The Study of Neural Networks for Suppression of Seismic Multiple Reflections

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The processes are repeated to remove other multiples. Finally, the seismic data contain the reflections without multiples, and can be used to the further seismic data processing and interpretation.

adaptive learning algorithm
Covariance matrix

The principal component analysis (PCA) also known as the Karhunen-Loeve transformation has been investigated and used in many applications. Given a set of random data $\overset{w}{X}$ with dimension N and $\overset{w}{M} = E[\overset{w}{X}] = \overset{w}{0}$, we can compute the correlation matrix (covariance matrix) $Q = E[(\overset{w}{X} - \overset{w}{M})(\overset{w}{X} - \overset{w}{M})^T] = E[\overset{w}{X}\overset{w}{X^T}]$ and find the eigenvalues and the corresponding eigenvectors. The principal eigenvectors can point to the principal directions of the distribution of the data.

The principal component analysis had been applied to seismic data set. Several neural networks algorithms have been proposed for principal components analysis (PCA). Huang (1999) had successfully applied the principal components neural network to the analysis of seismic data.

In this study the neural net with unsupervised generalized Hebbian learning algorithm (GHA) is adopted to find the principal eigenvectors of a covariance matrix from a seismogram after NMO. The neural net is shown in Figure 1.

Abstract

Usually there are many multiple reflections in marine seismograms. Traditionally, we used K-L expansion to extract principal components, here we use neural network. The neural network uses an adaptive learning algorithm to find the principal eigenvectors of a covariance matrix. Initially velocity analysis and normal moveout (NMO) using multiple velocity are applied to the seismic data, so that the multiple reflection shows the uniform horizontal property. Then neural network can extract one principal component that is the multiple reflection with uniform property. Afterward, the multiple reflection can removed from the seismogram (after NMO).

Velocity analysis

The procedure of multiple removal is shown in Figure 2. The experiments are on both synthetic and real seismic data.

In synthetic data experiment of Figure 3, the multiple reflections are suppressed, and the two primary reflections are clearly shown after the processing.

In real marine seismic data experiment of Figure 4, the multiple reflections are suppressed, and the primary reflections are clearly shown after the processing also.

: 100%

: 100%

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Neural network

518-520, 1967.

[2] H. Hotelling, "Analysis of a complex statistical variables into principal components," *J. Educ. Psychol.*, vol. 24, pp. 417-441 and pp. 498-520, 1933.

[3] E. Oja, "A simplified neuron model as a principal component analyzer," *Journal of Mathematics and Biology*, vol. 15, pp. 267-273, 1982.

[4] T. D. Sanger, "Optimal unsupervised learning in a single-layer linear feedforward neural network," *Neural Networks*, vol. 2, pp. 459-473, 1989.

[5] T. D. Sanger, "An optimality principle for unsupervised learning," in *Advances in Neural Information Processing Systems, vol. I*, D. S. Touretzky ed., San Mateo, CA: Morgan Kaufmann, 1989, pp. 11-19.

[6] F. Peper and H. Noda, "A symmetric linear neural network that learns principal components and their variances," *IEEE Trans. Neural Networks*, vol. 7, pp. 1042-1047, 1996.

[7] Kou-Yuan Huang, "Neural networks for seismic principal components analysis," *IEEE Trans. on Geoscience and Remote Sensing*, vol.37, no.1, pp.297-311, 1999.

[8] J. H. McBride, R. W. Hobbs, T. J. Henstock, and R. S. White, "On the wraparound multiple problem of recording seismic reflections in deep water," *Geophysics*, vol.59, pp.1160-1165, July 1994.
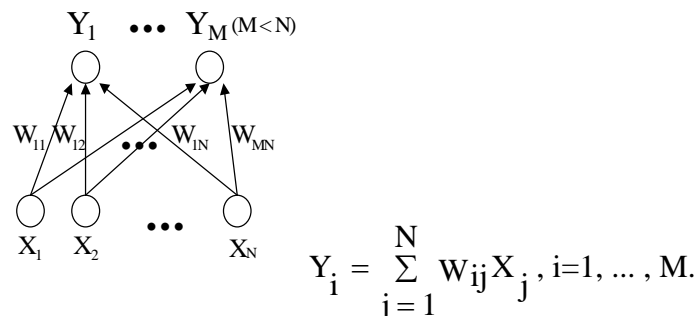
[1] Y. T. Chien and K. S. Fu, "On the generalized Karhunen-Loeve expansion," *IEEE Trans. Information Theory*, vol. 13, pp.

$Y_1 \quad \bullet\bullet\bullet \quad Y_M \, (M < N)$

$W_{11} \, W_{12} \quad \bullet\bullet\bullet \quad W_{1N} \quad W_{MN}$

$X_1 \quad X_2 \quad \bullet\bullet\bullet \quad X_N$

$$Y_i = \sum_{j=1}^{N} W_{ij} X_j \,, i=1, \ldots , M.$$

Fig. 1. Sanger's neural net.

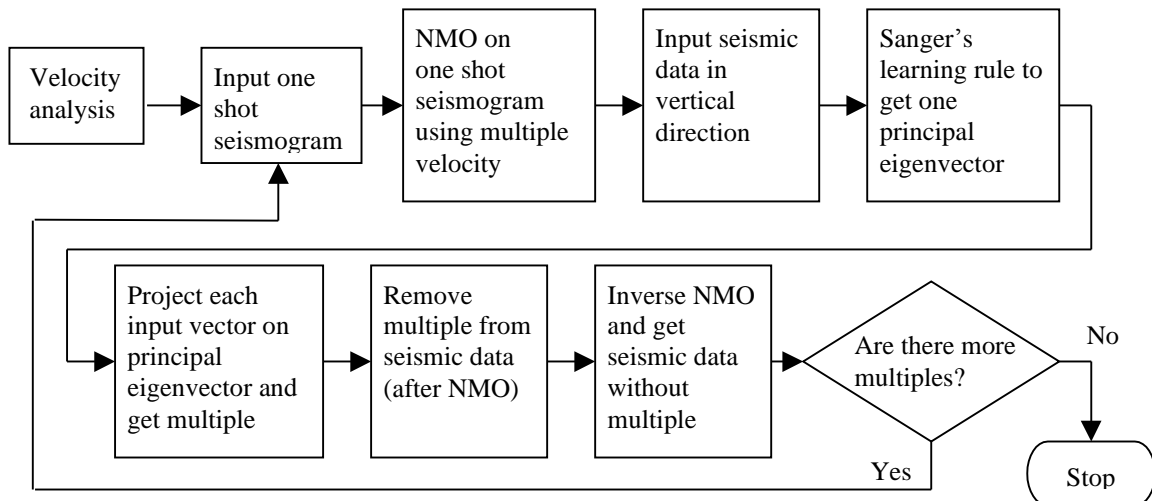Fig. 2. Steps of multiple removal using neural network.

(a)   (b)
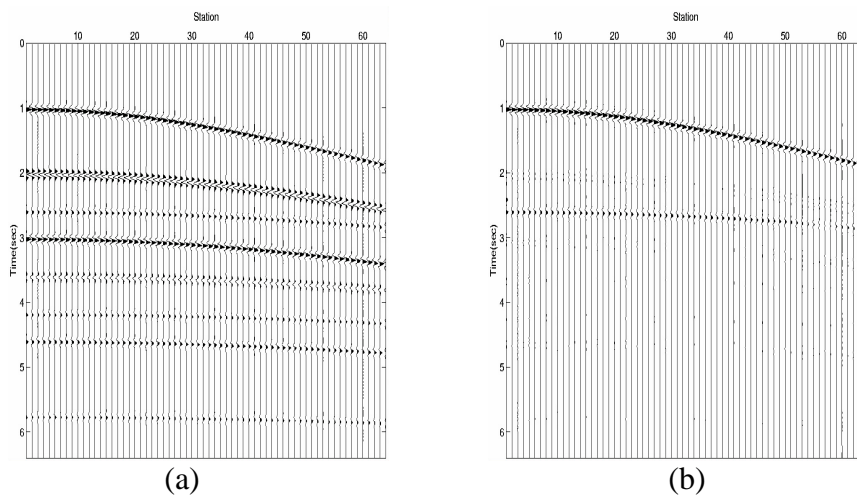
Fig. 3. Multiple removal on synthetic data. (a) A CMP gather, (b) after multiple removal.

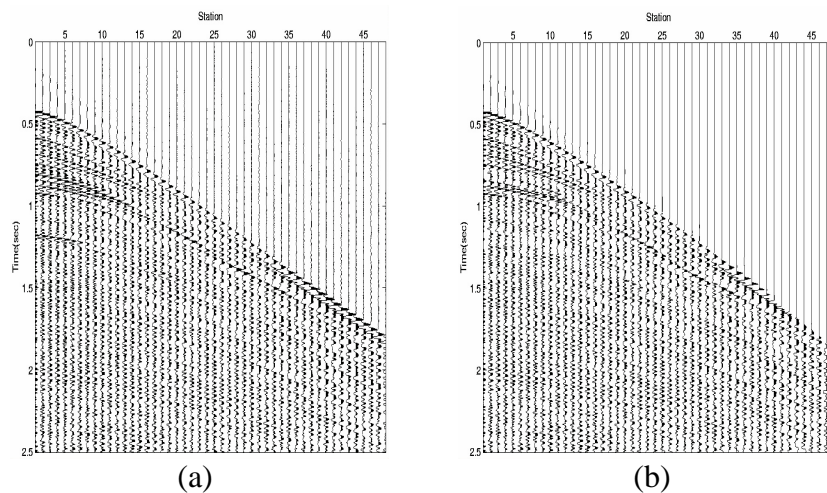(a)   (b)

Fig. 4. Multiple removal on real marine seismic data. (a) A CMP gather of marine seismic data, (b) after multiple removal