Research on Automatic Comparison System of Vehicle Tire Characteristics Based on Quick Query of Traffic Accident Vehicles

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Abstract: The use of traces left behind by traffic accidents can effectively help identify accidental escape vehicles. In the event of a traffic accident, the scene of the accident will generally leave traces of the tires of the vehicle. Inspect and analyze the tire traces to obtain information about the vehicle and help identify and identify the vehicle. Tire pattern image retrieval is an important means to obtain information for solving crimes in traffic accident handling and criminal case detection. Therefore, based on the research of the related literatures in the field of tire pattern image retrieval in recent years, this paper proposes a tire feature comparison system based on multi-level SVM for quick query of the vehicle. Using the database experiment, the comprehensive recognition rate of 99.5% is obtained. High, has great application potential.

1. Introduction

In the process of traffic accidents, the important evidence of traffic accident identification—the trace of the accident scene—has been left under the interaction of various elements of people, vehicles and road environment [1]. The traces of traffic accidents are objective records and reflections of the behaviors of various parties involved in traffic accidents. They mainly include road markings, body marks, human traces, and other traces [2]. In a traffic accident, the ground of the accident scene, the object or the body of the person being hit generally leaves traces of the vehicle tire. Extraction and analysis of tire tracks helps to analyze and deal with traffic accidents. Especially in escape cases, it is more important to study the traces of tires left behind at the scene of the accident to identify the vehicle information. Sometimes this is the only way [3]. Through the identification of tire tracks, you can get a lot of information about the vehicle, including the tire pattern, color, width and the track, wheelbase, wheel diameter and so on. Accurate comparison and judgment of the tire characteristics of traffic accident vehicles is the key to quickly find out the truth and accurately solve the case. At present, some scholars have carried out certain research on tire pattern recognition, and have achieved certain results, but the recognition rate cannot meet the requirements of actual cases [4, 5]. Therefore, research on more effective tire pattern feature extraction and recognition methods to improve traffic police and the work efficiency of public security officers is of great significance in quickly and accurately detecting traffic accidents and vehicle crimes. The Support Vector Machine (SVM) adopts the Structural Risk Minimization (SRM) criterion, which has training error and generalization ability, and can effectively solve pattern recognition problems such as small samples, high dimensionality and nonlinearity [6]. Studies have shown that the support vector machine classification method has achieved good results in plant disease identification and classification of various substances, and is an effective classification and recognition method [7].

2. Image texture feature extraction

In this paper, the feature extraction of non-subsampled Contourlet transform feature extraction and gray level co-occurrence matrix extraction is used. Inspired by non-subsampled wavelets, Donoho et al. proposed a non-subsampled Contourlet Transform (NSCT). Compared with wavelet

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transform and Contourlet transform, NSCT has multi-scale, multi-directionality and translation invariance, which can better express the edge information of the image and extract the texture features of the image to better express the graph and the nuances between the figures.

NSCT separates scale decomposition from direction decomposition. Firstly, the image is decomposed by multi-scale decomposition using Non Subsampled Pyramid (NSP) to obtain the low-pass sub-band coefficients and band-pass directional sub-band coefficients of the image; then pass the non-down sampling direction filter (Non Subsampled Directional Filter Banks (NSDFB) decomposes the bandpass sub-band into several directions, resulting in sub-band images (coefficients) of different scales and directions. After the image is decomposed by Q-level NSCT, one low-pass sub-band coefficient and $\sum_{q=1}^{Q} 2^{n_q}$ band-pass sub-band coefficients are obtained, where n_q is the direction decomposition series under the scale q. The NSCT decomposition structure is shown in Figure 1.

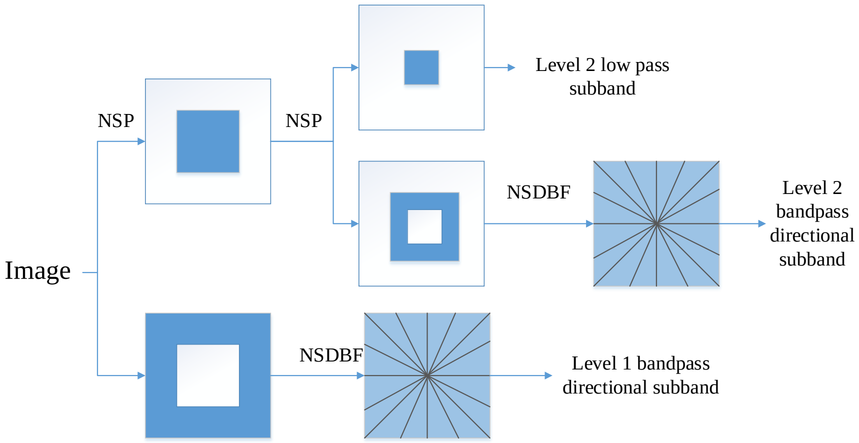

Figure 1. Two-layer NSCT structure

The Gray Level Co-occurrence Matrix (GLCM) feature extraction method dominates the statistical method and reflects the comprehensive information of the image in terms of interval, variation amplitude, direction and speed. It is simple and easy to implement, and has strong performance. Adaptability and robustness.

From the gray level co-occurrence matrix, the second order moment (ASM), contrast (Con), correlation (Cor), entropy (Ent), variance and (SV), inverse gap (IDM), variance difference (DV), etc. can be derived. However, calculating the gray level co-occurrence matrix is time consuming, and the resulting sparse matrix can lead to a large amount of redundant calculation and waste of storage space. Selecting the texture features that best represent the image features can effectively reduce the calculation; normalizing the co-occurrence matrix can not only effectively avoid the disadvantages of the sparse matrix, but also make the texture resolution higher. In addition, the study found that among the 14 texture features, the five characteristics of angular second moment (ASM), entropy (Ent), contrast (Con), inverse gap (IDM), and correlation (Cor) are easy to calculate and can give higher classification accuracy, so only the text is calculated

These five features are used as image features. The characteristic calculation formula is shown in Equations 1 to 5.

Angular second moment (ASM)

$$ASM = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \left[p_\delta(i,j) \right]^2 \tag{1}$$

Entropy (Ent)

$$Ent = -\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p_\delta(i,j) \ln\left[p_\delta(i,j) \right] \tag{2}$$

Contrast (Con)

$$Con = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{\substack{i=1 \\ |i-j|=n}}^{N_g} \sum_{j=1}^{N_g} p_\delta(i, j) \right\} \tag{3}$$

Inverse gap (IDM)

$$IDM = \sum_{i=1}^{N_g} \sum_{h=1}^{N_g} \frac{1}{1+(i-j)^2} p_\delta(i, j) \tag{4}$$

Correlation (Cor)

$$Cor = \frac{\left\{ \sum_{i=1}^{N_g} \sum_{h=1}^{N_g} i * j * p_\delta(i, j) - \mu_x \mu_y \right\}}{\delta_x \delta_\mathrm{y}} \tag{5}$$

3. SVM classification method based on decision tree

The main algorithms for solving multi-classification problems with support vector machines are: one-to-many method, one-to-one method, decision-oriented cyclic graph, k-class SVM method and layer (tree) classification method. Although the one-to-many method is simple, the classifier structure is complex and the generalization ability is poor, and the training time is proportional to the number of sample categories k, and the recognition accuracy for small sample categories is low. After learning, the error is unbounded, there are some disadvantages such as misclassification, sub-region, and the number of classifiers increases rapidly with the increase of the number of classifications; the biggest disadvantage of the decision-oriented cyclic graph is that the classification speed is slow; the k-class SVM algorithm is all The sample uses the same quadratic programming, and the classification can be determined in one time, but it also causes the constraint to increase sharply [8]. The secondary planning for classification is quite large; the tree SVM (multi-level SVM) classification method inherits one-to-many method. The method has the advantages of less training support vector and faster one-to-one method. It also overcomes the existence of unclassifiable regions that may occur in one-to-one, one-to-many, decision-oriented circular graph methods, and improves support vector machine multi-classification. Considering the above factors, this paper adopts SVM classification method based on decision tree.

The SVM classification method based on decision tree uses tree classifier to transform a complex multi-class classification problem into several classification problems of two classification problems, which is an improvement of one-to-one method. First, divide all the data into 2 large categories, then divide each large category into 2 sub-categories, and so on, to form different levels, each of which uses SVMs for classification. For the k-class classification problem, only k - 1 SVM classifiers need to be constructed, and there is no unrecognizable domain in the method. It is not necessary to traverse all the classifiers when classifying, thus greatly speeding up the classification. The optimal decision tree designed in this paper is shown in Figure 2.

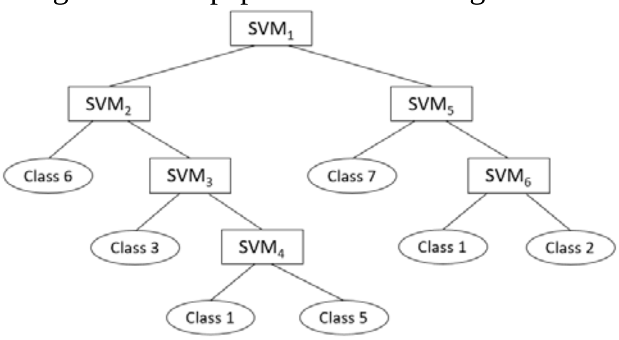

Figure 2. SVM decision tree

4. Database verification

Tire pattern images are difficult to obtain in large quantities due to the special source and application scenarios. In this paper, 210 tire pattern images were collected as experimental objects, including 7 types of tire patterns, 30 pieces in each category. Make full use of the amount of data by using cross-validation.

4.1 Evaluation indicators

The image retrieval algorithm aims to accurately and efficiently retrieve images that meet the user's requirements, and evaluates the retrieval performance by using the retrieval result evaluation mechanism. Image retrieval performance evaluation criteria can be divided into three categories: effectiveness, efficiency, and flexibility. Among them, the validity representative retrieves the success rate matching the example image, that is, the retrieval precision, the efficiency indicates the speed of image retrieval, and the flexibility indicates the adaptability to different application scenarios. The image retrieval performance evaluation index commonly used in the literature is mainly the precision rate, which refers to the percentage of the returned image that is returned by the retrieval system and the percentage of all returned images after the user submits the query sample image. The larger the value of the percentage, the higher the precision of the retrieval algorithm, which means that the retrieval performance of the system is better.

In this paper, the vehicle pattern is classified, and the classification accuracy, that is, the precision is used as the evaluation index. The calculation formula is shown in Equation 6.

$$precision = \frac{a}{a+u} \tag{6}$$

Where a is the actual number of correlations in the query results, and u is an irrelevant number.

4.2 Algorithm Flow

Based on the combined features and hierarchical SVM, this paper proposes a feature extraction classification method. The algorithm flow chart is shown in Figure 3. An algorithm for extracting tire tread image features using NSCT and GLCM, and combining the features extracted by the two algorithms as fusion features. Next, five valid features are selected in the fusion feature as the final recognition feature. Finally, five fusion features and a decision tree-based SVM classifier are used to identify and classify tire pattern images.

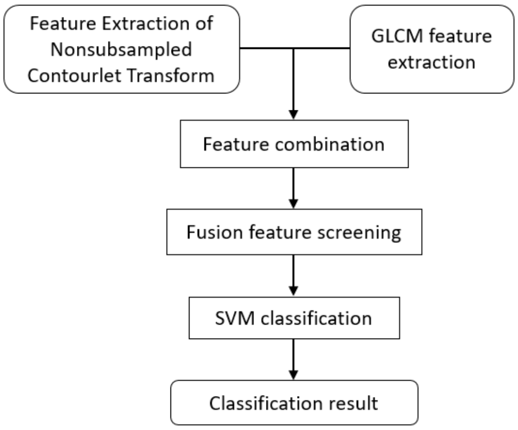

Figure 3. Algorithm flow

The 2-cross-validation method is used to compare the classification effects of one-to-one, one-to-many, and text methods. The classification accuracy rate is shown in Table 1.

It can be seen from Table 1 that the recognition rate of the proposed method is the highest, because the method can construct the optimal decision tree, and the cross-validation method for each SVM can obtain the optimal kernel function parameters σ and C, thus making each layer of SVM has the best classification effect. In addition, the total recognition rate of the three methods is above 95%, which indicates that the feature extraction method proposed in this paper is effective for the classification and identification of the 7 types of tire treads in the paper.

Table 1 Classification accuracy comparison (%)

Method	One-to-one	One-to-many	Text method
Training dataset	100.00	100.00	100.00
Testing dataset	95.60	92.97	97.32
Total accuracy	98.57	97.46	99.10

5. Conclusion

Vehicle tire tracks are one of the most important physical evidence on the scene and play an important role. In the process of dealing with road traffic accidents and accidents and escapes, it is necessary to scientifically use the tire trace test methods such as feature comparison method, feature measurement method and material analysis method to identify and identify the relevant information of tire traces, which can effectively help identify accidental escape vehicles. In this paper, a method based on NSCT and GLCM for feature extraction and multi-level SVM is proposed. The experimental results show that the method can effectively distinguish many types of tire patterns. However, the types of tire treads are far more than the 7 types mentioned in the paper. When the pattern type increases, the features extracted by the symbiotic matrix feature extraction method can distinguish the tire patterns with different distinctions. For the NSCT feature extraction method, the NSCT can be increased by decompose the series to improve the ability of the NSCT to express more image nuances. In addition, the feature selection method and classification recognition method mentioned in the paper can also be used for feature selection and classification recognition of other types of images. Therefore, the tire identification method in this paper is effective and feasible.

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