IDENTIFYING P- AND S-WAVES USING ARTIFICIAL NEURAL NETWORK

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INTRODUCTION
An artificial neural network (ANN) is used to identify P- and S-wave arrivals from seismic data. Identification is achieved by utilizing the polarization state as a function of time, input directly into a three-layer neural network. The results demonstrate that an ANN trained with small dataset can satisfactorily identify P- and S- arrivals with a success of 84% and 60% respectively and could be applied to automatic analysis of multicomponent seismic data.

METHOD
Three-component recordings are transformed using the 3x3 covariance matrix $C(t)$ defined as:

$$C = \begin{bmatrix}
CON(X,X) & CON(X,Y) & CON(X,Z) \\
CON(Y,X) & CON(Y,Y) & CON(Y,Z) \\
CON(Z,X) & CON(Z,Y) & CON(Z,Z)
\end{bmatrix}$$

where the covariance, averaged over N samples in a time window of variables X and Y, is given by:

$$CON(X,Y) = \frac{1}{N} \sum_{n} (x_n - \bar{x})(y_n - \bar{y})$$

where $\bar{x}$ and $\bar{y}$ are the average values. Here x, y and z represent displacements with time. The degree of polarization, $F(t)$, can now be defined as (Cichowicz, 1993):

$$F(t) = \frac{(\lambda_1 - \lambda_2)^2 + (\lambda_2 - \lambda_3)^2 + (\lambda_3 - \lambda_1)^2}{(\lambda_1 + \lambda_2 + \lambda_3)^2}$$

where the $\lambda_1$, $\lambda_2$, and $\lambda_3$ are eigenvalues of the covariance matrix at central time $\tau$ of a moving window of width N samples. $trS$, define as $\lambda_1 + \lambda_2 + \lambda_3$, is the trace of C and $trS^2$, defined as $\lambda_1^2 + \lambda_2^2 + \lambda_3^2$, is the trace of $C^2$. $F(t)$ is independent of the coordinate system and the source position, and only includes the polarization information. If $F=1$, the signal is linearly polarized, and if $F=0$, the signal can be considered as completely unpolarized or circularly polarized. Each arrivals has its characteristic pattern with $\tau$, not just one particular polarization state. Varying this quantity along the seismogram indicates the type of arrivals. Figure 1 shows an example on $F(t)$ segment extracted from a window which includes a possible arrival, used as input to the neural network during training.

The neural network is non-linear, multilayer and feed-forward with back-propagation of error for training (Rumelhart et al, 1986; Pao, 1988). It has an input layer with 50 nodes, a hidden layer with 10 nodes and an output layer with 3 nodes. The $F(t)$ segments are each fed separately into the input layer. The output nodes designed to have the values (1,0,0) when the input is a noise; (0,1,0) when the input is a P-arrival; and (0,0,1) when the input is a S-arrival.

This approach only deals with segments of the seismic trace which are picked by other method. Here, we use a neural network picker (Dai and MacBeth, 1994) which can pick both P- and S-arrival onset times. According to the onset times, $F(t)$ segments are selected with 50 samples and the onset time in their centres. These segments then are fed into the trained neural network. The maximum in the output of the network indicates their arrival types.
DATA EXAMPLE
We use this method to process a number of local earthquake data in Turkey which has a similar signal-to-noise ratio as marine VSP. Out of the 327 usable recordings, we can visually pick 333 P-arrivals and 317 S-arrivals. All these recordings are initially processed by a neural network picker to measure the onset tunes of all possible arrivals. Compared with manual analysis results, the ANN picks 323 (97%) P-arrivals and 292 (92%) S-arrivals.

The training procedure advances gradually in increasing the training dataset. At the beginning, we only select one group segment which includes one noise, one P-arrival, and one S-arrival, to train this network. Once the training finished, we use this trained neural network to process other recordings. By comparing with manual analysis result, we select another group segment combining with the former group to train it again. This procedure is repeated until the performance of trained neural network cannot be improved by increasing the training dataset or we are satisfied its performance.

For these data, the final training set was taken by using eight group segments. It took 1340 iterations, about 1.5 minutes on a VAX4000 to converge. The final trained neural network can identifying 84% (274) of P-arrivals and 60% (171) S-arrivals. 13% (42) of P-arrivals were classified as S-arrivals and 2% (7) as noise. 26% (76) of S-arrivals are classified as P-arrivals and 16% (47) as noises. The network can correctly classify 64% of 310 noise segments as noise, 15% as P-arrivals and 21% as S-arrivals.

CONCLUSION
This work shows that the neural network is capable to classifying the arrival type based on characteristic patterns of polarization state of a seismic wave with time. Its performance mainly depends on the training dataset and the judgement of the expert in making the initial classification. The network is easily applicable to exploration seismic data and will be of use in automatic analysis of multicomponent seismic data.

REFERENCES