Vehicle Recognition Using Curvelet Transform and SVM

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Abstract

This paper proposes the performance of a new algorithm for vehicles recognition system. This recognition system is based on extracted features on the performance of image's curvelet transform & achieving standard deviation of curvelet coefficients matrix in different scales & various orientations.

The curvelet transform is a multiscale transform with frame elements indexed by location, scale and orientation parameters, and have time-frequency localization properties of wavelets but also shows a very high degree of directionality and anisotropy.

This paper presents the application of three different types of classifiers to the vehicle recognition. They include of Support vector machine (one versus one), k nearest-neighbor and Support vector machine (one versus all). In addition, the proposed recognition system is obtained by using different scales information as feature vector. So, we could clarify the most important scales in aspect of having useful information. The performed numerical experiments for vehicles recognition have shown the superiority of curvelet and standard deviation preprocessing, which are associated with the Support vector machine structure (one versus one). The results of this test show, the right recognition rate of vehicle's model in this recognition system, at the time of using total scales information numbers 3&4 curvelet coefficients matrix is about 99%. We've gathered a data set that includes of 300 images from 5 different classes of vehicles. These 5 classes of vehicles include of: PEUGEOT 206, PEUGEOT 405, Pride, RENAULT55 and Peykan. We've examined 230 pictures as our train data set and 70 pictures as our test data set.

1. Introduction

Recently, vehicle based access control systems for buildings, outdoor sites and even housing estates have became commonplace. Additionally , various traffic monitoring and control systems that depend on user (man+ vehicle) identification , such as congestion charging would also benefit by augmenting existing number-plate recognition with an additional authentication mechanism. Given an image containing a backward view of a vehicle (car), a system is proposed here that determines it's exact class (model). The aim is to obtain reliable classification of a vehicle in the image from a multitude of possible classes (vehicle types) using a limited number of prior examples.

Although classification of road going vehicles has been a subject of interest in the past, e.g. traffic control systems and toll levy automation, vehicle type recognition has not hitherto been considered at this level of accuracy. Instead, Most of the systems either detect (classify vehicle or background) or classify vehicles in broad categories such as cars, buses, heavy goods vehicles (HGVs) etc. [5, 2, 6, 7, 3, 1].

V.S.Petrovic and T.F.Cootes [8] demonstrate that a relatively simple set of features extracted from sections of car's frontal images can be used to obtain good performance verification and recognition of vehicle type. The proposed recognition system in this case is based on recognizing rigid structure samples obtained using specific feature extraction techniques from an image of the object (vehicle). Recognition is initiated through an algorithm that locates a reference segment on the object, in this case the frontal number plate. The location and scale of this segment is used as reference to define a region of interest in the image from which the structure is sampled. A number of feature extraction algorithms that perform this task, including direct and statistical mapping methods are investigated. Feature vectors are finally classified using simple nearest neighbor classification.

Louka Dlagnekov [9] developed an LPR (License Plate Recognition) system for achieving a high recognition rate without needing a high quality video signal from expensive hardware. He also explored the problem of

International Conference on Information Technology (ITNG'07)
0-7695-2776-0/07 $20.00 © 2007 IEEE

car make and model recognition for purposes of searching surveillance video archives for a partial license plate number combined with some visual description of a car. His proposed methods will provide valuable situational information for law enforcement units in a variety of civil infrastructures.

The proposed recognition system in this paper is based on a new transform by the name of Fast Curvelet Transform & Statistic parameter of Standard deviation.

While fourier analysis works well on periodic structures (such as textures), and wavelet analysis works well on singularities (such as corners), neither particularly can reconstruct edges in a sparse matter. Curvelet were originally introduced in [4] as a non-adaptive transform that achieves near optimal m-term approximation rates in L^2 for twice-continuously differentiable curves (C^2). The performance rates for the Curvelet Transform are quite good.

In this paper, we could successfully use this new Transform to obtain invariant features. As it is proved, the kinds of features and the sizes of feature vectors are so important in our recognizing process. On the other hand, Because of existing a large number of curvelet coefficients from backward view of vehicles if these coefficients be performed to our classifier, the speed of our recognition system will be decreased. To remove this problem, we perform the standard deviation on curvelet coefficients in different angels & scales in its local way. As a result of this performance, the size of feature vector will be extremely decreased. Then, we perform our final feature vector to three kinds of classifiers. Three types of classifiers which are compared contain of:

-The Support vector machine (one versus one)
- The k nearest-neighbor
-The Support vector machine (one versus all).

Our achieved results shown the superiority of the Support vector machine (one versus one) structure, especially associated with the Curvelet preprocessing data.

We've gathered a data set that includes of 300 images from 5 different classes of vehicles. These 5 classes of vehicles includes of: PEUGEOT 206, PEUGEOT 405, Pride, RENAULT55 and Peykan. We've examined 230 pictures as our train data set and 70 pictures as our test data set.

2. Curvelet Transform

The Continuous Curvelet Transform has gone through two major revisions. The first Continuous Curvelet Transform [4] (commonly referred to as the "Curvelet '99" transform now) used a complex series of steps involving the ridgelet analysis of the radon transform of an image. The Performance was exceedingly slow. The algorithm was updated in 2003 in [10]. The use of the Ridgelet Transform was discarded, thus reducing the amount of redundancy in the transform and increasing the speed considerably. In this new method, an approach of curvelets as tight frames is taken. Using tight frames, an individual curvelet has frequency support in a parabolic-wedge area of the frequency domain (As seen in Figure 1.).

Using the theoretical basis in [10] (where the continuous curvelet transform is created), two separated digital (or discrete) curvelet transform (DCT) algorithms are introduced in [13]. The first algorithm is the Unequispaced FFT Transform, where the curvelet coefficients are found by irregularly sampling the fourier coefficients of an image. The second algorithm is the the Wrapping transform, using a series of translations and a wraparound technique. Both algorithms having the same output, but the Wrapping Algorithm gives both a more intuitive algorithm and faster computation time. Because of this, the Unequispaced FFT method will be ignored in this paper with focus solely on the Wrapping DCT method. The curvelet transform is a multiscale transform with frame elements indexed by location, scale and orientation parameters, and have time-frequency localization properties of wavelets but also shows a very high degree of directionality and anisotropy. More precisely, we here use a new tight frame of curvelets recently developed in [10].

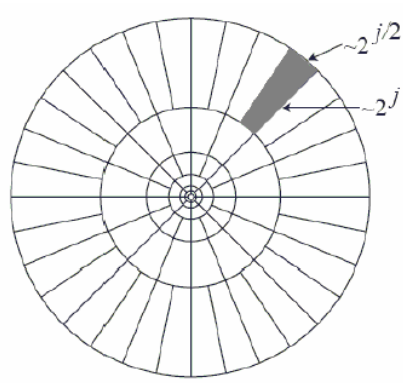

Figure 1. Continuous Curvelet support in the frequency domain

2.1. Why Curvelets?

The fundamental question should now be, *"Why should I exactly use this Curvelet Algorithm?"* This can be answered in one word, sparsity. When we perform the curvelet transform on a C^2 curve, a very

few curvelet coefficients will be above negligible magnitude values. In [10], it is declared that curvelets offer optimal sparseness for "curve-punctuated smooth" images, where the image is smooth with the exception of discontinuities along C^2 curves. Sparseness is measured by the rate of decay of the m-term approximation (reconstruction of the image using *m* number of coefficients) of the algorithm. Having a sparse representation, along with offering improved compression possibilities, also allows for improving denoising performance [11] as additional sparseness increases the amount of smooth areas in the image. In [12] it was shown that orthogonal systems have optimal m-term approximations that decay in L^2 with rate $O(m^{-2})$ (as a lower bound). Currently, a single computationally feasible transform that will obtain this lower bound does not exist. On images with C^2 boundaries, non-optimal systems have the rates:

Fourier Approximation:

$$\left\| f - f_m^F \right\|_{L2}^2 \cong O(m^{\frac{-1}{2}}) \qquad (1)$$

Wavelet Approximation:

$$\left\| f - f_m^W \right\|_{L2}^2 \cong O(m^{-1}) \qquad (2)$$

Curvelet Approximation:

$$\left\| f - f_m^C \right\|_{L2}^2 \cong O((\log m)^3 m^{-2}) \qquad (3)$$

As seen from the m-term approximations, the Curvelet Transform offers the closest m-term approximation to the lower bound. Therefore, in images with a large number of C^2 curves (i.e. an image with a great number of long edges), it would be advantageous to use the Curvelet Algorithm.

2. The proposed Recognition method

In this paper, we've proposed a new algorithm for recognizing vehicle system. This algorithm is based on curvelet transform & standard deviation criteria. The performing process of this algorithm are:

2.1. Normalization:

The size of all test & train images must be normalized to 128*128 pixels.

2.2 Feature extraction:

The feature extraction method suggested in this study consists of 3 stages. These stages are summarized as it's written below.

Stage-1

In this stage, images from the backward view of the vehicles are decomposed by using Discrete Curvelet Transform. As a result of performing Fast Curvelet Transform, curvelet coefficients in different 4 scales and various angels, will be obtained (for image 128*128). According to evidences, performing all curvelet coefficients to classifiers is not suitable.

The obtained curvelet coefficients include of complex values, so for getting more convenience we'll gain the norm of curvelet coefficients.

Stage-2

For extracting the best features, and also decreasing the size of feature vector for each picture, we obtain standard deviation criteria in scales & various angels of curvelet coefficients matrix and then we could reduce the dimension of our feature vector.

Stage-3

Then, we'll normalize the 81 obtained elements of feature vectors values from stage 2 in a distance of 0&1.

2.3 Classification

This stage is vehicle classification stage. In this here, the obtained features From stage 3 are used for intelligent classification. The related feature vector in each picture enter to the related classifier. Three types of classifiers have been used in this paper:

The Support vector machine (one versus one), the k nearest-neighbor and the Support vector machine (one versus all). The structure of algorithm for vehicle recognition is shown in Figure.2.

2.3.1 Support Vector Machine (SVM) classifiers

SVM is a learning system that uses a hypothesis space of linear functions in a high dimensional feature space to estimate decision surfaces directly rather than modeling a probability distribution across training data. It uses support vector (SV) kernel to map the data from input space to a high-dimensional feature space which facilitates the problem to be processed in linear form. SVs are samples that have

non-zero multipliers at the end of optimization process which is referred to equation (5). SVM always finds a global minimum because it usually tries to minimize a bound on the structural risk, rather than

the empirical risk . Empirical risk is defined as measured mean error rate on the training set as bellow

$$R_{emp}(\alpha) = \frac{1}{2l}\sum_{i=1}^{l}\left| y_i - f(x_i, \alpha) \right| \qquad \textbf{(4)}$$

Where l is number of observation, y_i class label and x_i is sample vector. And structural risk is defined as a structure of divided entire class of function into nested subset and finding the subset of function which minimizes the bound on the actual risk. SVM achieves this goal by minimizing the following Lagrangian formulation:

$$L_P \equiv \frac{1}{2}\|w\|^2 - \sum_{i=1}^{l} \alpha_i y_i (x_i.w + b) + \sum_{i=1}^{l} \alpha_i \quad \textbf{(5)}$$

Where α_i is positive Lagrange multipliers

A SVM is a binary classifier. In the case of more classes, two different strategies are possible: "one versus one" and "one versus all". In the first case one SVM for each pair of classes is constructed; an element x_i belongs to the class that produces the most positive output. In the second case one SVM for each class is constructed, in order to separate one class from the others [14,15].

2.3.2 KNN (K nearest neighbor classifier)

The k nearest-neighbor is used for classification [16]. Achieved consequences of this algorithm are discussed more in experimental result section.

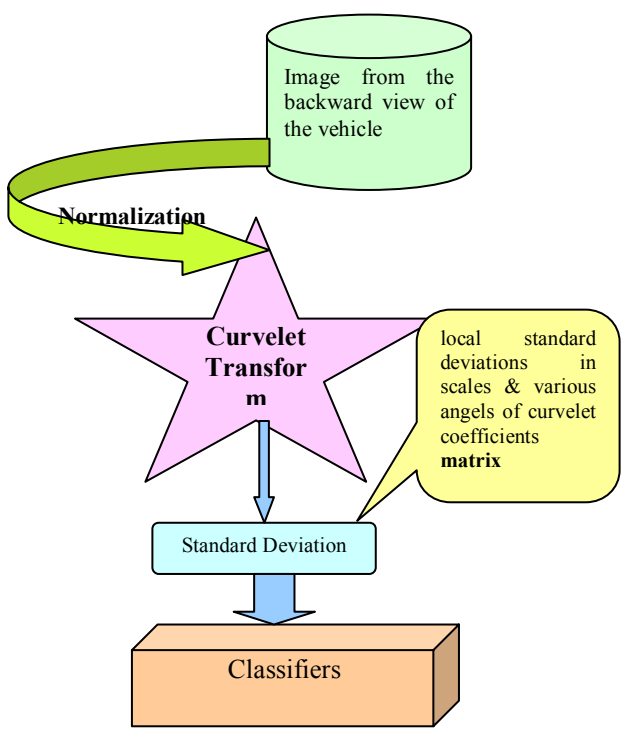

Figure 2. Recognition process block diagram

3. Experimental results

For testing the right performance of our proposed algorithm, we've examined 5 common classes of vehicles in Iran ,that include of PEUGEOT 206,PEUGEOT 405,pride, RENAULT55 and Peykan. Our total data set includes of 300 images from the backward view of the mentioned vehicles. Our training data set includes of 230 images & our test data set includes of 70 images.

In this study, to gain feature vector we perform the standard deviation on curvelet coefficients in different orientations & scales in its local way (Notice, curvelet coefficients are gained in 4 scales.)

Now this question is provided that, which scales is the important one in aspect of having useful information?

According to table 1, when we use the information of scale 4 for achieving feature vector, our recognition rate gets better. So, the scale 4 in aspect of having useful information is the best scale. According to table 1, scales in aspect of having useful information are in order, scale 4,3,2,1.

Another question is provided that, if we use different scale's information, our recognition rate will be better or no? Which of these scales for producing feature vector is better to be used?

As a response to all these questions & proposed results in table 1 and 2,we can claim, if we use scale's information numbers 2,3 and 4 our recognition rate will be improved & better. One of the reasons of this result can be using of image's information in different size partitions & various scales. As a result of this action, The obtained number of features from each image, will be decreased from 1894105(curvelet coefficients) to 81(standard deviation criteria in scales & various orientations of curvelet coefficients matrix) features. These 81 features are the obtained standard deviations from different scales & various orientations of curvelet coefficient matrix. In this feature vector, the feature number of 1 is related to scale 1, the feature numbers of 2 to 17 are related to scale 2, the feature numbers of 18 to 49 are related to scale 3 and the feature numbers of 50 to 81 are related to scale 4.

Fig.3 shows a typical set of curvelet coefficients of the image "PEGEOT 206" divided into four scales using the Digital Curvelet Transform (DCT) of [10,13].

Three structures of Support vector machine (one versus one), k nearest-neighbor and Support vector machine (one versus all) have been used as the classifiers.

The best results have been obtained by the Support vector machine (one versus one) classifier. There is a

big difference between the Support vector machine (one versus one) classifier and the Support vector machine (one versus all), which was found evidently inefficient at recognition process. We train SVMs with RBF kernel.

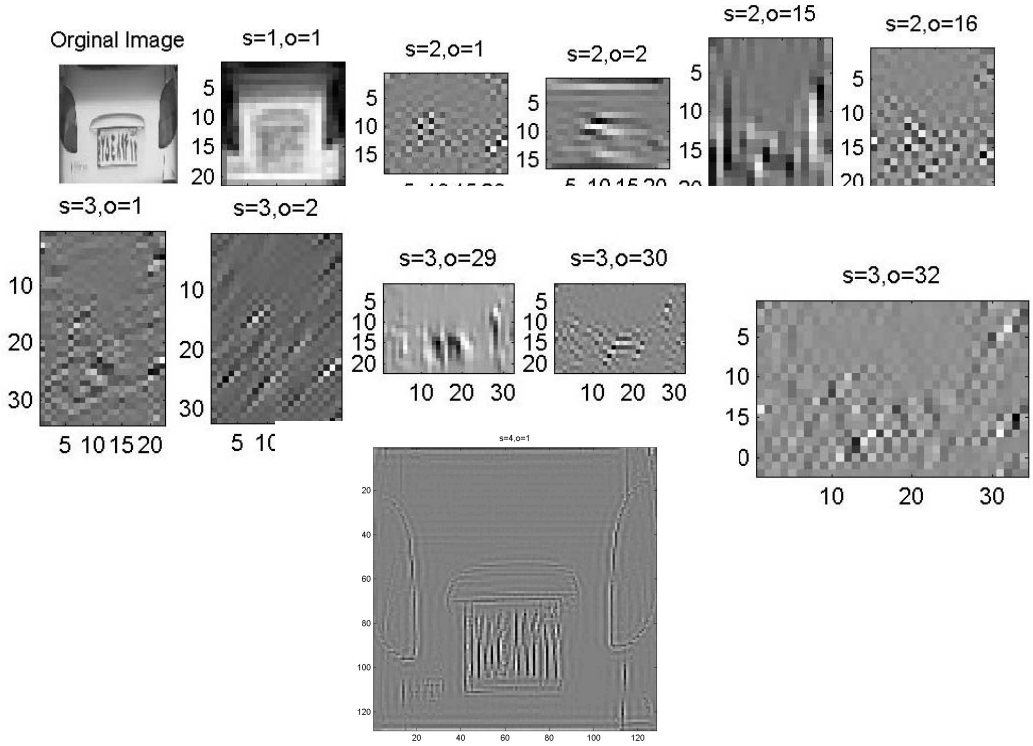

Figure.3. An example of digital curvelet transform of the image "PEGEOT 206".
(s: is the scale, o: is the orientation).
As you see in the related picture to scale 4-orientation 1 the edges have been extracted slowly.

Table 1 A comparison of the performances of various methods

	Scale									
	1	**2**	**3**	**4**	**1,2**	**2,3**	**3,4**	**2,3,4**	**1,2,3**	**1,2,3,4**
Recognition rate using SVM (one versus one)	38%	73%	96%	71%	70%	95%	99%	90%	82%	89%
Recognition rate using KNN	24%	62%	89%	70%	59%	89%	92%	78%	73%	78%
Recognition rate using SVM (one versus all)	18%	50%	78%	62%	42%	75%	81%	65%	60%	67%

4. Conclusion

In this paper, we showed to obtain feature vectors for creating a recognition vehicle system; we can use the backward views of vehicles. Also in this paper, a new algorithm for recognizing vehicle's model is proposed. In this method, for achieving feature vector the standard deviation criteria on Curvelet coefficients matrix are performed in different scales & orientations.

Also, this paper presents the comparison of different classifiers efficiency in the vehicles Recognition. Three types of classifiers have been compared: the Support vector machine (one versus one), the k nearest-neighbor and the Support vector machine (one versus all).The obtained numerical experiments for the vehicles recognition model have shown the superiority of the Support vector machine structure (one versus one), especially when is associated with the Curvelet preprocessing data.

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