Image Based Vehicle Traffic Measurement

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ABSTRACT

This research deals with measurement of the density of vehicles traffic. The traffic density is estimated from an image captured using the ordinary optical camera. An image processing methods is used and the edge of the objects is extracted. A two dimensional wavelet transform is used as a feature extraction. The extracted features were reduced by Multiple Region Centroid Estimation. A neural network is trained using many sets of images with different Traffic densities then it is used for traffic measurement. A classification rate of 98% can be achieved.

Keywords: Traffic Measurement, Edge Detection, 2D Wavelet, MRCE, Neural Network.

الخلاصة:

يتناول هذا البحث عرض طريقة لقياس الكثافة المرورية للمركبات في الطرق. تتضمن الطريقة تخمين الكثافة المرورية من خلال اخذ صورة بواسطة الكامرا العادية (الضوئية) . وبواسطة طرق معالجة الصور يتم تحويل الصورة الى شكل اخر يتضمن الحافات لمكونات الصورة فقط. ثم بواسطة خوارزمية (2D-Wavelet) يتم تحديد الخواص المهمة والتي يتم تقليص حجمها بواسطة الطريقة المقترحة (Multiple Region Centroid Estimation). ان قياس الكثافة المرورية تم باستخدام شبكة عصبية تم تدريبها على خواص منتزعة من صور لكثافات مرورية مختلفة تم تصنيفها يدويا . ان الشبكة العصبية تقوم بتصنيف الكثافة المرورية بمعدل تصنيف 98%.

INTRODUCTION

R oad Traffic congestion and jam is one of the big problems which continue to increase in most cities around the world. Many researches and studies about this problem has been recently published [1]. Important solution can be achieved through using intelligent traffic control methods. The intelligent traffic control means the using of intelligent techniques to improve the utilization of current infrastructures by reducing the congestion. Many works can be found in literature that concerned this idea [2]. Traffic control is mainly dependent on the traffic measurement techniques. Vehicle(s) detecting is required by any traffic monitoring or measurement. Vehicle detectors divided into two main groups [3], in-situ detectors deployed in

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2412-0758/University of Technology-Iraq, Baghdad, Iraq This is an open access article under the CC BY 4.0 license <u>http://creativecommons.org/licenses/by/4.0</u> locations of interest and mobile detectors located in vehicles. A performance comparison between existence detector technologies can be found in [4].

Currently the video based surveillance systems is widely used, so good image based measuring methods is needed. Either for intelligent monitoring or control. Many researches and works on using visual (image processing) can be found in literature and a pointing to some of them is in the following , Madhavi Arora[5], they used a technique based on the matching between edges on current road picture and the edges on the background picture, then the traffic light control was based on the percentage of matching. Benjamin Coifman[6], using feature based tracking method based on video to measure true traffic density. Celil Ozkurt and Fatih Camci[7], proposed a method for automatic traffic density estimation using neural networks, the method is applied to real traffic videos used in Istanbul Traffic Management company(ISBAK) and promising results were achieved. Chiu [8], proposed a real time traffic surveillance system by using moving object segmentation for automatically separating vehicles from image sequences. Amol A. Ambardekar[9], proposed a traffic surveillance system where two methods were used for vehicle detecting a color contour matching and gradient based matching. J.M. Wang et. al.[10], they described a vision based traffic measurement system for automatically collecting data from road ways. The techniques used including progressive background image generation, lane marks detection based on filters, illumination assessment technique and shadow detection and removing. Erhan[11], presents a vehicle counting method based on invariant moments and shadow aware foreground masks. For background estimation and foreground segmentation either Mixture of Gaussians model (MoG) or an improved version of the Group Based Histogram (GBH) technique. Jie Zhou[12] et. al., they used moving vehicle detecting method to count the number of vehicle passing specified area. The method consists of background estimation using improved algorithm for adaptive background estimation based on kalman filtering. Then the histogram was used for feature extraction which then reduced using Principal Component Analysis(PCA). the classification was done using SVM an average accuracy of 94% was reported. A. Faro et. al[13], they applied two algorithm which is W4 algorithm and H algorithm to calculate the traffic intensity from images taken by web-cam. Then using Neuro-Fuzzy approach for vehicular traffic monitoring accuracy of 92% and 97% was reported for the two algorithms respectively. George Scora et. al. [14], The VEhicle Classifier and Traffic flow analyzeR (VECTOR) was used for traffic density measurement by moving vehicles detection using background subtraction and global nearest neighbor optimization. K. Takahashi et. al. [15], they developed an image sensor for measuring traffic flow. The operation of the sensor is based on template matching at the gray level in order to track and count different types of images at different conditions. The sensor could count vehicles with error less than 3%. In this paper a proposed method for estimating traffic density is presented. This method is depicted by the block diagram on the figure (1). In this method a feature is extracted from road image in gray level. These features are related to the traffic density on the road. After subtracting the background from the image the remaining foreground image is translated into edges image. The two dimensional Wavelet Transform (2DWT) is used to filter out unwanted features. The large set of features is reduced by Multiple Region Centeroid Estimation(MRCE) proposed in this paper. A set of images for different traffic density is used to train Neural Networks (NN). Then the NN is used to classify the input image into one out of four density classes (Full, Large, Medium and Low). Experiments were conducted on images taken offline for the different traffic density and the results was promise. This method of traffic density estimation or classifying into one of four classes can be fused into an intelligent traffic light controller.

EDGE DETECTION

Since the vehicles appeared in the road images as objects well defined by their edges. And the edges are highlighted very well, so the edges of those objects can supply the important information concerned to the number of vehicle in the road image taken. There are many techniques for edge detection , most of them are 2D digital filters and the one that give good result even with images contains noise is the Canny's edge detection algorithm [16] . Many of Fuzzy logic based edge detection algorithms has been emerged[17,18] which was reported to perform well. For the work presented by this paper the Canny Edge detection was used because it was a good compromise between accuracy and processing time and it was enough for this work. When the edge detection algorithm is performed upon a gray image it will be converted to binary image (i.e. contains only '1' and '0').examples for this process can be seen in figure (2).

TOW DIMENTIONAL DISCRETE WAVELET TRANSFORMATION.

The continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function ψ :

$$C(scal, position) = \int_{-\infty}^{\infty} f(t)\psi(scal, position) \qquad \dots \dots (1)$$

The results of the CWT are many *wavelet coefficients* C which are a function of scale and position calculating wavelet coefficients at every possible scale is a fair amount of work, and it generates an awful lot of data. What if we choose only a subset of scales and positions that if we choose scales and positions based on powers of two so called *dyadic* scales and positions then our analysis will be much more efficient and just as accurate[19]. Then the 2D discrete Wavelet (2D DWT) can be seen in figure(3). This is the level one 2D DWT in which the input is a 2D signal (image) and the output is four 2D matrices (LL, LH,HL,HH). LL is the Approximation part of the input, LH is the diagonal details part of the input. Each matrix dimension size is half of the input size. In our work only the HL part is used for feature extraction.

MULTIPLE REGION CENTROID ESTIMATION(MRCE).

In this method the 2D feature set is divided into multiple regions R_i . The arithmetic mean C_i for each region R_i is calculated. the set of arithmetic means C is being the new feature set. The number of regions used was 20, hence the features will be reduced from 12649 features into 20 features only.

.....(2)

$$C_i = \frac{1}{N} \sum_{y}^{n^2} \sum_{x}^{n^1} R_i(x, y)$$

Where: $y_{,x}$: are the spatial dimension of region R.

n1,n2: are the size of x and y dimensions. N=n1+n2.

NEURAL NETWORKS (NN)

Artificial neural networks are computational models of the brain[20]. Neural networks generally consists of a number of interconnected processing elements (PEs) or neurons. The type of NN which we have used is known as feed-forward network. In this type the signals flow from the input layer to the output layer via unidirectional connections. Example of feed forward that is the multilayer perceptron is shown in figure(4). And the perceptron structure is shown in figure(5). The learning algorithm used for the NN was the supervised Back propagation algorithm. The input-output relationship of a generic node, the ith node in the kth layer is given by:-

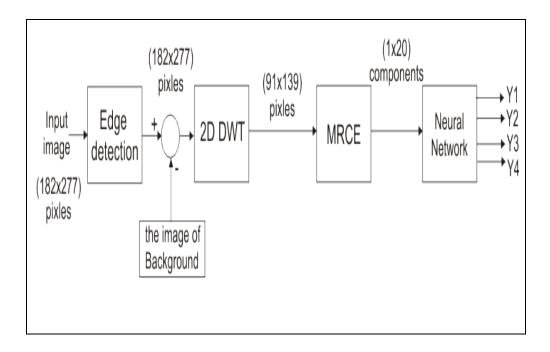
$$Z_{i}^{(k)} = \sum_{j=1}^{n_{k-1}} \eta_{ij}^{(k)} x_{j}^{(k-1)} + \mu_{i}^{(k)} \qquad \dots (3)$$
$$x_{i}^{(k)} = a\left(z_{i}^{(k)}\right) \qquad \dots (4)$$

Where $\eta_{ij}^{(k)}$ are the connections weights and $\mu_i^{(k)}$ is the threshold; and $a(z_i^{(k)})$ is the activation function. The network was trained using multiple samples (with sufficient numbers) of input images belonged to each class of traffic. Then the NN is used to classify the input image into one out of four density classes (Full, Large, Medium and Low).

EXPERIMENTS AND EVALUATION.

In order to carry out experiments using the proposed method. Many images have been taken for different roads and intersections. Each image is of size (182 x 277) pixels. The images are converted into gray scale images then they are transformed into edge images which was black and white images. For each road or intersection to be monitored at least one image was taken for the case when there were no cars seen in the road or intersection. This image was used for background subtraction. The mentioned process can be demonstrated in figures (2, 6, and 7). Five experiments were conducted for different number of images per class of traffic density (10, 20, 30, 40, and 50). Each set was divided into three sets (training, validation and testing set) this can be seen in table (1). It is evident from table (2) that when the number of images taken for each class of traffic intensity between 40 and 50 yields very good classification rate. The classification task performed by the NN can be demonstrated by the tables (3). The confusing matrix for the case of 30 images/per class and 50 images/per class can be seen in figures (8 and 9) respectively. Also the Receiver Operating Condition(ROC) curves can be shown in figure (10) for the case of 50 images/per class.

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Figure(1) : The Block Diagram of the traffic density system

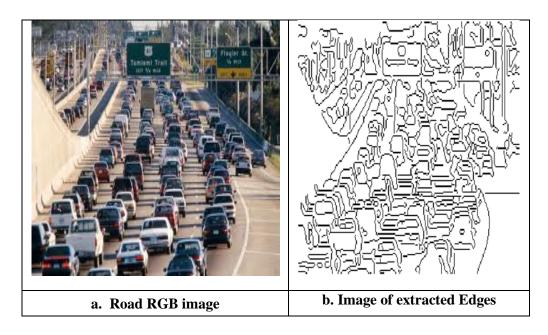


Figure (2). RGB image and the corresponding Black and white image of Edges

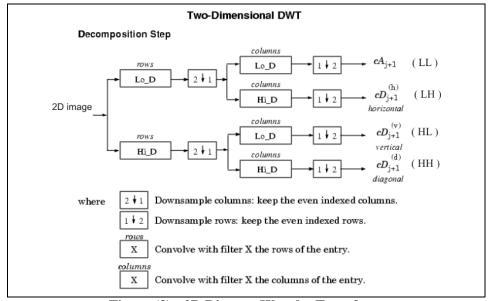


Figure (3) :2D Discrete Wavelet Transform

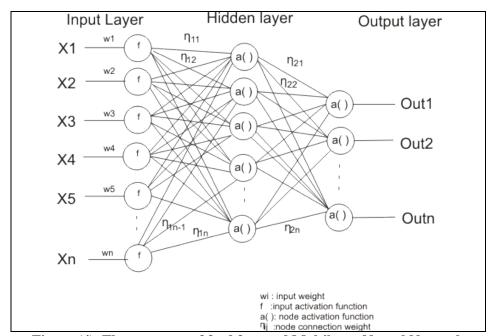
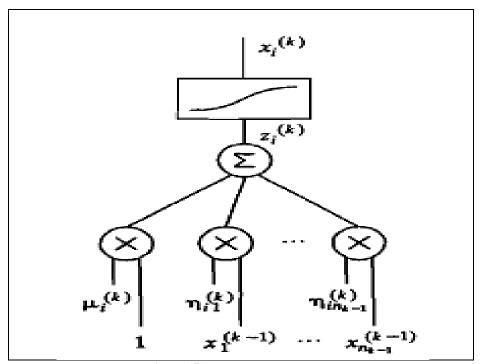


Figure (4). The structure of feed forward Multilayer Neural Network



Figure(5). Percepton structure

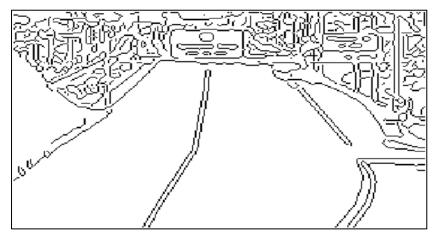
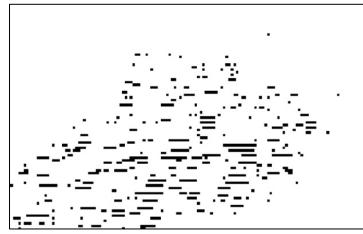


Figure (6). Edge Image for The Background image for the road image .



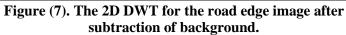


Table (1). The data sets used for learning the NN

			-	
Number of images/class	Total images	Training set 70%	Validation set 15%	Testing set 15%
10	40	28	6	6
20	80	56	12	12
30	120	84	18	18
40	160	112	24	24
50	200	140	30	30
60	240	168	36	36

Table (2).The Classification Rate with respect of
the number of images per class

Number of images/class Classification Rate 10 83.3% 20 91.7% 30 98% 40 100% 50 100% 60 100%			
2091.7%3098%40100%50100%			
30 98% 40 100% 50 100%	10	83.3%	
40100%50100%	20	91.7%	
50 100%	30	98%	
	40	100%	
60 100%	50	100%	
	60	100%	

tranic density.					
Y1	Y2	Y3	Y4	Selected class	
0.9328167	0.2099085	5.896266e-05	0.0001538245	Y1:: Low density	
0.9536426	0.1909533	5.638420e-05	0.0001232300	Y1:: Low density	
0.9418210	0.2018803	6.620072e-05	0.0001280599	Y1:: Low density	
0.006042530	0.6115329	0.01572750	0.0007563781	Y2: Medium density	
0.001557167	0.5159822	0.1284855	0.0008305665	Y2: Medium density	
0.004661424	0.5205711	0.03764386	0.0008278719	Y2: Medium density	
1.997225e-07	0.2607664	0.8614216	0.03412536	Y3: Large density	
9.462584e-08	0.1536517	0.9422817	0.03196843	Y3: Large density	
7.600883e-07	0.3380274	0.9405792	0.01059642	Y3: Large density	
1.081912e-13	4.519205e-05	0.009853560	0.9997854	Y4: High density	
2.332579e-13	0.004155229	0.03410823	0.9981706	Y4: High density	
3.725908e-13	1.661542e-05	0.03833042	0.9998520	Y4: High density	

 Table (3). Samples of NN outputs for deferent inputs for each class of traffic density.

All Confusion Matrix

Output Class	1	10 25.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	2	0 0.0%	9 22.5%	<mark>6</mark> 15.0%	0 0.0%	60.0% 40.0%
	3	0 0.0%	1 2.5%	4 10.0%	1 2.5%	66.7% 33.3%
	4	0 0.0%	0 0.0%	0 0.0%	9 22.5%	100% 0.0%
		100% 0.0%	90.0% 10.0%	40.0% 60.0%	90.0% 10.0%	80.0% 20.0%
		1 2 3 4 Target Class				

Figure (8). The confusion matrix for the case of 10 images/class

1	60	0	0	0	100%
	25.0%	0.0%	0.0%	0.0%	0.0%
2	0	<mark>60</mark>	0	0	100%
\$	0.0%	25.0%	0.0%	0.0%	0.0%
Output Class	0	0	60	0	100%
ပ	0.0%	0.0%	25.0%	0.0%	0.0%
0	0	0	0	60	100%
4	0.0%	0.0%	0.0%	25.0%	0.0%
	100%	100%	100%	100%	100%
	0.0%	0.0%	0.0%	0.0%	0.0%
	1	2 Ta	3 rget Clas	4 55	

All Confusion Matrix



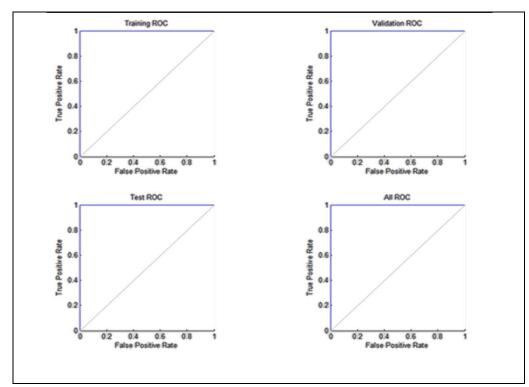


Figure (10): The Receiver Operating Condition (ROC) for 50 images per class.

Conclusions and Future Works

In this paper the image processing techniques (particularly the Canny's edge detection algorithm as well as the 2D wavelet) was used to extract the features that are related to the traffic density from a road image. The extracted features were reduced into small size using MRCE method. The feed forward NN was successfully used for classification. The traffic can be classified into one of four classes. The class with largest value of the NN outputs was selected. The NN must be trained with at least 30 images per class of traffic (this means that 120 images must be taken). This can led to 98% classification rate. It was showed that using large Dataset can produce good classification rate. One of the suggested future works is to integrate this method of traffic density measurement into an intelligent traffic light controller. Then assist its validity using true traffic measurements on local and urban bases .

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