Car's detection by Gaussian receptive field features, the eigenvalues and MLP

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ABSTRACT

The car's detection is one of the current research topics; it is characterized by the presence or absence of cars in a special place. Several recent works were made in this context; there's three class of car detections method, one based on the study of the move, another based on a geometrical model and the last one based on the use of the learning process.

In this paper, we implement a method for car detection based on the monocular vision by Gaussian receptive fields features; when getting features extracted, we reduce the size of the vectors samples, which were used as input for our learning step and learning procedure based on the neural network MLP.

Keywords

Monocular vision, cars detection, learning process, Gaussian receptive field's features, eigenvalues technics, neural network MLP.

1. INTRODUCTION

The cars detection is a very delicate task because of the many disturbing facts as, the presence of unfavorable condition's capture (shadow) in a part, and in another part the multi shape of the cars (colors, and size).

Many works has been made in the context of the cars detection, within them we can quote [1], where authors has proposed two steps, the first one is the HG hypothesis generation application and the second one the is HV hypothesis verification of application. In the first step, the hypothesis of generation was made based on the edge detection and this whith the aim to locate the car, while the second part was the feature extraction with Haar parameter's combined to SVM. Other technics tested in [2], where BGF was used for feature extraction for an SVM training. [3], outlined a technic based on a representation of the vehicle in the shape of a geometric model, after an energy function include information about this shape (the symmetry and the shadow of the car) was calculated. The used the genetic algorithm for reduce the space of the features, by selecting the good features. Jun Kong and his colleagues proposed a new approach [4] for extraction of the image from the background and the update of the features based on the quantification of the gray level and the mitigation of the weight in order to reduce the effect of the lighting of the light. At the end, they use a a discrimination function to separate between the two parts the object and the background in order to locate the area in move. The paper [5], talks about a new technic combining approach by appearance, a geometric model and approach in motion. In the first approach, we used the Adaboost training algorithm. A geometric model was used in order to have a good localization of the cars, and the last approach was applied to determine al the area in move. The merger of the various information obtained has been made by adopting the principle of the Bayes.

In our method, the cars detection was based on training; with Gaussian receptive fields features, eigenvalues and the MLP (neural network). Our approach was tested on the "UIUC"database's.

2. THE PROPOSED APPROACH FOR CARS DETECTION

in this method, we get a good cars detection by the training process devised in three steps : feature extraction based on the Gaussian receptive field (Eigenvalues) and the training by the neural network MLP.

A. Features extraction

Features extraction with Gaussian receptive fields was applied using five cores shown in the figure below.

Because of the variability of the size of the cars in the pictures, this phase was applied on an intrinsic space and for the three levels of size, largest to smallest.

The figure 1 presents the results obtained for the feature extraction step by the Gaussian receptive field on one of the three cores.

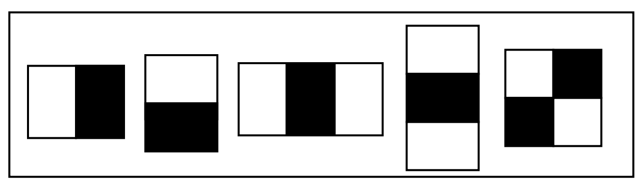

Figure 1 the cores of the Gaussian receptive fields

After applying the different kernels to extract the features of Gaussian receptive field, we organized these features into vectors.

Two types of vector were built, the haves vectors positive examples or the healthy carriers of negative examples. Of course, this operation was used separately for each intrinsic level.

For example, on an intrinsic level of size 40 * 100, one can built a vector of size 5 * 40 * 100, knowing that 5 represents the number of cores used.

Note that the vector size is very large (20,000 items). If one considers that the number of positive examples is 500 examples and the number of negative examples is 500 examples, calculates becomes very heavy. To remedy this problem, it has been applied

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in this phase by the clean space called a technical method for reducing the size of these vectors; in effect a covariance matrix Q uses the relationship in (1):

$$Q = S.S^T \qquad (1)$$

Knowing that S is a matrix of size 20000 * 1000.

After the SVD, we can find three types of matrices U, V, and UT

Reducing the size of the vectors was made using the first eigenvectors of the matrix U.

Tests and tests with different image sizes, ranging from 5, 10 through 100 and reaching up to 500 led us to limit the size to 100.

Finally, this technique allows us to reduce the size of our sample training vectors in size to a size of 20 000 100.

A. The neural network MLP

The last step was performed by applying an artificial neural network MLP.

A multilayer perceptron (MLP) is a feedforward artificial neural network model that maps sets of input data onto a set of appropriate outputs. A MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training the network. MLP is a modification of the standard linear perceptron and can distinguish data that are not linearly separable.

Figure 2 shows the general scheme of a multilayer perceptron neural network. If a multilayer perceptron has a linear activation function in all neurons, that is, a linear function that maps the weighted inputs to the output of each neuron, then it is easily proved with linear algebra that any number of layers can be reduced to the standard two-layer input-output model (see perceptron).

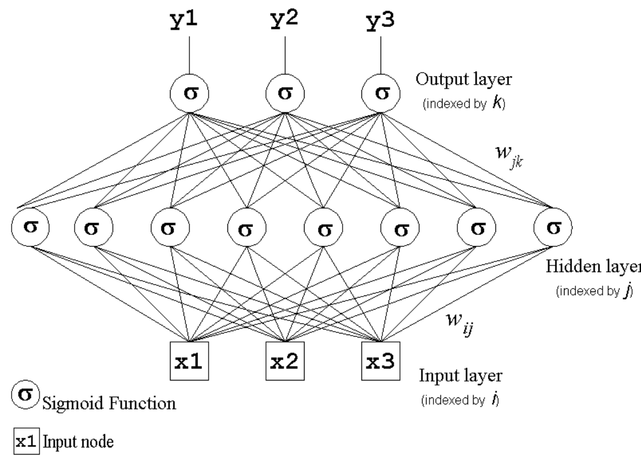

Figure 2 Multilayer Perceptron Scheme

In this phase, we applied an artificial neural network MLP with one hidden layer, further setting the number of neurons in the hidden layer was achieved by adopting (2):

$$N_c = |N_e - N_s| \qquad (2)$$

Nc : Number of neurons in the hidden layer.

Ne : Number of neurons in the input layer.

Ns : Number of neurons in the output layer.

Th best results obtained was with, 98 neurons in the hidden layer. The activation function was sigmoid. Matrices weight and bias vectors were fixed randomly, the number of iterations equal to 100, and the error of the gradient was set at 0.01.

After initialization of the artificial neural network MLP, come the learning step to finally get all the reference models.

To calculate the amount of evaluation of our vehicle detection method, we applied formula (3):

$$TR = \frac{BD}{FD + BD}.100 \qquad (3)$$

TR : recognition rate.

BD : good detection.

FD : bad detection.

Our tests were on a database of (500 examples of vehicles and 500 examples of non-vehicles), we managed to achieve a recognition rate of 95.8%.

Following is a comparison between our features used and the characteristics of the wavelet Haar as regards the variation of the recognition rate depending on the variation of the length of the vectors.

Table 1. Comparative study between the Gaussian receptive field features type and the wavelet Haar features.

Vectors length \type des features	5	10	50	100	200	500
CRG	43.25	58.47	85.39	95.8	95.54	95.04
OH	40.05	46.21	61.25	83.47	83.28	81.04

Figure 3 displays the results obtained after features extraction by Gaussian receptive fields with the negative and the positive example.

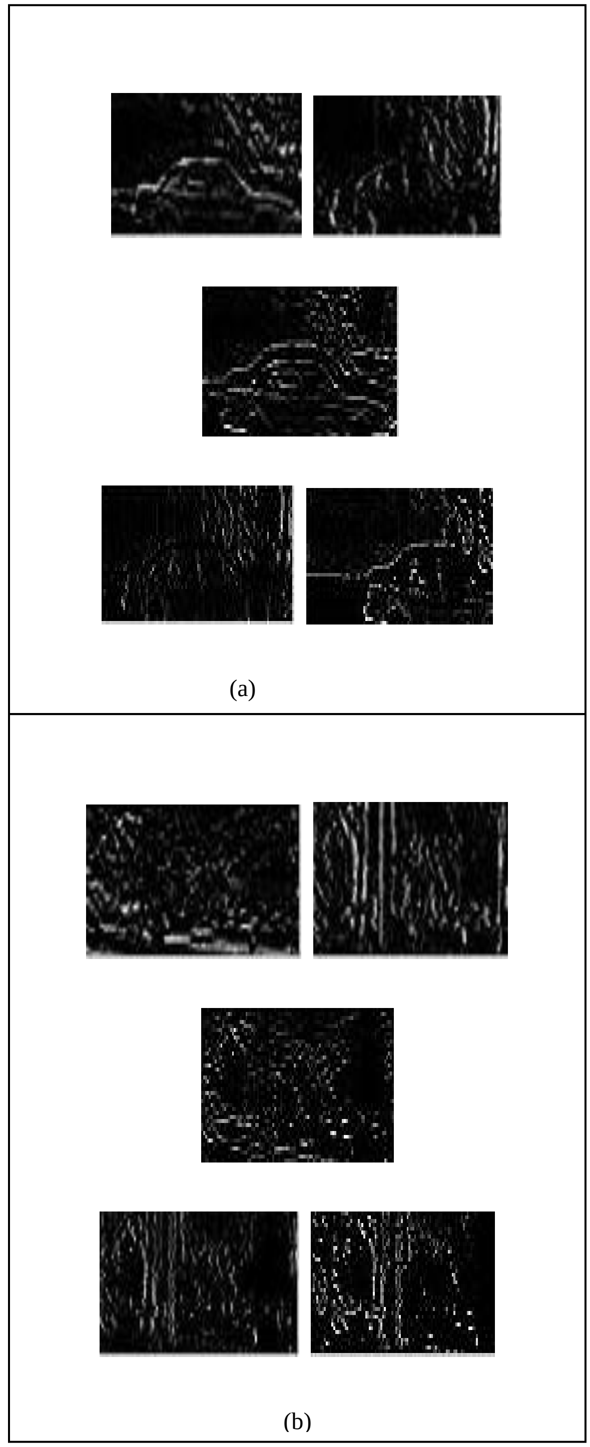

Figure 3 The features of the type of Gaussian receptive field: (a) positive example, (b) negative example.

3. The final results of our vehicle detection method

After having presented our vehicle detection method. Here is the presentation of some final results of the tests.

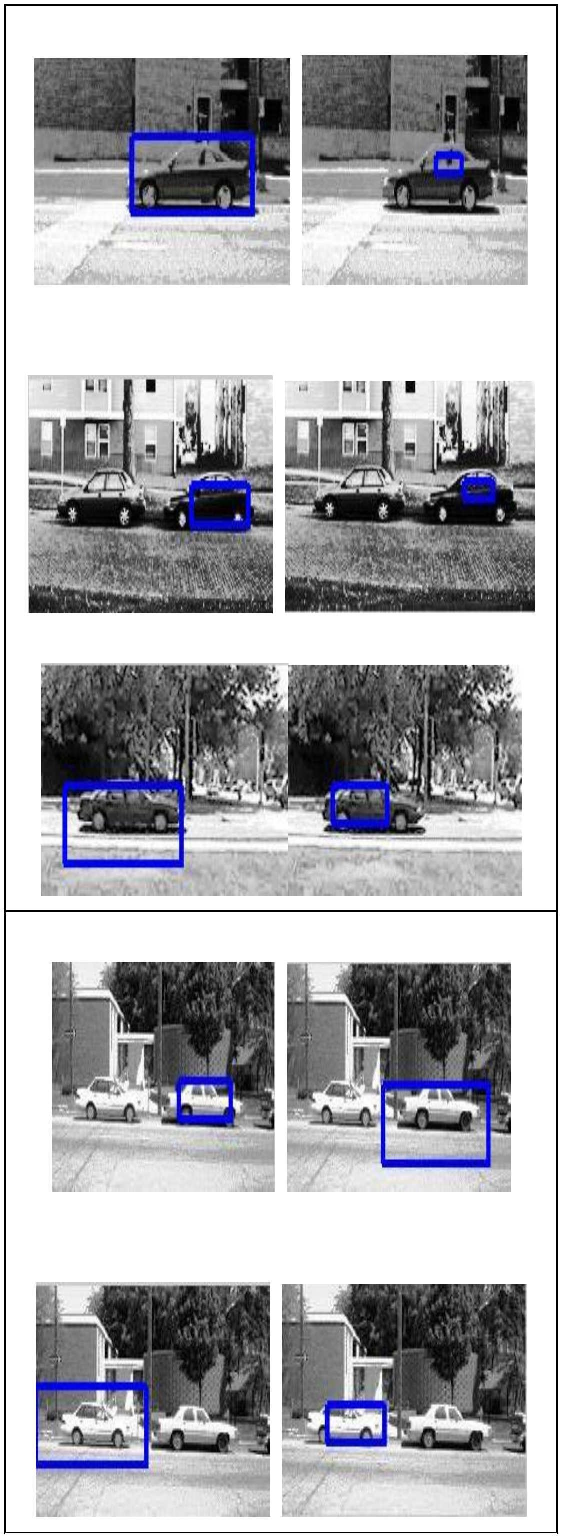

Figure 4 The results of the test

4. Conclusion et perspective

In this study we realized an effective method for the detection of vehicles, and the application of a learning process allowed us to have very good results with a very high detection rate.

As a perspective, we try to use the principle of this method in a work referred to detect vehicles in highways.

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