行政院國家科學委員會專題研究計畫　成果報告

蜂巢式類神經網路於震測圖型識別之研究

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計畫主持人：黃國源

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行政院國家科學委員會專題研究計畫成果報告

蜂巢式類神經網路於震測圖型識別之研究

The Study of Cellular Neural Network for Seismic Pattern Recognition

計畫編號：NSC 93-2213-E-009-067

執行期限：93 年 8 月 1 日至 94 年 7 月 31 日

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一、中文摘要

本研究運用蜂巢式類神經網路於震測圖型識別，我們依據儲存圖樣將蜂巢式類神經網路設計成聯想記憶體，完成網路的訓練，然後我們利用這聯想記憶體來辨識震測圖型。震測圖型識別將有助於震測資料之探油分析及解釋。

關鍵詞：蜂巢式類神經網路、圖型識別、震測圖型。

Abstract

Cellular neural network is adopted for seismic pattern recognition. We design cellular neural network to behave as associative memory according to the stored patterns, and finish the process of network training. Then we use this associative memory to recognize seismic patterns. Seismic pattern recognition can help the analysis and interpretation of seismic data.

Keywords: Cellular neural network, pattern recognition, seismic patterns.

二、緣由與目的

Seismic pattern recognition can help us to analyze and interpret seismic data. We use associative memories to store seismic patterns and recognize noisy seismic patterns. Cellular neural network (CNN) is used for associative memory. Each memory pattern corresponds to a unique globally asymptotically stable equilibrium point of the network.

Fig. 1(a) shows a simulated seismogram. A seismogram consists of many seismic traces. Each trace contains many peaks (wavelets). We can extract peak data from seismogram. Then we transform peak data to bipolar data. The seismogram passes through preprocessing to extract peak data. Fig. 1(b) shows the result of preprocessing of Fig. 1(a), the value of pixel "1" is for peak point and "0" is for background. Fig. 2 shows the preprocessing steps of seismogram. It contains enveloping, thresholding, peaking, thinning, and compression in the time direction. Fig. 3 shows the seismic pattern recognition system using CNN. The process of seismic pattern recognition is composed by two parts. In the training part, the training patterns can construct the associative memory using cellular neural network. In the recognition part, associative memory can recognize the input test pattern.

The process of CNN network training is summarized in the following. Given m bipolar training patterns as input vectors $\mathbf{u}^i$ and output vectors $\mathbf{y}^i$, i = 1, 2, …, m, for each $\mathbf{u}^i$, there is only one equilibrium point $\mathbf{x}^i$ satisfying the equation of motion:

$$\mathbf{x}^i = \mathbf{A}\mathbf{y}^i + \mathbf{B}\mathbf{u}^i + \mathbf{e},\ i = 1, 2, \ldots, m \qquad (1)$$

The equation (1) can be expressed as compact matrix form:

$$\mathbf{X} = \mathbf{AY} + \mathbf{BU} + \mathbf{J} \qquad (2)$$

where $\mathbf{X} = [\mathbf{x}^1\ \mathbf{x}^2\ \cdots\ \mathbf{x}^m]$, $\mathbf{Y} = [\mathbf{y}^1\ \mathbf{y}^2\ \cdots\ \mathbf{y}^m]$, $\mathbf{U} = [\mathbf{u}^1\ \mathbf{u}^2\ \cdots\ \mathbf{u}^m]$, and $\mathbf{J} = [\mathbf{e}\ \mathbf{e}\ \cdots\ \mathbf{e}]$.

Equation (2) can be rewritten as equation (3):

$$\mathbf{BU} + \mathbf{J} = \mathbf{X} - \mathbf{AY} \qquad (3)$$

Matrix **A** can be designed to a circulant matrix. The eigenvalues of **A** can be derived as follows:

$$S(2\pi q/n) = \sum_{h=-r}^{r} a(h) e^{-j2\pi hq/n} ,$$

$$q = 0, 1, 2, \ldots, n\text{-}1. \qquad (4)$$

Discrete time CNN with circulant matrix **A** are globally asymptotically stable if and only if

$$|S(2\pi q/n)| < 1, \ q = 0, 1, 2, \ldots, n\text{-}1 \qquad (5)$$

Notice that equation (3) must be solved for **B** and **J**. The steps are as follows. Let all training patterns be $\mathbf{u}^i$ and $\mathbf{y}^i$. Then we can get matrices **U** and **Y**. Choose a sequence $\{a(-r) \ \cdots \ a(-1) \ \ a(0) \ \ a(1) \ \cdots \ a(r)\}$ for which the stability criterion (5) holds. Then design matrix **A** as a circulant matrix. Let **X** = α **Y** with α>1. **B** and **J** in equation (3) can be computed using pseudo-inversion techniques.

Algorithm 1: Design a cellular neural network to behave as an associative memory in the training part.

Input: *m* bipolar patterns $\mathbf{u}^i$, *i* = 1,……, *m*

Output: **B** and **e**

Methods:

(1) Calculate matrix **U** from training patterns $\mathbf{u}^i$.

$$\mathbf{U} = [\mathbf{u}^1 \ \ \mathbf{u}^2 \ \cdots \ \mathbf{u}^m]$$

(2) Establish matrix **Y** = matrix **U**.

$$\mathbf{Y} = \mathbf{U}$$

(3) Design matrix **A** as the circulant matrix which satisfies globally asymptotically stable condition.

(4) Set the value of α (α > 1), and calculate **X** = α**Y**.

(5) From **BU** + **J** = **X** − **AY**, using pseudo-inverse technique to calculate **B** and **J**. And from **J**, select one column of **J** as **e**.

After training, the process of recognition is summarized in the following. Input the test pattern as **u** and **A**, **B**, **e** to the equation of motion, **x**(*t*+1) = **Ay** + **Bu** + **e**. After getting the state value **x**(*t*+1) at the next time, we use output function to calculate the output **y**(*t*+1) at the next time. We calculate the state value and the output until all output values are not changed anymore, then final output is the classification of the test pattern.

Algorithm 2: Use associative memory to recognize the test pattern

Input: Test pattern **u** and **A**, **B**, **e** in the equation of motion

Output: Classification of the test pattern **u**

Methods:

(1) Set up initial output vector **y**, its element values are all in [-1, 1] interval.

(2) Input test pattern **u** and **A**, **B**, **e** into the equation of motion to get **x**(*t*+1)

$$\mathbf{x}(t+1) = \mathbf{A}\,\mathbf{y}(t) + \mathbf{B}\,\mathbf{u} + \mathbf{e}$$

(3) Input **x**(*t* + 1) into activation function, get new output **y**(*t* + 1).

For activation function:

$$\begin{cases} x > 1, \ \text{then } y = 1 \\ -1 \le x \le 1, \ \text{then } y = x \\ x < -1, \ \text{then } y = -1 \end{cases}$$

(4) Compare new output **y**(*t* + 1) and **y**(*t*). Check whether they are the same. If they are the same, then stop, otherwise input new output **y**(*t* + 1) into equation of motion again. Repeat (2) to (4) until output **y** is not changed.

三、結果與討論

The two simulated peak data of bright spot pattern and pinch-out pattern is shown in Fig. 4(a) and 4(b). The size of input data is 19x29. We use these two patterns as the training patterns. Fig. 4(c) is the first noisy test pattern. Fig. 4(d) is the second noisy test pattern. We set α = 3 and neighborhood radius r = 3. The recognition results are shown in Fig. 5.

The value of α and matrix **A** do not affect the network performance. The network performance strongly depends on the number of patterns to be stored.

四、成果自評

研究內容與原計畫相符程度: 100%
達成預期目標情況: 100%
研究成果的學術或應用價值: 建立蜂巢式類神經網路震測圖型識別系統
是否適合在學術期刊發表: 是
主要發現或其他有關價值: 可用於其他有關圖型識別的應用

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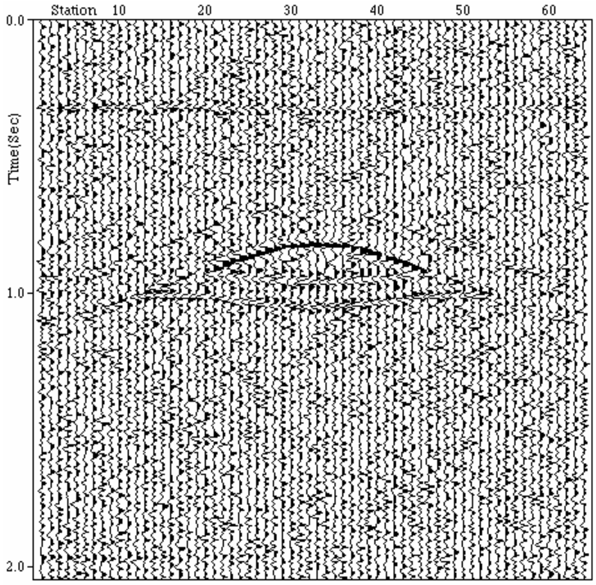

Fig. 1. (a) Simulated seismogram.

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Fig. 1. (b) Preprocessing from Fig. 1(a).

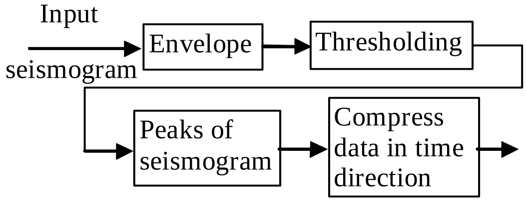


Fig. 2. Preprocessing steps of seismogram.

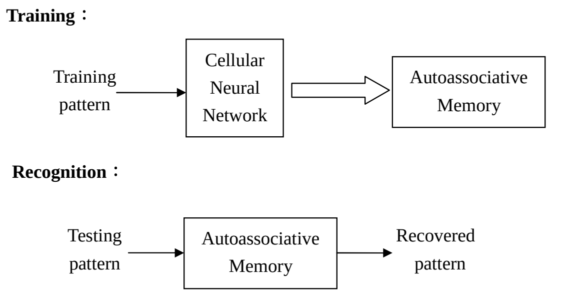
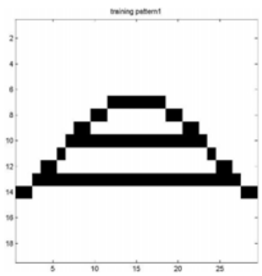
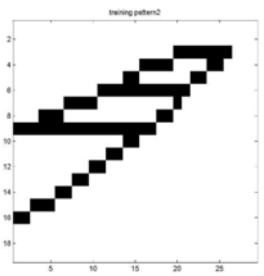
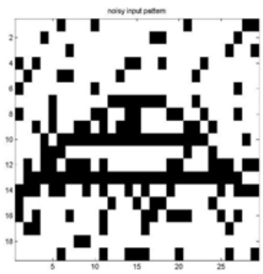
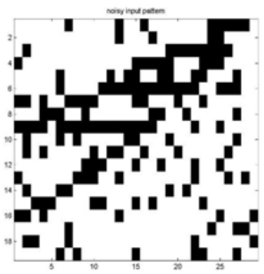


Fig. 3. Seismic pattern recognition system using cellular neural network.

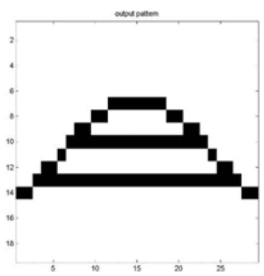
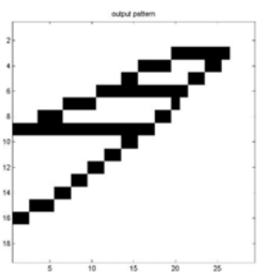



(a) bright spot (b) pinch-out

(c) (d)

Fig. 4. Two simulated seismic training patterns and two noisy test patterns.

(a) (b)

Fig. 5. Two recovered seismic patterns.