■ 論 文 ■

Queue Detection using Fuzzy-Based Neural Network Model

퍼지기반 신경망모형을 이용한 대기행렬 검지

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목 차

Key Words : Queue Detection, Intelligent Transport Systems(ITS), Neural Networks, Fuzzy ARTMAP, Image Processing

요 약

실시간 교차로의 대기행렬길이 검지는 지능형교통체계의 중요부분인 교통관제를 위해서 매우 중요하다. 특히 교통정보수집을 위한 영상기반 기술은 전통적인 루프검지기 또는 기타 타 검지기에 비하여 내재된 여러 이점 때문에 많은 연구가 진행되어 왔다. 그러나 현장 적용시 흔히 발생하는 영상에서의 잡음 및 주변 물체로부터 투영되는 음영 등에 의해 나타나는 차량의 오검지율을 줄이고 수집되는 교통정보의 신뢰도를 높이기 위해서는 보다 효과적인 알고리즘개발이 요구된다.

본 연구에서는 영상처리를 이용한 대기행렬길이 검지를 위한 알고리즘을 제시하였다. 실시간 데이터 수집 및 분석 그리고 패턴분석에 우수한 것으로 알려진 신경망 모형을 이용하였으며, 특히 시스템 신뢰성을 높이기 위하여 퍼지이론이 접목된 퍼지 뉴런모델인 Fuzzy ARTMAP을 모형에 도입하였다. 실험결과 본 연구에서 제시한 대기행렬 측정 방법은 매우 우수한 검지 능력을 보였으며, 대기행렬 검지뿐만 아니라 신뢰성 높은 차량검지 및 차종분류를 위해서도 활용할 수 있을 것으로 기대된다.

Ⅰ. Introduction

Computer vision extracting meaningful information from the image collected by the video camera is a key element for integrated automatic traffic surveillance and control systems, and it is one of main ITS research subjects(Hoose, 1990; Rourke, 1994). There has been increasing research on image processing for automatic traffic data collection - vehicle counting, vehicle speed detection, vehicle tracking, congestion and incident detection(Hoose et. al., 1992).

Even though there has been growing interest in the application of image processing in transportation engineering, detection algorithms are still unreliable in complicate circumstances, and a more efficient algorithm should be developed.

The frame differencing method that has been conventionally used in the image processing for traffic data collection, and it is not efficient in a more complex application on noise, shadow, occlusion and perspective problems.

This research proposed a queue detection algorithm which could be much more tolerant to the problems of occlusion, shadow from other objects, and noise. The proposed method includes a camera calibration model and the Fuzzy ARTMAP(Carpenter et. al., 1992) neural network model which is applied for recognizing different patterns coming from vehicle movement and illumination change. Fuzzy ARTMAP is capable of rapidly learning to recognize and predict the consequences of analog or binary input patterns occurring in a non-stationary time series. Moreover, the Fuzzy ARTMAP has been claimed to have better performance than the Backpropagation which is the most popular neural network model, in terms of predictive accuracy, on the experiment with benchmark data(Carpenter and Grossberg, 1994) and with signal processing data(Young, 1995).

Ⅱ. Model Description for Queue Detection

For detecting a queue length at intersections, the proposed method follows the steps; 1. Define the ROI(Region of Interest), 2. Vehicle detection on the road, and 3. Camera calibration for determining queue lengths.

1. Define the ROI(Region of Interest)

The two-dimensional image projection from the vehicle in the queue with proper spacing will appear in the given region on the image plane. For the experiments in this research, 5 vertical and 18 horizontal ROI lines are defined. The vertical lines will be used for queue detection and the horizontal lines are for validation of vehicle occupancy on the given ROI. The horizontal lines are determined using line marking on the road since they give world coordinate information. Even though, ROIs have been defined manually for experiment in this paper, they could be obtained automatically by using the following process; (1) detect the straight line of the line mark using Hough Transform (Duda and Hart, 1972), (2) find vanishing points from the straight line of the line marking on he road, (3) define the ROI using the vanishing point and straight lines.

2. Vehicle detection on the road

The vehicle appearance on the road shows different patterns of gray values on the pre-defined region of the image plane. The fluctuation of gray level of each pixel comes from vehicle occupancy on the road and significant changes of illumination, and shadow, etc. The Figure shows gray value distribution of pixels on the pre-defined ROI(Region of Interest).

Even though the vehicle occupancy on the road may be detected by thresholding gray scale of pixels on the image, it may not be reliable on the complicate real-world traffic images. In this research, pattern recognition approach has been used to detect vehicle appearance in the queue.

Pattern recognition is the identification of the semantic regularities in the image, and it aims to classify the pattern in an input image using the information that was extracted from example patterns previously supplied to the system. Even though there have been many different methods, largely statistical, neural network models have the greatest potential for pattern recognition. The advantages of neural networks are, the ability to adjust when new information is given, computational property of massive parallelism, and fault tolerance to missing and noisy data. On the other hand, fuzzy set theory has proved to be a powerful tool for dealing with uncertainty, which is a common problem in pattern recognition(Bezdek and Pal, 1992). The combination of neural networks and fuzzy logic is a new research subject attracting a great deal of interest, because of the advantages of both systems. In effect, the introduction of fuzziness into the neural network model makes it better adapted to the study of the behavior of systems which are imprecisely defined by virtue of their high degree of complexity. In this research, the fuzzy ARTMAP neural network which is a combination of fuzzy logic and Adaptive Resonance Theory (ART)(Carpenter and Grossberg, 1987) neural network model is used.

The fuzzy ARTMAP consists of two fuzzy ART modules, ARTa and ARTb, connected by an inter-ART module, Fab, called the map field. The ARTa and ARTb create stable recognition categories in response to arbitrary sequences of input patterns. Each module receiving either the input or output component of each pattern pair to be associated. The main function of the map field is to associate representations of the pattern pair components. When there is mismatch between the prediction by ARTa and actual ARTb input, the map filed subsystem, match tracking, is activated. The match tracking raises the ARTa vigilance a by just the amount needed to cause a mismatch and reset in the ARTa module. Then, ARTa search system is activated to have either an ARTa category that correctly predicts an actual ARTb input or a previously uncommitted ARTa category node. the algorithm can be summarized as follows:

[Step 0]

Let m be the number of input units, n be the number of output units, M be the number of units on F_2^a, and N be the number of units on F_2^b.

Initially, the all adaptive weights W_j^a, W_k^b and W_{jk}^{ab} are set equal to 1, i. e.

$$\mathbf{W}_{j1}^{a}(0) = \ldots = \mathbf{W}_{j2m}^{a}(0) = 1$$

$$\mathbf{W}_{k1}^{b}(0) = \ldots = \mathbf{W}_{k2n}^{b}(0) = 1$$

$$\mathbf{W}_{jk}^{ab}(0) = 1$$

where $j=1, \ldots, M$ and $k=1, \ldots, N$. Initialize all category nodes of ART modules, ARTa and ARTb, by making them uncommitted. Set the parameters: the choice parameter $\alpha > 0$; the learning rate parameter $\beta \in [0,1]$; Set the ARTa vigilance parameter, ρ_a, to the baseline vigilance, $\overline{\rho_a}$.

[Step 1]

Present a binary or analogue vector **a** and the corresponding class vector **b**. The vector **a** is input to module ARTa and the vector **b** is input to module ARTb. All input values of vector **a** must be within the range [0,1]. If not, i. e. the inputs to the ARTa are analogue, then the input vector **a** should be normalized. The complement coding is also required to preserve amplitude information, then the complement coded input vector $\mathbf{A} = (\mathbf{a}, \mathbf{a}^c) = (a_1, \ldots a_m, a_1^c, \ldots, a_m^c)$ is input to the field F_1^a and the input vector $\mathbf{B} = (\mathbf{b}, \mathbf{b}^c) = (b_1, \ldots b_n, b_1^c, \ldots, b_n^c)$ to the field F_1^b. These are 2m-dimensional and 2n-dimensional vectors respectively. Complement coding and normalization of input vectors solve the category proliferation problem.

[Step 2]

For each input **A** and **B**, the jth node in the layer, F_2^a, and kth node in the layer, F_2^b, are given by

$$T_j(\mathbf{A}) = \frac{|\mathbf{A} \wedge \mathbf{W}_j^a|}{\alpha + |\mathbf{W}_j^a|} \text{ and } T_k(\mathbf{B}) = \frac{|\mathbf{B} \wedge \mathbf{W}_k^b|}{\alpha + |\mathbf{W}_k^b|},$$

where the fuzzy MIN operator $\wedge$ is defined to be $(x \wedge y)_i = min(x_i, y_i)$, α is a choice parameter, and the norm | . | is defined to be $|\mathbf{x}| = \sum_i |x_i|$ for for any vectors **x** and **y**.

[Step 3]

Use a winner-take-all rule to select the winner. This yields the maximum weighted sum. The winners of ARTa and ARTb are indexed by J and K respectively, where

$$J = \max\{T_j(\mathbf{A}) : j = 1, \ldots, M\} \text{ and}$$
$$K = \max\{T_k(\mathbf{B}) : k = 1, \ldots, N\}$$

If more than one node is maximal on each module, the node with the smallest index is chosen to break the tie.

[Step 4]

Check the vigilance criteria. If nodes J and K satisfy the conditions

$$\frac{|\mathrm{A} \wedge \mathrm{W}_\mathrm{J}^\mathrm{a}|}{|\mathrm{A}|} \geq \rho_a \text{ and } \frac{|\mathrm{B} \wedge \mathrm{W}_\mathrm{K}^\mathrm{b}|}{|\mathrm{B}|} \geq \rho_b$$

then nodes J and K are chosen to represent the input patterns **A** and **B**, and proceed to Step 5. After the categories represented by nodes J and K are selected for learning, they become committed. If they violate the above condition, then node J and K are reset, and move back to Step 3. Search for another node in the F_2^a and F_2^b that satisfies vigilance criterion respectively.

[Step 5]

Check to see whether the match tracking criterion is satisfied. If $\frac{|\mathbf{y}^b \wedge \mathbf{W}_J^{ab}|}{|\mathbf{y}^b|} \geq \rho_{ab}$ then we have achieved the desired mapping and continue to Step 6 for LTM(Long Term Memory) learning. If $\frac{|\mathbf{y}^b \wedge \mathbf{W}_J^{ab}|}{|\mathbf{y}^b|} \langle \rho_{ab}$ then the mapping between J and K is not the desired one. In this case, the vigilance parameter ρ_a is increased until it is slightly larger than $|\mathbf{A} \wedge \mathbf{W}_J^a|/|\mathbf{A}|$; this leads to an immediate reset of node J in ARTa and a move to Step 3 with the new vigilance parameter for the selection of another node in F_2^a that will achieve the desired mapping.

[Step 6]

The weights $\mathbf{W}_J^a$ and $\mathbf{W}_K^b$ are updated by the equations

$$\mathbf{W}_J(t) = \beta(\mathbf{A} \wedge \mathbf{W}_J(t-1)) + (1-\beta)\mathbf{W}_J(t-1) \text{ and}$$
$$\mathbf{W}_K(t) = \beta(\mathbf{A} \wedge \mathbf{W}_K(t-1)) + (1-\beta)\mathbf{W}_K(t-1)$$

where the learning rate $\beta$is chosen in the range [0,1]. In the fast learning mode, β is set to 1. The weights $\mathbf{W}_j^a$, $j \neq J$ and $\mathbf{W}_k^b$, $k \neq$K of non-winning nodes are not updated.

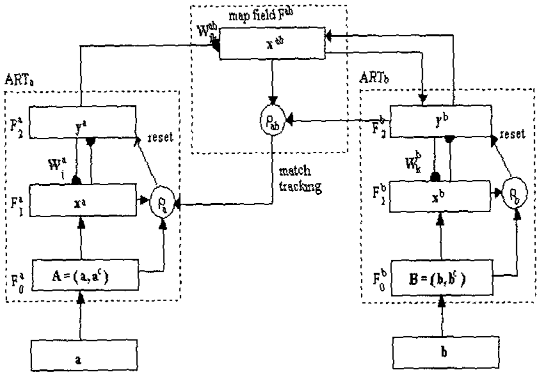
For efficient coding of noisy input sets, fast-commit and slow recording , which is to set $\beta = 1$ when J is an uncommitted node and take $\beta \langle 1$ after the category committed, is normally being used.

Map field weights with fast learning are determined by

$$\mathbf{W}_{jk}^{ab}(t) = \begin{cases} 1 & \text{if } j = J,\ k = K \\ 0 & \text{if } j = J,\ k \neq K \\ \mathbf{W}_{jk}^{ab}(t-1) & \text{otherwise} \end{cases}$$

[Step 7]

Go to Step 1 and present a next pattern pair.



〈Figure 1〉 Fuzzy ARTMAP architecture

3. Camera calibration

camera calibration for three-dimensional computer vision is the process of determining the extrinsic and intrinsic parameters of the camera. The extrinsic parameters of the camera specify the relationship between the two-dimensional image that a camera perceives and the three-dimensional object(i. e. the position and orientation of the camera with respect to a world co-ordinate system). The intrinsic parameters characterize the inherent properties of the camera optics, including the focal length and the image plane centre.

The image perspective co-ordinates (x, y) which correspond to the three-dimensional world co-ordinates (X, Y, Z) is given by

$$x = \frac{U_{11}X + U_{12}Y + U_{13}Z + U_{14}}{U_{41}X + U_{42}Y + U_{43}Z + U_{44}} \quad \text{and}$$

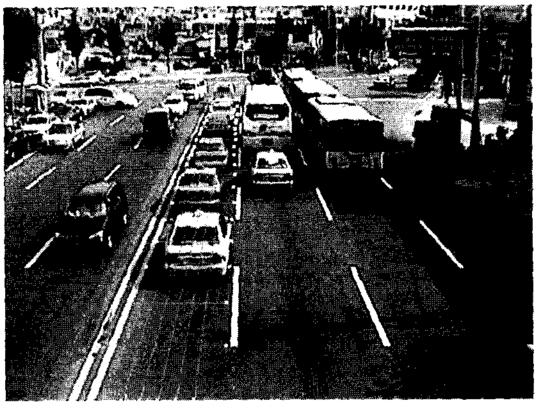
$$y = \frac{U_{21}X + U_{22}Y + U_{23}Z + U_{24}}{U_{41}X + U_{42}Y + U_{43}Z + U_{44}} \qquad (1)$$

On the equation (1), there are twelve unknown variables for two equations. However, we disregard Z-coordinate, then the unknown parameters are eight variables for two equations. Given enough pairs(more than four) of corresponding two-dimensional image and three-dimensional world points, we can solve the unknown parameters U_{ij} $(i, j=1, 2, 4)$ by using an appropriate numerical technique. If the unknown parameters U_{ij} are determined, then the queue length can be calculated using equation (1).

Ⅲ. Experiments and Results

1. Data collection and experimental design

The traffic scene images were taken from a video camera which was installed at height of 6.8M and with distance of 65.5M from the stop line at the intersection(see 〈Figure 2〉).



〈Figure 2〉 Experimental images and ROI

The image data contained various situations, which are expected in the real world, such as shadow and changes of illumination, and had some noise due to improper focus of the camera. The ROI (Region Of Interest) are the straight vertical and horizontal lines on the image. They are parallel and perpendicular to the line marking on the road. For the experiments, 500 different images in the ROI according to vehicle movement in the queue have been used. The total data sets were split into two subsets, Data set I(100sets) and Data set Ⅱ(400 sets) - Data set I for training and Data set Ⅱ for testing.

In order to cope with illumination change and shadow effect, the original gray value of each pixel has been converted by the equation (2)

$$D(j) = | I(j) - I(j+1) | \quad (2)$$

where I is gray value of each pixel and j is pixel position. Equation (2) could be used for determine adaptive threshold gray value.

The input vectors for the neural network model are the modified gray values of each pixel using equation (2) from five vertical lines. The pixel gray-level intensity difference of a neighboring region could be obtained from the equation (2). For validation of the results from previous step, gray value of each pixel from horizontal lines has been given for other inputs. The output vectors are defined as two different patterns, occupancy (on) and vacancy (off) of vehicle.

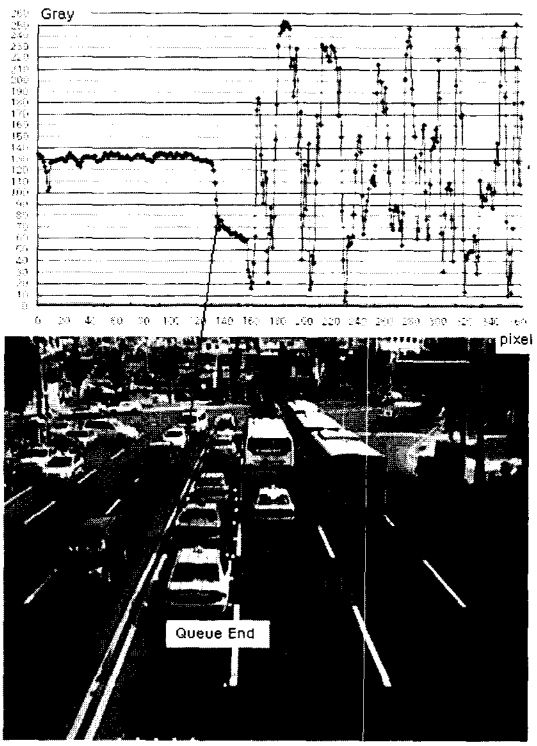
The experiments have been done with off-line learning, i. e. a fixed training set is repeatedly presented to the system until 100% accuracy is achieved on that set. The ARTa baseline vigilance is set to 0, and the ARTb baseline vigilance is set to 1, i. e. $\overline{\rho_a}=0$ and $\overline{\rho_b}=1$. The input for the ARTb module is the pattern category to learn and predict correctly, corresponding to the output vectors of the supervised neural network model, as in the Backpropagation network. In order to achieve the maximum generalization for the training patterns, the baseline vigilance of ARTa is set to 0. If the ARTa baseline vigilance is set to the high value initially, the generalization will be very low since each pattern which is only slightly different will have its own winning vector on F_2^a.

For the learning algorithm, fast-commit and slow recording is used with a learning rate parameter β=0.001 for all experiments in this research. Given a limited training set, voting across a few simulations can improve predictive accuracy(Carpenter et al., 1992). For the experiment in this research, 5 votes have been used.

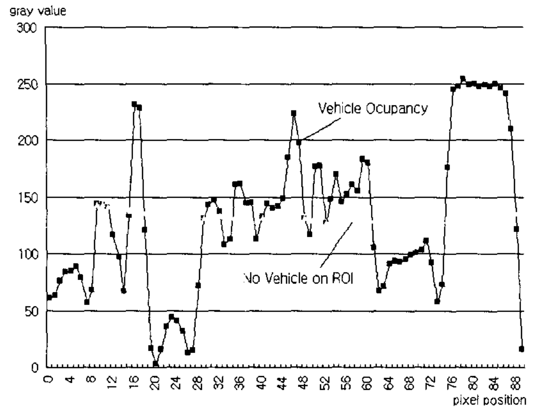
In this research, the filtering processing has been applied to reduce the noise effect and increase prediction accuracy by using a one-by-three dimension mask; i. e. [1 1 1]=[1 1 1] and [0 0 0]=[1 0 1]=[0 1 0]=[0 0 0].

2. Queue length detection

⟨Figure 3⟩ shows the intensity distribution of pixels gray levels from vertical ROI lines. As on the figure, the fluctuation of pixels gray value is very high when the ROIs are occupied by vehicles. On the other hand, the amount of gray value variation is very small if there is no vehicle on the ROI. In addition, ⟨Figure 4⟩ shows the intensity distribution of pixels gray levels from horizontal ROI lines. The figures show that vehicle occupancy can be detected by checking variation of neighbour pixel values.



⟨Figure 3⟩ Intensity distribution of pixels gray levels on the vertical ROI



〈Figure 4〉 Intensity distribution of pixels gray levels on the horizontal ROI

〈Table 1〉 shows the experimental results on the test data set. Each experiment needed only 3 to 4 epochs to learn all training set exemplars to 100% accuracy so that the computing cost can be disregarded on the fuzzy ARTMAP. The correct recognition rate of vertical ROI on the test sets range from 91.3% to 98.8% according to the distance of object from the stop line. As can be seen on the 〈Table 1〉, the prediction accuracy can be improved by using filtering mask which reduces the noise effect and maximizes the utility of neighboring pixel information. For on horizontal ROI, the prediction shows 100% accuracy after 9th line since they use a large number of inputs with significantly different gray level to neural networks. The results imply that the horizontal line can be used to validate the vehicle detection from vertical ROI and we may achieve very accurate queue detection system if we define a large number of horizontal lines.

〈Table 1〉 Prediction accuracy on vertical and horizontal ROI

Position from the stop line	Prediction on vertical ROI		Prediction accuracy on horizontal ROI
	Prediction from Fuzzy ARTMAP	Filtering from predicted output	
Stop line to 3rd line	91.3%	94.7%	98.2%
to 6th line	93.6%	96.5%	99.8%
to 9th line	95.3%	98.1%	100.0%
to 12th line	97.4%	99.2%	100.0%
to 15th line	97.6%	99.2%	100.0%
to 18th line	98.8%	99.8%	100.0%

〈Table 2〉 Average queue measurement accuracy on test data

Distance from stop line(M)	Less than 15	Over 15 to 30	Over 31 to 50
Estimated queue length accuracy	93.6(%)	96.8(%)	98.2(%)

〈Table 2〉 shows the average queue measurement accuracy. The value on the table for queue measurement accuracy has been calculated following equation (3).

$$1-\frac{|(Queue\ Detection\ by\ Model)-(Real\ Queue\ Length)|}{(Real\ Queue\ Length)} \quad (3)$$

The results for accuracy measurements on the test data sets have been grouped; i. e. the stop line to 15m, 15m to 30m, and 30m to 50m for convenient analysis. On the table, the results shows more accurate queue measurement by coming near to the view point. The accuracy of queue measurement is highly dependent on the information accuracy of the world-coordinate corresponding to image-coordinate meaning that we may need exact world-coordinate information in order to achieve the best results. The accuracy is sensitive to the viewpoint and object projection on the image plane.

Ⅳ. Conclusion

This paper proposed a method for detecting exact queue lengths at signalized intersections using image processing techniques and the Fuzzy ARTMAP neural network model. The experimental results show that the method proposed in the paper could be efficient for traffic queue detection in real world images with noise, shadow and partial occlusion. Even though the proposed method has been used for queue detection, this approach could be substitute for the traditional frame differencing method for real-time application and better performance in image processing for vehicle detection. More importantly, the Fuzzy ARTMAP neural network model could be much more efficient for vehicle classification which is one of important ITS research subjects .

The detection of vehicles at intersects is essential for queue detection, the camera calibration is also important issue for exact measurement of queue length. In order to have accurate queue measurement, we may need the accurate information on the 2D image projection form 3D world-coordinate. The line marking which is marked in regular or any installed objects on the road could be used for camera calibration for the queue length detection.

References

1. Bezdek, J. C. and Pal, S. K.(1992). Fuzzy Models for Pattern Recognition. New York: IEEE Press.
2. Carpenter, G. A. and Grossberg, S.(1987). A massively parallel 0architecture for a selforganizing neural pattern recognition machine. Computer Vision, Graphics, and Image Processing, 37, pp.54~115.
3. Carpenter, G. A., Grossberg, S., Markuzon, N., Reynolds, J. H., and Rosen, D. B.(1992) Fuzzy ARTMAP: A neural network architecture for incremental supervised learning of analog multidimensional maps. IEEE Transactions on Neural Networks, Vol.3 No.5, pp.698~712.
4. Carpenter, G. A. and Grossberg, S.(1994). Integrating symbolic and neural processing in a self-organizing architecture for pattern recognition and prediction. In V. Honavar and L. Uhr(Eds). Artificial Intelligence and Neural Networks: Steps toward Principled Integration. London: Academic Press, pp.387~421.
5. Duda, R. O. and Hart, P. E.(1972). Use of the Hough Transform to detect lines and curves in pictures. Communications of the Association of Computing Machine Intelligence, Vol.15, No.1, pp. 11~15.
6. Hoose, N.(1990). Computer Image Processing in Traffic Engineering. Taunton, Somerset, England: Research Studies Press; New York: John Wiley & Sons.
7. Hoose, N., Vicencio, M.-A. and Zhang, X.(1992). Incident Detection in Urban roads using Computer Image Processing, Transport Engineering and Control, Vol.33, No.4, pp.236~244.
8. Rourke, A.(1994). Applications of image processing techniques to data collection and monitoring in transport. Ph. D. Thesis, University of Newcastle upon Tyne, UK.
9. Young, C. D. P. A.(1995). Fuzzy ARTMAP neural network speech recognition system based on formant ratios. Masters thesis, Royal Military College of Canada, Kingston, Ontario, Canada.

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A Study of the Analysis on the Accident Reduction Effect of the Median

KIM, Gyeong-Seok · KANG, Seung Lim

A median is a safety feature most commonly used to separate opposing traffic on a divided highway. In designing highways, the selection and installation of a median can be a critical part from a safety viewpoint because road crossing accidents are definitely more serious than other accidents. In regard to the important function of the median, the proper countermeasure ought to have been provided and thorough study should have been carried out. In this paper, traffic accident data are analyzed to examine the accident reduction effect of the median, which are gathered from all over 4-lane national roads in Korea. The traffic accident data were categorized into two groups by the existence of a median. For more effective analysis, the data have been classified by accident type, severity, and occurrence time. To compare the effectiveness of median installation, not only the accident frequency but also the accident severity, EPDO, and the occupancy rate of specific accidents have been used as a mode of effectiveness. The analysis of the effectiveness of medians shows that both the accident frequency and the accident severity could decrease by providing a median. Also the section where a median was supplied showed the improvement of overall safety through fewer serious and fatal crashes as well as fewer head-on crashes. Therefore, conclusions can be drawn from results of this study that the median installation is an important means to increase the safety of over 4-lane national roads. This study is expected to provide the reasonability of the median installation by identifying the reduction of traffic accident after the median installation and to play a major role in selecting sections where the median is to be offered.

Queue Detection using Fuzzy-Based Neural Network Model

KIM, Daehyon

Real-time information on vehicle queue at intersections is essential for optimal traffic signal control, which is substantial part of Intelligent Transport Systems(ITS). Computer vision is also potentially an important element in the foundation of integrated traffic surveillance and control systems. The objective of this research is to propose a method for detecting an exact queue lengths at signalized intersections using image processing techniques and a neural network model. Fuzzy ARTMAP, which is a supervised and self-organizing system and claimed to be more powerful than many expert systems, genetic algorithms, and other neural network models like Backpropagation, is used for recognizing different patterns that come from complicated real scenes of a car park. The experiments have been done with the traffic scene images at intersections and the results show that the method proposed in the paper could be efficient for the noise, shadow, partial occlusion and perspective problems which are inevitable in the real world images.

Shortest Path Problems of Military Vehicles Considering Traffic Flow Characteristics

BANG, Hyunseok · KIM, Gunyoung · KANG, Kyungwoo

The shortest path problems(SPP) are critical issues in the military logistics such as the simulation of the War-Game. However, the existing SPP has two major drawbacks, one is its accuracy of solution and the other is for only one solution with focused on just link cost in the military transportation planning models. In addition, very few previous studies have been examined for the multi-shortest path problems without considering link capacity reflecting the military characteristics. In order to overcome these drawbacks, it is necessary to apply