Kochonen Neural Model for Destructive Seismic Waves

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ABSTRACT: The paper is devoted on the problem of real-time earthquake prediction. An approach for real-time prognoses, based on classification algorithm of strong motion waves with neural network and fuzzy logic models is suggesting. As input information for the neural network, build with Kochonen learning rules, are given the parameters of recorded part of accelerogram, principle axis transformation and spectral characteristics of the wave. With the help of stochastic long-range dependence time series analysis is determined the beginning of destructive phase of strong motion acceleration. Developed seismic waves classification gives possibility to determine different kind prognoses models for different king of classified waves. The prognoses of destructive seismic waves are realized with learning vector quantization and self-organizing map.

1 INTRODUCTION

A very promising method in earthquake engineering for protection of height – risk and very important structures against destructive influence of strong motion seismic waves is developing systems for structural control. One of the critical problems there is the problem of forecasting the behavior of seismic waves, in particular in real time for implementation of these prognoses in devices for structural control. Prognoses for further development of the waves can be made from recorded in real-time data for certain part of destructive seismic wave registrated in three directions. These prognoses are based on general, tectonic, seismic and site parameters. During these prognoses is supposed that waves can be classified as destructive or non-destructive and can be taken decision for switching structural control devices.

For such prognoses it can be developed different kind of models, for modeling the behavior of seismic waves main parameters during seismic waves spread in soil layers (Radeva and Radev, 2005). For practical purposes of possible records for displacements, velocities and accelerations as time history, most often accelerograms are used, which are characterized with certain duration, frequency and peak ground acceleration. They are involved in models and systems for estimation of elasticity response spectrum. For each point of registrated accelerogram the parameters of her displacement in soil layer are presented with three components in three directions of the orthogonal axes. The most practical usage in structural engineering and design has their peak values, independently of their sign and direction. That's why the modeling of the behavior of seismic waves is used as input information in the process of calculation of the structural response spectrum (Radeva at all, 2004a).

In this paper is suggesting an approach for real-time prognoses of earthquake excitation, with fast estimation of seismic wave's characteristics with implementation of classification methods and Kochonen neural modeling for destructive part of seismic waves.

2 DETERMINING OF DESTRUCTIVE PHASE FROM ACCELEROGRAM

The purpose of stochastic modeling is the defining of the three phases of the earthquake wave and identification of the main parameters for each phase, such as resonance frequency, damping ratio, peak value. According to implemented stochastic model, each wave is dividing into three separated phases: primary (P- waves), transversal or secondary (S-waves) – on the second phase, and converted and guided waves (C-/G- waves) on the third phase. For evolutionary power spectrum estimation were used the time dependent stochastic principal axes method (Scherer and Zsohar, 1998). According to this method earthquake accelerograms are delivered as representations of the three-dimensional acceleration vector in a Cartesian coordinate system, generally with axes parallel to east –west, north-south and vertical direction, as is shown on Fig.1, where is presented registrated records from Loma Pierta Earthquake, 1989.

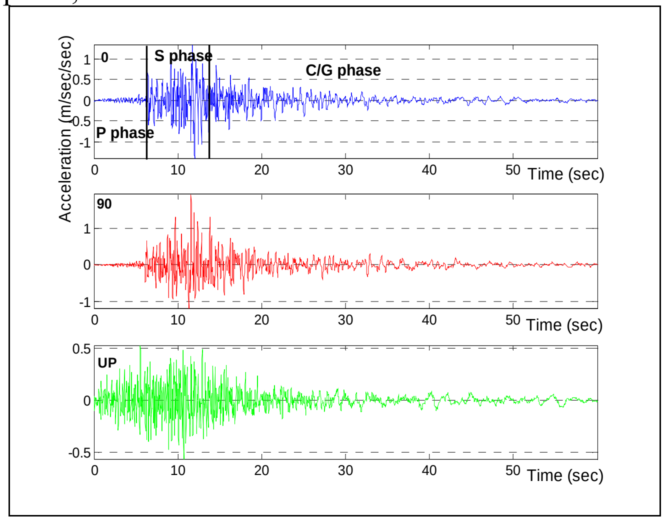

Figure 1. Recorded accelerograms with axes parallel to east –west, north-south and vertical direction.

On Fig 1 is shown as well determining the boundaries of three separated phases, which is realized with scene-oriented model. For determining boundaries between separated classes were analyzed 4300 strong motion seismic records, registrated in Europe and North America and to these records were implemented different stochastic models. We are suggesting the scene-oriented model as best fitting for determining boundaries of destructive S-phase (Radeva at all, 2004b). The scene-oriented model is a modification of simple Markov chain model, where the time series $\{x_t\}$ was transformed into discrete states $\{y_t\}$, where the number of states is the same as the number of target classes, and the size of the model y_i for each state is determined. At the scene-oriented model as three scenes are separated the three phases of the seismic waves. Consider the S-phase as a second scene. The target values in classes of the second scene are determined with (1).

$$SM_j = \frac{\sum_{t=1}^{M} x_t \cdot y_t}{\sum_{t=1}^{M} y_t}, \qquad y_i = SM_j \tag{1}$$

The next step is forecasting the resonance frequency of S-wave on the base of prognoses made with the help of principle axes transformation and further estimation of probability density with neural network and vector quantization.

3 DETERMINING OF DESTRUCTIVE PHASE DURATION AT AXIS TRANSFORMATION

Principle axes transformation is based on composing the components corresponding to the maximum, medium and minimum eigenvalues from all time windows. Consider each accelerogram with her three transformations. Let determine duration of destructive phase according to previous paragraph. Each transformation is a result from different accelerogram time histories that are ordered by seismic energy for every chosen time interval, (Scherer and Bretschneider, 2000). Principle axes transformed accelerograms can be visualized in the coordinate system of the original record. These transformed components, called stochastic principal axis accelerogram T1, T2 and T3 have different duration of destructive phase, as is seen on Fig. 2.

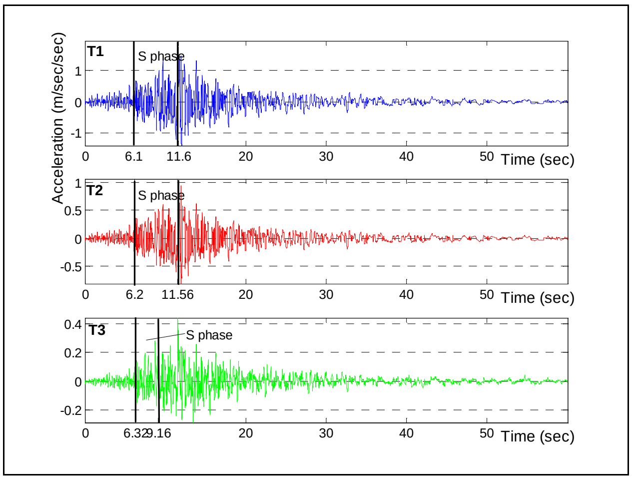

Figure 2. Determining of S-phase boundaries for principle axes transformed records.

Because of this different duration of destructive phase in each transformation, if we will implement one-dimensional vector quantization, it will give different results. That's why for prognoses model here is suggesting two-dimensional vector quantization, based on this time-series transformed records.

This process of time-series transformation gives possibility to use for empirical hazard analyses transformations T1 and T2. As most significant in seismic hazard analyses, for two-dimensional vector quantization and determination of basic classes further are used transformed accelerograms T1 and T2.

4 KOCHONEN NEURAL MODEL FOR 2D DESTRUCTIVE PHASE ESTIMATION

The suggested method for real-time prognoses is developed for fast estimation of strong motion seismic waves on the base of their main characteristics. The fast estimation of seismic waves is based on belonging of prognoses waves to certain class and subclass (Radeva at all, 2004b). The classification helps to select proper prognoses stochastic model for each of selected classes or subclasses.

The proposed real-time classification and prognoses are realized with neural models build on principle of Kochonen learning rules. For different classes and subclasses of seismic waves is suggesting two basic kinds of neural modeling - Learning Vector Quantization (LVQ) and Self-Organizing Map (SOM).

For probability density estimation of destructive phase in this research is suggesting a modification of two-dimensional vector quantization, where on axes are absolute values of transformed accelerograms T1 and T2. The main goal of a learning neural model for vector quantification is to determine the probability density function for T1 and T2.

The two-layered neural network for two-dimensional vector quantization consists of competitive and linear layers. LVQ learning in the competitive layer is based on a set of input/target pairs (2),

$$\{\mathbf{x}_1,\mathbf{C}_1\},\{\mathbf{x}_2,\mathbf{C}_2\},\ldots,\{\mathbf{x}_j,\mathbf{C}_j\},\ldots,\{\mathbf{x}_N,\mathbf{C}_N\} \tag{2}$$

with the help of which is trained the neural network. Here $\mathbf{x}_j$ are two N-dimensional input vectors, and the M- dimensional vector $\mathbf{C}_j$ describes the condition of target classes, presented at (3).

$$\begin{aligned} \mathbf{x}_j &= \{X_j^{(1)}, X_j^{(2)}\}, \quad && j=1,\ldots,N \\ \mathbf{C}_j &= \{S_1, S_2, \ldots S_k, \ldots S_M\}, \quad && k=1,\ldots M \end{aligned} \tag{3}$$

Each target vector has a single 1 and the rest of its elements are 0. The 1 tells the proper classification of the associated input. The hidden neurons from first layer compete via initializing of the weight matrix $\mathbf{W}_{kj}$ and are determining the winner. This is the neuron, which has minimal Euclid distance d_k to the input vectors $\mathbf{x}_j$. Then the corresponding target class receives value 1 and the rest target classes receive 0, as is presented by (4).

$$\begin{aligned} &S_k = 1, \quad \textit{for} \quad d_k^{\min}, \qquad d_k = \sum_{j=1}^{N}\left(X_j - W_{kj}\right)^2 \\ &S_k = 0, \quad \textit{otherwise} \end{aligned} \tag{4}$$

The neuron-winner has feedback negative links to the rest of neurons and strong positive link to himself, which is used for learning in linear layer. During the training in the next q epoch are changing the coefficients of all neurons according to Kochonen learning rule, which is summarized at (5).

$$\begin{gathered} W_{kj}(q) = W_{kj}(q-1) \pm \xi\left(X_j(q) - W_{kj}(q-1)\right) \\ 0 < \xi \le 1 \end{gathered} \tag{5}$$

The coefficient ξ depends on the number of training epochs q and can be adjusted in advance in interval [0,1], where standard is determined equal to 0,1. The sign before the training coefficient ξ is positive for the neuron-winner, and negative for the neighbor neurons. As a result during the process of the training is changed the area of neighbor neurons for the neuron-winner, e.g. decreases the Euclid distances.

With LVQ we determine the function of density distribution with amplitudes, received from the real accelerograms. The vector quantization gives density distribution for each class and redistributes the target values in such a manner to have the same number of target values in each class (Radeva et all, 2004b). The density distribution of the values of time series was received via approximation of the linear target layer of the vector quantization.

For the proper determining of the function of density distribution is necessary to optimize the approximation of the target layer. The network was trained to classify the input space according to parameters of scene-oriented model. With the help of LVQ was determined the optimal number of target classes for destructive phase and prognoses were realized with this number.

Afterward with one layered neural network and self-organizing map (SOM) was determined the function of density distribution with amplitudes, received for transformed accelerograms T1 and T2.

Self-organizing neural networks have one-layered neural competitive structure, which can learn to detect regularities and correlations in the input patterns. The neural maps learn both, the distribution and topology of the input vectors, to recognize neighboring clusters of the attribute space.

Kochonen's network algorithm provides a tessellation of the input space into patches with corresponding code vectors. It has an additional feature that the centers are arranged in a low dimensional structure (usually a string, or a square grid), such that nearby points in the topological structure (the string or grid) map to nearby points in the attribute space.

The Kochonen learning rule is used when the winning node represents the same class as a new training pattern, while a difference in class between the winning node and a training pattern causes the node to move away from training pattern by the same distance. In training, the winning node of the network, this is nearest node in the input space to a given training pattern, moves towards that training pattern. It drags with its neighboring nodes in the network topology. This leads to a smooth distribution of the network topology in a non-linear subspace of the training data. In two-dimensional output space is expected a map, corresponding to the k - dimensional array of output neurons C_j, which can be one or two-dimensional. The connection between n-dimensional input vector and k-dimensional output neural vector is realized with the weight matrix **W**. At competitive learning for winner is selected the output neuron j^*, which weight vector is closer to the current input according to (6).

$$\begin{gathered} \left|W_{jm}^* - X_m\right| \le \left|W_{jm} - X_m\right| \\ \forall j \in [1,\ldots,k], \qquad \forall m \in [1,\ldots n] \end{gathered} \tag{6}$$

The Kochonen learning rule is differ from vector quantization rule and is determine by (7).

$$\Delta W_{jm} = \xi \wedge \left(j, j^*\right)\left(X_m - W_{jm}\right) \qquad (7)$$

The neighborhood function $\wedge(j, j^*)$ is equal to 1 if $j = j^*$, and decreases with increasing of distance between neurons j and j^*in input space. The neurons closer to the winner j^*, changes their weights more quick than remote neurons, for which the neighborhood function is very small.

The topological information contents in the fact, these closer neurons, which are changing almost in the same way and in this manner corresponds to neighbor input patterns. The learning rule (7) attracts the winner's weight vector to the point X_m.

The self-organizing map is supposed to be an elastic set in input space, which wants to be moved maximal closer to the input values. The set has topology of attribute space and it points have as coordinates weight vectors.

Here is suggesting a modification of VQ, with implementation of logarithmic scale and absolute values for T1 and T2. On Fig. 3 is shown modified two-dimensional vector quantization where with black points are depicted weight centers of target classes. We are interesting of last three classes (10, 11 and 12), because for them is observed higher deviation. With Manhattan distance are determined deviations from trajectory of axis and points in corresponding class according to (8).

$$M_j = \sum_{i=1}^{n} \left\| x_{ij} - s_j \right\| \qquad (8)$$

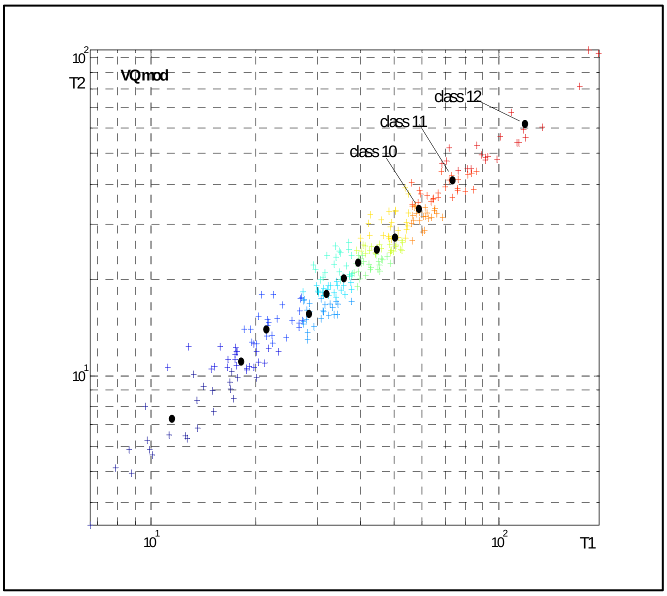

Figure 3. Two-dimensional vector quantization in 12 classes with Self-organizing map (SOM).

In Table 1 is shown estimation of the probability density distribution in each class for S-phase with two-dimensional learning vector quantization and self-organizing map.

Table 1. Estimation of probability density distribution (in percent) with LVQ and SOM

Classes	LVQ	SOM	Classes	LVQ	SOM
1	2.56	7.69	7	12.42	7.18
2	14.72	18.19	8	14.45	14.53
3	4.67	5.05	9	7.62	11.90
4	13.98	7.62	10	3.23	6.01
5	17.95	11.18	11	1.05	2.42
6	7.23	8.14	12	0.12	0.09

From Table 1 is seen, that for last three classes (10, 11 and 12), which are more interesting for prognoses model, there are observing similar results with both neural networks.

5 CONCLUSIONS

An approach for real-time prognoses of destructive phase of strong motion seismic acceleration was suggested, based on classification algorithm of strong motion waves with neural network with Kochonen learning rules. On the base of principle axis transformation and spectral characteristics of the wave, with stochastic long-range dependence time series analyses are determined the boundaries of destructive phase of strong motion acceleration.

For selected diapason of transformed accelerograms was implemented two-dimensional vector quantization with Kochonen learning rules. The prognoses are realized with the help of two-dimensional vector quantization and with self-organizing map. The probability density function for destructive phase was determined with both neural networks.

Received results can be used for analyses of structural response spectrum and in devices of structural control for very important and high-risk structures.

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