Study on Expressway Crack Segmentation Algorithm Combined with Pulse-Coupled Neural Network and Cross-Entropy Algorithm

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ABSTRACT: The expressway crack identification is significantly important for the expressway safety maintenance, and the crack detection is one of key technologies for the crack identification. This paper proposed an expressway crack detection method based on improved Pulse-Coupled Neural Network (PCNN), used minimum cross-entropy algorithm to obtain the optimal iterations of PCNN algorithm, and then complete the segmentation of expressway images by combining the simplified PCNN algorithm. The results showed that this method could inhibit the background noise and better extract continuous crack edge to provide good characteristics for crack identification in the next step.

1. INTRODUCTION

The pavement preservation of expressway was inevitable with the rapid development of expressway in contemporary society. During the use process of expressway, some factors, such as overload traffic, the influence of natural and artificial environments, and so on, resulted in the different types of damage for roadbed and pavement in different degrees, and the pavement crack was a common type of damage. Moreover, the pavement crack damage would result in insufficient durable bearing capacity of pavement and cause influence on the speed, fuel consumption, comfortableness, and so on in different degrees in the process of vehicle driving. Especially, it would result in prominent traffic safety hazard for expressways. The traditional crack detection for the expressway pavement was mainly accomplished by manual work, however, this method has low automation degree, inefficiency and large error, as well as it is very difficult to objectively and accurately determine cracks. Hence, these factors forced the expressway crack detection to develop into an automated detection technology method [1,2].

In recent years, digital image technology was widely applied to solve the industrial problems with the improvement of computer performance and the development of digital camera technology. Figure 1 shows the structure diagram of pavement detection by digital image technology. Firstly, the industrial camera was used to collect the pavement crack images, then cracks and backgrounds were separated by the image segmentation technology. Finally, the segmented images were input into the machine learning system to accomplish crack identification and judge whether there were cracks. The pavement crack detection algorithm was very key, and the good image segmentation method can not only inhibit noise but also retain complete crack characteristics. For machine learning system, the good characteristic images were the premise to guarantee the identification rate of stable fault. Thus, this study used an improved PCNN algorithm to complete the expressway crack segmentation so as to provide good fault characteristics for subsequent pattern identification system.

When the traditional PCNN method was used for the image segmentation [3–5], there needed multiple iterations for better image segmentation effect, but the iterations usually could not be determined in advance. For this problem, this paper proposed a kind of image segmentation algorithm in combination of minimum cross-entropy method [6] and PCNN.

The rest of the paper is organized as follows. In Section 2, the simplified PCNN method [7] was used to accomplish the image segmentation, including the principle of continuous PCNN, the principle of discrete PCNN and the image segmentation using PCNN.
The Pulse-Coupled Neural Network and cross-entropy combining algorithm is proposed in Section 3 in detail, including the minimum cross-entropy principle, the segmentation threshold determination and Pulse-Coupled Neural Network and cross-entropy combining algorithm. In Section 4, the experimental and analysis of the results are described. First, the testing condition and platform are analyzed. Then, the iteration results and analysis is demonstrated. Finally, the study results showed that compared with the Kmeans method [8], maximum between-cluster variance algorithm (Otsu) [9] and traditional PCNN method. The paper ends with some concluding remarks in Section 5.

2. BASIC MODEL AND PRINCIPLE OF PCNN

Our approach for PCNN using for image segmentation consists of three parts, as follows: first, we conduct the principle of the continuous PCNN; then, the discrete PCNN is deducted; finally, the segmentation of images using PCNN is proposed in Section 2.3.

2.1. Principle of Continuous PCNN

PCNN was a new-type neural network [10] based on the artificial intelligence and was proposed after the phenomenon of sync pulse release was found by the cerebral cortex test [11] of animals. The studies on PCNN were very hot in recent years. The PCNN was fundamentally different with the traditional neural network theory and provided good theoretical basis and thought for analysis of the complicated problems, moreover, it has been widely used in the pattern identification, image processing, optimization decision, and so on.

PCNN model was mainly composed of receiving region, modulation link and pulse generation part, as shown in Figure 2. In addition, the receiving region mainly received the external signals of neuron, and the signals would be transmitted in two channels after the receiving region received the external input signals of neuron. One of the two channels were called as $F$, and the other one was called as $L$. It was stipulated that the impulse response of $F$ was slower than that of $L$. Then the specific process was shown in Equations (1)–(5). Where $W_{kj}$ and $M_{kj}$ in Equations (1)–(2) referred to the synapse connection weight, $\alpha_{kj}^L$ and $\alpha_{kj}^F$ were the time constants, and $J_j$ and $I_j$ were the input constants, respectively. In the modulation link, the signals in $L$ channel were added to an offset (positive value), the sum of two was multiplied by the signal $F_j$ from $F$ channel, and then the signals were modulated, as shown in Figure 2. The simplified PCNN model was used in this study, the offset was normalized to 1, and the connection strength of neuron was $\beta_j$. The change of signal $F_j$ from $F$ channel was slower than that of signal $L_j$ from $L$ channel, and $F_j$ and $L_j$ were multiplied together to obtain the modulation signal $U_j$. And then the modulation signal $U_j$ can be regarded as an addition of a signal changing rapidly and a signal close to a constant. It is thought that the pulse generation part was composed of a comparator with changeable thresholds and pulse generator which can generate pulse. When working, the pulse generator would release constant pulse outward with a certain frequency. In Equation (4), $V_{j}^{T}$ referred to the amplitude coefficient of image threshold, and $\alpha_{j}^{T}$ referred to the time constant. When the neuron was activated each time, there would be a pulse to be output. Moreover, the relationship between comparator generating pulse and the pulse generator can be replaced by a step function, and the Equation (5) showed the pulse output form under this circumstances.
\[ L_j = \sum_k W_{kj} e^{-\alpha_{kj} t} \times Y_k(t) \]  
\[ F_j = \sum_k F_{kj} = \sum_k M_{kj} e^{-\alpha_{kj} t} \times Y_k(t) + I_j \]  
\[ U_j = F_j (1 + \beta_j L_j) \]  
\[ \frac{d\theta}{dt} = e^{-\alpha_j} \theta_j + V^T \lambda_j(t) \]  
\[ Y_j = \begin{cases} 1, & (U_j \geq \theta_j) \\ 0, & (U_j < \theta_j) \end{cases} \]

\[ M_{ij,kl} = \begin{cases} 0, & (i,j) = (k,l) \\ 1, & (i,j) \neq (k,l) \end{cases} \]

2.2. Principle of Discrete PCNN

For discrete signals, such as digital image in this paper, each pixel \((i, j)\) in image \(I\) can be considered as a neuron, thus, Equations (1)–(5) can be transferred to iteration model as:

\[ L_y(n) = e^{-\alpha_y} L_y(n-1) + \sum_{kl \in N_y} W_{ij,kl} Y_{ij}(n-1) \]

\[ F_{ij}(n) = e^{-\alpha_y} F_{ij}(n-1) + \sum_{kl \in N_y} M_{ij,kl} Y_{ij}(n-1) + I_{ij} \]

Where \(ij\) and \(kl\) denote the positions of image pixels corresponding to neurons, \(\alpha_F\) and \(\alpha_L\) were the time constants the same as \(\alpha_{ij}^L\) and \(\alpha_{ij}^F\). And \(W_{ij,kl}\) and \(M_{ij,kl}\) were weight matrix, which were used for connecting eight neighboring neurons, where \(n\) denotes the \(n\)-th iteration. The element of matrix \(W_{ij,kl}\) and \(M_{ij,kl}\) can be obtained as:

\[ M_{ij,kl} = \begin{cases} 0, & (i,j) = (k,l) \\ 1/\| (i,j) - (k,l) \|^2, & (i,j) \neq (k,l) \end{cases} \]

Then, Equations (3)–(5) can be changed as:

\[ U_{ij}(n) = F_{ij}(n)[1 + \beta L_y(n)] \]

\[ \theta_{ij}(n) = e^{-\alpha_j} \theta_{ij}(n-1) + V^T \lambda_j(n-1) \]

\[ Y_{ij}(n) = \begin{cases} 1, & U_{ij}(n) \geq \theta_{ij}(n-1) \\ 0, & \text{else} \end{cases} \]

Where the meanings of the parameters in Equations (9)–(11) were the same as in Equations (3)–(5).

2.3. Image Segmentation

When PCNN algorithm was used to segment the images, the image with \(N \times N\) pixels should be corresponded to \(N \times N\) PCNN neurons. During the process of the first iteration, external stimulus \(I_{ij}(1)\) was equal to the external activity items of neurons. If \(U_{ij}(n)\) was more than the threshold, the output value of neuron was 1, the neuron was in a status of activation, as well as its threshold \(\theta_{ij}(n)\) would rapidly increase and de-
cayed in a form of exponential function. The activated neurons would use the interconnected characteristics among the neurons to activate adjacent other neurons in each iteration process in the future. If the output of adjacent internal action items of the neuron was more than this threshold, this neuron would be activated. Obviously, if the gray values of pixels of nearby neurons were close to those of activated neurons in the last iteration process, these neurons would be activated, otherwise, these neurons would not be activated. It can be observed that the activation of specific neurons can also trigger some neurons in the adjacent field to be activated. Both this principle and the characteristic that sets composed of all neurons in the adjacent field had similar properties were used for the image segmentation. When the algorithm was used to segment images, each pixel in the image was regarded as one neuron and each neuron can be activated when capturing the surrounding pixels ignited. In the first iteration, a global threshold \( \theta_{ij} \) (1) was firstly given and all the pixels in the image were activated. Then the threshold for the next iteration was generated according to the Equation (9), and the loop iteration was carried out by the iteration algorithm similar to above iteration algorithm. When there appeared gray values of similar pixels in the internal connection matrix \( W_{ij,kl} \) and adjacent field as well as one of gray value of input pixels was less than the threshold, the pulse signal triggered by this pixel would always be transmitted. This would cause that the pixels corresponding to nearby similar neurons were inhibited, and the pulse sequence \( Y_{ij} (n) \) was output. Binarization discrete image sequence \( Y_{ij} (n) \) composed of the nth image within a certain time was the output results of PCNN segmentation. How to determine iterations so as to realize the automatic segmentation of optimal images needed to be faced as the classic PCNN algorithm was used for image segmentation.

3. IMPROVED PCNN IMAGE SEGMENTATION ALGORITHM

In this paper, we adopted simple PCNN and minimum cross-entropy to implement the proposed improved method. The minimum cross-entropy principle is introduced in Section 3.1. In Section 3.2, the segmentation threshold is determined. Finally, the PCNN and cross-entropy combing algorithm is demonstrated.

3.1. The Minimum Cross-entropy Principle

This paper used the minimum cross-entropy principle to process the expressway crack image and calculate the optimal times to segment the expressway crack image by PCNN. Entropy was a standard to measure the uncertainty, and Shannon entropy was used to measure the average amount of information of all the target information sources. The minimum Shannon entropy criterion was mainly used to highlight the uniformity of internal information of system, as well as it was used for the image threshold segmentation in order to obtain the optimal threshold of homogeneous distribution of target intensity or background intensity. The cross-entropy is often used to measure the difference in the amount of information between two kinds of probability distribution, and it is a convex function. The minimum cross-entropy criterion was used for the image threshold segmentation [12–14], and it is usually used to obtain the threshold which makes the difference in the amount of information between before and after image segmentation. It was assumed that there were two probability distribution sets, namely, \( P = \{p_1, p_2, \ldots, p_N\} \) and \( Q = \{q_1, q_2, \ldots, q_N\} \). The cross-entropy is used to measure the difference in the amount of information between two sets of probability distribution, as shown in Equation (12), the equation was symmetrical.

\[
D(P, Q) = \sum_{i=1}^{N} p_i \times \ln \frac{P_i}{Q_i} + \sum_{i=1}^{N} q_i \times \ln \frac{Q_i}{P_i}
\]  (12)

3.2. Segmentation Threshold Determination

For the minimum cross-entropy technology to obtain segmentation threshold, \( P \) was used to denote the images before processing, and \( Q \) was used to denote the images after segmentation. Then the cross entropy among the targets as well as among the backgrounds were calculated, respectively. Furthermore, the sum of cross entropy among the targets was defined as the cross entropy of images before processing, as well as the sum of cross entropy among the targets was defined as the cross entropy of images after segmentation. The concrete equation was as follows.

\[
D(P, Q : T) = \sum_{g=0}^{T} g \times h(g) \times \ln \frac{g}{\mu_1(T)} + \mu_1(T) \times h(g) \times \ln \frac{\mu_1(T)}{g}
\]

\[+ \sum_{g=0}^{T} g \times h(g) \times \ln \frac{g}{\mu_2(T)} + \mu_2(T) \times h(g) \times \ln \frac{\mu_2(T)}{g}\]  (13)
\[
\mu_1(T) = \frac{1}{\sum_{g=0}^{T} h(g)} \sum_{g=0}^{T} g \times h(g)
\]

\[
\mu_2(T) = \frac{1}{\sum_{g=T+1}^{L} h(g)} \sum_{g=T+1}^{L} g \times h(g)
\]

In Equation (13), \( g \) was the gray value of images, \( h(g) \) was the histogram of grayscale for the images described, \( L \) was an upper limit of gray value for images, \( T \) was the assumed threshold, and \( \mu_1(T) \) and \( \mu_2(T) \) were the mean of the intraclass, and referred to the average values in two intraclass of target and background, respectively, similar to the average gray value defined in the Otsu algorithm. When calculating, the Equation (13) was normalized. The segmentation results of original images under this specific circumstances can make \( T \) corresponding to the minimum of \( D(P, Q : t) \) be the optimal segmentation threshold \( T_{opt} \). The \( t \) was searched in the scope of gray.

### 3.3. Pulse-Coupled Neural Network and Cross-entropy Combining Algorithm

The iterations \( N_{min} \) of minimum threshold \( D_{min} \) was optimally divided in the iteration process with the given times, and \( N_{min} \) was the minimum iterations. The output of this model was the results of comparison between internal matrix \( U \) and threshold matrix \( T \), compared with the usual image threshold segmentation method, the only difference was that the traditional threshold segmentation algorithm could obtain a constant threshold, but this algorithm could obtain a threshold matrix. There were different standards to determine whether the segmentation results of common threshold segmentation procedure were good or bad, but only a single gray value can be chosen as a threshold without fully considering the information in adjacent field of pixel in most images processing process. However, the algorithm proposed in this paper can adjust the neuron input in the next stage by the neuron weighting and make the long-term internal activity of neuron not only include the gray information of corresponding pixels but also fully embody the information in adjacent field of pixel. Hence, the internal activity composed of matrix can be regarded as a image, and the threshold matrix can also be regarded as the image with the same pixel. The corresponding results of the two were output to the corresponding binarization image matrix. Namely, the result matrix was the segmentation output image, and the output image after the \( N_{min} \) th iteration corresponded to the optimal segmentation image. The flow chart of the combing algorithm are shown in Figure 3.

![Figure 3. Flow diagram of improved PCNN image segmentation algorithm.](image)

### 4. ANALYSIS FOR EXPERIMENTAL RESULTS

In this section, we evaluate the proposed algorithm presented in this paper and compare it with the Kmens method, Otsu segmentation method and traditional PCNN algorithms. The testing condition and the platform is tested in Section 4.1. In Section 4.2, the iteration results and analysis of the proposed method are discussed in detail. Finally, the proposed method with respect to the peak signal to noise ratio and quantitative evaluation are tested by comparing it with the other three algorithms.

#### 4.1. Testing Condition and Platform

In order to verify the effectiveness of the method proposed in this paper, Matlab r2012b was used to programme in a PC of Windows 7 with Intel core i7 4790
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CPU and the memory of 4 G. Figure 4 showed the collected original expressway crack image and original image histogram with strong noise interference. After experiments repeated for many times, the parameters of PCNN model were selected as \( \alpha_F = \alpha_L = \alpha_T = 0.1, \beta_j = 0.1, V_{ij}^T = 0.01 \) and the weight matrix was, \( W = M = [0.707 \ 1 \ 0.707; 1 \ 0 \ 1; 0.707 \ 1 \ 0.707] \) and for the first iteration, the threshold was set to \( \theta_{ij}(1) = 255 \). Figure 5 showed the process curve to determine the iterations by the minimum cross-entropy principle of PCNN algorithm, and the total of iterations were 15. As shown in Figure 5, when the iterations were 7, the cross entropy took the minimum, and the optimal segmentation image results were output.

4.2. Iteration Results and Analysis

In order to better show the image segmentation effect of the proposed method, this paper presented the image segmentation results as the iterations were \( i = 1, 2, 4, 7, 10, 15 \), as shown in Figure 6. When \( i = 1, 2, 4 \), the image noise after segmentation was higher in Figure 6. When \( i = 10 \) and 15, the segmentation results of images were the crack disconnection. When \( i = 7 \), the entropy was minimum, and the crack was segmented as well as inhibited to a certain extent, hence, the segmentation effect was the best.

4.3. Comparison and Analysis

In order to further verify the algorithm performance in this paper, peak signal to noise ratio (PSNR) was used to objectively evaluate the experimental results, and the PSNR was defined as follows [15].

\[
\text{PSNR} = 10 \log \frac{M \times N \times 255^2}{\sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (f(i,j) - y(i,j))^2}
\]

Figure 5. Minimum cross-entropy iteration curve.
Figure 6. Images of improved PCNN algorithm in iteration process.
mentation method and traditional PCNN method were used to segment the expressway crack images, respectively. Figure 7 showed the effect of images segmentation with different algorithms, and the comparison results of PSNR were shown in Table 1. It is observed that the PSNR by the algorithm proposed in this paper is the highest, so the segmentation performance is superior to the other three methods.

Moreover, this paper used the uniformity measure (NU), contrast (GC), shape measure (SM) and ambiguity D to quantitatively evaluate the segmentation effect for expressway crack image by the above methods according to the comprehensive evaluation function \( J = NU \times GC \times SM \times (1 - D) \) [16] in order to further evaluate the performance of image segmentation, and the results were shown in Table 2. Obviously, the comprehensive evaluation result of the algorithm proposed in this paper has the highest score and is slightly better than that of Otsu algorithm. However, the evaluation result of original PCNN algorithm has the lowest score, so the segmentation effect is the worst.

To sum up, compared with the other three algorithms, the algorithm proposed in this paper has better segmentation effect for the expressway crack images and has better ability to resist noise whether from the visual sense or from the perspectives of qualitative

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**Table 1. Comparison for Performance of Different Algorithms.**

<table>
<thead>
<tr>
<th>Method</th>
<th>PNSR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kmeans Method</td>
<td>22.85</td>
</tr>
<tr>
<td>Otsu</td>
<td>23.91</td>
</tr>
<tr>
<td>Improved PCNN Method</td>
<td>29.52</td>
</tr>
</tbody>
</table>

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*Figure 7. Comparison for the image segmentation results with different algorithms.*
Table 2. Quantitative Evaluation of Different Algorithms.

<table>
<thead>
<tr>
<th>Method</th>
<th>NU</th>
<th>GC</th>
<th>SM</th>
<th>D</th>
<th>J</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kmeans</td>
<td>0.9796</td>
<td>0.4851</td>
<td>0.5256</td>
<td>0.3345</td>
<td>0.1978</td>
</tr>
<tr>
<td>Otsu</td>
<td>0.9903</td>
<td>0.4931</td>
<td>0.7438</td>
<td>0.3527</td>
<td>0.2351</td>
</tr>
<tr>
<td>PCNN</td>
<td>0.9712</td>
<td>0.4678</td>
<td>0.5012</td>
<td>0.3138</td>
<td>0.1561</td>
</tr>
<tr>
<td>The proposed method</td>
<td>0.9923</td>
<td>0.5234</td>
<td>0.7518</td>
<td>0.3496</td>
<td>0.2539</td>
</tr>
</tbody>
</table>

and quantitative evaluation indexes. Furthermore, this algorithm can achieve good crack information as segmenting crack images.

5. CONCLUSIONS

This paper mainly put forward an expressway crack detection method based on improved PCNN. This algorithm firstly determine minimum iterations of PCNN model by the minimum cross-entropy algorithm, then the simplified PCNN algorithm was used to accomplish the crack image segmentation. This algorithm can effectively inhibit noises and obtain good crack edge images under the uneven illumination of original image and the strong noise interference. It is shown by a large amount of experiments that this algorithm can completely segment expressway crack images and obtain complete and continuous edge information of image segmentation. Compared with other methods mentioned in the paper, this algorithm has strong anti-noise ability and can provide good characteristics for crack identification in the next step, thus increasing the identification rate of expressway cracks.

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7. REFERENCES