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Study on Simulation of Sea Sky Infrared Imaging based on Neural Network and Measured Data

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Abstract. There is great application value in military and engineering for the ocean infrared imaging simulation technology, which has been deeply studied by many researchers. However, the current research only focuses on the simulation calculation, and the accuracy is lack of the effective support. In this paper, the neural network is used to the measured ocean data, the characteristic of each ocean infrared image was extracted, trained and analyzed by neural network, and the law of the infrared characteristic value under different weather parameters was obtained. The infrared of the sea and sky was calculated by using the weather parameters. The infrared background of the ocean was reconstructed. The method would be high accuracy and high engineering application value.

1. Introduction
In 1990s, the infrared imaging system[1-5] has been widely used in the military fields such as optical remote sensing, night navigation, target detection and precision guidance. Together with radar and television, the three major sensing systems are formed. The weapon system with infrared imaging technology has the characteristics of high precision, anti-interference ability and flexible use. A variety of operational tasks in the future war could be carried out, that is closely concerned and vigorously developed by military departments of various countries. The infrared image of the scene is the thermal image that its own infrared radiation which is received by the imaging system, and the existing illumination model of computer graphics describes only the illumination effect of visible light on the surface of the scene, which can not simulate the infrared image of the scene, so the modeling and realistic display of the infrared image are infrared imitation. The difficult and key technology of the sea infrared imaging technology is the model built and realistic display [6-7] has become one of great interest to infrared simulation researchers.

With the development of science and technology, especially information technology, image processing technology has become an indispensable powerful tool for scientific research. Researchers have begun to explore new and more effective methods, and the use of neural network to process image processing is the most active direction [8-9]. The neural network algorithm shows great superiority over the traditional algorithm. (1) The high parallel processing capability is much faster than the traditional sequence processing algorithm; (2) It has adaptive function and can find and output the internal relation of data according to the data samples provided by the learning; (3) Many problems in image processing are nonlinear problems, and neural networks provide useful tools for dealing with these problems; (4) It has a generalization function that can handle noisy or incomplete data. Initially, artificial neural network is applied as a pattern recognition classifier and clustering technology in the field of image processing. Then, with the further research of neural network theory, the characteristics of neural network are fully recognized, and have been fully applied in various fields of image
processing, such as printed and handwritten character recognition, speech recognition, fingerprint, face recognition, image compression restoration and so on.

Most literature are based on the theory of ocean background simulation calculation, simulation results are still lack of effective comparison of measured data. Based on a large number of data the ocean background, this paper uses the neural network as the input of meteorological parameters (such as temperature, humidity, pressure, solar radiation and solar angle) as input, the characteristic value of the ocean infrared background as the output, and reconstructs the image through the neural network. The simulation of the ocean infrared background based on the experiment was achieved.

2. Neural Network Model and Initial Simulation

2.1. Competitive Neural Network Structure

Competitive neural network is a typical and widely applied unsupervised learning neural network. Its structure is shown in Figure 1. The competitive neural network is composed of input layer and competition layer. Similar to the RBF and other neural networks, the input layer only realizes the transfer of the input mode, and the neurons in the competitive layer win the response to the input mode in the form of competition. In the end, only one neuron wins the victory, and the connection weights and thresholds associated with the winning neuron move forward the direction of competition development are more beneficial, while the weights and thresholds corresponding to other neurons remain unchanged.

![Figure 1. Competitive neural network structure](image)

2.2. Competitive Neural Network Learning Algorithm

2.2.1. step 1 network initialization as shown in Figure 1, the input layer is composed of $R$ neurons, and the competition layer is made up of $S_i$ neurons. For the generality, the input matrix of training samples is:

$$ P = \begin{pmatrix} p_{11} & \cdots & p_{1Q} \\ \vdots & \ddots & \vdots \\ p_{R1} & \cdots & p_{RQ} \end{pmatrix}_{R \times Q} \quad (1) $$

In the formula: $p_{ij}$ is the $i$ input variable of the $j$ training sample; $Q$ is the sample number of the training set.

$$ p_i = (p_{i1}, p_{i2}, \cdots, p_{iQ}), \quad i = 1, 2, \cdots, R \quad (2) $$

The initial connection weight of the network is

$$ IW_{11} = (\omega_1, \omega_2, \cdots, \omega_R)_{S \times R} \quad (3) $$

Where
The initial connection weight of the network is

\[
b_1 = [e^{1 - \frac{\ln i}{S}}, e^{1 - \frac{\ln i}{S}}, \ldots, e^{1 - \frac{\ln i}{S}}]_i^{S',i}
\]  

(5)

Before learning, the relevant parameters should be initialized. The learning rate of weights is \(\alpha\), the learning rate of threshold is \(\beta\), the maximum iteration number is \(T\), and the initial number of iterations is \(N=1\).

2.2.2. step 2 calculation of winning neurons. Random selection of a training sample \(P\), based on

\[
n_i^j = \left(\sum_{j=1}^{S'} (p_j - IW_{ij}^{1,1}) + b_i^j, i = 1, 2, \ldots, S'\right)
\]  

(6)

The input of the neurons in the competitive layer is calculated. In which \(n_i^j\) represents the output of the \(i\) neuron in the competition layer; \(p_j\) represents the value of the \(j\) input variable of the sample \(P\); \(IW_{ij}^{1,1}\) represents the connection weight of the competition layer \(i\) neuron and the input layer \(j\) neuron; \(b_i^j\) represents the threshold of the next neuron of the competition layer. When the \(k\) neurons in the competition layer are the winning neurons, they should be satisfied:

\[
n_i^j = \max n_i^j, i = 1, 2, \ldots, S', k \in [1, S']
\]

2.2.3. step 3 weight, threshold update. The weights and thresholds corresponding to the neuron \(k\) are in accordance with:

\[
IW_{i}^{1,1} = IW_{i}^{1,1} + \alpha(P - IW_{i}^{1,1}), \\
b_i^j = e^{1 - \beta i(1 - \frac{\ln i}{S}) - \ln b_i^j + \beta i^j}
\]  

(7)

the weights and thresholds of the remaining neurons remain unchanged. \(IW_{i}^{1,1}\) is the \(k\)th row of \(IW^{1,1}\), and represents the weight corresponding to the winning neuron \(k\); the output of \(a_i\) competitive layer neurons, i.e.

\[
a_i = (a_i^1, a_i^2, \ldots, a_i^S), \\
a_i^j = \begin{cases} 1, i = k \\ 0, i \neq k \end{cases}, i = 1, 2, \ldots, S
\]  

(8)

2.2.4. step 4 the judgment of iteration end. If the sample has not been finished, another sample is randomly selected and returned to step 2. If \(N < T\), \(N = N+1\) is returned to step 2; otherwise, the iteration ends.

2.3. Neural Network Modeling

Based on the image recognition algorithm of the competitive neural network, the ocean infrared background simulation system was achieved. The composition of the system is shown in the figure. The system consists of two parts, one is the training process and the other is the whole system work flow.
In the initial stage of the system, because the parameters of the network were not initialized, the neural network was without classification ability, so training the network with useful samples was necessary. The training sample from was sent into the neural network input layer after preprocessing, and the output is compared with the ideal output of the sample, and the error is calculated. After a number of training, the error of the neural network satisfies the requirements of the system, and the network has entered a stable state. After the system has completed training, the neural network will enter the stable state and the system can be put into work. The image is preprocessed first, the image feature value is sent into the neural network, the trained neural network is used to detect the image, and the result is output. The system will classify the detected eigenvalues according to the results of the the characteristic values.

3. Image Simulation

3.1. Image Segmentation

The infrared background of the ocean is composed of the sky background and the ocean background. Because of its different imaging principles, the infrared imaging of the ocean and sky needs to be processed separately, and the image needs to be segmented in the preprocessing. Image segmentation is one of the most important contents in the field of computer vision. It is the first operation to be completed when automatic image analysis is realized. It is based on the similarity criteria of some features or feature sets of the image. The image pixels are grouped and the image plane is divided into a series of "meaningful" regions, which greatly reduces the amount of processing in the advanced processing stages, such as image analysis and recognition, while preserving information about the features of the image structure. Since the error in segmentation will directly affect the subsequent feature analysis, the accuracy of segmentation is very important. The general model of image segmentation as follows:

Let \((x, y)\) the spatial coordinates of the pixels of the digital image, \(G=0, 1, ..., L\) is a pixel gray level, and a digital image \(I(N\times N)\) is composed of \(N\times N\) pixels, so the number of images can be defined as a kind of ejection \(f: N\times N \rightarrow G\), and the intensity of the image at the point \((x, y)\) is recorded as \(f\). According to the characteristics of gray scale and texture, the region \(R\) in the image can be defined as a homogeneous subset of \(I\). Let \(P\) be a logical criterion for defining consistency measurement in \(R\) area.

\[
P(R) = \begin{cases} 
\text{true} & \quad (H(R) \in \hat{E}) \\
\text{false} & \quad \text{(other)}
\end{cases}
\tag{9}
\]
Definition: $H: \mathbb{R} \rightarrow \mathbb{E}$ is the function of the consistency estimate of $R$, and is the sub-region of $E$ defined. Image segmentation is to divide the entire column $I(x, y)$ into uncontrolled subset $R_1, R_2, \ldots, R_m$, according to the consistency measurement, and the following relationship should be satisfied:

$$I = \bigcup_{i=1}^{m} R_i$$

$$P(R_i) = \text{true} \quad (i = 1, 2, \ldots, m)$$

$$R_i \cap R_j = \emptyset \quad (l \leq i, j \leq m, i \neq j)$$

$$P(R_i \cap R_j) = \text{false} \quad (l \leq i, j \leq m)$$

(10)

Image segmentation based on region feature can be achieved by measuring the gray level, spatial texture and geometric structure of the region. In this paper, because the sea-sky boundary is very obvious, and because the sea-sky infrared imaging mechanism is different, the horizon is used as the segmentation line.

3.2. Image Eigenvalue Extraction

Compared with the original information, the feature information is not only greatly reduced in the amount of information, but also a feature information usually contains only one aspect of the target information to be easily distinguished. So the classification of the target is carried out by using the characteristic information of one or more information of one aspect of the target, and the selection and extraction of the features. It is of key significance to pattern recognition. Different kinds of information can be extracted through different processing methods of the original information of the target.

There are many kinds of features for image recognition, which can be roughly divided into four categories.

- **Visual features of the image:** refers to the image can be observed by the naked eye features, mainly: shape, contour, brightness, color, texture and so on.
- **Image statistical characteristics:** the statistical distribution of pixels in the image reflects the characteristics, such as: gray histogram, mean, variance, moisture content, etc.
- **Transform features:** features obtained by using various mathematical transformations of the image. Fu Liye's depiction is a characteristic of transformation.
- **Algebraic characteristics:** image is taken as a digital matrix, and the features obtained by various linear algebraic transformations are obtained. For example, the feature obtained by singular value decomposition of image matrix.

The measured image is 256 bitmap, the histogram analysis is the key step of the image processing. It can get the data segment feature of the digital image, and sum up its division rule by the large scale characteristic value contrast.
Figure 4. Image feature value extraction flow chart

Firstly, the image is converted into gray image, then the bar graph is displayed and analyzed by image analysis, and the histogram is analyzed, then the law of bit distribution was obtained. Then the eigenvalues of image matrix are analyzed, and the law of eigenvalues is studied, and the distribution rules of different gray values are analyzed.

3.3. Image Reconstruction

According to the results of neural network training, we predict the simulation image.

- According to the samples trained by neural network, we can infer the characteristic values of digital graphics.
- Reconstruct the infrared background of ocean and sky according to the eigenvalue and distribution rule.
- Reconstruction of infrared image of sea and sky background is completed with stitching map.

Figure 5. Eigenvalue reconstruction of ocean background image
|                       | Maximum gray value of the sky | Maximum gray value of the sea | Average gray value of the sky | Average gray value of the sea | The rate of gray value greater than average of sky | The rate of gray value greater than average of sea |
|-----------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|-----------------------------------------------|-----------------------------------------------|
| original image         | 255                           | 178                           | 231                           | 173                           | 63%                                           | 44%                                           |
| Reconstructed image    | 255                           | 172                           | 220                           | 188                           | 55%                                           | 38%                                           |

By comparing the reconstructed image with the original image, the error of the eigenvalue is less than 10%, and the reconstructed image has high accuracy.

4. Conclusion

In this paper, the composition and implementation of competitive neural network are studied and applied to the reconstruction of measured ocean infrared images. The numerical image is converted into gray image, then the gray value analysis, the probability of different gray value distribution and the reconstruction of the ocean infrared image was carried out. The results show that the competitive neural network has a high application value. The reconstructed image has a small error with the original image under the contrast of multiple gray values. This reconstruction technology would have a broad prospect of development and application in other image processing fields.

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