2003 International Symposium on Advanced Intelligent Systems
September 25-28, 2003, Jeju, Korea

Real Time Multiple Vehicle Detection Using Neural Network with Local Orientation Coding and PCA

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***Abstract* - In this paper, we present a robust method for detecting other vehicles from a forward-looking CCD camera in a moving vehicle. This system uses edge and shape information to detect other vehicles. The algorithm consists of three steps: lane detection, vehicle candidate generation, and vehicle verification. First, after detecting a lane from the template matching method, we divide the road into three parts: left lane, front lane, and right lane. Second, we set the region of interest (ROI) using the lane position information and extract a vehicle candidate from the ROI. Third, we use local orientation coding (LOC) edge image of the vehicle candidate as input to a pretrained neural network for vehicle recognition. Experimental results from highway scenes show the robustness and effectiveness of this method.**

I. INTRODUCTION

In developing driver assistance systems, to recognize the road environment around the host vehicle is essential. Specifically, the recognition of preceding vehicles is fundamental. To detect vehicles on the road, a laser radar system and a vision-based system are mainly used.

The vehicle recognition system incorporating laser radar has been reported [1]. However, the radar system cannot recognize the exact lane the preceding vehicle is traveling in, because the radar is able to detect only the distance between the host vehicle and the preceding vehicle. On the other hand, a vision-based system [2], [3] and [4], can detect not only the preceding vehicle but also the lane information on the road.

In the vision-based system, almost every vehicle detection system follows two steps to recognize a vehicle on the road image: "Candidate Generation," and "Candidate Verification." In the Candidate Generation step, the vehicle candidates are found by scanning with the classifiers [2] or using the edge histogram [5], [6]. However, scanning the whole region of the image takes a long time, and constructing the edge histogram is only effective when the surroundings of the vehicle are simple (problem 1). In the candidate verification step, most vehicle detection systems use edge or symmetry information of a vehicle [4] [5] [6]. However, there are many symmetric objects having rectangular edge image on the road (problem 2).

To solve problem 1, we use the localization of the vehicle shadow or tires on the road because most vehicles on the road have a dark shadow between the bottom of the vehicle and the road. So we set the ROI on the basis of a vehicle shadow position. After setting the ROI, we extract Vehicle Candidate from ROI using an LOC edge histogram [5].

To distinguish a vehicle from a Vehicle Candidate, we construct the "Eigen Vehicles" and represent each Vehicle Candidate as a linear combination of the Eigen Vehicles [3]. Using the coefficients of the Eigen Vehicle, we are able to formulate the feature vector of the Vehicle Candidate. Because these feature vectors express the texture information of the vehicle, we can solve problem 2. The whole process is shown in Figure 1.

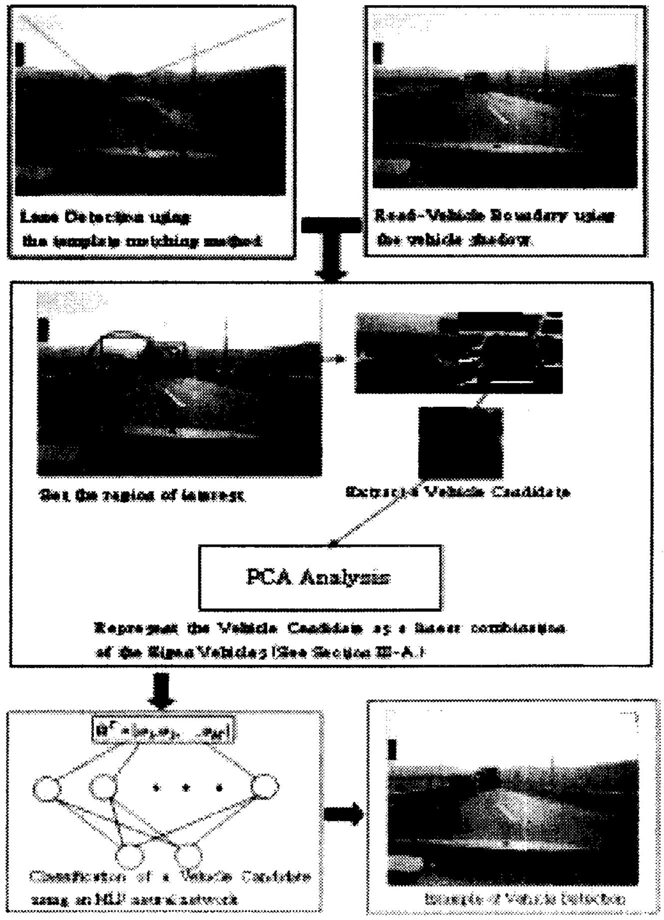


Figure 1. Flow chart of the proposed vehicle detection method

II. VEHICLE CANDIDATE GENERATION

Every vehicle on the road normally lies between lanes except a lane changing vehicle, and all vehicles have a dark shadow between the bottom of the vehicle and the road. So we set the ROI to locate a vehicle on the basis of the position of a vehicle shadow and lane width. This enables us to save processing time.

A. Lane Detection

Our lane recognition method uses lane features that distinguish the lane from the road, for example, prescribed lane width and color. First, lane candidates are extracted from template matching and the resulting correlation error [7]. Second, final lane models are confirmed in line models that acquire a high score among lane candidates [8]. And the ROI for next lane recognition is set up as the neighboring area of final lane model.

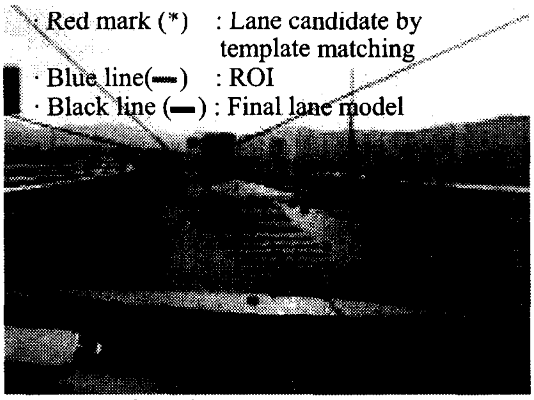


Figure 2. Lane detection

B. Boundary Detection between the Vehicle and the Road

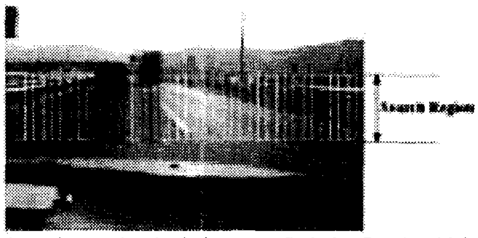
In this paper, we set the search region scheme ranging from a 90 pixel position to a 160 pixel position in vertical direction and divide the search region into forty equal subwindows. The height of each subwindow is 70 pixels and the width is 8 pixels. After dividing the image into small subwindows, we build an intensity histogram of the subwindow in vertical direction and find the point where the intensity level drops rapidly. We define these boundaries between the road and the vehicle as "the Road-Vehicle Boundary." (See figure 2)

C. Setting of ROI

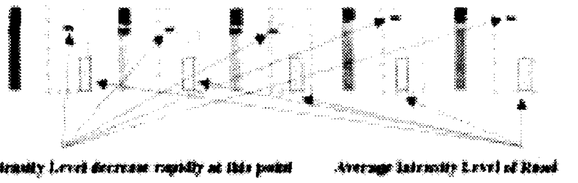
As previously mentioned, we divide the road into three regions: left lane, center lane, and right lane. Secondly, we calculate the average position of Road-Vehicle Boundary belonging to each region. Finally, we obtain the lane width at the average point of Road-Vehicle Boundary and set ROI which has a square form. Its length is equal to the lane width at average point of the Road-Car Boundary (See figure 3).

D. Edge Detection in ROI

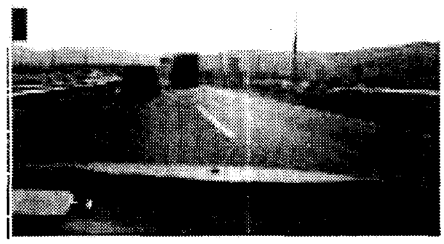
We use the LOC method ([5]) to construct an edge image of the road. The LOC method uses a predefined coefficient matrix and equation (1), to represent the directional intensity level variation in the pixel's neighborhood.



(a) Set the search region and subwindows to find the Road-Vehicle boundary

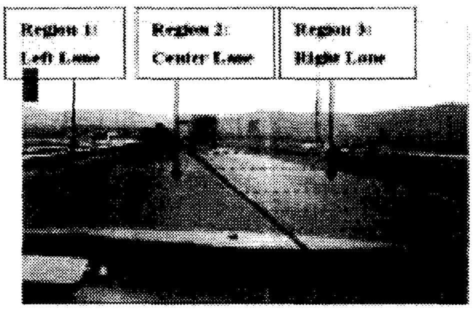


(b) Find the Road-Vehicle Boundary from an intensity histogram of the subwindows

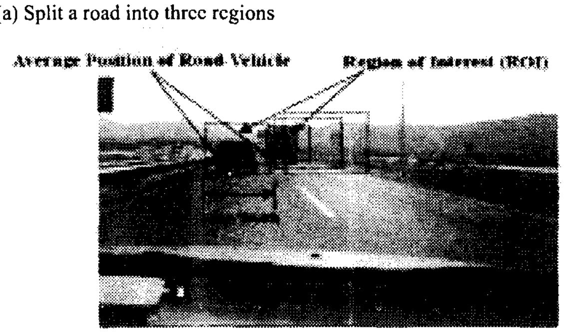


(c) Result of finding the Road-Vehicle Boundary

Figure 3. Boundary detection in a search window using an intensity histogram



(a) Split a road into three regions

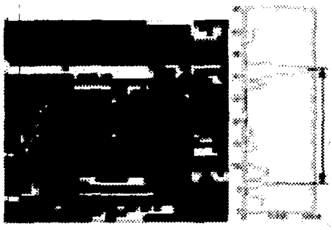


(b) Setting of the ROI

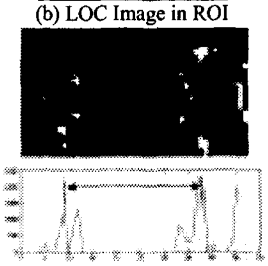
Figure 4. Setting of the ROI

(a) Original Image in ROI

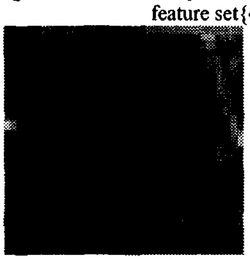
(b) LOC Image in ROI



(c) Horizontal direction of LOC components and histogram of feature set{7, 224}



(d)Vertical direction of LOC components and histogram of feature set{41, 148}



(e) Extraction of a Vehicle Candidate from ROI

Figure 5. Extraction of a Vehicle Candidate from ROI

In a formal fashion the operation is defined as

$$b'(n,m) = \sum_{i,j \in I} k(i,j) \cdot u(b(n,m) - b(n+i, m+j) - t) \tag{1}$$

where $b(n,m)$ denotes the gray-scale input image, $b'(n,m)$ the output representation, $k(i,j)$, a coefficient of the neighborhood matrix, t (= 10) a threshold value, I a neighborhood (usually N_4 or N_8), and $u(\cdot)$ the unit step function.

$$\begin{bmatrix} 0 & 1 & 0 \\ 2 & R & 4 \\ 0 & 8 & 0 \end{bmatrix} = \textit{neighborhood matrix for } N_4$$

$$\begin{bmatrix} 1 & 2 & 4 \\ 8 & R & 16 \\ 32 & 64 & 128 \end{bmatrix} = \textit{neighborhood matrix for } N_8$$

where, R is the reference position.

We apply the LOC with N_8 neighborhood matrix to the road image. The output of the LOC has a value from 0 to 255. In LOC output values, 7 and 224 represent the horizontal direction edge components, and 41, 148 represent the vertical direction edge components. So, we make a histogram of feature set {7, 224} and estimate the upper and bottom boundary of the vehicle (see figure 4(c)). In the same manner, we estimate the left and right boundary of the vehicle from the histogram of the feature set {41, 148} (see figure 4 (d)).

We extract the inside of the boundary from the ROI, and resample it to a 32 x 32 size image. It is defined as a "Vehicle Candidate."

III. VEHICLE CANDIDATE VERIFICATION

In vehicle detection system, verifying a Vehicle Candidate is essentially a two-class pattern classification problem: vehicle vs. non-vehicle. To distinguish a vehicle from the Vehicle Candidates, we represent Vehicle Candidates as a linear combination of the Eigen Vehicles.

A. The Eigen Vehicle

If the size of Vehicle Candidate is $N \times N$, then a $N^2 \times 1$ feature vector is formed from the Vehicle Candidate by raster-scanning of the pixels. Let the training set of vehicle feature vector be $\mathbf{\Gamma}_1, \mathbf{\Gamma}_2, \cdots, \mathbf{\Gamma}_M$. We then calculate the covariance matrix.

$$\mathbf{C} = \frac{1}{M} \sum_{n=1}^{M} (\mathbf{\Gamma}_n - \mathbf{\Psi})(\mathbf{\Gamma}_n - \mathbf{\Psi})^T \quad \textit{where} \quad \mathbf{\Psi} = \frac{1}{M} \sum_{n=1}^{M} \mathbf{\Gamma}_n \tag{2}$$

Consider the eigenvectors $\mathbf{v}_i$ of $\mathbf{C}$ such that

$$\mathbf{C}\mathbf{v}_i = \lambda_i \mathbf{v}_i, \qquad \textit{for} \quad i = 1, 2, \cdots N^2. \tag{3}$$

We select M' orthonormal vectors $\{\mathbf{u}_l\}$ from the eigenvalues and eigenvectors of the covariance matrix, and call them "Eigen Vehicles."

B. Neural Network with sample images

We represent 100 vehicle candidates and 100 non-vehicle candidates as a linear combination of the eigen vehicles and formulate feature vectors using the coefficients of the eigen vehicles. Then these feature vectors are used to adapt MLP neural network via back propagation to estimate the vehicle/non-vehicle decision boundary.

IV. EXPERIMENTAL RESULTS

A. Evaluation images

The test is executed 2000 frame length image from two different test roads.

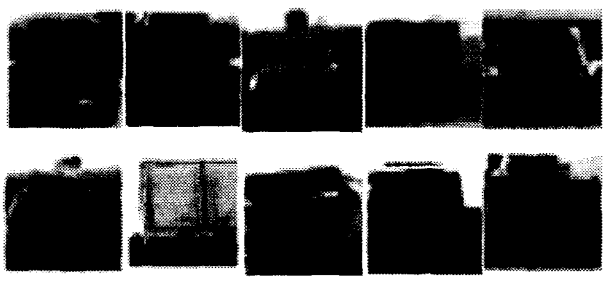


Figure 6. Examples of the Vehicle Candidates from ROI.

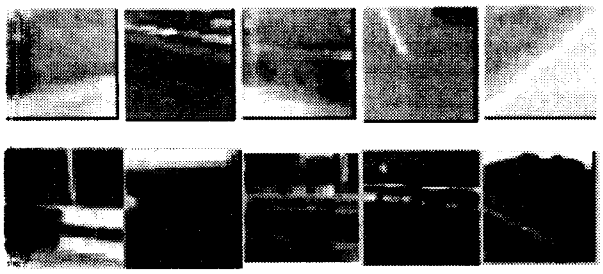


Figure 7. Examples of the Non-Vehicle Candidates from ROI.

We extracted 477 vehicle images and 297 non-vehicle images from various driving environments and selected 00 vehicle images and 100 non-vehicle images to make the training data set for MLP neural network

B. Results

Table 1 Classification results

Desired \ Result		Classification results using the Eigen Vehicle images: Vehicle	Non-Vehicle
Size of Vehicle Candidates : 8 x 8	Vehicle	449	28
	Non-Vehicle	270	27
Size of Vehicle Candidates : 16 x 16	Vehicle	462	15
	Non-Vehicle	294	3
Size of Vehicle Candidates : 32 x 32	Vehicle	467	10
	Non-Vehicle	282	15

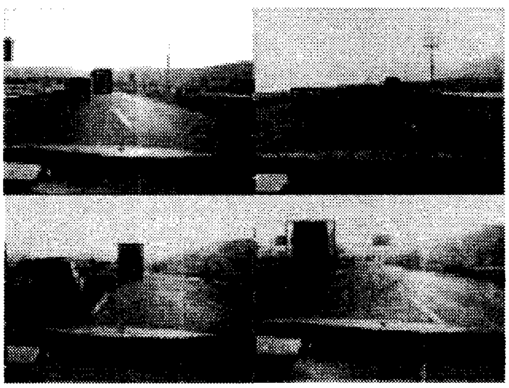


Figure 8. Examples of vehicle detection results.

V. CONCLUSION

We have designed and built a robust vehicle detection system. The vehicle detection method has two steps. The first step is "the Candidate Generation Step." In this step, we use the information of lane position and the boundary of vehicle. Using this information, we can set ROI, and extract Vehicle Candidate from the ROI.

The next step is "the Candidate Verification Step." We use the feature vectors of the Vehicle Candidate to distinguish a vehicle from the Vehicle Candidates. Using the Eigen Vehicle space to classify the vehicle candidates, we are able to obtain more robust result.

For future work, we plan to use bootstrapping to enhance system performance and develop a vehicle tracking algorithm.

VI. REFERENCES

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