gonzalez and Woods, 1992). The derivatives based on the Sobel operator are

$$\begin{aligned}
&\nabla_x f(x,y) \\
&\quad = \{f(x+2,y) + 2f(x+2,y+1) + f(x+2,y+2)\} \\
&\qquad - \{f(x,y) + 2f(x,y+1) + f(x,y+2)\}, \text{ and} \\
&\nabla_y f(x,y) \\
&\quad = \{f(x,y+2),y) + 2f(x+1,y+2) + f(x+2,y+2)\} \\
&\qquad - \{f(x,y) + 2f(x+1,y) + f(x,+2,y)\}
\end{aligned} \tag{8}$$

where f (χ, y) is the gray level of each pixel.

The output of the first derivatives across the edge tends to be bell-shaped or flat. As a result, the edges located may be several pixels wide. In order to achieve a good single-pixel-wide edge, many edge detection algorithms have been proposed (Canny, 1986 ; Castan, 1992).

Canny (1986) established three properties of a good edge detector : i) low probability of wrongly marking non-edge points and low probability of failing to mark real edge point (i.e. good detection) ; ii) points marked as edges should be as close as possible to the center of true edges (i.e. good localization) ; and iii) only one response to a single edge point. These three criteria were also used by Castan(1992), to extend the design of optimal filters. He proposed the optimal linear filter based on the one step model and multi- edge model. His method is used for edge segmen- tation in this research.

2. Parameter Extraction and Vehicle Identification

An object which is mapped on the parameter space will be characterized by the peaks according to the attributes of edges like shape, length and position on the image. From the parameter extraction of the object on the Hough Space, we may find some attributes which are structural relationship of vertices, the value and position of peaks. Whale(1988) proposed following properties on the Hough Space to derive polyhedral objects.

- A cluster in Hough Space corresponding to a line or a set of collinear lines in image space. This corresponds to one or more edges in the 3-dimensional scene.
- Parallel edges in 3-dimensional scene correspond to parallel lines in image space and vertically aligned clusters in Hough Space.
- *n* Collinear clusters in Hough Space ($n \geq 3$) correspond to *n* lines intersecting each other at one location in image space or to a vertex of order *n* in 3-dimensional space.
- *n* Collinearities sharing one cluster correspond to one line intersection by at least two lines at n different locations in image space or to *n* collinear vertices in 3-dimensional space. The edges corresponding to the common cluster are called super-edges for $n \geq 3$.

In addition to the above, two more properties, which can be deduced from the parameter space, are proposed in this research as following.

- The value of the peaks on the Hough Space express edge length attribute. The accumulation array indicates how many edge points in the image actually lie on a given line.
- Objective position on the image can be deduced from Hough Space. On the Hough Space, each point of the edge is mapped with its own slope and distance from the origin.

As a result, there are parameter characteristics which correspond to vehicles, and so vehicles from the background image can be detected by the parameters which are extracted. The following properties are proposed for vehicle detection on the traffic image in this research.

- The detection edge image of a vehicle will have a certain shape in the Hough Space which consists of a particular configuration of peaks on the Hough Space.
- The value of peak points on the Hough Space, which are mapped from the vehicle image will depend on:
  - The vehicle location with respect to the camera position
  - The number of vehicles
  - Whether there is occlusion or not from the other objects
  - The classification of the vehicles.
- Each edge of the vehicle image is mapped with certain slop (θ) and distance (ρ) from the origin on the parameter space.

We have some information on the vehicle size appropriate for each classification, so the variation of peak value may can be deduced by camera calibration.

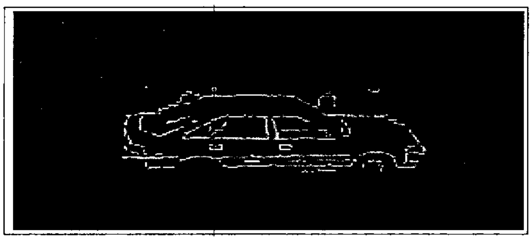
Ⅳ. Experimental Results and Discussion

The sample data for this research is a 512 by 512 pixel image for a vehicle. 〈Figure 4〉 shows edge image of a vehicle. 〈Figure 5〉 shows the Hough network from the vehicle. Each strong node represent the existence of a large number of collinear points in the image space. A straight line is a number of collinear points. It is difficult to get Wahls third and forth properties in the image data of the real world. They do not appear on the sample image data of this research, that is because some edges of vehicle like bumper, window appear as a circle line. However, we can deduce the presence of a vehicle from the restricted network form. For example, if there is another vehicle behind the same vehicle image, there will be two more parallel edges which correspond to vertically aligned cluster in Hough Space with $\theta \cong 0$. As well, there will be other points which are aligned vertically with first vehicle image. This kind of information could make it possible to obtain any information on the vehicle occurrence and its position in real world coordinate. Moreover, if we have the positional information of each vehicle exactly frame to frame and time slice of each frame, the speed information of each vehicle can be determined easily.

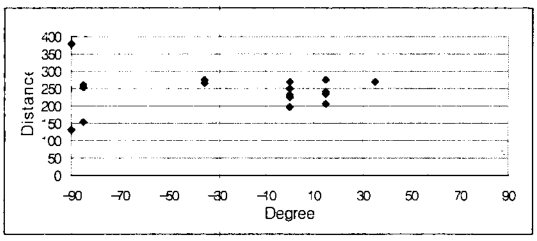
The peak point attribute in the Hough Space is given in the 〈Table 1〉. As can be seen in the 〈Table 1〉, the strongest edge is the horizontal line of the vehicle.

〈Table 1〉 Attribute of peak points on the Hough Space

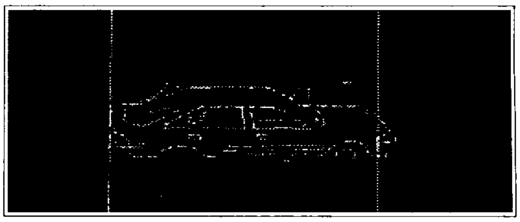
Degree(θ)	Distance(ρ)	Peak Point Value	Figure
-90	130	3559	6-1
	379	2966	
-90 ~ -80	253	4388	6-2
	154	4212	
	259	4436	
-40 ~ -30	265	3652	6-3
	275	4289	
-5 ~ +5	230	17399	6-4
	226	18554	
	251	13762	
	270	21314	
	197	16187	
+10 ~ +20	235	7772	6-5
	242	6538	
	205	9497	
	276	6521	
+30 ~ +40	269	5060	6-6
+50 ~ +60	270	3131	6-7



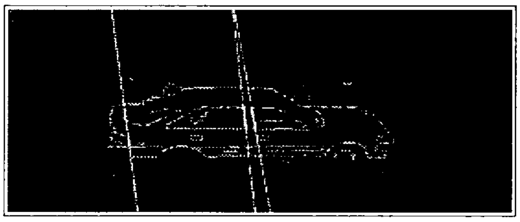
〈Figure 4〉 Vehicle edge image



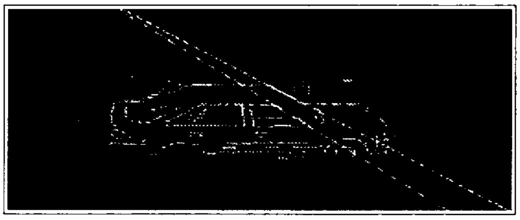
〈Figure 5〉 Hough Net image from the vehicle



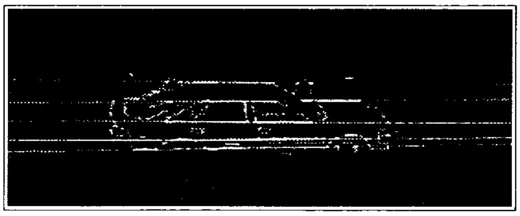
(6-1)



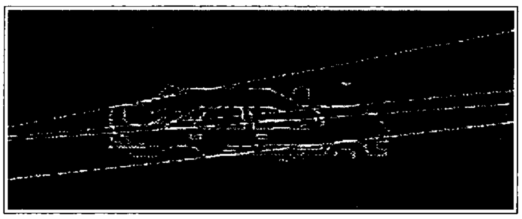
(6-2)



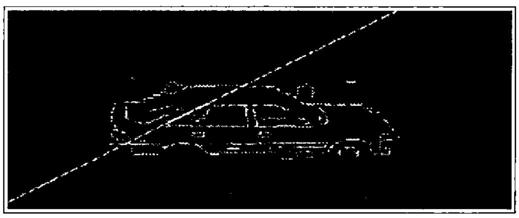
(6-3)



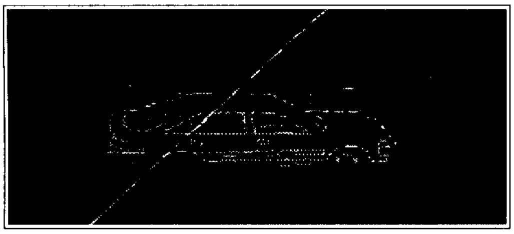
(6-4)



(6-5)



(6-6)



(6-7)

〈Figure 6〉 Strong edge on the Hough Space according to degree from 90° to 0° (6-1 ~ 6-7)

V. Conclusion

This paper has described a new method for vehicle detection in a car park using the Hough Transform. The vehicles in the image could be detected with information on peak points on the Hough Space. The method described in this paper has the potential to overcome some of shortcomings of the method which is currently used. It has the potential to be more efficient where the image is noisy and where there are occlusions and perspective problems.

Even though, an image with only one vehicle has been used in this research, the method could be extended to more complicated images with lots of vehicles and other objects. In addition, this method could be used as a new algorithm for queue detection for traffic control as well as vehicle detection.

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