Identification of hidden dangers in transmission line corridors based on hybrid algorithms

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Abstract. Computers automatically recognize hidden dangers in photos taken from transmission line corridors to greatly reduce the workload of transmission line patrol personnel. However, transmission line corridors are complex and hidden dangers in the scene are diverse, which bring great difficulties to the identification of hidden dangers. To solve this problem, this paper proposes various algorithms to identify various hidden dangers separately based on their sample size and characteristics of hidden dangers. Firstly, we identify construction machinery based on CNN algorithm by making use of massive samples. Secondly, we identify fires by using features including color and texture based on SVM. Finally, we identify foreign objects on transmission lines with Bresenham algorithm based on the geometric characteristics of transmission lines. In order to verify the practicality of the above algorithms, we collect tens of thousands of photos taken by cameras deployed on transmission towers and select different samples from them to test the above algorithms separately, whose results show that our algorithms achieved acceptable recognition accuracy.

1. Introduction

With the increasing scale of power grids, the pressures and challenges faced by transmission line protection are also increasing. Especially the line trips caused by external damage such as construction machinery, mountain fires and floating objects are increasing year by year. Taking Shandong power grid as an example, local power failures caused by hidden dangers and external forces are tens of times each year, accounting for more than 60% of the factors affecting the entire line. At present, the existing online monitoring system mainly uses surveillance cameras mounted on transmission towers to take photos regularly to obtain images in the corridor of the transmission line, and then transmit the photos back to the background server system. The traditional hidden danger identification algorithm deployed on servers is relatively simple, and only recognizes engineering machinery. The recognition accuracy is mostly below 80%, and it is impossible to identify fires and foreign matter on wires. Most of the current back-end servers use deep learning algorithms for image recognition [1][2][3], which is not applicable to hidden dangers with a small sample size.

Based on the study of the hidden danger photos of various transmission lines, this paper proposes different identification algorithms according to the different characteristics of construction machinery, fires and foreign matter on wires. Firstly, we identify construction machinery based on CNN algorithm by making use of massive samples. Secondly, we identify fires by using features including color and texture based SVM. Finally, we identify foreign matter on wires with Bresenham algorithm based on the geometric characteristics of transmission lines.
2. Identification of construction machine based on CNN

Construction vehicles mainly including cranes, forklifts and excavators are potential threat of transmission lines. CNN can directly input the original image for classification, avoiding the complicated pre-processing of the image and obtaining a wider application.

The selected training samples are shown in figure 1. The sample size needs to be specified to 64 × 64 pixels. Finally, there are 8000 non-target samples and 6000 construction vehicles samples. We randomly select 80% of the images in equal proportions for training.

![Figure 1. Training samples.](image)

After many tests and improvements, the CNN model we finally use is shown in figure 2. The parameters of each layer are as follows:

![Figure 2. CNN network structure.](image)

The data layer uses a three-channel 64 x 64 color image as the input for training. It is necessary to calculate the mean of each channel of all samples and perform a 0-mean normalization process to ensure that the data deviation is not too large.

All convolutional layers use a 5×5 convolution kernel with an outer boundary size of 2 pixels, and the number of features of the 4-layer convolution layer training is 32, 32, 64 and 64 respectively.

All pooling cores are 3×3 in size and the step size is 2. Obviously, overlapping pooling is used, so that the influence of adjacent pixels on the features is considered more, which can improve the network accuracy and reduce the over-fitting phenomenon. In addition to the first convolutional layer, all others layers use average pooling in order to reduce the noise caused by overlapping pooling.

Rectified linear unit (ReLU) introduces a large amount of sparsity for the network, which accelerates the dissociation of complex features and improves the feature learning speed.

3. Identification of mountain fires

Most of current fire monitoring systems use remote sensing and infrared thermal imaging to detect fires, which require professional equipment. The time series information of the fire change cannot be obtained in the static picture, so fires can only be judged by using some information of a certain state of the fire in a single picture. The features that may be used for detection are as follows:

Color is the most important manifestation of the static characteristics of the flame. Simple use of color features may be interfered with by objects of similar color, and is usually only used for preliminary region selection during detection.

Fractal means a self-similar nature [4]. The self-similarity in fractals can be identical or statistically similar, while the former is called a fractal and the latter is a random fractal. Obviously, the flame can be regarded as a kind of random fractal, which has similarities on different scales.

For the detection of flame, we first use color information for preliminary screening and then do further identification based on its texture features.

3.1. Flame area screening method based on color histogram
The color histogram describes the proportion of different color components in the entire image, and can reflect the statistical distribution and basic color of the color in the image [5]. Conversely, we can find the desired color from an image based on the color histogram.

In order to accurately find the flame color area using color histogram, it is necessary to consider the color components used in designing the color histogram. H in HSV space indicates the brightness and can better describe the essential characteristics of the flame color, while S in HSV indicates the degree of color vividness [6], so H and S components are better choices. The color differences Cb and Cr in YCbCr space reflect the color characteristics to a certain extent [7], and its mapping with the RGB space is linear, which can overcome the nonlinear jump of the HSV space to some extent. Therefore, the color histogram is calculated by selecting four components of hue H, saturation S, color difference Cb and color difference Cr. We first select sample images of flame target as shown in figure 3.

![Figure 3. Sample images of flame.](image)

After obtaining sufficient samples of fires, the color histogram of the selected component of each sample in the HSV and YCbCr color spaces needs to be calculated, as shown in figure 4. The obtained color histogram is denoted as \( H_i \), where \( i \) is the sample number, and any value \( H_i(x) \) in \( H_i \) represents the number of pixels in the image whose corresponding component is equal to \( x \), and the range of \( x \) is determined by the value range of the component.

![Figure 4. Color histograms.](image)

Each color histogram represents the color distribution of the sample. The color histogram of each sample is mapped onto the image to be detected with equation (1), and the result map after each sample mapping is obtained.

\[
I(x, y) = H_i[I(x, y)]
\]  

(1)

where \( I(x, y) \) is the pixel value of the image at coordinate \((x, y)\).

Since the color histogram distribution of each sample is different, the brightness distribution of the mapping result is not uniform, and it needs to be equalized and binarized. Finally, the resulting images are combined to obtain a complete flame-matching area.

3.2. Flame recognition based on multi-scale texture features and svm

Flame areas extracted with only the color information contain many grounds and engineering vehicles with similar colors, so it is necessary to further analyze the other features of the flame to distinguish the real flame from other targets.

Due to the unique fractal nature of the flame, the texture feature is chosen to determine the flame. The fractal characteristics means that the texture of the flame have certain similarity and consistency at different scales, so analyzing texture at different scales can help identify the flame. The feature \( E \) of the target is defined in equation (2), where \( k \) is determined by the size of the scale.

\[
E(x, y) = \frac{1}{n^2} \sum_{i=-k}^{k} \sum_{j=-k}^{k} [I(i,j|x,y) - \mu(x,y)]^2
\]  

(2)
\[
\mu(x, y) = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{k} I(i, j | x, y)
\]  

This feature describes brightness fluctuations in local areas of the image. Fluctuation of the flame and land varies at different scales.

After obtaining the texture image, we use SVM for training and classification [8]. Since the dimensions of the input data of SVM needs to be consistent and the detected target area size is different, it is necessary to convert the calculated texture images of different scales. The mean and variance of the texture image at multiple scales of the target area are used as input, and the scale of the texture image is 5 scales of 3×3, 5×5, 7×7, 9×9 and 11×11, so the input is a 10-dimensional vector.

4. Identification of foreign objects on transmission lines

For foreign objects on the wire, we choose to locate the power line first and then look for foreign objects along the line.

4.1. Positioning of high voltage transmission lines

Most of the transmission lines have a slight arc in the image. Since the image is a continuous coordinate system, the transmission line can be expressed as \( f(x) \) which is continuous and guidable. After that, \( f(x) \) performs Taylor series expansion at point \( x_0 \) as follows [9]:

\[
f(x) = f(x_0) + f'(x_0)(x-x_0) + f''(x_0)(x-x_0)^2/2 + o(x^2)
\]  

(4)

Since the high voltage transmission line has a small arc, when \( x \rightarrow x_0 \), equation (4) can be expressed as follows:

\[
\frac{f(x) - f(x_0)}{x - x_0} = f'(x_0)
\]  

(5)

Suppose the seed point is \( p_0(x_0, y_0) \), and the next point to locate is \( p_1(x_0+m, y_0+n) \), and \( p_1 \) can be converted as the result of equation (6):

\[
\arg\max \{ c(p_0(x_0, y_0), p_1(x_0 + m, y_0 + n))\}
\]  

(6)

where \( c(*) \) is the number of pixels on the transmission line of the straight line segment formed by the two points on the image. If \( m \) and \( n \) are solved, the search radius needs to be \( r \), then \( p_0 \) and \( p_1 \) satisfy the following constraints:

\[
\|p_1 - p_0\|^2 = r \rightarrow m^2 + n^2 = r^2
\]  

(7)

therefore, the problem of finding the next point \( p_1 \) based on point \( p_0 \) on the power line is converted into the problem of \( m \) and \( n \) in equation (6) according to the constraint condition as equation (7).

The points that satisfy the constraint condition in the discrete graph is limited, so all the points satisfying the constraint condition can be composed into the point set \( O_0 \) and then solved by voting, where the point set satisfying the constraint condition is generated by the Bresenham algorithm including a circular Bresenham algorithm and a straight Bresenham algorithm, which respectively generate circles and straight lines in discrete images.

Suppose that the set of points \( O_0 \) composed of all the satisfied points is represented as \( p_{1,j}(x_{1,j}, y_{1,j}) \), \( j \in \{0, 1, 2...k\} \), where \( x_{1,j} - x_0 = m_j, y_{1,j} - y_0 = n_j \), so the point set \( O_0 \) is a set of circular points with \( p_0 \) as the center and \( r \) as the radius in the image.

\( O_0 \) is generated with the circular Bresenham algorithm [10], so the next point \( p_1 \) can be:

\[
p_1 = \arg\max \{ c(p_0, p_{1,j})\}, j \in \{1, 2,...k\}
\]  

(8)
The line segments $p_0$, $p_1$, $j$ is generated with the straight line Bresenham algorithm. After $p_1$ is determined, $m$ and $n$ are obtained.

The vector represented by $p_1-p_0$ is one of the extension directions of the power transmission line. The power transmission line is generally bidirectionally extended, so there is also an extension direction in the direction in which $p_1$ is symmetric with respect to $p_0$.

After the two search directions for the power line were found, we need to iterate through the two directions until we find the complete power line.

4.2. Location of foreign objects based on connected region

Firstly, we select 13 photos including 6 recent photos, the photo of the same moment from the most recent day of the same weather, and the latest 6 photos before it. Secondly, we calculate the feature vectors of the photo $v_0$ and the 13 photos above $\{v_i\}$, $i = 1\sim 13$. Thirdly, we calculate the Euclidean distance between the feature vector of current photo and that of each photo in the 13 photos above. the historical photo that has the highest similarity and closest time to the current photo is selected as a reference photo.

$$D_{\min} = \min_{i=1,\ldots,13} \| v_i - v_0 \|$$ (9)

We use the image to be matched and the reference image for image difference, which can achieve rough matching to maximize the area of the image that cannot be matched.

We make use of Haar feature density map to filter the differential image [11], by which we can not only remove discrete pixel points caused by small disturbances effectively, but also preserve the information in the connected region and its neighbors well.

We mark and segment the partial region with the help of connected regions, and then segment the original photo portion within the circumscribed rectangle corresponding to the connected region. We take the connected region that intersects with the wire as foreign objects.

5. Experiments and conclusions

5.1. Construction machinery identification

To test our algorithm for detecting construction machinery, we selected 10000 photos taken from the scene for testing, whose results are shown in table 1.

| Hidden Type          | Accuracy |
|----------------------|----------|
| Crane                | 91.6%    |
| Tower crane          | 92.1%    |
| Other construction machine | 82.3%    |

Because of the wide distribution of transmission lines, it is easy to get live photos with construction machinery. After getting enough samples, we can take full advantage of the deep learning algorithm and get good recognition results.

5.2. Identification of mountain fires and foreign objects

We select 200 pictures with mountain fires and 200 pictures with foreign objects on transmission lines to test our algorithm, as a contrast, different deep learning frameworks and algorithms are also deployed on those samples, whose results are shown in figure 5.
Due to the scarcity of samples of mountain fires and foreign objects on transmission lines in reality, convolutional neural networks and other classification methods that require large samples are difficult to exploit their advantages. For such a small sample, our hybrid algorithms based on target features mean better adaptability and achieve better recognition results.

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