

Image Recognition Algorithm Based on Convolution Neural Network and Particle Swarm Optimization SVM

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Abstract: For the problems existing in the traditional design of feature extraction, image recognition and classification, this paper proposes to use CNN (Convolutional Neural Nets) for preliminary image recognition based on single feature of color or texture, and establishes a basic probability assignment according to the output of CNN as evidence. Then the recognition results of CNN are fused by DS evidence theory, and finally the image recognition results are obtained. The simulation results show that the average recognition accuracy rate of DS-CNN can reach 92.19%, which is much higher than that of single feature recognition and simple combination recognition, and it improves the stability and accuracy of image recognition with a more reliable result.

1. Introduction

With the rapid development of computer image, image analysis has been widely used in many fields, such as space detection, remote sensing image classification, image tracking, robot vision and communication engineering. Image recognition is a key step in image analysis and its recognition effect plays an important role in image understanding. Thus it has become an important topic in the current image research, [1].

2. Image Automatic Recognition Model

2.1 Structure diagram of image automatic recognition system

The image automatic recognition system based on DS-CSS mainly include two aspects: The inference of CNN and DS evidence theory is improved and its structure framework is shown in Fig 1. First, the color and texture feature of image are separately extracted; Then they are respectively put into CNN neural network for preliminary recognition. And the genetic algorithm is used to optimize the parameters of CNN neural network. Finally, integrate the information based on the DS evidence to obtain a final recognition result.

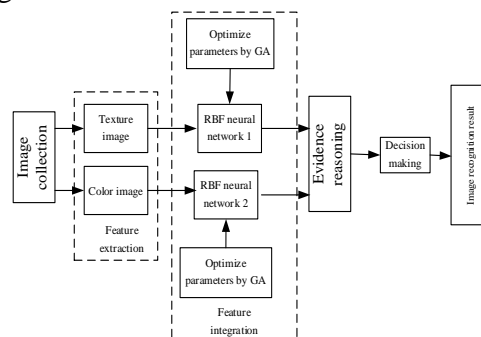


Fig 1 Image Automatic Recognition System Structure Framework

2.2 Extract image feature

Color is an important visual feature. In order to extract the color feature, the first step is to select the color space. The current color space mainly includes RGB color space and HIV color space. And RGB color space is to extract color feature from image based on three components of RED, GREEN AND BLUE and it's very flexible. Therefore, This research is using RGB color space to extract color

features from image .

Specifically Quantization mode is: Divide them evenly into four equal parts according to the range of R,G,B and the quantization formula is as follows:

$$R = \begin{cases} 0 & \text{if } r \in [0, 63] \\ 1 & \text{if } r \in [64, 127] \\ 2 & \text{if } r \in [128, 191] \\ 3 & \text{if } r \in [192, 255] \end{cases} \quad (1)$$

$$G = \begin{cases} 0 & \text{if } g \in [0, 63] \\ 1 & \text{if } g \in [64, 127] \\ 2 & \text{if } g \in [128, 191] \\ 3 & \text{if } g \in [192, 255] \end{cases} \quad (2)$$

$$B = \begin{cases} 0 & \text{if } b \in [0, 63] \\ 1 & \text{if } b \in [64, 127] \\ 2 & \text{if } b \in [128, 191] \\ 3 & \text{if } b \in [192, 255] \end{cases} \quad (3)$$

So, the color feature vector can be

$$\vec{C} = (R_0, \dots, R_3, G_0, \dots, G_3, B_0, \dots, B_3) \quad (4)$$

2.3 Extract texture feature

Texture feature, like color feature, is an important visual feature. The current gray changes dramatically. If the color is almost the same in the image but the texture feature of the image is rather distinct, then the image can't be recognized from its color feature. However, the texture feature can distinguish the image. The current image texture feature extraction method includes: structure method, statistical method and other signal analysis methods. Gabor filter is the most effective method to extract texture feature, so we use 2-D Gabor filter to extract texture feature of image in this research.[10].

Suppose that the variance of Gaussian envelope in the direction of x and y is denoted by σ_x and σ_y and λ represent the wavelength of sinusoidal wave. Then the multi-scale characteristics of Gabor filters are described through λ , σ_x and σ_y . In fact, the basis function of a two-dimensional Gabor filter is a Gaussian function. It is as below:

$$h(x, y, \theta_j, \lambda, \sigma_x, \sigma_y) = \frac{1}{2\pi\sigma_x\sigma_y} \bullet \exp\left(\frac{2\pi i x \cos \theta_j}{\lambda}\right) \bullet \exp\left\{-\pi \left[\left(\frac{x \cos \theta_j + y \sin \theta_j}{\sigma_x}\right)^2 + \left(\frac{-x \sin \theta_j + y \cos \theta_j}{\sigma_y}\right)^2 \right]\right\} \quad (5)$$

In this formula, θ_j Indicates the direction of a sine wave and the calculation formula of θ_j is :

$$\theta_j = \frac{\pi}{n_o}(k-1), j = 1, 2, \dots, n_o \quad (6)$$

In this formula, n_o determine the number of filter directions

The definitions of x_{θ_j} and y_{θ_j} are as follows

$$\begin{cases} x_{\theta_j} = x \cos(\theta_j) + y \sin(\theta_j) \\ y_{\theta_j} = -x \sin(\theta_j) + y \cos(\theta_j) \end{cases} \quad (7)$$

Say the image as $i(x, y)$, then the Gabor filter can be defined as:

$$T(x, y) = O_h(i(x, y)) = |i(x, y) * h(x, y)| \quad (8)$$

In this formula, $*$ represents convolution; $|\cdot|$ represents modular arithmetic; $T(x, y)$ indicates filter output.

Steps for extracting texture feature is as follows:

(1) Select the scale number and direction number of Gabor filter bank.

(2) Calculating the scale factors of each filter on the transverse axis, here it is:

$$a = \left(\frac{U_h}{U_l}\right)^{\frac{1}{n_F - 1}} \quad (9)$$

In the formula, U_k and U_l represent the highest and lowest digital frequencies respectively.

(3) The standard deviations of the horizontal and vertical axis direction filters were calculated respectively

$$\begin{cases} \sigma_{x_i} = \frac{a-1}{a+1} \frac{U_h}{\sqrt{2 \ln 2}} a^{i-n_F} \\ \sigma_{y_i} = tg \frac{\pi}{n_o} \sqrt{\frac{U_h^2}{2 \ln 2} - \frac{a-1}{a+1} \frac{U_h}{\sqrt{2 \ln 2}}} a^{i-n_F} \end{cases} \quad (10)$$

In the formula,

The central frequency and standard deviation of the filter at different scales are obtained when $\theta_1 = 0$. Then switch the angle to get the central frequency and standard deviation of the filter of θ_2, θ_3 and θ_4 .

(4) $T_{ij}(x, y)$ represents the image transformed by Gabor and the value and Standard deviation of transformed Image are taken as texture Features. Vector \vec{T} of the image texture feature is as below:

$$\vec{T} = (\mu_{11}, \sigma_{11}, \dots, \mu_{1n}, \sigma_{1n}, \dots, \mu_{mn}, \sigma_{mn}) \quad (11)$$

$$\begin{cases} \mu_{ij} = \frac{1}{XY} \sum_{x=1}^X \sum_{y=1}^Y |T_{ij}(x, y)| \\ \sigma_{ij} = \frac{1}{XY} \sum_{x=1}^X \sum_{y=1}^Y \sqrt{(|T_{ij}(x, y)| - \mu_{ij})^2} \end{cases} \quad (12)$$

3. Improve the Image Classification of CNN Neural Network

CNN neural network is a three-layer feedforward neural network, which includes input layer, hidden layer and output layer. And CNN Neural Network is a Local approximation Network only, in which only a small number of weights need to be adjusted for each input / output data. It has the advantages of fast learning, global approximation and optimal approximation performance.

The output of CNN network is:

$$y = f_i(x) = \sum_{K=1}^N W_{ik} \phi_K(\|x - c_K\|^2) \quad (13)$$

Using Gaussian function as Radial basis function,

$$\varphi_K(x) = \exp\left(-\frac{\|x - c_K\|^2}{2\sigma_K^2}\right) \quad (14)$$

There are three learning parameters in Gaussian Function network: w_k is the output weight, c_k represents as the center of the K th CNN hidden node, σ_k represents the width of the CNN hidden node.

4. Results and Analysis

The recognition results for each model are shown in Table 2. Here is the conclusion drawn from comparing each recognition results in table 2.

Due to the close color of trees and grasslands and their vulnerability to the influence of light conditions, the recognition rate of trees and grasslands by using a single color feature is rather low. However, natural environment has little influence on texture features, and its recognition accuracy is higher than that of single color. However, in the process of sign extraction, the total error is accumulated continuously, with the affection of image processing, the recognition rate will be reduced. In a word, the misrecognition rate is higher based on single feature and the recognition accuracy rate is low. What's worse, the recognition result is unstable and unreliable.

The image recognition accuracy of traditional combined feature model is higher than that of single color or texture feature model. It shows that the fusion of many features can provide more image information and improve the accuracy and stability of image recognition.

The DS-CNN recognition is optimal among all recognition models. It indicates that the shortcomings of simple combination features, such as high dimension, large computation and so on can be conquered by fusing the recognition results of color and texture features through evidence theory and the misrecognition rate can be reduced. The accuracy rate of image automatic recognition is further improved and it's an effective image recognition method.

Table 2 Comparison of recognition results of each model

Image category	color	texture	color-texture	DS-CNN
grass	54.43%	58.58%	88.15%	95.81%
tree	64.61%	76.65%	80.27%	80.62%
sky	89.67%	93.28%	94.72%	95.07%
road	64.05%	73.43%	83.50%	77.63%
house	79.51%	98.10%	94.05%	97.82%
Average recognition rate	85.65%	88.41%	88.78%	93.19%

5. Conclusion

In view of the shortcomings of single feature image automatic recognition algorithm, such as unstable recognition results and low recognition accuracy, an image automatic recognition algorithm based on evidence theory and improved neural network fusion is proposed. First of all, the color and texture features which can reflect the image category information are extracted. Then CNN neural network is used for preliminary recognition of single feature. And the recognition result is used as evidence. Finally, the final recognition result is obtained by using the evidence theory to integrate the decision-making of the preliminary recognition result. The simulation results show that the average recognition accuracy rate of this algorithm is 92.29%. Compared with the single feature recognition algorithm, the reliability and accuracy of the image recognition results have been greatly improved, which has a good application prospect.

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