Forest Fire Image Intelligent Recognition based on the Neural Network

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Abstract—To avoid the drawbacks caused by the long-distance and large-area features of the outdoor forest fires in the traditional fire detection methods. A new forest fire recognition method based on the neural network is proposed, which recognizes the fire based on the static and dynamic features of the fire. The method combines the multiple parameters of the flames and the shapes of the fire to distinguish fire image. Then the extracted features were tested by the Back Propagation Neural Network. The experiment results show that the method outperforms in terms of the recognition rate, recognition speed, and the Anti-jamming capability compared with the traditional fire recognition method. Thus, the results illustrate the validity and the generalizability of the method.

Index Terms—Fire Recognition; Neural Network; Image Processing

I. INTRODUCTION

Nowadays, the fire is still a major threat to the safety of our human beings’ lives. Over the past decade, the severity of forest fires was increasing. Coupled with the objective conditions of global warming, experts predict that forest fires will become a serious threat to the ecosystem in future. Due to the sudden and destructive characteristics of forest fire, it was very difficult and expensive to fight with the fire. In addition, the prevention of forest fires was also difficult as the forest area was large and there were many combustible materials under forest. It’s very meaningful to forecast the forest fire as early as possible for the forests and resources prevention.

The fire detection relies on the mutual coupling process of the sensing technology and the fire physical features, that is to say, for the certain physical parameters, we can use some detection method and make sense in practical to detect the fire accurately [1-4]. Currently, the focus of the fire detection is how to quantify the fire and non-fire environment where the fire detector located. There are two main develop directions: one is longitudinal extension, to develop the new fire criterion, the new fire recognition model and the detector based on that and also the complexity fire detector; the other is lateral extension, to cross the existing principles and methods with other technology, and improve the system performance by signal acquisition and processing methods. Now, there are dozens of detectors have been developed which can be classified as gas sensitivity detectors, temperature sensitivity detectors, smoke sensitivity detectors, light sensitivity detectors and sound sensitivity detectors.

The traditional fire recognition methods describe the information clues based on the infrared or temperature identifier and search the fire using the image temperature changing, which is very easy to operate but can only be efficiency in small area for example indoors because the infrared or temperature detective signal would be too weak to work in the large area with various interferences. Then some researches proposed a new fire detective method based on the smoke thickness monitoring, which avoids detecting the fire flames but with the drawbacks of the high misstatement rate and the long detection time and even cannot detect the fire in some circumstances for example the flames without smoke. And later a long distance fire detection method based on the ultraviolet and infrared image sensor was proposed, but disadvantages that the lack of reconstruction of modules and the simple flame detection algorithm results in a high misstatement rate. In 1990s, the forest fire monitoring methods focused on the infrared, visible light and fireworks monitoring. The ground infrared fire detection method uses the infrared to detect and locate the fire through the smoke and can work normally even at night. The method can not only detect the small fire and implicitly fire efficiently but also can shoot continuously and record the whole process of the development of the fire. The most commonly used fire detection systems include the long distance forest fire monitoring system, automatic forest fire alarm system, the TV monitoring system of forest fire, the forest fire infrared monitoring and so on [5-8].

With the long-term using of these monitoring systems, the drawbacks of the large amount of the information and the high complexity of the processing time begin to emerge. Recently, there are more and more researches focus on the image features based forest fire recognition and various related algorithms have also been proposed, which recognizes the fire using the flame grayscale levels, color features and shape features. These methods can not only recognize the flames and disrupters in particular occasion, but also make up the drawbacks of fire detection based on the video features to some extent.

While the methods always use the only one of the features in the images, so the anti-interferences capability
and the flame recognition rate cannot achieve the desired results.

In the view of that in this paper, we proposed an improved fire recognition method which combines the multiple features based on the colors and shapes of the fire image as the distinguish criterions. The main theory of the method is as follows.

First, extract the fire color feature parameters to exclude the obvious interferences based on the color;

Then, calculate the shape feature parameters of the object region and combine the features of the colors and shapes to construct the multidimensional vectors.

Finally, use the Back propagation Neural Network method to recognize the flame.

II. RELATED WORK

References [9] and [13] described the importance of sea computing model for the development of IOT. Reference [9] pointed out that the cost of sensor is very high now, it still need to continue to reduce costs. We couldn’t leave the sensor’s data to be calculated in the cloud, it needed sea computing to assist to deal with 90% of basic data in sensing layer and cloud computing (network layer) is only responsible for processing complex data which was “evaporated” from the sea. Reference [13] also stated that sea computing is the key technology of the development of IOT in future, the technology of the sensing layer tend to embedded technology, the goal is that IOT have a certain degree of intelligence.

References [8] and [10] made research on the application of sea computing model in different situation. In reference [8], the author combined the traditional vehicle security collaboration system with sea computing model, adjust the transmission control unit to make it intelligent. According to the self-position and actual position, it will decide whether to send its own position information, and automatically adjust the frequency of transmission and the message length, thereby improving the robustness and extensibility of the system. Reference [10] combined sea computing model with traditional routing protocols of wireless sensor network, proposed a new routing protocol CASCR (Context-Awareness in Sea Computing Routing Protocol) according to context-aware computing, it applied routing protocol in the network layer of the IOT to the sensing layer.

References [16, 17, 18, 19] and [20] introduced different types of fire recognition. Reference [17] detected fire through adaptive Gaussian mixture model, fuzzy c-means clustering algorithm and support vector machine. Reference [18] presented a flame image-based burning state recognition system using a set of heterogeneous features and fusion techniques. According to the flame characteristics such as flicker, references [19] and [20] separately proposed fire recognition algorithm of adaptive multi-feature fusion and region segmentation algorithm. Reference [16] used reaction-diffusion equations to establish a forest fire model in order to determine whether the fire occurred.

In addition, references [11, 12, 14] and [15] made research on different forest fire prevention. Reference 11 transformed speech signal to digital signal in order to expand the range of digital surveillance; reference [12] used DSS (Decision Support Systems) to help foresters determine the fire situation; reference [14] determine whether the fire occurred by the visual smoke detection algorithm; reference [15] took measures to prevent forest fires via satellite sensor.

III. THE FLAME IMAGE FEATURES OF FOREST FIRE

The flame image features can be classified into two classes: the static features and the dynamic features, where the static features include the flame color, the flame texture and the flame shape, and the dynamic features include the changing of the areas, edges and shapes and so on.

A. The Static Features of the Flames

Color Feature. Due to the correlations between the color and the temperature, as the temperature increases the color of the flame changing from the dark red to white. In the image process, we can recognize the flame by the color of the pixels.

Texture Feature. In the image process, the texture features of the images are always used to reflect the homogeneous phenomenon of the image, which is the intrinsic property of all the surfaces of the objects. The texture features of the image mainly include the Tamura Texture, Autoregressive texture model and GLCM. In this paper we focus on the GLCM of the image.

Shape Feature. The shape feature is a main considered factor in the image retrieval and image expression process, which always expressed based on the profile feature and the region feature. The profile feature only has a relationship with the object edge and the region feature has a relationship with the region feature. The typical way to express the shape features is based on the Fourier descriptors and shape unrelated moments. In this paper we extracted the flame region features based on the area of the region, mean gray and centroid shapes.

B. The Dynamic Features of the Flames

Area changing. The fire began to expand after ignition, so the area of the fire in the video is showing a continuously increasing trend. In order to get the area of the fire, we can calculate the number of the highlight points whose grays are bigger than the set threshold. But a moving non-fire highlight object can be an interference to the fire area.

Edge changing. At the beginning of the fire, the corner of the flames shows a regular changing. And at the fully developed stage, the fire flame become stable and doesn’t change significantly. In the image processing, we can extracted the edge feature vectors based on the encoding of the shape and the curvature of the edge.

Shape changing. The spatial distribution of the shape and the height of the flame have a unique variation at the early stage of the fire growth and the fire begins to stable at the fully developed stage. We get these features
according to the relative positional relationship between the pixels.

Overall movement. At the early stage of the fire, the flames are extending outwards continuously, as the old combustion is burned out the fire begin to move to the new combustion, so the movement of the fire is non-jumping. In the image processing, we always detect the movement of the flames based on the video frames sequences.

In this paper, a fire detector based on the image features was proposed, which combines the color feature, area changing, edge changing, and the overall movement of the fire to detect the forest fire.

IV. THE FOREST FIRE DETECTION AND RECOGNITION

The proposed fire detection and recognition method is mainly based on the digital image process theory, which includes the image segmentation and the image recognition. The image segmentation is a process to separate the object parts from the background and identify the parts needing to be processed, and the main idea of the method is based on the threshold adjustment. The image recognition is a further process to analyze, detect and recognize the image. In the view of that we can describe the image using the non-graphical symbol, after the image segmentation and features extraction, and recognize the fire after analyzing the features of the segmented region.

Therefore, the solution of the forest fire recognition can be described briefly as follows:

First, to segment the image and get the features that can describe the fire properly;

Then, to recognize the forest fire based on the gotten features.

A. The Detection of the Forest Fire in Video

The detection of the forest fire is to detect and calculate the suspicious flames to get the image information such as the flame color, and the changing of the flame area, and construct the criterion to distinguish the fire based on gotten information.

1) The Extraction of the Color Feature of the Forest Fire

The extraction of the image features is a process to get the image information and a basis to the detection and recognition of the images. But the extracted features always have a high dimension and include many redundant features at the beginning of the feature extraction process, so we need to select the features that can not only represent the uniqueness of the image but also reduce the features dimension. The color feature is widely used for it has a closely relationship to the objects and the environment of the image and independent with the size and orientation of the image. The color feature of the flame as the most obvious characters of the fire image is the firstly choice of the flame features.

Let $I_x$ as the processed image, where the height is $H$ and the width is $W$, the steps of the color features extraction are as follows:

First, get the pixels of the image shown as Fig. 1 where a rectangle grid represents a pixel which account for 24 bits and RGB components represent with 8 bits ranging from 0 to 255.

The storage pool capacity is $H \times W \times 3$ when storage the bitmap. The Graphics Device Interface accepts the COLORREF parameters and the each component of the Red, Green and Blue contains 8 bit which is shown as Fig. 2.

As shown in Fig. 2 the 00R, 00G and 00B in the first 3 grid represent the 3 components of RGB in Fig. 1 of the 00 grid. After gotten the COLORREF value we can get the value of the color using GetRValue(), GetGValue() and GetBValue().

Then, let $p$ as the long integer variable $x$ as the horizontal movement steps and $y$ as the vertical movement steps, and extract the color components in Fig. 2 by the line scanning method.

According to the empirical data, the flame parameter values in the RGB space are as

$$V(R,G,B) = \begin{cases} 117 \leq R \leq 255 & 88 \leq G \leq 255 \\ & 44 \leq B \leq 255 \end{cases}$$

The flame color is changing as the temperature changing. In this paper, the method fuzzy the value of each component and enlarge the arrangement of the feature values to achieve the human psychological characteristics of similarity measurement. At the same time, in order to get color difference between the flame region and background in different environment, we constructed the following color features set according to a large amount of literatures.

The extracted flame color features are constructed to the feature vectors to represent the certain forest fire image.

2) The Segmentation of the Forest Fire Image
The most commonly used image segmentation methods include edge based segmentation method, regional segmentation, regional growth and so on. While the regional segmentation is a process that focuses on the uncontinuous of the features and separates the image into several independent regions.

In this paper, according to the extending feature of the fire we combine the regional segmentation and extending method to segment the suspicious region. The detailed steps are as follows.

First, segment the image. Divide the original image into 25 regions, determine the belonging area based on the color feature of the image shown as Fig. 3. The area surrounded by the yellow line is the suspicious region, and the other part is the background. In the view of that we can only calculate the suspicious area which not only avoid the useless calculation and but also improve the computing efficiency greatly.

![Figure 3. The image after region segmentation](image)

Then, extend the selection area shown as Fig. 4. The detailed steps are as follows.

Raster scanning the suspicious area in the image, until the point is the flame point.

Find the similar flame points nearby the flame point.

Judge whether the number of the flame points reaches the set threshold and calculate the flame points.

If the number is bigger the threshold then merger the point to the surrounding area else delete.

For the flame points repeat the step 2), 3), 4), until the region is not extending.

Return to step 1), search the new start point.

![Figure 4. Selected area by the perfect extension](image)

In processing, the preset threshold is 5. If threshold is too large the connectivity region is wide and the features are easy to blur; if the threshold is too small, we cannot get a proper connectivity region. According to the segmentation results, the method can separate the similar or the same information from the background and generate several suspicious fire region, which can solve the forest fire detection and extraction problem efficiently.

**B. The Forest Fire Recognition**

After extraction the feature parameter of the object region, we need to choose the proper method to distinguish whether the region is in fire. In this paper, we focus on the fire automatic recognition based on the extracted feature information without the human interference.

The artificial neural network has a good performance when handling the non-linear, incomplete and vague data, which can not only get the second optimal solution to the problem under the normal circumstance but also can get a satisfied result when the data is incomplete. The combustion process is a strongly nonlinear dynamical system, which is more complex than that of the common devices and the stability is reflected by the flame state. The state of the fire has a close relationship to the numbers and the classes of the combustions and the combustion region and so on, which has a strong fuzziness and randomness. So the flame is a typical nonlinear signal, we can improve the accuracy and reliability of the fire recognition based on the artificial neural network theory.

The Error Back Propagation (BP) model is the most widely used network, which can be divided into three layers: the input layer, hidden layer and the output layer. In this paper, we use the three layer BP model to recognize the fire.

The input signal of the neural network

In this paper the input signals of the neural network are determined based on the flame color features and the shape features including the color moment, the circularity of the flame zone and the total anglers of the flame.

The hidden nodes of the neural network

The numbers of the input and output nodes are determined based on the flame color features and the shape features including the color moment, the circularity of the flame zone and the total angels of the flame. The numbers of the input and output nodes are determined by the problem itself, but the determination of the hidden nodes is lack of an efficient method. Generally, the more complex of the problem the more hidden nodes are needed; or to the same problem the more hidden nodes represents the easier to converge. But as the number of the hidden nodes become larger not only the calculation complexity become higher but also the can emerge the “over-learning” phenomenon.

It’s necessary to construct the hidden layer or reduce the search space, considering that it’s easy to converge into the local minimum when the back propagation neural network was used for more than three feed forward networks. In this paper we calculate the hidden nodes as follows.

\[
y = \frac{1}{2} \frac{c \times r^3 + \frac{3}{2} c \times r - 1}{c + r}
\]  

(3)
where $y$ represents the number of the hidden nodes, $c$ represents the number of output nodes, and $r$ represents the number of the input nodes.

Generally, if there is a decimal calculation, after rounding and add 1, the input nodes number is 5 and the output number is 3, the calculated hidden nodes number is 8.

The output signal of the neural network

To normalize the output of the neural network, the network divided the image into 3 classes, so the output nodes is 3 and the corresponding recognition results can be “the fire”, “interference object”, and “forest scene”, the output vector $\{Y_1, Y_2, Y_3\}$ is as follows.

- The fire $\{1, 0, 0\}$
- The interference object $\{0, 1, 0\}$
- The forest scene $\{0, 0, 1\}$

The vector $\{Y_1, Y_2, Y_3\}$ represents the membership of the fire, the interference objects, the forest scene, where $Y_i \in \{0, 1\}$ $i=1, 2, 3$.

Learning samples

In order to recognize the flame we have construct the sample library to get the right class samples based on the criterion after training the known samples.

In this paper, the flame images are captured lively and part of the network images; and the interferences are human set including the car lights, street lights and torch lights and so on.

V. EXPERIMENTS AND RESULTS

In order to verify the effectiveness of the proposed method, in this part, we use the Back Propagation Neural Network to identify the flame based on the extracted features.

The Back Propagation Neural Network consists two phrases:

- The Training or Learning Phase. Learn and revise the connection weights of the input and output nodes by the numerical and parameter optimization method, until achieving the expected output.

Generalization phase. Train the network to predict the unknown samples.

Widely speaking, the process of learning or training is a parameter optimization problem, but on neural networks, there are many of their own features, so the adjustment of the weights has some more efficiency rules. The connections between the different layers are formed based on the weights in the Error Back-Propagation Neural Networks and neurons at the same layers do not connect with each other. The standard Back Propagation Neural Network is a gradient descent learning algorithm, the weights revising process is along the opposite direction of the gradient of the error performance function.

The fire recognition structure based on the Back Propagation Neural Network is shown as Fig. 5.

Neural Network

The input layer of the neural network is consisted by the extracted features including the color moment $I_1$, $I_2$ and $I_3$, the circularity of the suspicious region $\rho$, and the number of the corners of the flames $N$. The output layer is made of three normalized neurons, which is used to train the human given results of the images. If there is fire in the image then $Y = [0 0 1]$; if there are disturbing objects like red candles, lights, and sunrise in the image then $Y = [1 0 0]$; If there is only forest background and no fire and other interferences in the image then $Y = [0 0 1]$. The nodes in the hidden layer is 8 calculated according Eq. (3).

The detailed steps of the Back Propagation Neural Network are as follows.

Initialization: let the nodes in the input layer correspond the output nodes, and the input vector is $X = [x_1, x_2, x_3]$; the output vector is $Y = [y_1, y_2, y_3]$, the hidden neuron vector is $M = [m_1, m_2, m_3]$. The number of the connection lines between the input nodes and the hidden nodes is $i*k$ and the connection weight is $W_{ak}$ and the number of that between the hidden nodes and the output nodes is $k*j$ and connection weight is $V_{kj}$.

Let the connection weight between $W_{ak}$ and $V_{kj}$ as a random number between -1 to 1, and the input samples as the number ranging from 0 to 1.

The forward transformation process of the information: calculate the input of the hidden layer according $S_j = \sum_i X_i W_{ij}$, and the fitness function of the hidden layer is $f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$, so the output function of the hidden layer is $M_j = f(S_j)$.

Similarly, the input of the output layer can be calculated according $Q_k = \sum_j M_j V_{kj}$, and the fitness function of the output layer is $f(x) = \frac{1}{1+e^{-x}}$, the output function of the layer is $Y(k) = f(Q_k)$.

Back Propagation: the actually output of the output layer is $Y(k)$ and the expected output is $O_k$ and the Mean Square Error (MSE) of the samples model is $E_n = \frac{1}{2} \sum_k [O(k) - Y(k)]^2$ and the total error is $E = \sum_n E_n$. Calculate the learning error of the input layer...
and the hidden layer $d_i$, adjust the weight value $W_{ij}$, repeat the steps from (3) to (5), until the error is smaller than the expected error.

Test the new data based on the calculated weights, if it belongs to the fire image then start the fire position and alarm module, else quit the Back Propagation Neural Network.

Due to the space limitations, we select 20 images as training samples and 5 images as testing samples, and all of the samples are gotten in the same background. Tab.1 shows parts of the training samples.

<table>
<thead>
<tr>
<th>TABLE I. THE TRAINING SAMPLES</th>
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<tr>
<td>$l_1$</td>
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In the 5 testing samples there are 4 fire images and 1 non-fire image shown as Tab. 2.

<table>
<thead>
<tr>
<th>TABLE II. THE TESTING SAMPLES</th>
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<td>.5257</td>
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<td>.1356</td>
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After the parameters of the neural network are set, we input the training samples in the designed network to train the network, and input the testing data as shown in Tab.2 to test accuracy of the network, and formulate the decision criterion based on the testing results which shows that if the output value is larger than 0.8 we can think the image in a fire image.

For the long-distance video of fire image, we use the proposed method based on the VC6.0 platform and achieve the forest fire recognition as shown in Fig. 6.

![Figure 6. (a) the original forest fire; (b) the recognized forest fire](image)

According to the Fig. 6 we can see the proposed method can detect and recognize efficiency on the forest fire which is feasible.

Currently, the most commonly used standards to measure the performance of the fire detection system include sensitivity which represents the sensitivity of the measurement of the fire parameter, and the reliability which represents the responding accuracy and the anti-jamming capability.

In the fire recognition method proposed in this paper, we use the Charles probability and the recall rate to balance the effects of the algorithm. The Charles probability is the rate of the number of the identified real fire to the number of the identified flames. The recall rate is the rate of the identified flames to the total number of the suspicious flames. The comprehensive weight indicator is the overall weight of the fire determination which refers to the relative input of the Charles probability and the recall rate gotten according to the practical and experience.

$$\text{Charles Probability} = \frac{A}{A + C}$$

$$\text{Recall Rate} = \frac{A}{A + B}$$

Comprehensive weight rate= Charles Probability $\times 60\% + \text{Recall Rate} \times 40\%$ where, $A$ represents the number of the identified real flames, $B$ represents the number of the unidentified flames and $C$ represents the number of the misidentified flames.

According the above experiment, the measure standards of the proposed fire recognition method are as follows:

$$\text{Charles Probability} = \frac{A}{A + C} = \frac{3}{4 + 1} = 60\%$$

$$\text{Recall Rate} = \frac{A}{A + B} = \frac{3}{3 + 1} = 75\%$$

Comprehensive weight rate= Charles Probability $\times 60\% + \text{Recall Rate} \times 40\%$ $= 60\% \times 60\% + 75\% \times 40\% = 66\%$.

VI. CONCLUSION

The original intention of the forest fire recognition based on the Neural Network is to identify the flames by imitating the human semantics and get the high level semantic function after the automatic computing. In other words, the focus of the forest fire detection method is how to describe the features of the flame as real as the as possible.

The proposed forest fire recognition method in this paper can not only minimize the human duty, but also notify the relevant people of the fire condition which can reduce the loss and the risk of the forest fire greatly.

Currently, the largest forest fire recognition theory is still in the development stage, and the theoretical basis and practical technology is still not perfect. Although the proposed method has made some achievements, but there are still some deficiencies for example, the lack of adequate fire researching data and methods. Therefore, the future work will focus on the collecting the forest fire data and the combination the flame recognition method with the smoke recognition methods.

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