Motor Side-View Recognition System Based on Wavelet Entropy and Naïve Bayesian Classifier

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Abstract—As the traffic accident becomes a serious problem, we need some more efficient methods to identify the car. Luckily, we can use artificial intelligence to recognize the motors by using side-view images. It will help a lot to solve the traffic accident. We used the wavelet entropy to extract the feature of the images. Then we employed the naïve Bayesian theory as the classifier. And we used 10-fold cross validation in our experiment. We used a three-level decomposition for WE. It got an overall accuracy of 75% in recognizing motors. In the future we will try to improve the accuracy of this method and try to identify cars from different brand.

Keywords—artificial intelligence; wavelet entropy; naïve Bayesian classifier; cross validation

I. INTRODUCTION

As the motors become more and more popular in china, the traffic accident become more serious and frequent than before. In these situations, we need to recognize the motors. However, it is difficult for us to extract the pictures of the front of the motors from the camera [1]. But it is easier for us to get the images of the side view of the motors. This technology will help police to solve the accident and judge the responsibility of the motors involved in the accident.

At the present, there is not a technology can recognize the car brand from the side view. We searched on Web of Science, Engineering Index, Scopus, IEEE, and other well-known databases, we did not find some related articles, so we believe that we are one of the first team to work on it.

We use Wavelet Entropy (WE) [2-5] to obtain the features of the motor images. This method is better than the Scale Invariant Feature Transform (SIFT) [6-8], which will cause some features match problems. WE has a lot advantages, it can isolate each images which will make the recognition easier. And also WE had some benefits over Fourier transforms on specific frequencies.

The naïve Bayesian (NB) classifier [9, 10] is used to identify the motors brand from 20 images. We assume every feature the WE extract is independent of any other feature, and likelihood of each feature is same. This classifier can be set very efficiently and only need a small number of data to estimate the parameters, which is more appropriate than other classifier in this survey.

II. METHODS

A. Wavelet Entropy

Our method is made up by four stages, including shooting the images of motors, image processing, obtaining features of motors, and NB classification.

Our method is to use wavelet entropy (WE) to get the features of motors. WE is based on wavelet entropy and information entropy [11]. The formula can be described like this:

$$W_{\psi}(a, c) = \int_{-\infty}^{+\infty} x(t) \psi_{a,c}(t) dt \quad (1)$$

And

$$W_{a,c}(t) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-c}{a}\right), a \neq 0, c \in R \quad (2)$$

In the formula, a means scale factor, c means translation factor. Ψ is called orthonormal wavelet, which is decided by factor a and c . And the formula above is called continuous wavelet transform (CWT). However, if the samples of the wavelets are discrete, the transform will become discrete wavelet transform (DWT), which is used in our method. DWT has an advantage which can get frequency and location information at the same time [12-18].

We will use two-dimensional (2D) DWT twice. After the first DWT, we can get four images, the upper-left is the low-pass filtered images, which contain the most features of the image [19-27]. And the use 2D-DWT to the upper-left image again, and we get seven images, each including different features. The low frequency images contain the most information, while the upper-right contain the information about horizontal features, the left lower contain the information about vertical feature, and the right lower contain the information about diagonal features [28-35].

As it shown in Figure I, $x[n]$ is input, $g[n]$ means low pass filter, $h[n]$ means high pass filter, while Q means a

downsampling filter, and we take the factor of 2 as an example. The Figure II demonstrate the twice 2D-DWT.

FIGURE I. 2D-DWT

FIGURE II. TWICE 2D-DWT

B. Naïve Bayesian Classifier

In our method, naïve Bayesian (NB) classifier is used. Bayes theory is an important tool for dealing with uncertain information. As an uncertain method for reasoning, it depends on the theory of probability and statistics and it has a solid mathematical basis [36]. NB classifier is a learning method with supervision. We assume that each value of feature is independent of other features, which make the classifier easier and efficient, but also accurate. So, it will save the computing time and memory space of the computer. Naïve Bayesian classifier can be described as following formula [37]:

$$P(B|A) = \frac{P(B|A)P(B)}{P(A)} \quad (3)$$

And if we can get the value of $P(A|B)$, $P(B)$, $P(A)$, then we can find the value of $P(B|A)$.

Now we make this formula easier to understand.

$$P(outcomes|features) = \frac{P(features|outcomes)P(outcomes)}{P(features)} \quad (4)$$

In the formula, sometimes there are different features.

$$P(outcomes|features) = P(outcomes|features_1, features_2, features_3, \dots) \quad (5)$$

Now we need some data to set our classifier. We need to teach our NB classifier to how to identify the brand of motors. Now we need a database, and we calculate the likelihood of each feature. Then we have the value of the likelihood of each feature.

FIGURE III. NB CLASSIFIER

We assume that every feature is independent. So we have:

$$\begin{aligned} P(features|outcomes) &= P(features_1|outcomes) \\ &\quad * P(features_2|outcomes) * P(features_3|outcomes) \\ &= \prod_{x=1}^n P(features_x|outcomes) \end{aligned} \quad (6)$$

From Figure III, we can know how NB classifier works. We calculate the likelihood of each possibility and choose the most likely situation to be outcomes.

After 2D DWT, we can extract the features of the images. Now we know the likelihood of each features, so we can solve the problems by using naïve Bayesian classifier.

III. EXPERIMENTS AND RESULTS

The dataset is shown below in Figure IV. Each image was resized to 255×255. We have in total 80 Ford vehicle images and 80 non-Ford vehicle images, including Buick, Hyundai, Shanghai Volks, and Toyota.

FIGURE IV. SAMPLES OF DATASET

FIGURE V. ILLUSTRATION OF 10-FOLD CROSS VALIDATION

We used a three-level decomposition for WE. The statistical results of 10x10-fold cross validation were shown below in Table I, Table II, and Table III, respectively. The average sensitivity is $75.25 \pm 2.93\%$, the average specificity is $75.25 \pm 3.27\%$, and the average accuracy is $75.25 \pm 0.67\%$.

TABLE I. SENSITIVITY OF OUR METHOD BY A 10X10-FOLD CROSS VALIDATION

Sen	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Total
R1	100.0	62.5	100.0	87.5	100.0	75.0	62.5	50.0	87.5	37.5	76.25
R2	87.5	87.5	75.0	75.0	87.5	75.0	75.0	75.0	62.5	50.0	75.00
R3	100.0	87.5	75.0	50.0	75.0	75.0	87.5	62.5	62.5	100.0	77.50
R4	87.5	87.5	75.0	62.5	62.5	75.0	75.0	100.0	62.5	100.0	78.75
R5	100.0	87.5	75.0	75.0	100.0	75.0	50.0	100.0	75.0	62.5	80.00
R6	75.0	62.5	75.0	75.0	75.0	62.5	62.5	75.0	87.5	87.5	73.75
R7	75.0	62.5	75.0	87.5	75.0	75.0	87.5	62.5	75.0	62.5	73.75
R8	62.5	87.5	50.0	87.5	87.5	75.0	75.0	62.5	75.0	87.5	75.00
R9	75.0	87.5	62.5	75.0	62.5	87.5	50.0	75.0	75.0	62.5	71.25
R10	50.0	75.0	87.5	87.5	75.0	62.5	75.0	37.5	75.0	87.5	71.25

TABLE II. SPECIFICITY OF OUR METHOD BY A 10X10-FOLD CROSS VALIDATION

Spc	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Total
R1	75.0	62.5	75.0	75.0	37.5	100.0	87.5	62.5	87.5	62.5	72.50
R2	62.5	75.0	62.5	75.0	75.0	87.5	100.0	75.0	87.5	75.0	77.50
R3	75.0	75.0	50.0	62.5	75.0	87.5	87.5	62.5	75.0	75.0	72.50
R4	62.5	37.5	62.5	75.0	75.0	75.0	100.0	75.0	62.5	75.0	70.00
R5	50.0	75.0	75.0	100.0	62.5	87.5	75.0	50.0	87.5	62.5	72.50
R6	75.0	50.0	87.5	75.0	75.0	87.5	87.5	62.5	87.5	75.0	76.25
R7	75.0	75.0	62.5	87.5	75.0	75.0	62.5	75.0	87.5	100.0	77.50
R8	87.5	75.0	87.5	62.5	75.0	87.5	62.5	87.5	50.0	75.0	75.00
R9	87.5	87.5	75.0	62.5	100.0	100.0	62.5	62.5	87.5	62.5	78.75
R10	75.0	50.0	87.5	87.5	75.0	75.0	50.0	100.0	100.0	100.0	80.00

TABLE III. ACCURACY OF OUR METHOD BY A 10X10-FOLD CROSS VALIDATION

Acc	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Total
R1	87.50	62.50	87.50	81.25	68.75	87.50	75.00	56.25	87.50	50.00	74.38
R2	75.00	81.25	68.75	75.00	81.25	81.25	87.50	75.00	75.00	62.50	76.25
R3	87.50	81.25	62.50	56.25	75.00	81.25	87.50	62.50	68.75	87.50	75.00
R4	75.00	62.50	68.75	68.75	68.75	75.00	87.50	87.50	62.50	87.50	74.38
R5	75.00	81.25	75.00	87.50	81.25	81.25	62.50	75.00	81.25	62.50	76.25
R6	75.00	56.25	81.25	75.00	75.00	75.00	75.00	68.75	87.50	81.25	75.00
R7	75.00	68.75	68.75	87.50	75.00	75.00	75.00	68.75	81.25	81.25	75.63
R8	75.00	81.25	68.75	75.00	81.25	81.25	68.75	75.00	62.50	81.25	75.00
R9	81.25	87.50	68.75	68.75	81.25	93.75	56.25	68.75	81.25	62.50	75.00
R10	62.50	62.50	87.50	87.50	75.00	68.75	62.50	68.75	87.50	93.75	75.63

The box plot of proposed WE+NB method is shown in Figure VI. We can observe the accuracy has a slight variation compared to sensitivity and specificity.

FIGURE VI. BOX PLOT OF PERFORMANCES OF PROPOSED METHOD

Finally, we compared the results of using different decomposition levels of wavelet entropy. The results are listed in Table IV. We can observe that 3-level decomposition obtained the greatest performance. While 1-level decomposition yields a sensitivity of $68.50 \pm 3.81\%$, a specificity of $68.00 \pm 3.34\%$, and an accuracy of $68.25 \pm 1.21\%$. The 2-level decomposition yields a sensitivity of $73.25 \pm 2.90\%$, a specificity of $73.50 \pm 3.81\%$, and an accuracy of $73.38 \pm 0.73\%$. The 4-level decomposition yields a sensitivity of $74.13 \pm 2.89\%$, a specificity of $74.13 \pm 2.70\%$, and an accuracy of $74.13 \pm 0.53\%$. In the future, some optimization techniques (such as bacterial chemotaxis optimization [38, 39], biogeography-based optimization, multiverse optimizer, etc.) shall be tested to check whether they can improve the classification performance.

TABLE IV. COMPARISON OF DIFFERENT DECOMPOSITION LEVELS

Decomposition	Sensitivity	Specificity	Accuracy
1-level	68.50 ± 3.81	68.00 ± 3.34	68.25 ± 1.21
2-level	73.25 ± 2.90	73.50 ± 3.81	73.38 ± 0.73
3-level (Proposed)	75.25 ± 2.93	75.25 ± 3.27	75.25 ± 0.67
4-level	74.13 ± 2.89	74.13 ± 2.70	74.13 ± 0.53

IV. CONCLUSIONS

From the experiment, we can find that our method worked, and it can be used to identify the motors. But in our experiment, we just took the Ford brand as the examples, which achieved the accuracy of 75%. But the accuracy is not high when test different brands. Hence, our next step is to make some improvements in identifying different brands and we are trying to achieve a high accuracy in detecting. And in our experiment, the dataset is small, which just contains 160 images. We will enlarge it in our next step.

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