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STRONG MOTION WAVES CLASSIFICATION AND PROGNOSES WITH NEURAL NETWORKS

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SUMMARY

The paper is devoted on the problem of strong motion waves classification and real-time prognoses with neural network. As input information for the neural network are given the parameters of recorded part of accelerogram, principle axis transform and spectral characteristics of the wave. With the help of stochastic long-range dependence time series analyses are determined the separated phases of strong motion acceleration. The boundaries between separated phases of seismic waves are determined with scene-oriented model. Determining the scene boundaries are based on the coefficient of variation for a sequence of consecutive accelerogram values. We add values to current scene until its weighted coefficient of variation is changing more than a preset value. The last added value is defined as the beginning of a new scene.

Developed approach for classification gives possibility to determine the method for real time prognoses. For different king of classified waves we suggest different kind prognoses models. The prognoses are realized with the help of neural network, build on the principle of vector quantization. A new approach for adjusting the boundaries of selected classes during the process of vector quantization is used. The determined statistical function of density distribution of recorded data from accelerogram can be generating in real time. The received prognoses of destructive phase of strong motion waves can be used in devices for structural control. Examples of received prognoses are compared with real data of strong motion waves. Simulation and numerical results are shown.

INTRODUCTION

A very promising method in earthquake engineering for protection of height – risk and very important structures against destructive influence of seismic waves is anti-seismic structural control. One of the critical problems there is the problem of forecasting in real-time of the behavior of seismic waves.

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Prognoses for further development of the waves can be made from recorded in real-time data for certain part of destructive seismic waves registrated in three directions. These prognoses are based on classification of strong motion seismic waves made 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 on the devices for structural control, Radeva [1].

Another application of classification and real-time prognoses of development of seismic waves is prognoses of further seismic activity after primary ones. For making such prognoses it is necessary to develop different kind of models. Modeling gives possibility to study the behavior of seismic waves and relationships between their parameters during their spread in soil layers, where for each point the parameters of her displacement are presented with three components in three directions of the orthogonal axes. 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. 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.

In this research is accepted the approach for separating of seismic waves into three phases, Scherer [2], where each has different spreading velocity of longitudinal or primary (P- waves), transversal or secondary (S- waves) and resonance C/G phase. To each phase correspond certain model of the waves behavior. Determining of the boundaries between the phases has significant influence on the application of non-stationary seismic models. From the other side, the method of dividing of seismic waves into three phases gives possibility instead chaotic time series analyses, for analyze and prognoses to be used stochastic models of time series with Long Range Dependant (LRD) correlation, autoregressive models, moving average models, scene-oriented model etc.

Nowadays increase implementation of artificial intelligence methods for describing the behavior of seismic waves. Most of them are based on neural networks for analyzing of earthquake records, which are trained, with real strong motion seismic records, Radeva [3]. Other models are based on the fact that crisp values as earthquake parameters can be successful described with the help of fuzzy logic models. One of the very promising trends is creating models, which combines different approaches like Neuro-Fuzzy models, models combining stochastic and artificial intelligence approach etc. Such hybrid models uses the machine learning capabilities of neural networks and combines it with transparency and representation power of fuzzy logic and stochastic models.

The main purpose of the work is to develop a method for classification of strong motion seismic waves for quick estimation of characteristics of their destructive phase, with the help of evolutionary power spectrum models, stochastic models of time series with LRD correlation and neural networks. This method can be used for classification, real time analyses and prognoses of strong motion waves.

PROGNOSES AND CLASSIFICATION OF SEISMIC WAVES

The prognoses of earthquake occurrence can be classified according to the prognoses time duration. The most popular is their dividing into long-term (for next ten years), intermediate-term (for next few years), short-term (for next months-weeks) and real-time. Other kind of prognoses is prognoses of the area of occurrence of earthquake excitation of certain magnitude. Both approaches for prognoses are connected with difficult problems, when are applied the traditional stochastic time series analyses instead of applying methods for crash prognoses, where is dealing with reaching of certain critical threshold, Kossobokov [4]. Concerning the gap stretch of expected earthquake GL_e it is necessary to take the space localization in more wide diapasons. The classification of kind of earthquake prognoses is presented on Table1.

Table 1. Classification of earthquake prognoses according to time and place determination

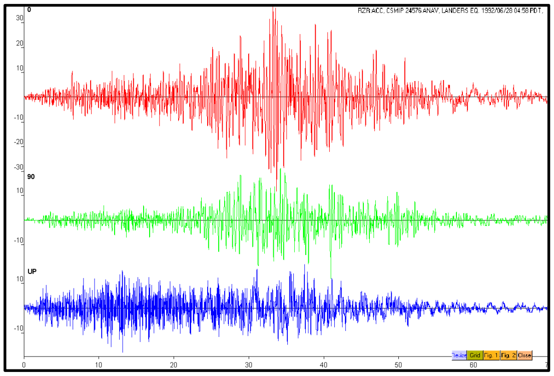
Temporal, in years		Spatial in sources zone GL_e	
Long-term	10	Long duration	up to 100
Intermediate-term	1	Middle duration	5-10
Short-term	0.01-0.1	Short duration	2-3
Real-time	0.0001	Exact	1

In this paper we fix our attention on real-time prognoses of earthquake excitation, which is very important, because we have to receive very precise estimation of the development of the process. The suggested method for classification is developed for fast estimation of strong motion seismic waves on the base of their main characteristics. This fast estimation of seismic waves is necessary for real-time prognoses, which is based on belonging of prognoses waves to certain class and subclass.

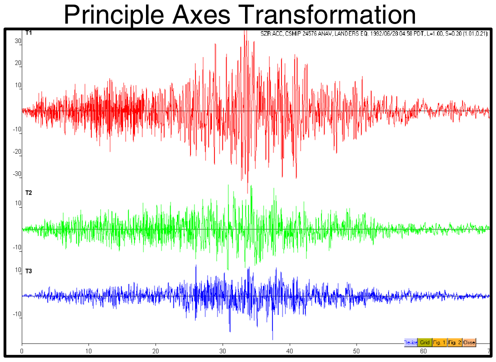
According to the stochastic model, presented in Scherer [5], each wave is dividing into three separated phases and has different spreading velocity. First come the longitudinal or primary (P- waves) and after that the transversal or secondary (S- waves), causing an S-wave of the same origin to arrive later than the corresponding P-wave. The third phase (C-/G- waves) is connected with converted and guided waves. Waves with three separated phases were classified as "classic". Waves with two phases (where presents S-waves and C-/G- waves) are belonged to second class and chaotic waves are separated into third class. According to separated phases recorded waves were classified into three main classes: classic (with three separated phases), chaotic, and with two phases. This classification can be made with neural network, based on multy layer perceptron with error back propagation. From recorded part of seismic record in three directions was provided real-time analyses of the type of the wave and her belonging to one of separated classes, which is realizing on the first layer of neural network. On the base of evolutionary power spectrum characteristics of the recorded part of the wave is making decision that the wave belongs to one of separated subclasses, according to provided seismic waves classification in the second layer of the neural network.

A database for strong motion records was created after classifying the main parameters of stochastic seismic waves. The records in database was sorted according to their belonging to one of separated classes and subclasses and the most important parameters characterized each subclass, like resonance frequency, damping ratio, peak value, density distribution etc. The process of wave classification is parallel with the real time recording. For each subclass was developed different prognoses model.

The prognoses models are realized with the help of several basic models: autoregressive model, simple Markov chain model and scene oriented model, Radeva [1,6]. The boundaries between separated phases of seismic waves are determining with scene-oriented model. Determining the scene boundaries are based on the coefficient of variation for a sequence of consecutive accelerogram values. We add values to current scene until its weighted coefficient of variation is changing more than a preset value. The last added value is defined as the beginning of a new scene. After making a decision that the wave belongs to certain class on the base of principle axes transformation and to certain subclass on the base of evolutionary spectrum estimation, the prognoses model for this subclass is starting with the input wave characteristics. For example, the prognoses models for all subclasses of the class "classic" are based on scene-oriented model. The process of classification is shown on Figure 1. The prognoses model starts and determines the target classes for multy layered error back propagation perceptron neural network, presented on Figure 1, right.



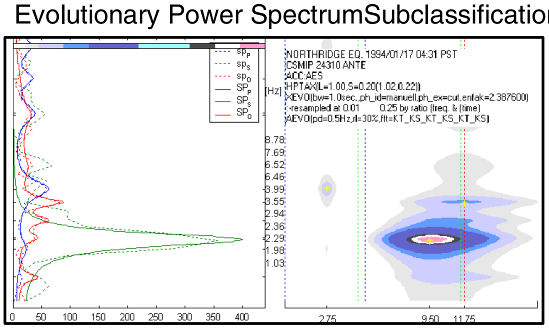
Principle Axes Transformation



Basic Phases Classification

Classes	Phases	Description	Total number
Class 1	P +S +C/G	Classic	2165
Class 2	Without phases	Chaotic	946
Class 3	S +C/G or P+S	Two phases	1189

Evolutionary Power SpectrumSubclassification



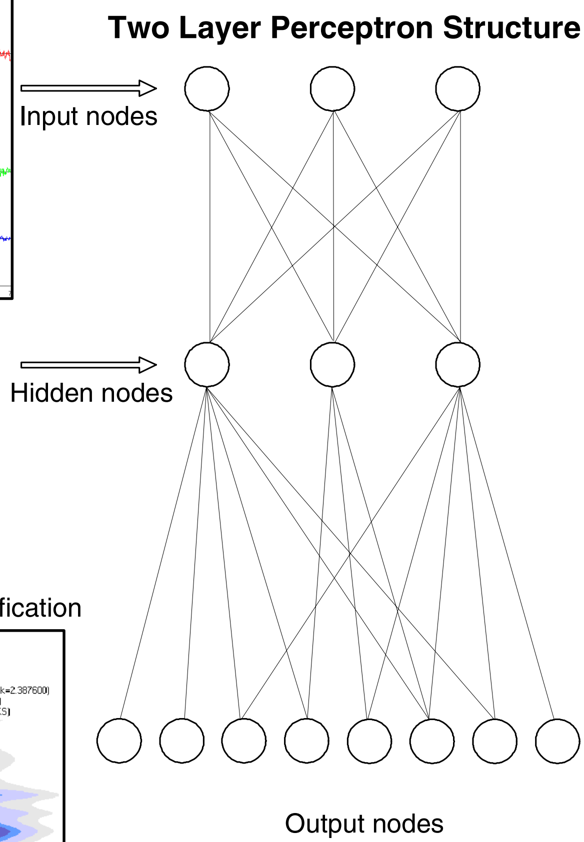


Figure 1. Classification with neural network

PHASES AND PARAMETERS OF CLASSIFICATION WITH NEURAL NETWORK

Principle axes transformation for classes determination

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. Recorded waves were classified with neural network into three main classes according to different characteristics, like peak values, damping ratio and spectral characteristics of the wave. For receiving this classification were analyzed 4300 strong motion seismic records, registrated in Europe and North America. For defining the three phases (P-, S- and C-/G-) were used window parameters and principal axes transformation, for searching the most dominant and energetic component for every phase, Scherer [7]. For a certain given time t_0 time delay τ and window length L the cross-covariances are presented in equation (1) and would consist of components, which are statistically independent within selected intervals.

$$C_{ij} = \mathbf{Cov}_{i,j}(t_k, \tau, L) = \int_{t_0-\frac{1}{2}}^{t_0+\frac{1}{2}} a_i(t') \cdot a_j(t'+\tau)dt' \qquad \text{for} \qquad i, j = x, y, z = \text{EW, NS, VT} \qquad (1)$$

Principle axes transformed accelerograms can be visualized in the coordinate system of the original record. For the covariance matrix of the three components of an acceleration record, its eigenvalues are the squared variances of the respective components and transformation of the 3D accelerogram into the coordinate system of the eigenvectors of the covariance matrix yields an accelerogram with statistically independent components. Composing the components corresponding to the maximum, medium and minimum eigenvalue from all time windows will result in accelerogram time histories that are ordered by seismic energy for every chosen time interval. These transformed component are called the stochastic principal axis accelerogram T1, T2 and T3, presented after the original ones in three directions on Fig. 2.

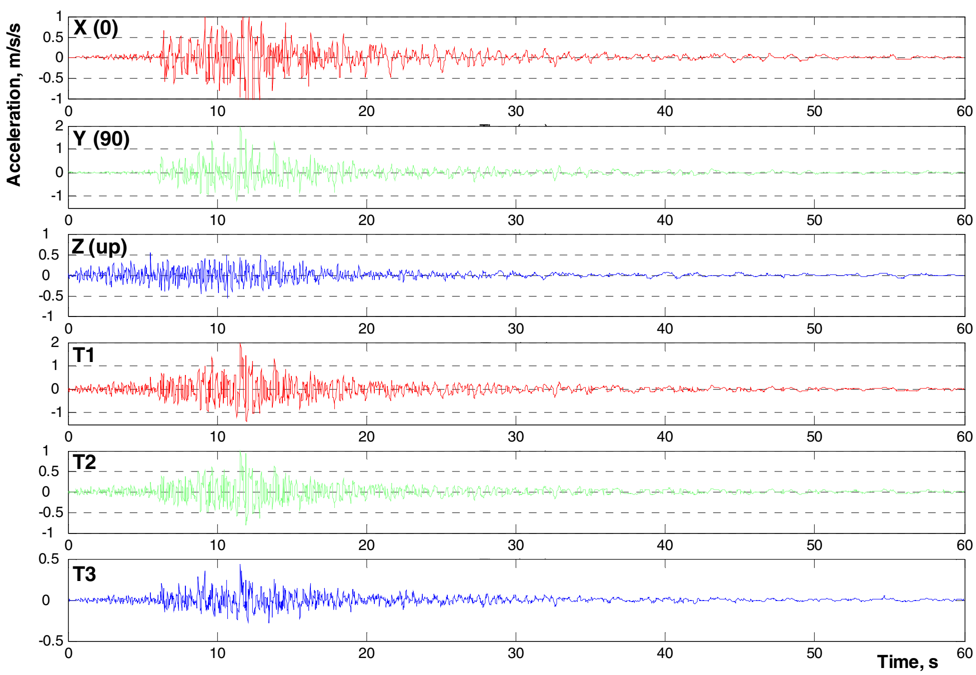


Figure 2. Time-series transformation

This process of time-series transformation gives possibility to use for empirical seismic hazard analyses the stochastic principal axis accelerogram T1. It can be thought of as a projection of the 3D acceleration onto a rotating principal plane following the strongest acceleration. That's why the received accelerogram T1 is used on second layer of the neural network for separating subclasses.

The three phases and three selected basic classes, received on the first layer of the neural network, are presented on Figure 3. Provided analyses show that there are a big differences between significant parameters for each subclass. That's why it would be necessary to separate subclasses and to develop different prognoses models for each subclass. For the separated subclasses can be made further classification and selection of new subclasses according to their specific parameters.

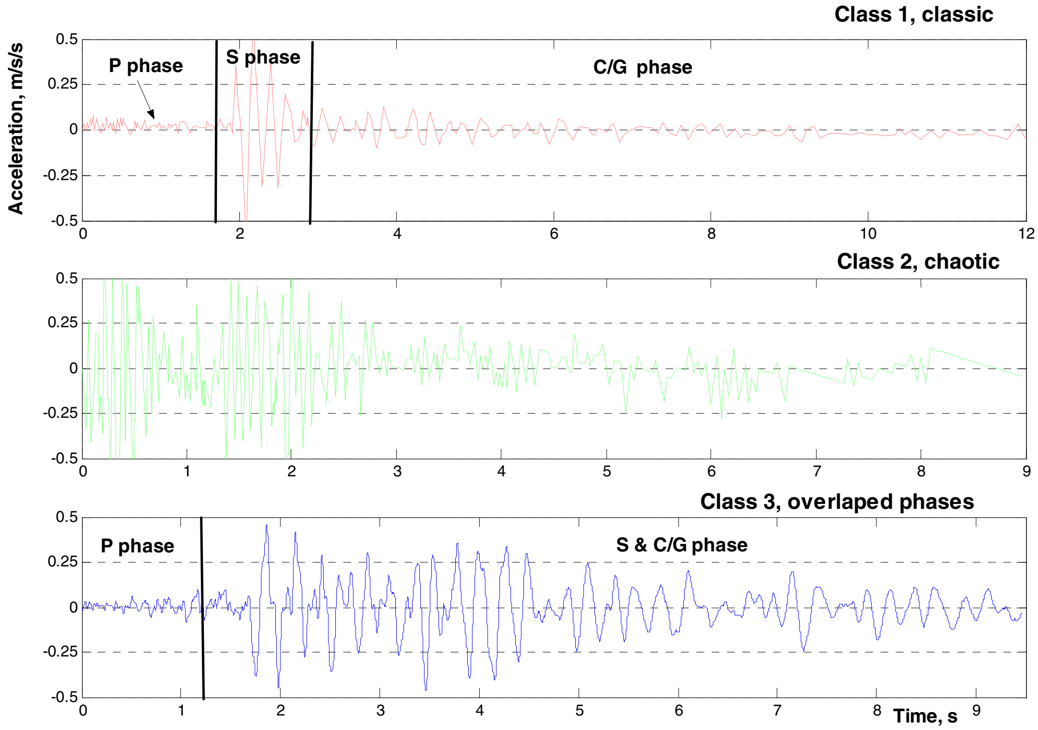


Figure 3. The three basic classes of seismic waves

Evolutionary power spectrum for subclasses determination

On the second layer of the neural network is making classification according to parameters of evolutionary power spectrum for each of separated classes. For receiving the stable estimation of the evolutionary power spectrum of stochastic principal axis accelerogram T1, was used a multy-filter technique Kameda-Sugito, presented in Kameda [8], which was adapted in order to propose the evolutionary power spectrum as a non-stationary seismic load model.

The evolutionary power spectrum of each phase of accelerogram T1 was modeled as a product of two form function, as is presented on Figure 4. For the form function *f* for frequency slice was chosen Kanai-Tajimi-spectrum, because there are several more than one resonance frequencies due to more layers of sediments. The amplitude modulation function of choice is a product of a polynomial for the increasing and an exponential function for the decreasing, or damping part. The model assumed that most of the relevant energy of every wave field is concentrated at the maximum peak of the evolutionary spectrum in every phase. This is in most cases a distinct point clearly locatable in the time and frequency domain as well. The form functions are adapted onto extracted and slightly modified slices of the evolutionary spectrum along the frequency and time coordinates of this point by appropriate nonlinear least squares methods. Let the stochastic process $X(t)$ has corresponding evolutionary power spectrum $S(f, t)$ with form functions p, presented on (2),

$$X(t) = \int_{-\infty}^{\infty} e^{i2pft} A(t,f)\,dZ(f) \qquad S(f,t)df = E\left\{\left[A(t,f)\,dZ(f)\right]^2\right\} \tag{2}$$

where $dZ(f)$ is differential of the orthogonal stochastic processes $Z(f)$, $A(t, f)$ is the amplitude-modulation function, and $E\{\ldots\}$ is the expected value of deviation presented on (3).

$$\sigma_x^2 = E\{X^2(t)\} = \int_{-\infty}^{\infty} S(f,t)df \tag{3}$$

For determining the power spectra were used a form of inverse discrete Fourier transform. The Fourier coefficients are estimated by the absolute value of the 2D evolutionary power spectrum $S(f, t)$ according to (4),

$$A_S(t_i) = \sum_{k=1}^{m} \sqrt{2 \cdot S(f_k, t_i) \cdot dff} \cdot \sin(\omega_k \cdot t_i + \alpha_k) \tag{4}$$

for i = 1,…,n discrete time coordinates t_i, k = 1,…,m discrete frequency ordinates f_k of the evolutionary power spectrum, $\omega_k = 2\pi \cdot f_k$, and α_k are uniformly distributed random phase angles in the interval $[0,2\pi]$.

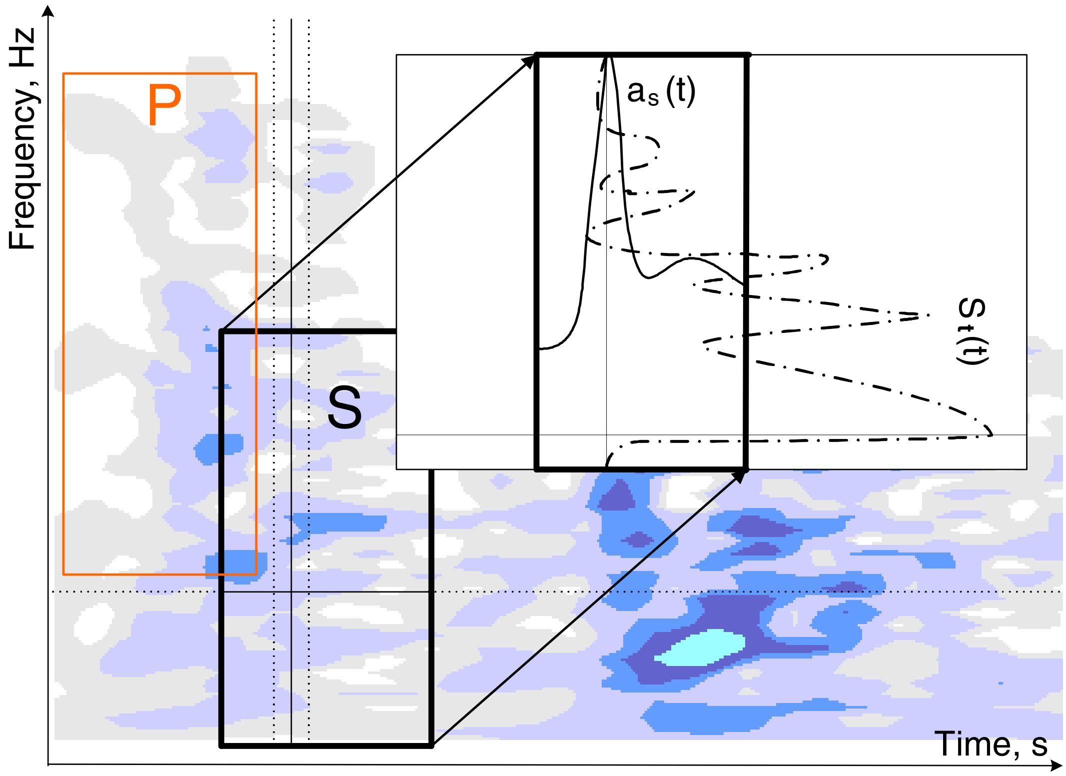


Figure 4. The evolutionary power spectrum of the destructive S-phase

The parameter dff is necessary to resample the frequency axis and is an artificial high amplitude frequency into the accelerogram A(t). Determination of the load is based on the principle of superposition for each type of the waves w=P, S, C/G as is shown in (5),

$$ELM_w(f,t) = S_w(f, p_1) \cdot A_w(t, p_2) \tag{5}$$

where ELM is the used evolutionary load model and (p_1, p_2) are used form functions.
On the base of evolutionary load model analyses the neural network classify the waves to certain subclass and the prognoses model of destructive phase for this subclass is starting with the input wave characteristics.

NEURO MODEL OF DESTRUCTIVE PHASE

For each subclass is suggesting different prognoses model of destructive phase because of variety of characteristics of evolutionary load model between classes and subclasses. The prognoses are realized with neuro model, which is based on Learning Vector Quantization (LVQ). The model includes a neural network with standard LVQ, and the principle of it functionality is presented on Figure 5, where is shown an example for prognoses model for S-phase of class1 – classic. For this class the best fitting is the scene-oriented model, because of more clear determination between separated phases (Figure 5 –left). On the base of the registrated input part of time series $\{x_{k,p-n},\ldots,x_{k,p}\}$ are making prognoses of the next values $\{x_{k,p+1},\ldots,x_k\}$ of time series $\{x_k\}$. The neural network has two layers: a first competitive and a second linear. The competitive layer learns to classify the input vector. It learns all subclasses that belongs to the linear target layer $SM = SM_1, SM_2,\ldots,SM_M$. The module of vector quantization (VQ) gives density distribution between classes in such a manner that in each class we have the same number of target values. The linear layer transforms the competitive layer's classes into target classifications defined by the user. The competitive neurons of the vector **i** will have weights of 1 to one neuron in the linear layer, and weights of 0 to all other linear neurons.

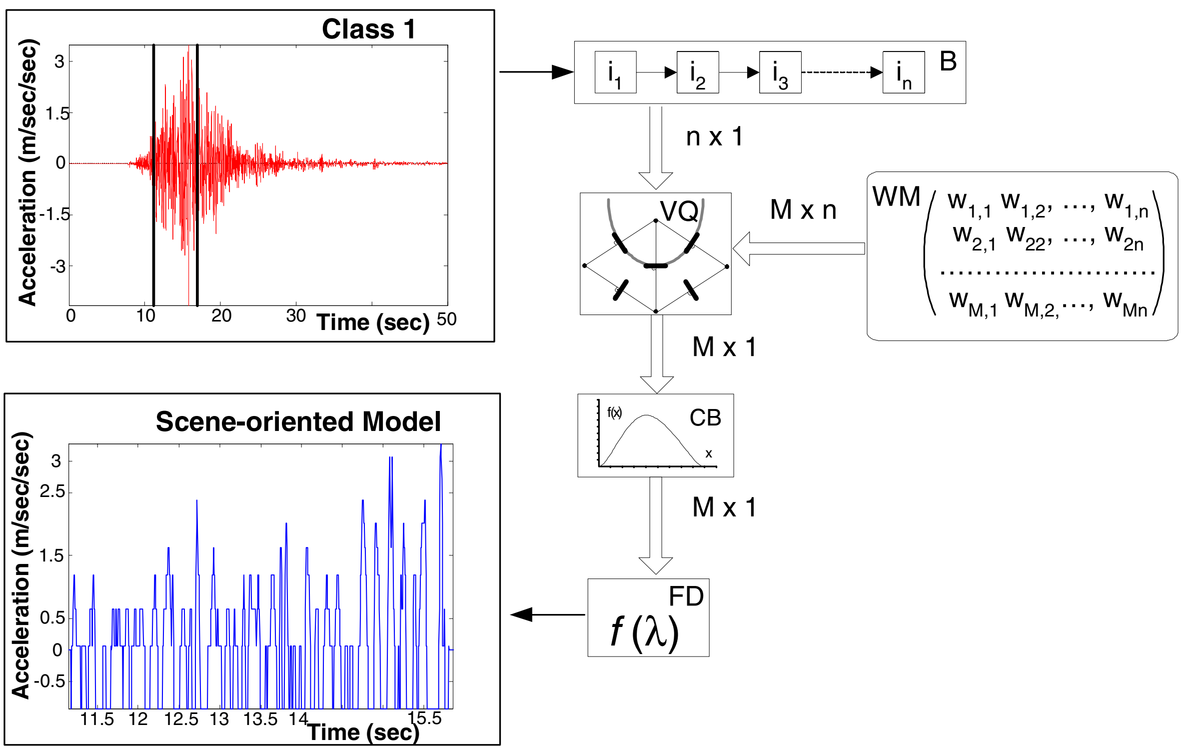


Figure 5. Neuro modeling of strong motion waves

LVQ learning in the competitive layer is based on a set of input/target pairs. 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. 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. The density distribution of the values of time series was received via approximation of the linear target layer *SM* 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.

The scene-oriented model, suggested for destructive phase (S-waves) for Class 1 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 $\grave{I}$, 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. As a second scene is consider the S-phase. The target values in the classes of the second scene are determined with (6).

$$SM_j = \frac{\sum_{t=1}^{M} x_t \cdot y_t}{\sum_{t=1}^{M} y_t}, \qquad y_i = SM_j \tag{6}$$

With the help of learning vector quantization is determining, that the values for the second scene are distributed into five target classes. On Figure 6 is presented the received second scene of destructive phase, with five target classes of the LVQ model.

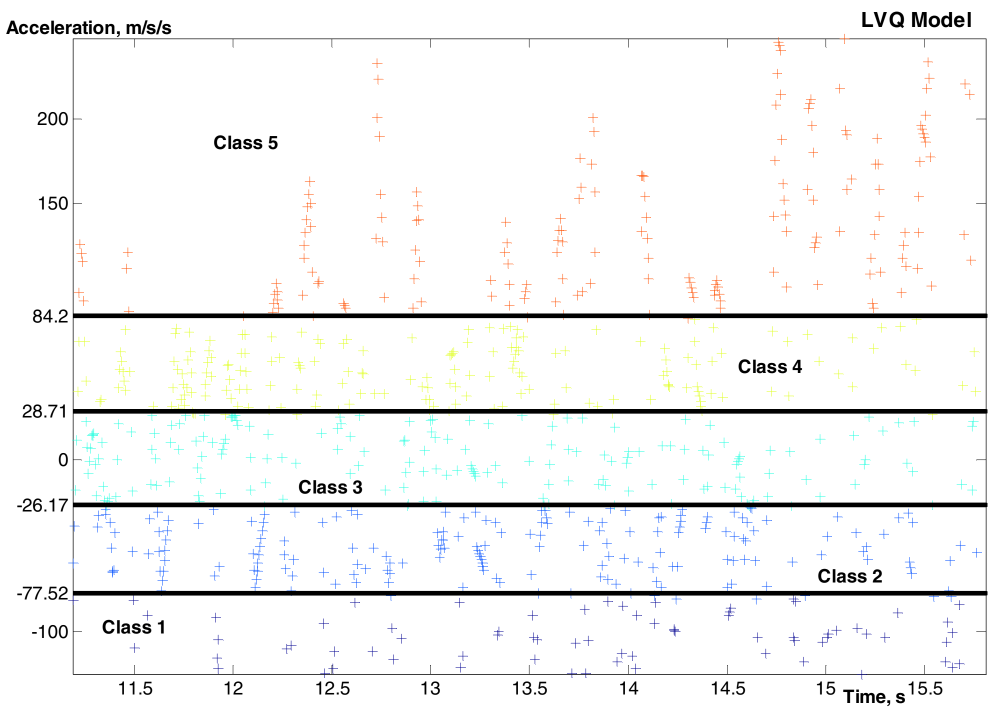


Figure 6. Prognoses model of S- phase with LVQ

CONCLUSIONS

An approach for classification and real-time analyses for estimation of strong motion seismic waves with stochastic modeling and neural network is presented. From recorded part of accelerograms is making classification of the waves according to their principle characteristics, with the help of two-layered neural network. At the first layer of neural network is making classification into separated basic classes and at the second layer is making further classification into subclasses. For different king of classified waves are suggested different kind prognoses models.

The prognoses of destructive phase of strong motion seismic waves are realized with the help of stochastic models and neural network, build on the principle of learning vector quantization. In real time are generating the statistical function of density distribution of recorded data from accelerogram. The received prognoses values are compared with real ones.

The received prognoses of destructive phase of strong motion waves can be used in devices for structural control. Examples of received prognoses are compared with real data of strong motion waves. Simulation and numerical results are shown.

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