Automatic Identification of Traffic Accidents based on Intelligent Identification

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Abstract: The traffic accident process system is complex, by extracting the traffic accident information, the real-time state monitoring of the traffic accident image can be realized. A method of traffic accident information extraction and automatic recognition is proposed based on depth neural network and intelligent image analysis. The remote sensing method is used to collect the traffic accident image, the traffic accident remote sensing image is adaptively de-noised, and the block feature matching method is used to deal with the traffic accident image block fusion. The feature extraction of traffic accident state is carried out in the subspace component of traffic accident image, and the image feature classification of traffic accident is processed by using depth neural network classifier to realize image feedback recognition of traffic accident state feature quantity. A large number of traffic video images are selected for experiments. The simulation results show that the proposed method is more intelligent and accurate.

1. Introduction

With the increase of vehicles and roads, the probability of traffic accidents is increasing. Traffic accidents have become one of the biggest killers to capture human life and property. In order to reduce traffic accidents, it is necessary to identify the traffic accidents, use the image processing method to identify the traffic accidents and improve the analysis and judgment of traffic accidents. In order to optimize the handling capacity of traffic accidents, improve the handling efficiency of traffic accidents, this paper image processing methods are used to identify traffic accidents, and it provide visual information for drivers and traffic accident processing centers by effective detection and identification of vehicle characteristics. It has great significance to deal with the efficiency[1].

With intelligent recognition of vehicle features, combined with vehicle networking technology and
wireless communication technology, traffic accident transportation condition monitoring and road traffic information monitoring and evaluation are carried out to extract vehicle speed GPS position and three-dimensional information features[2]. Real-time evaluation and three-dimensional visualization analysis of traffic accidents are carried out by intelligent classification and identification method. The research of intelligent recognition method for traffic accident features is based on the image information collection and feature extraction of traffic accidents. By extracting the category attribute features of traffic accident images, such as pixel information features, the features of edge contour and corner are classified and recognized by classification algorithm. The common classification algorithms are BP neural network, support vector machine and fuzzy C-means classification[3]. The extracted features are input into the classifier to realize the traffic accident identification and monitoring[4]. According to the above principles, the relevant scholars have carried out the research on the intelligent recognition method of the traffic accident features, and obtained some research results, among which, in reference(Zhang et al., 2016), a traffic video traffic accident retrieval method based on improved SURF algorithm is proposed[5]. SIFT(Scale-Invariant Feature Transform) corner detection method is used to detect the corner distribution of traffic accident image in traffic video, and SURF algorithm is used to realize image classification and recognition. The method has high recognition accuracy, but the computation cost of this method is high, and the real-time performance of the method is not good for large-scale traffic video traffic accident feature recognition. In reference(Salinas D et al., 2013),a method of traffic accident feature recognition based on multi-feature suppression of traffic accident shadow detection method is proposed, and the feature segmentation and block feature matching of traffic accident monitoring image based on LWT wavelet decomposition method are presented[6]. Support vector machine (SVM) is used to classify and recognize multi-features, which improves the accuracy of fuzzy traffic accident video surveillance image and traffic accident image with shadow. However, this method has some problems such as poor resolution and low clustering convergence[7].

In order to solve the above problems, this paper presents a method of traffic accident information extraction and automatic recognition based on depth neural network and intelligent image analysis. We used to collect the traffic accident image with the remote sensing method ,the traffic accident remote sensing image is adaptively de-noised, and the block feature matching method is used to deal with the traffic accident image block fusion. The traffic accident state feature is extracted from the subspace component of the traffic accident image, and the Radon scale transform is used to classify the traffic accident image feature to realize the image feedback recognition of the traffic accident state feature quantity. Finally, the simulation results show the superiority of this method in improving the ability of automatic identification of traffic accidents.

2. Traffic accident Image acquisition and preprocessing

2.1 Construction of image acquisition model for traffic accidents

In order to realize the intelligent recognition of traffic accident features, image acquisition is the first step. In this paper, 3D area contour scanning method is used to collect the traffic accident image and analyze and judge the geometric shape. The feature points of traffic video monitoring image are analyzed and the 3D area contour scanning model of traffic accident image acquisition is constructed under the road network model, Road network model for image collection of traffic accidents is shown in figure 1.
Figure 1. Road network model for image collection of traffic accidents

In figure 1, under the system of road network and vehicle network, the intersection nodes are used as Sink points for traffic accident video information monitoring and image acquisition, and $\alpha$ and $90^\circ - \alpha$ angles are selected as the phase angles of video surveillance. According to the Boolean model, the Euclidean distance between the traffic accident image sampling node and the Sink node can be obtained. The traffic accident image scan frame number is $V = \{C_1, C_2, \ldots, C_k\}$, the cluster of the head node $v$ satisfies $C_i \subseteq V$, $1 \leq i \leq k$, $k \leq |V|$, and the distance between the different traffic accident sampling nodes $x$ and $y$ is $\text{distance}(x, y) \leq d$.

In the feature subspace, $\Theta = \{w_1, w_2, \ldots, w_n\}$ is the initial information parameter of 3D image scanning point cloud data. The time stamp and geographical information of traffic accident node are represented by $v(t)$, the distance between two traffic accident nodes is calculated, and the traffic accident image is three. The edge contour distribution region of the feature scan points satisfies $\mu \in (-\infty, +\infty), \sigma \geq 0$. The 3D contour scanning points are at any point $V = \sum_{i=1}^{k} C_i$, and the sampling sequence $i \in [k]$ of any image pixel has $C_i \cap C_j = \Phi$, $j \in [k], i \neq j$. Based on the 3D reconstruction of the shape features of traffic accidents and the edge contour detection method, the shape geometry of traffic accidents is judged, and the state characteristic equation of the traffic accident image acquisition model is obtained as follows:

$$
a(t) = \begin{cases} 
a(0) & a(0) > 0, t \leq \frac{v_{\max} - v(0)}{a(0)} \\
0 & \text{otherwise} 
\end{cases}$$

$$
a(t) = \begin{cases} 
a(0) & a(0) < 0, t < \frac{-v(0)}{a(0)} \\
0 & \text{otherwise} 
\end{cases}$$

In 3D mesh vertex $y$, $y \in C_i$, the initial speed of traffic accident is $v(0)$. Under uniform pixel sampling, the pixel offset of traffic accident edge contour reconstruction is:

$$v(t) = v(0) + \int_0^t a(x) dx$$

Where, $a(x)$ is the initial pixel sampling information, according to the traffic accident image acquisition results, traffic accident feature recognition.

2.2 Traffic accident edge profile

In order to improve the ability of expressing the information features of the traffic accident image, detected information and make enhanced processing for it, it is necessary to detect the edge contour and
enhance the information of the collected traffic accident image. When the original image of the traffic monitoring video is used as the input image, it is necessary to take the image of the traffic accident image as the input image. The remote sensing method is used to collect the traffic accident image, and the traffic accident remote sensing image is processed by adaptive noise reduction[8]. It is assumed that the camera detected by the image is approximately parallel to the traffic accident in the horizontal direction, remember the traffic. The pixel value space of accident edge distribution is \( g_i = (g_{x_i}, g_{y_i}, g_{z_i}) \) (i = 0,...,N - 1). Define the duty cycle of traffic accident image pixels \( R_{area} = R_k / R_a \), aspect ratio \( R_{HW} = R_{H} / R_{W} \), RH, RW are the length and width of the outer rectangle of traffic accident edge contour, respectively. In the affine invariant region, according to the cloud map of sampling point, we define the length and width of the traffic accident image pixel. At the position of the first vertex in \( G \), the 3D distribution structure model of traffic accident edge contour detection is obtained as follows:

\[
\begin{align*}
\sin \theta \cos \phi & \leq x \leq \sin \theta \cos \phi + 2 \pi \\
\sin \theta \sin \phi & \leq y \leq \sin \theta \sin \phi + \pi \\
\cos \theta & \leq z \leq \cos \theta + \frac{D}{2}
\end{align*}
\]

Where, \( \eta \) indicates the duty cycle of vehicle driving area, \( \phi \) indicates the driving azimuth of traffic accident, \( R \) indicates the radiating radius of traffic surveillance video, and \( D \) indicates the distribution distance of vehicle in adjacent traffic accident[9].

In order to enhance the contrast of the moving region in the image, the subspace denoising method is used to enhance the image information. In each connected region, the transfer function of image denoising is defined as follows:

\[
c_{j,k} = \sum_n h_{n-2k} c_{j-1,n}
\]

In the formula, \( c_{j,k} \) is the template matching value of the apriori pixel point distribution, and the \( h_n \) is the impulse response of the subspace denoising filter. The edge sub block \( P(i,j) \) of the traffic accident area is matched with the feature matching processing, the center line \( Z(i,Z_i) \) of the traffic accident area is obtained by the boundary image segmentation, and the record \( R_i \) is the column coordinates of the segmented curve, and \( L_j \) is the column of the sub block distribution in the traffic accident area. The information entropy of traffic accident attributes in each sub block is obtained as follows:

\[
Z_i = \frac{L_i + R_i}{2}
\]

The two value functional of the extracted information entropy is carried out, and the proportion of the left and right sides of the pixel edge block \( Z(i,Z_i) \) after the traffic accident image enhancement is obtained, and then the edge contour features of the left and right sub blocks of the traffic accident are detected under the dynamic video surveillance:

\[
L = \sum_{i=1}^n \sum_{j=1}^{C_i} H_{ij}
\]

\[
R = \sum_{i=1}^n \sum_{j=1}^{C_i} H_{ij}
\]

In the formula, \( C_i \) represents the coordinates of the pixel distribution of the i row; \( L_i \) represents the image grid distribution set of the pixel matrix of the i line from left to right; \( R_i \) represents the maximum offset of the pixel characteristics of the first row, and \( H_{ij} \) represents the subblock of i,j. Judging the appearance characteristics of traffic accidents, the appearance features of traffic accidents have a continuous smooth region \( H_{ij} = 1 \), otherwise \( H_{ij} = 0 \). With the above methods, the edge contour
detection and information enhancement of the collected traffic accident images are carried out, and the feature points of the traffic accident category attributes are highlighted, which provides input characteristic parameters for the traffic accident feature identification[10-12].

3. Realization of Traffic accident feature recognition

3.1 Traffic accident feature extraction
On the basis of the traffic accident image acquisition and analysis and image enhancement preprocessing, the intelligent recognition algorithm of traffic accident characteristics is designed, and the traffic accident remote sensing image is adaptively de-noised. The block feature matching method is used to process the traffic accident image[13]. In this paper, the traffic accident information extraction and automatic recognition method based on remote sensing image analysis are proposed. The block feature matching method is used to deal with the block fusion of traffic accident image, and the information of traffic accident corner distribution is processed by histogram equalization in the affine invariant region, and the pixel feature point extraction of traffic accident is realized. The mean square error function between the original image and the coded image is:

\[ x(n) = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X(k) \exp(j2\pi kn / N), n = 0,1,...N-1 \]  \( (8) \)

Where: \( X(k) \) is the pixel sequence of 3D contour feature distribution of traffic accident, \( \exp(j2\pi kn / N) \) is the scale coefficient of template. In the Markov chain model[14], the corner distribution characteristic sets of traffic accidents are obtained as follows:

\[ e = \frac{1}{|\nabla u|} \left( \frac{\partial u}{\partial y} - i \frac{\partial u}{\partial x} \right), f = \frac{1}{|\nabla u|} \left( \frac{\partial u}{\partial x} + i \frac{\partial u}{\partial y} \right) \]  \( (9) \)

Based on sub-pixel segmentation of corner information of traffic accident, combined with statistical histogram equalization method, the multimode state equation of corner detection is obtained as follows:

\[ \frac{\partial u(x, y; t)}{\partial t} = \frac{\partial^2 u(x, y; t)}{\partial \xi^2} + c^2 \frac{\partial^2 u(x, y; t)}{\partial \eta^2} \]  \( (10) \)

Along the edge contour of traffic accident segmentation curve direction \( f \) carries on the image information fusion, realizes the traffic accident characteristic information retrieval, the traffic accident characteristic point recognition corner point matching result is obtained as:

\[ \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} \cos \alpha & -\sin \alpha \\ \sin \alpha & \cos \alpha \end{bmatrix} \begin{bmatrix} p \\ q \end{bmatrix}, \ \alpha = \arctan\left(\frac{\partial u}{\partial y} / \frac{\partial u}{\partial x}\right) \]  \( (11) \)

Under the training of the deep neural network, the second moment expression of the output layer of the neural network is obtained as follows:

\[ \min_{\tilde{u}, \tilde{v}} \| \tilde{u} \| + \| \tilde{v} \| + \rho \| \tilde{y}_c \| \]  \( (12) \)

In affine invariant region, the pixel sequence is clustered. The objective function of fuzzy C-means clustering is obtained as follows:

\[ \begin{align*}
    f(x_i, x_j) &= r_1 x_i (1 - \frac{x_i}{N_i} - \frac{x_j}{N_j}) = 0 \\
    g(x_i, x_j) &= r_2 x_j (1 - \frac{x_i}{N_i} - \frac{x_j}{N_j}) = 0
\]  \( (13) \)

In the upper formula, \( r_1 \) denotes the convergence density of pixels at the center of the initial clustering, \( r_2 \) denotes the prior point cluster, \( \sigma_i \) denotes the edge pixel value, and \( N_i \) is the affine invariant moment. From this, it is obtained that the feature points of traffic accident pixels are extracted from the distribution neighborhood of traffic accident corner histogram:
\[ L = J(w,e) - \sum_{i=1}^{N} a_i \left\{ w^T \phi(x_i) + b + e_i - y_i \right\} \]  

(14)

Where, \( J(w,e) \) is an edge subspace of a traffic accident area, \( a_i \) is a large low frequency image such as an original traffic accident image, and \( \phi(x_i) \) is a noise sensitive coefficient.

### 3.2 Classification and recognition of deep neural network

The pixel features extracted above are classified and the feature classification is carried out by using the deep neural network training method. The neural network structure model is shown in figure 2. In the figure, the depth neural network model is based on the BP neural network model prototype, and the neural network is divided into three layers of structure system, the first input layer is the output contact (set as \( N \)), second input layer is the input layer, it is belong to information processing center, third input layer is the traffic accident special quantity, it’s input node is below\(^{[15]}\).

![Figure 2. Deep neural network structure model](image-url)

Intelligent recognition of traffic accident features is carried out in the depth neural network classifier constructed in figure 2. The extracted pixel feature points are classified and trained by depth neural network. The steps are expressed as follows:

Step 1: Initializing the vector pattern and each vector element of the input layer of the neural network, given the number of input nodes \( G \), traversing the smooth region of the image, making the pixel value of the traffic accident image \( x(t), t = 0,1,\ldots,n-1 \), given the training sequence of pixel characteristics, setting the time count \( t = 0 \).

Step 2: In the input layer of the neural network, the exponential function \( \alpha(e_j) = A_i e^{-\epsilon_j t_j} \) is used to train the traffic accident characteristics, and the new training vector mode \( x(t) = (x_1(t), x_2(t), \ldots, x_k(t)) \) is inputted into the neural network, which is used as the input training vector set of the depth neural network.

Step 3: This paper responded to the adaptive weighting of the neural network by setting a frequency counter, the distance between the input vector \( x(t) \) of the traffic accident pixel and the weight vector \( \omega_j \) of the hidden layer are obtained:

\[ d_j = \sum_{j=0}^{k-1} (x_j(t) - \omega_j(t))^2, \quad j = 0,1,\ldots,N-1 \]  

(15)

Where \( \omega_j = (\omega_{0j}, \omega_{1j}, \ldots, \omega_{nj}) \).

Step 4: Finding out the characteristics of Pixel Vision difference in traffic accidents \( N_j \),
\[ d_j = \min_{0 \leq j \leq N-1} \{ d_i \} \]

Step 5: According to the characteristic difference of traffic accident, the information is classified. In the neural network classifier, the weights connected with the output node \( N_j \) are adjusted, and the weight of classification is judged according to the edge contour \( NE_j(t) \) and the geometric neighborhood \( N_j \) of the traffic accident. The iterative formula for classification and identification of traffic accident characteristics is as follows:

\[
\omega_j(t+1) = \omega_j(t) + \alpha(t)(x_j(t) - \omega_j(t))
\]

Where, \( N_j \in E_j(t), \quad 0 \leq i \leq k - 1 \quad 0 \leq \alpha(t) \leq 1 \) is a variable learning speed.

Step 6: If the termination condition is satisfied, the end algorithm, otherwise continue to input the traffic accident pixel feature sample data, \( t = t + 1 \), go to step 2.

Based on the above analysis, the image feedback recognition of traffic accident state characteristic quantity is realized, and the realization flow of the intelligent recognition method of traffic accident feature based on depth neural network is obtained as shown in figure 3.

![Figure 3. Realization flow of traffic accident feature identification](image)

**4. Simulation experiment and result analysis**

In order to test the application performance of this method in realizing intelligent identification of traffic accident characteristics, the simulation experiment is carried out. The experiment is based on Matlab 7 simulation tool, and a large number of traffic video images are selected as the experimental sample set.

The search range of the edge contour feature of traffic accident is \( [x_{min}, x_{max}] = [-1, 1] \), the scale partition coefficient of traffic accident contour line is 0.23, the single measurement error of edge contour detection is \( d = 0.45 \), the length of image sequence is 320 frames, the block template of image is \( 22 \times 20 \), and the gray level neighborhood is obtained. The size is 22*14. According to the above simulation environment and parameter setting, a group of video images with similar shape characteristics of traffic accidents are selected as the research object, and the traffic accident monitoring images are collected as shown in figure 4.
The traffic accident image shown in figure 4 is processed with information enhancement, and the pixel feature information is highlighted. The result of information enhancement is shown in figure 5.

It can be seen from Figure 5 that the method of this paper is used to enhance the image intensity equalization of traffic accident image and to improve the expression ability of feature information. On this basis, the edge contour detection and feature extraction of traffic accidents are carried out by using this method, and the results are shown in figure 6.

The result of analysis figure 6 shows that using this method to detect the edge contour of traffic accident can accurately extract the edge contour and appearance geometric feature of each traffic accident, and take this as the feature input to get the depth neural network score. In the classifier, the classification and recognition of traffic accident features are realized, and compared with the traditional classification method of support vector machine, the accuracy of traffic accident feature recognition is compared as shown in figure 7.
The comparison of the results of figure 7 shows that the accuracy of the proposed method is higher than the traditional method, and the convergence is better and the performance is superior.

5. Conclusions
In this paper, a method of traffic accident information extraction and automatic recognition is proposed based on depth neural network and intelligent image analysis. The remote sensing method is used to collect the traffic accident image, the traffic accident remote sensing image is adaptively de-noised, and the block feature matching method is used to deal with the traffic accident image block fusion. The feature extraction of traffic accident state is carried out in the subspace component of traffic accident image, and the image feature classification of traffic accident is processed by using depth neural network classifier to realize image feedback recognition of traffic accident state feature quantity. A large number of traffic video images are selected for experiments. The simulation results show that the proposed method is more intelligent and accurate. This method has good application value in automatic identification of traffic accident.

Acknowledgment
Project information: 1. Guangzhou education system innovation academic team project, numbered: 1201610034, project name: pedestrian detection and tracking innovation team in complex visual scene 2. The ninth batch of Guangzhou City educational reform project, number: 2017F06, the name of the project: creating apprenticeship system in workshop practice

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