T3.7-P10

Non-linear kernel methods for seismic event characterization

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Abstract

Seismic event characterization is an important component of the CTBT verification regime. In this work, we apply advanced machine learning technique called diffusion maps for characterizing events. Diffusion maps is a nonlinear kernel method, which learns local similarities between data points to create a global parameterization of the observed data set. We apply diffusion maps for constructing a geometric representation of the seismograms that capture the intrinsic structure of the signal at each channel. As a pre-processing step, the seismograms are converted to the normalized sonograms. In the obtained low-dimensional representation, seismic events with similar source mechanism from the same region have a similar representation.

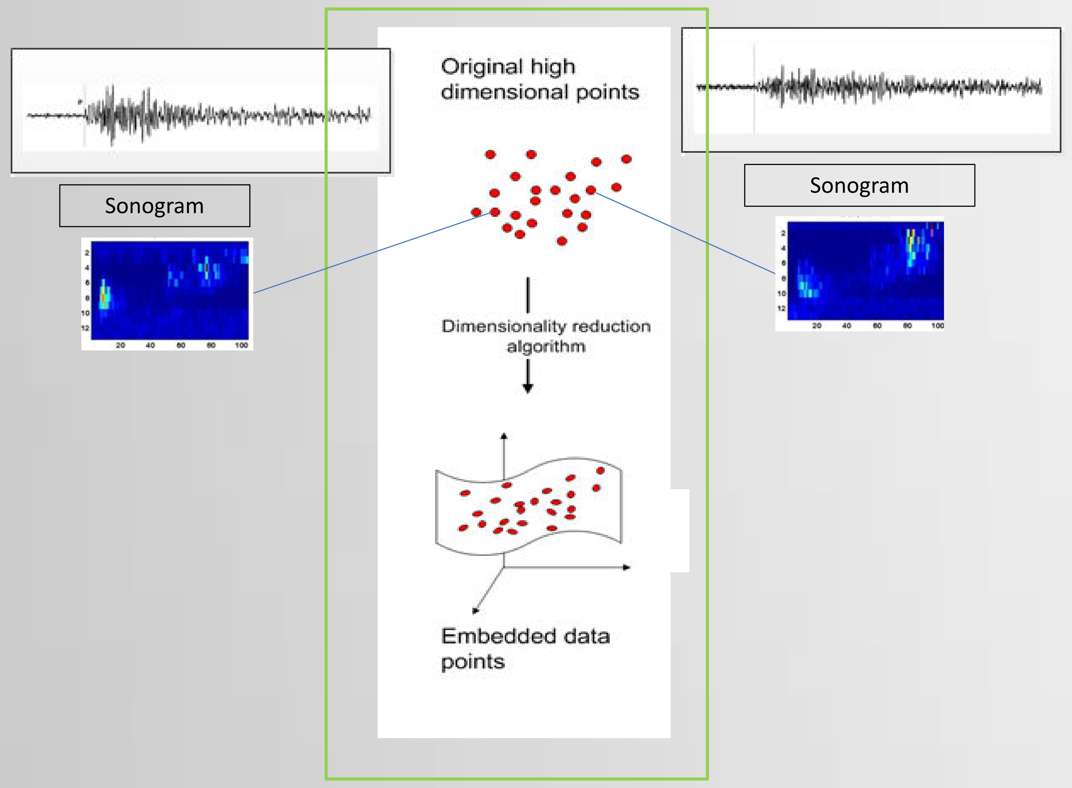
Introduction

We propose a two step method for characterizing seismic events in a low-dimensional space.

The first step includes construction of a time-frequency representation, named a Sonogram. This is a feature extraction step.

The second step utilizes a non-linear dimensionality reduction method, diffusion maps, and results in a low-dimensional representation of the collected data.

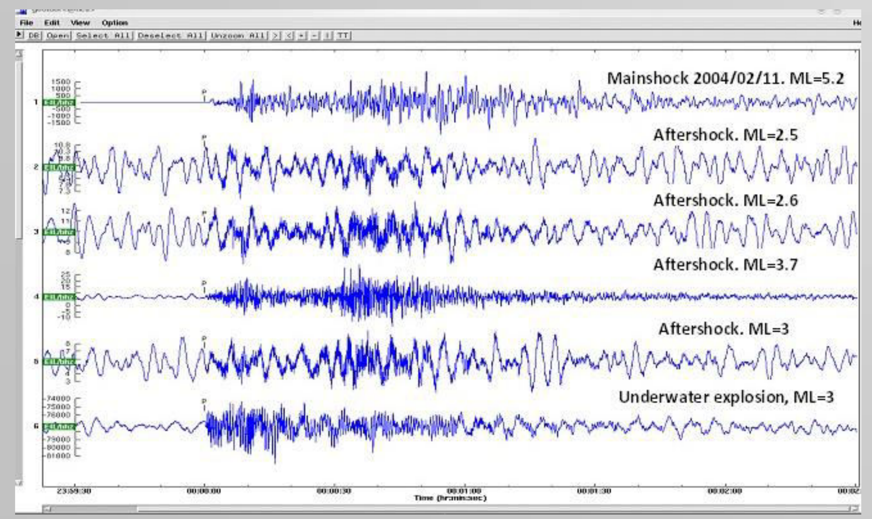
Analysis tasks such as discrimination , classification or anomaly detection may then be carried out in the low dimensional space. The following figure illustrates the two-step method



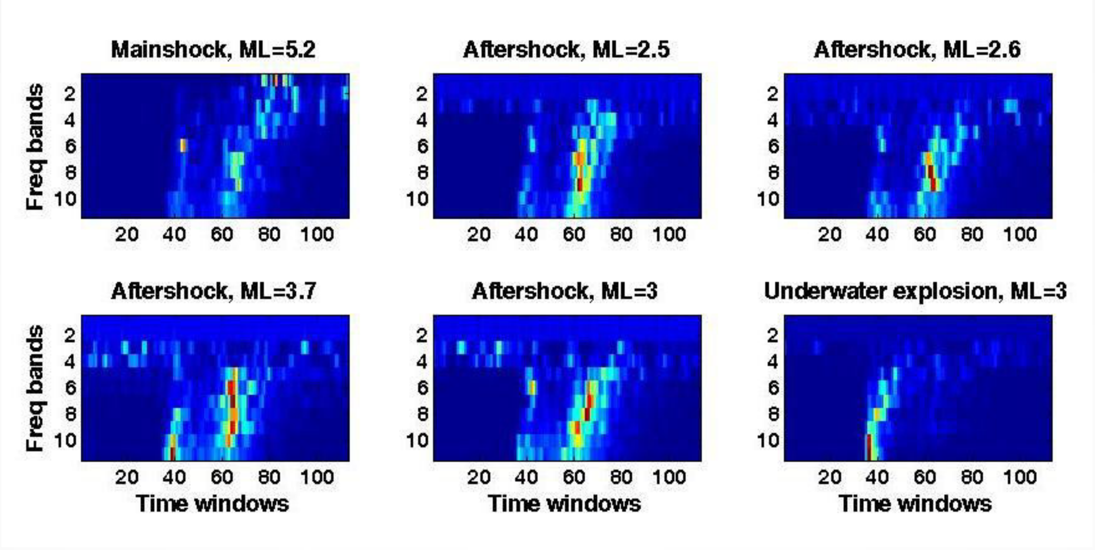
Step I: Feature Extraction via Sonograms

The feature extraction step constructs a time-frequency representation from the given waveforms. The method is based on sonograms (Joswig 1990) with some modifications. It enables to characterize a transient seismic signal by its time varying spectra.

The figure below displays six seismograms that were recorded at the IMS station EIL in southern Israel. The first seismogram is a main shock of magnitude 5.2, the next four recordings are of aftershocks (magnitudes between 3.7 and 2.5) and the last seismogram is an underwater explosion of magnitude 3.



The following figure presents the six sonograms that were processed from each recording. Notice that the sonograms are normalized, thus events of the same type (natural events) but with different magnitudes have similar sonograms. The sonogram that was processed from the explosion has a different structure.



Step II: Dimensionality Reduction

Diffusion maps (Coifman 2006) is a non-linear dimensionality reduction method. It assumes that patterns in a high dimensional ambient space lie in fact in a lower dimensional manifold and that the intrinsic manifold metric is given by an appropriate diffusion distance.

Here, diffusion maps is applied to the set of sonograms, denoted by $X=\{x_1,x_2,\ldots x_m\}$. Each Sonogram is saved as a high-dimensional vector.

A symmetric and positive definite Gaussian kernel is defined by $K=k(x_i,x_j)=\exp\left\{-\|x_i-x_j\|^2/2\varepsilon\right\}$.

The Gaussian kernel is normalized to be a Markov probability matrix

$$P \propto K=\exp\left\{-\|x_i-x_j\|^2/2\varepsilon\right\}.$$

This matrix captures the pairwise distances between the sonograms. The eigen-decomposition of the matrix P is computed by

$$p(x_i,x_j)=\sum_{l\geq 0}\lambda_l\psi_l(x_i)\varphi_l(x_i).$$

It yields a set of diffusion maps coordinates

$$\Psi(x_i)=\left(\lambda_1\psi_1(x_i),\lambda_2\psi_2(x_i),\lambda_3\psi_3(x_i),\ldots\right).$$

These embed the sonograms into Euclidean space.

Diffusion distances

Diffusion distance – a local preserving metric

$$D^2(x_i,x_j)=\sum_{x_l\in\Gamma}\frac{(p(x_i,x_l)-p(x_l,x_j))^2}{\varphi_0(x_l)}$$

In the embedding space it becomes the Euclidean distance

$$D^2(x_i,x_j)=\sum_{k\geq 1}\lambda_k(\psi_k(x_i)-\psi_k(x_j))^2.$$

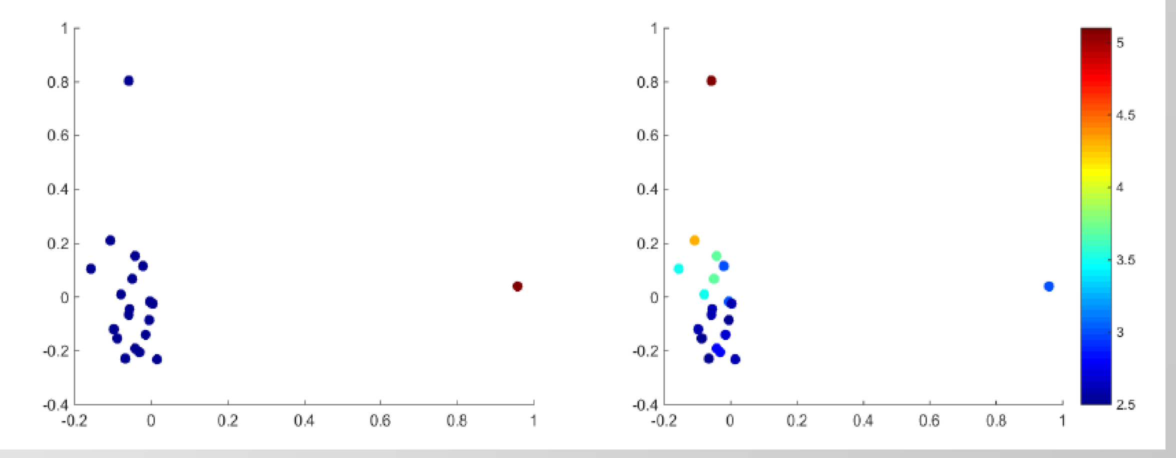
Example: Event Characterization

The dataset comprises of 20 events that occurred in the northern Dead Sea area within latitudes 31:6N-32N and longitudes 35:3E-35:6E.
The first 19 events are earthquakes with duration magnitudes ranging between 2.5 and 5.1. The last event is an underwater explosion of magnitude 3.

Utilizing Step I, each event is replaced by a normalized Sonogram . Next, in Step II, the diffusion maps algorithm is applied. A Markov matrix of size 20x20 is constructed.

Its spectral decomposition is computed and results in Diffusion maps coordinates (Rabin 2016).

The figure bellow plots the diffusion maps embedding of 20 events.



Left: the blue points are earthquakes and the red point is an explosion.
Right: the embedded points are colored by their magnitudes. It can be seen that the y-axis captures this intrinsic property.

For more applications – see poster: Application of diffusion maps for seismic event characterization in Israel

References
Coifman, R., Lafon, S., 2006. "Diffusion Maps", Applied and Computational Harmonic Analysis 21, pp. 5–30.
Joswig, M., 1990. Pattern recognition for earthquake detection. Bull. Seism. Soc. Am., 80: 170-186.
Rabin N, Bregman Y, Lindenbaum O, Ben-Horin Y, Averbuch A, 2016, Earthquake-explosion discrimination using diffusion maps,
Geophysical Journal International, vol. 207, pp. 1484-1492.

Acknowledgment
This research was supported by the PAZY Foundation