Evaporite mapping using high resolution passive seismic tomography and Kohonen neural networks

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Abstract

Passive seismic tomography application for exploration shows great potential. We present two case studies in Greece that successfully use the passive seismic tomography method in combination with Kohonen neural networks in order to better map subsurface features.

Introduction

Evaporite identification from geophysical data is an important task for oil prospecting in new regions where few or no wells have been drilled. As the amount of geophysical digital data is rapidly growing, there is an urgent need for a new generation of computational theories that can support the extraction of useful geophysical information and delineate interesting geological features such as evaporite bodies.

In this paper, we propose to approach the problem of evaporite identification through the use of a two step procedure. Initially estimating seismic parameters such as P and S wave velocities and Poisson ratio for the area of interest through the use of passive seismic tomography and then using Kohonen neural networks techniques to perform data clustering, pattern recognition and classification.

Passive seismic tomography

During the last few years passive seismic tomography, taking advantage of advances in seismograph design, monitoring methodologies and inversion algorithms has been successfully applied for hydrocarbon exploration showing its potential to map large regions for a relatively low cost compared to conventional 3D seismic surveys (Kapotas et al., 2003; Martakis et al., 2006; Tselentis et al., 2007).

Data acquisition of passive seismic data for hydrocarbon exploration requires a different field set up and operational considerations that follow more or less the logic of 3D seismic surveys. The various processing stages of passive data followed in the paper are depicted in Figure 1.

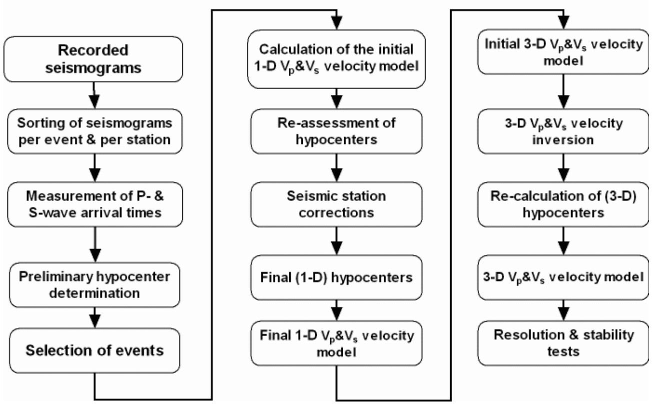


Figure 1. Processing stages of surface passive seismic tomography

Self-Organizing maps (SOM)

To further analyze the clustering of the data and reveal the major lithological units in the region, we use Kohonen neural networks or self organizing maps (SOMs). These are unsupervised artificial neural networks developed by Kohonen (1982), who intended to provide ordered feature maps of input data after clustering. That is, SOMs are capable of mapping high-dimensional similar input data into clusters close to each other on a n-dimensional grid of neurons (units). That grid forms what is known as the output space, while the input space is the original data space.

Each input layer unit, has as many weights or coefficients as the input patterns, and can thus be regarded as a vector in the same space as the patterns. To train a SOM with a given input pattern, we calculate the distance between that pattern and every unit in the network and select the unit that is closest to the "winning unit" and accept that the pattern is mapped onto that unit. The overall learning process of a SOM is accomplished through the iterative process depicted in Figures 2a, b.

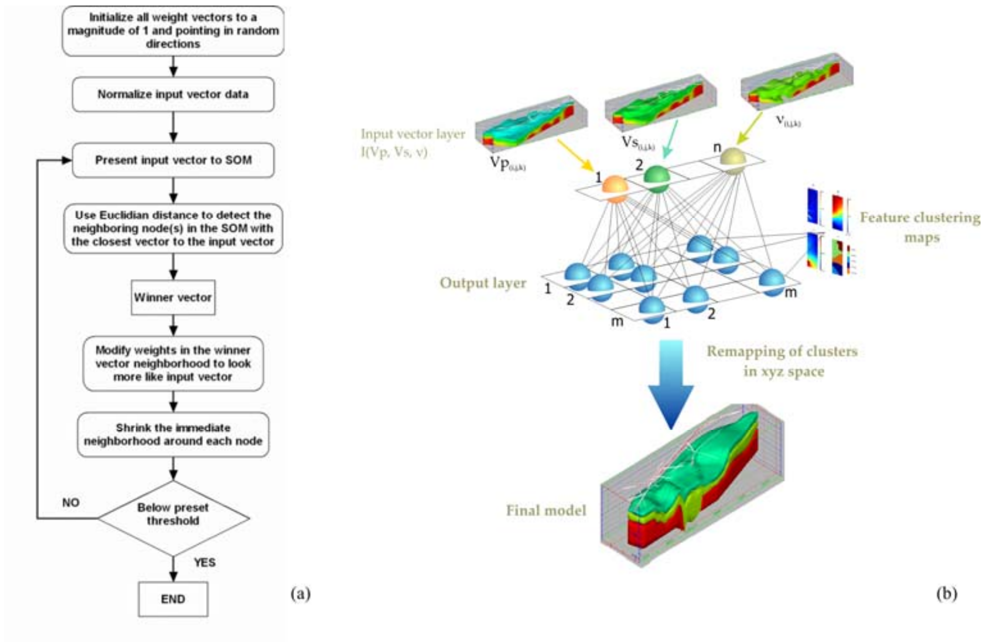


Figure 2. (a) Training of a SOM, (b) All three passive seismic parameters (Vp, Vs, Poisson's ratio) are used to train the SOM.

The initial step for analyzing the data is to read all parameters (P and S wave velocities as well as Poisons ratio) from the tomographic inversion and construct the component planes for each one of them, as well as calculating the Unified distance matrix 'U-matrix'. The U-matrix is a representation of a SOM in which distances, between neighbouring neurons are represented. If distances between neighbouring neurons are small, then these neurons represent a cluster of patterns with similar characteristics. If the neurons are far apart, then they are located in a zone of the input space that has few patterns, and can be seen as a separation between clusters. The next step is to define and separate the clusters that are formed by the data (Figure 5d). For this, k-means are used to define the clustering of the data; from the average maximal distance of each cluster to the others, the Davies-Bouldin index is calculated. This index is used as a measure of the cluster separation. The resulting clustering information is projected back in the space domain where the spatial distribution of the clusters can be examined.

Case study I: Rio (W Greece)

The area under investigation in located around the Rio-Antirrion Strait (Figure 3) and spans an area of 10x15 km^2. The microearthquake network was deployed during a three-month seismic experiment, over a grid with an average spacing between nodes of 500 m grid and consisted of 70 recording stations. Record sampling was 200 samples per second. Our initial data set consisted of 9330 P-wave and 5591 S-wave arrival time readings, corresponding to 220 local microearthquake events with magnitudes M_L ranging between -0.5R and 3.0R. Hypocentral locations of the earthquakes extend to depths of 15 km but the majority of the events were located between 2-9 km. Tomographic inversion of the above dataset, results in the 3d models estimation for the seismic velocities of the area of interest. Figure 4b shows a 3D view of the resulting Vp model, Vp values less than 3 km/sec and Poisson's ratio more than 0.26 (Vp/Vs more than 1.9) correspond to Quaternary and Neogene formations.

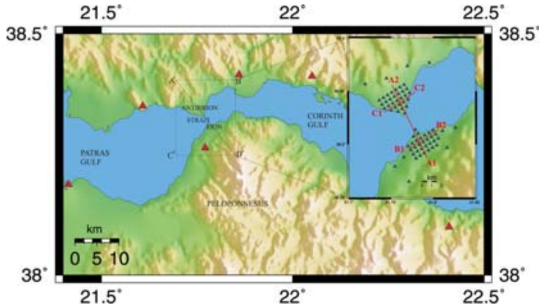
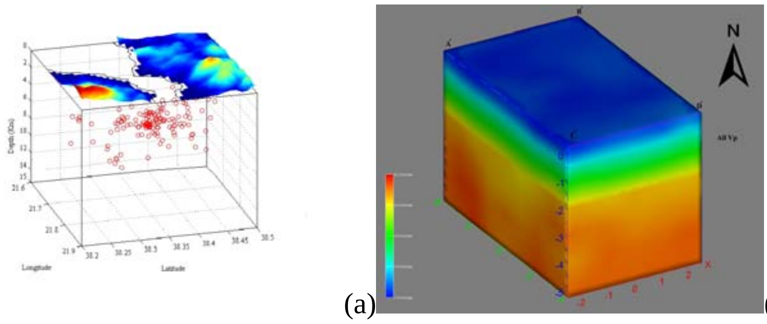
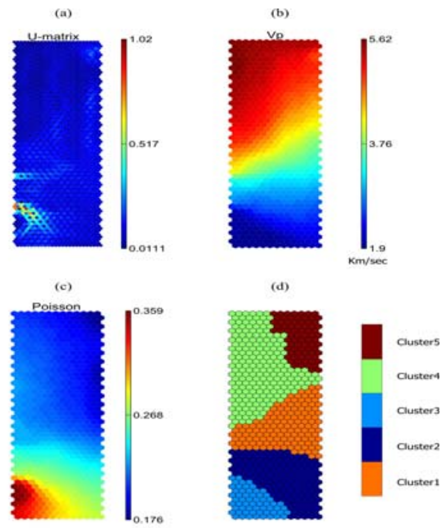


Figure 3. The area of interest and the network deployed.



(a) (b)

Figure 4. (a) 3D view of the located seismograms, (b) a 3D view of the resulting Vp model from seismic tomography.

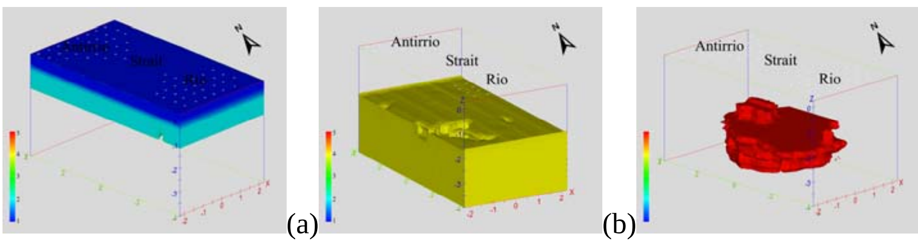


Following the steps outlined above for using the SOMs component planes (figure 5 b,c) and the 'U-matrix' (figure 5 a) are calculated for this dataset, as well as the clusters that this data space can be divided in (figure 5d).

For further investigation of the classification of the data the 3D distribution in the investigated area of the derived clusters is reconstructed and visualized. The corresponding 3D mapping of the data clusters is presented in Figures 6a, b and c. In particular figure 6c, shows cluster 5, not previously identified in the velocity tomographic results.

Drilling data in the vicinity of the Gulf of Patras showed that evaporates were located at a depth of 1850 m. This is consistent with the results of the present investigation, and the results of MT investigations.

Figure 5. (a) The'U-matrix' calculated, (b), (c) two of the component planes calculated and (d) the clustering of the data.



(a) (b) (c)

Figure 6. (a) (b) 3D view of the clusters (c) the cluster corresponding to the evaporite.

Case study II: Epirus (NW Greece)–hydrocarbon exploration

Geologicaly this study area is located in a particularly complex thrust-belt zone situated in the NW Greece. The seismic network installed covered an area of about 3000 km^2, consisting of 40 stations. During the 10 months that was the duration of recording data 900 earthquakes were recorded and 450 located events were used for the tomographic inversion. The hypocentre depths of the selected events range from 500 m down to 35 km with the majority located between 500 m and 15 km. The 450 events satisfied the following criteria: they were located within the seismic network and they had at least 20 P- and S-wave arrivals.

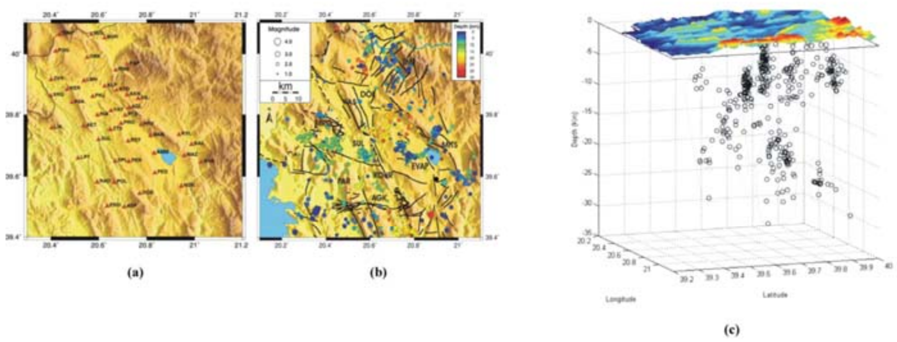


Figure 7. (a),(b) Area of interest and (c) 3D view of located seismograms.

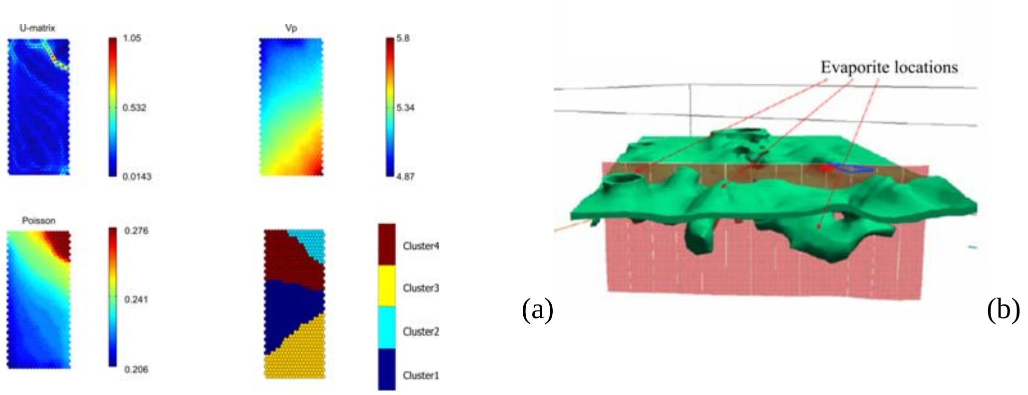


Figure 8. (a) SOM processing and clustering results, (b) tomographic interpretation.

Following the steps outlined above for this area the tomographic inversion produces the models for the seismic velocities and parameters that is consequently used in the calculation of the SOM's component planes and the 'U-matrix' (Figure 8a). Using these data their clustering is determined similarly to the case study I.

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