Based the Morphological Filtering BP Algorithm of SAR Image Recognition

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Abstract-SAR image recognition is an important content of of aviation image interpretation work. In this paper, the characteristics of SAR images a practical significance of morphological filtering neural network model and its adaptive BP learning algorithm. As can be seen through the experimental results, the algorithm can not only adapt to the complex and diverse background environment, and has a displacement of the same continuous moving target detection capability, telescopic invariant and rotation invariant features.

Keywords-morphological filtering; BP algorithm; neural network; Image Recognition

Using imaging radar photographs, called the SAR images. SAR image, unlike the general aerial photos as truthfully reflect the target image, it is based on a different light and dark spots and stripes to display the target image, and the general aerial photographs images has significant difference. With the rapid development of technology of aerial reconnaissance, SAR image reconnaissance occupy an increasingly important position in its all-weather, real-time image transmission and other unique advantages in reconnaissance systems, image interpretation and identification method has become a hot research topic.

In this paper, the characteristics of SAR images a practical significance of morphological filtering neural network model and its adaptive BP learning algorithm. The morphological filtering neural network system has a self-organizing structure in the process of learning (for example involved in the interaction of the external environment), each neuron compete with each other and collaborate, to constantly adjust the value of the network weights and Distributed stored at each nerve element in giving some intelligence neural network to achieve optimization of image morphological filtering and target recognition. Solving performance applications of knowledge into the learning process to improve the practical problems (moving target detection) to be binding and boot, dynamic tracking learning algorithms use heuristic methods combined with the learning rules, trying to meet efficiency and the versatility requirements, to obtain the overall performance better learning outcomes.

I Morphological filtering neural network model

Assignment preprocessing the search space for a limited range of values, and improve the efficiency of algorithm optimization, the need for the dynamic range of the structural element. At this time, the available sequence images to assess gray upper and lower bounds to determine the sample on the gray layer remaining space, and in order to standardize the number of structure element B tolerance. Set grayscale range of the SAR image, the variable range of the B component, wherein. Unified Analysis for ease of model samples, the same time, the need to implement a measure of the normalization processing, the energy value of each mode samples a unified unit. When a hardware operation, this quantization pretreatment is also beneficial to reduce the dynamic range of the image signal, to save storage space. Set of morphological filters the input of the first model the distribution of the sample data in the form of ..., and the corresponding structural elements ... The normalized image gray upper bound and the value calculated using the assessment mode samples and structural elements, limit the range [0,1]. At this point, can be directly calculated ... of N, and ... Taking into account the erosion and dilation operations has duality Thus, the expression of morphological erosion and dilation operations modified to:

$$\gamma_k = F_k \Theta B = \min\{\max[0, f_{k1} - b_1],\ \max[0, f_{k2} - b_2],\ \ldots,\ \max[0, f_{kM} - b_M]\} \qquad (1)$$

$$\gamma_k = F_k \oplus B = \max\{\min[1, f_{k1} + b_M],\ \min[1 + f_{k2} + b_{M-1}],\ \ldots,\ \min[1, f_{kM} + b_1]\} \qquad (2)$$

According to formula (1), (2) the morphology operation relationship can be designed directly corrosion and expansion operation of the neural network structure. The logic of the combination of erosion and dilation operations can be further designed morphological opening and closing operation of the three-layer feedforward neural network model, as shown in Figure 1. When the hidden layer for corrosion computing network output layer for the expansion of computing network, constitute the morphological opening operation of neural networks. Conversely, when the hidden layer is a dilation operation network while the output layer is a corrosion operation network constituting the morphological closing operation neural network.

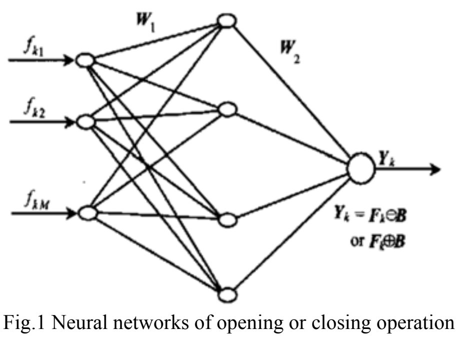

Fig.1 Neural networks of opening or closing operation

The structure element B as a specific template window in the entire image plane, a sliding filter (in this case involved in the operation of only the image data within the template window) can be completed to the image expansion or etching operations. While the opening and closing operation when the structure element B is required in the image plane, respectively sliding twice filtering the image data of the input layer thus participate in operation on each node in the output layer has exceeded the scope of the template window B. The result of the operation and the hidden layer:

$$G = \{(z, g(z)) \mid z \in R, R \subseteq E^2\} \quad (3)$$

The stringent constraints ensure that the template window for each layer of the input data, and will be in the open, closing operation of the neural network structure, the introduction of defined weighting vectors W1 and W2 binarized. Namely:

Corrosion: $z + n \in R, n \in S$

Expansion:

$$W_2(z,n) = \begin{cases} 1 & \\ 1 & z - n \in R, n \in S \\ 0 & \text{Other} \end{cases} \quad (4)$$

II The adaptive BP learning algorithm

In this paper, the concept of learning method is a heuristic search space concept description and concept description space state optimization learning rules to complete the original image data (training sample set). Learning rules need to be constrained, the introduction of relevant prior knowledge and statistical regularities and preferred criteria (cost function) to guide the solution process. For filtering parameters optimization training, the most critical is the form of the nonlinear filter mapping output to try approaching the expected value of the training samples that require optimal solution consistent with the examples given and for the shortest description. At the same time, the need to take into account the termination of the maneuverability of the algorithm (stopping criterion). Therefore, the choice of the optimal solution relative error rate of the target as a corrective traction to optimize the search for the ideal cost function. Error rate based on the definition of the function, can be obtained as the gradient vector of the network weights

$$. \ \delta = \frac{\partial e}{\partial B} = \left[\frac{\partial e}{\partial b_1} \ \cdots \frac{\partial e}{\partial b_m} \ \cdots \ \frac{\partial e}{\partial b_M} \right] \cdots. \quad .(5)$$

Since the expression of e open square operation, the gradient expression is more cumbersome. In order to achieve the same purpose, analysis of the intrinsic variation and reduce the computational complexity, it is defined:

$$E = e^2 = \frac{1}{N} \sum_{k=1}^{N} (\gamma_k - d_k)^2 \Big/ d_k^2 \quad (6)$$

For the cost function of the signal power of the error rate. Where Yk is the output value of the morphological filters; DK corresponding to a desired signal as an output k. Thus, the corresponding gradient vector:

$$\delta = \frac{\partial e}{\partial B} = \left[\frac{\partial e}{\partial b_1} \ \cdots \ \frac{\partial E}{\partial b_M} \ \cdots \ \frac{\partial E}{\partial b_M} \right]^T \ \cdots (7)$$

This way:

$$\delta_m = \frac{\partial E}{\partial b_m} = \frac{2}{N} \sum_{k=1}^{N} \{(\gamma_k - d_k) \times g(\gamma_k, b_m) \quad / d_k^2 \ \} \quad (8)$$

When the morphological transformation of grayscale erosion operation:

$$g(\gamma_k, b_m) = \begin{cases} -1 & \gamma_k = f_{km} - b_m \quad f_{km} - b_m \rangle 0 \\ 0 & \text{其他} \end{cases} \quad (9)$$

In this case, the right value of the correction amount for:

$$\nabla b_m = -\eta \delta_m = -\frac{2\eta}{N} \sum_{k=1}^{L} \{(\gamma_k - d_k) \times g(\gamma_k \ , \ b_m) \ / d_k^2\} \quad (10)$$

Here η is the learning rate. So the network weights iterative formula:

$$b_m(t+1) = b_m(t) + \nabla b_m = b_m(t) - \eta \delta_m \quad (11)$$

Actual computing process in order to speed up the convergence rate, often used the overrelaxation method that increase the weight change of momentum term to smooth. Thus, the formula (11) becomes:

$$b_m(t+1) = b_m(t) - \eta \delta_m + \alpha [b_m(t) - b_m(t-1)] \quad (12)$$

Wherein: $1 \le m \le M$; α is the momentum factor ($0 < \alpha < 1$).

Holding the formula (8) and formula (12) is unchanged, only the formula (9), slightly modified, the grayscale dilation operation when the iterative calculation formula can be obtained. In this case, the formula (9) is rewritten as:

$$g(\gamma_k \ , \ b_m) = \begin{cases} 1 & \gamma_k = f_{km} + b_m, \quad f_{km} + b_m < 1 \\ 0 & other \end{cases} \quad (13)$$

In order to overcome some inherent defects of BP learning algorithm, the article will get rid of η and α are constant constant restrictions, into the regulation of adaptive (dynamic variable) guided learning. Guided heuristic strategy: the selected learning early stage learning rate η, can make the learning speed, in and close to the optimum point, η becomes relatively small, in order to prevent the oscillation of the weight values and the higher the accuracy of (smaller steps) approximation to the optimal solution. Thus, the function of the adjusted change the learning rate with the number of iterations t η (t, m) can be chosen as:

$$\eta(t \ , \ m) = \eta_{\max}(m) \bullet \left[1 - \Gamma^{\left(1 - t/T\right)^S} \right] \quad (14)$$

Γ is a random number; S adjust the parameters of the convergence rate, often take S ∈ [1,2] [0,1]; T BP algorithm set the maximum number of iterations.

Selected each weight component bm ($1 \le m \le M$) has its own learning rate, and that the function η (t, m) returns [0, ηmax (m) on a dynamic value and This value along with the increase of the number of iterations t asymptotic to 0. It allows the algorithm the initial weights component bm in each scalable space along the maximum gradient direction changes, At this pace and the right amount of random perturbations to jump out of local extrema trap approximation to the optimal solution direction. Algorithm late stride and disturbance gradually become smaller, so that the protection of high-quality solution close to the optimal solution neighborhood differentiation destruction and converge at the peak point.

For momentum factor α, by the formula (13) is easy to see, the greater inertia of α the greater the momentum adjustment, i.e., every time the learning adjusted with the previous state of learning more closely related. Intuitively, each iteration weights dynamically adjust the learning rate changes (especially algorithm early), then added momentum solid role in promoting, is bound to accelerate the convergence process. Use as a rule of thumb, often take $\alpha = 0.6$.

The set mode template vector dimension (corresponding to the network input nodes) to learn the number of samples for mode sample of connection weights matrix (structural elements). Network after the first training sample input, the output value of the output contacts, the desired signal. The adaptive morphological neural network learning algorithm processes can be described as follows:

Algorithmic process:

(1) initialize the network weights bm ($1 \le m \le M$);
Set the error rate E error precision ε;
Select the learning rate amplitude ηmax;
Determine the momentum factor α ($0 < \alpha < 1$).
(2) training initialization and defines the maximum number of iterations T;
Beginning of the training: t = 1.
(3) calculate the gradient component:
Dynamically adjust the learning rate:

$$\delta_m = \frac{2}{N}\sum_{k=1}^{N}\left\{(\gamma_k - d_k)\times g(\gamma_k\text{, } b_m)\ /d_k^2\right\} \qquad (1 \le m \le M)$$

And $\eta(t,m) = \eta_{\max}(m)\bullet\left[1-\Gamma^{\left(1-t/T\right)\ S}\right]$

Adaptive correction weights:

$$b_m(t+1) = b_m(t) - \eta(t,m)\delta_m + \alpha\left[b_m(t) - b_m(t-1)\right]$$

Calculate the error rate:

$$E = \frac{1}{N}\sum_{k=1}^{N}(\gamma_k - d_k)^2 \Big/ d_k^2$$

Iterative training: t = t +1.
(4) training session: $E \le \varepsilon$ or $t \ge T$.
Closing operation network

$$g(r_k, b_m) = \begin{cases} -1 & r_k = f_{km} + b_i - b_m, i \ne m \\ 1 & r_k = f_{km} + b_m - b_j, j \ne m \\ 0 & \quad\quad other \end{cases}$$

Which, off the computing network $g(r_k, b_m) = \begin{cases} -1 \\ 1 \\ 0 \end{cases}$

$$r_k = f_{km} - b_m + b_j, j \ne m$$
$$r_k = f_{km} - b_i + b_m, i \ne m$$
$$other$$

The formula: f_{km}, b_m using the weight vector W1 (see Figure 4) through the corresponding scan mode in the hidden layer neuron of the input layer of the two-dimensional image data and the structure function is transformed into a set of M-dimensional vector data, and ($1 \le i \le M$, $1 \le j \le M$) is the use of the W2 corresponding to the output layer neurons on the conversion result.

III Results

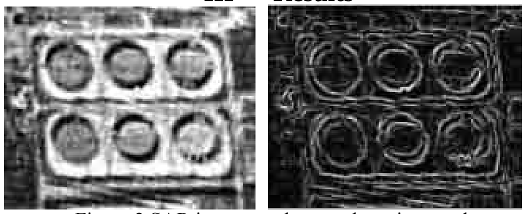

Figure 2 SAR images and target detection results

Figure 2 shows a photo of a certain type of imaging radar target shooting on a fuel depot in 2002, and its detection results. As can be seen, the proposed algorithm to extract the target is more truly reflect the change characteristics of the original image in the oil depot goal of image understanding and scene interpretation provides an important basis for the identification.

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