Vehicle Identification Using Wavelet Entropy and Particle Swarm Optimization Support Vector Machine

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Abstract: In order to identify Ford vehicles from non-Ford vehicles, this paper proposed a novel method based on the combination of wavelet entropy, particle swarm optimization, and support vector machine. We collect a 100-image dataset, 50 are Ford vehicles and the rest 50 are non-Ford vehicles. The results show that our method obtained a sensitivity of $82.20 \pm 3.94\%$, a specificity of $81.60 \pm 3.50\%$, and an accuracy of $81.90 \pm 0.74\%$. In all, this method is promising in vehicle identification.

1. Introduction

With the rapid growth of the number of vehicles, the demand of vehicle production line supervision, traffic video surveillance is increasing [1, 2]. As a result, the accuracy in vehicle identification is required to be getting higher. The core mission is to identify and classify vehicle in images [3, 4].

In this study, we used a model mixed by wavelet entropy and support vector machine based on particle swarm optimization (PSO-SVM). By applying wavelet entropy [5-9], we can extract a better expression of image signal from original image, which will be viewed as features of the image. As a result, extracted features will be the inputs of PSO-SVM. In the end, PSO-SVM will output the correct result of this task. According to our experiments, this method can provide both high accuracy and high speed, which makes it an advantage compared with neural networks.

With the perspective of practical application, we collect images of vehicles from multiple directions, instead of images of frontal view only. The cross validation technique [10] was used to report the out-of-sample errors.

2. Method

2.1 Wavelet Entropy

Information entropy is defined as the average amount of information produced by a stochastic source of data. We measure the information entropy of signals applied wavelet transform, which is called wavelet entropy (WE) [11-17].

The wavelet is a smooth and quickly vanishing oscillating function with good localization in both frequency and time [18]. A wavelet family $wf_{a,b}$ is the set of elementary functions generated by dilations and translations of a unique admissible mother wavelet $wf(t)$:

$$wf_{a,b}(t) = \frac{1}{\sqrt{|a|}} * wf\left(\frac{t-b}{a}\right) \quad (1)$$

where $a, b \in R, a \neq 0$ are the scale and translation parameters respectively, and t is the time.

Assuming the signal sequence is $S(n)$ ($n = 0, 1, \dots, M$), $N = \log_2 M$. Then the wavelet coefficients are given by:

$$C_j(k) = \langle S, wf_{j,k} \rangle \quad (2)$$

The energy at each resolution level $j = -1, \dots, -N$, will be the energy of the detail signal and the energy at each sampled time k will be:

$$E_j = \sum_{k=-N}^{-1} |C_j(k)|^2 \quad (3)$$

As a result, the total energy can be calculated by:

$$E_{total} = \sum_{j<0} E_j \quad (4)$$

We can use p_j to represent the relative wavelet energy:

$$p_j = \frac{E_j}{E_{total}} \quad (5)$$

In the end, we can obtain the wavelet entropy [19-23] based on the equation obtained in (5):

$$WE = - \sum_{j<0} p_j * \ln[p_j] \quad (6)$$

2.2 Particle Swarm Optimization

Particle swarm optimization (PSO) is an evolutionary algorithm that optimizes (minimizes) an objective function by iteratively trying to improve a set of candidate solution with regard to a given fitness metric [24]. It solves a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the solution space according to simple mathematical formula over the particle's position and velocity. Each particle's movement is influenced by its local best known position, but is also guided toward the best known positions in the solution space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions.

PSO starts from the random solution and iteratively finds the optimal solution. It also evaluates the quality of the solution through fitness, but it is simpler than the genetic algorithm rules. It does not have the "crossover" and "mutation" operations of the genetic algorithm. It seeks the global optimum by following the current searched optimal value [25-30].

PSO simulates birds by designing massless particles. Each particle has 2 properties: velocity (V) and position (P), where V represents how fast it can move and P indicates where the particle is in the solution space. Each particle searches global optimum in the solution space. The best position experienced by i -th particle will be saved as $pbest_i$. Fitness of each particle will be shared among all particles. And the global optimum will be saved as $gbest$. Normally, d -th component of the solution vector will be clipped in the range $[x_{min}^d, x_{max}^d]$.

Then, we can use following formula to update particle's velocity:

$$v_i^d = w * v_i^d + c_1 * r_1 * (pbest_i - x_i^d) + c_2 * r_2 * (gbest_d - x_i^d) \quad (7)$$

And we use following formula to update particle's position:

$$x_i^d = x_i^d + v_i^d \quad (8)$$

where c_1 , and c_2 are learning rate of PSO and $r_1, r_2 \sim U[0, 1]$, v_i^d represents d -th component of i -th particle's velocity, x_i^d represents d -th component of i -th particle's position.

After initialization, PSO will iteratively update velocity and position of each particle and save $pbest$ and $gbest$, until satisfies the termination condition. In the end, $gbest$ will be the solution of given problem. Due to page limit, we shall compare PSO with latest bioinspired algorithms, e.g., biogeography-based optimization [31-34], ant colony optimization, multiverse optimizer, etc.

2.3 Support Vector Machine

Support vector machine (SVM) which is also called large margin classifier is a model which can classify samples into 2 categories.

The set of points closest to the maximum margin decision boundary are known collectively as the support vectors [35]. The name comes from the fact that they define, or support, the decision boundary. In many situations, this will make the decision become a function of only a small subset of the training samples. For problems with large dataset, this can be a very useful feature. Consider classifying a test point using KNN when the training set containing a large number of objects. To

find the set of neighbors, distances must be computed between the sample and all of the training objects. For an SVM trained on the same data, the decision function might just involve a much smaller subset of the training data.

When classification, we use following formula to determine the label of given sample x_n :

$$label = \begin{cases} 1, & \text{if } w^T * x_n > 1 \\ -1, & \text{if } w^T * x_n < -1 \end{cases} \quad (9)$$

where w is the weight vector which represents the normal vector of the decision boundary. Here we use PSO algorithm to find best w , instead of using some traditional algorithm such as SMO [36-38].

Original SVM can only classify samples which are linear separable. While, kernel functions such as Gaussian Kernel make it able to classify samples with non-convex decision boundary.

2.4 Dataset and Implementation

Figure 1 Pipeline of our method

In this study, we calculate the wavelet entropy of preprocessed input image. This entropy will be viewed as extracted features of input image and sent to SVM. Apparently features extracted by wavelet entropy are better than raw pixels of input image. PSO algorithm will be used to optimize parameters of SVM during training. We train SVM using mini-batches, which can save some training time. Performance of our algorithm will be shown in later Section.

Figure 2 Samples of Dataset

100 vehicle images are obtained, 50 are Ford vehicles, and the rest include Buick, Hyundai, Shanghai Volks, and Toyota. Each image was resized to 256×256. For simplicity, we converted the color images to gray-level images.

3. Experiments and Results

3.1 Cross Validation Techniques

Here we use our proposed ‘WE-PSOSVM’ approach to identify Ford vehicle from other categories of vehicles. The parameters are obtained by grid searching approach. We used a four-level wavelet entropy decomposition. A 10x10-fold cross validation was used, since our dataset merely contains 100 image. One example of 10-fold division was shown in Figure 3.

Figure 3 Division of ten folds

Table 1 Statistical Results of proposed methods

Sen	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Total
1	60	80	60	40	100	80	100	100	60	80	76
2	100	40	80	80	60	80	80	100	100	100	82
3	60	100	60	80	80	80	80	80	100	60	78
4	80	100	80	100	80	80	60	80	80	80	82
5	100	80	80	100	100	80	80	60	40	100	82
6	100	100	100	100	80	80	80	80	100	80	90
7	60	100	100	100	80	60	60	100	80	100	84
8	60	80	20	100	100	100	100	100	100	100	86
9	100	60	60	100	60	100	100	100	60	80	82
10	80	80	100	60	100	100	100	80	40	60	80
Spc	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Total
1	100	100	80	80	100	100	100	80	40	80	86
2	80	80	100	100	60	80	60	100	100	60	82
3	100	60	80	80	100	80	100	100	100	80	88
4	40	80	80	80	80	100	100	100	80	80	82
5	100	100	80	80	60	100	80	80	80	60	82
6	60	60	80	80	80	80	60	80	80	100	76
7	40	100	80	60	60	100	80	100	100	80	80
8	80	40	100	80	40	80	100	80	80	100	78
9	80	100	100	80	100	80	60	60	100	40	80
10	100	60	80	100	100	80	100	80	80	40	82
Acc	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Total
1	80	90	70	60	100	90	100	90	50	80	81
2	90	60	90	90	60	80	70	100	100	80	82
3	80	80	70	80	90	80	90	90	100	70	83
4	60	90	80	90	80	90	80	90	80	80	82
5	100	90	80	90	80	90	80	70	60	80	82
6	80	80	90	90	80	80	70	80	90	90	83
7	50	100	90	80	70	80	70	100	90	90	82
8	70	60	60	90	70	90	100	90	90	100	82
9	90	80	80	90	80	90	80	80	80	60	81
10	90	70	90	80	100	90	100	80	60	50	81

3.2 Statistical Analysis

The 10-fold cross validation repeated 10 times, each time the division is randomly generated. The statistical results are listed in Table 1. The average sensitivity, average specificity, average accuracy are $82.20 \pm 3.94\%$, $81.60 \pm 3.50\%$, $81.90 \pm 0.74\%$.

4. Conclusions

This paper proposed a new method of 'WE-PSOSVM' to identify Ford vehicles. The results showed our method yields a sensitivity of $82.20 \pm 3.94\%$, a specificity of $81.60 \pm 3.50\%$, and an accuracy of $81.90 \pm 0.74\%$. In the future, we shall test advanced variants of SVM, including kernel SVM. We shall also try to use PSOSVM to identify vehicles of other brands.

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