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Seismic detection using support vector machines

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ABSTRACT

This study describes research to design a seismic detection system to act at the level of a seismic station, providing a similar role to that of STA/LTA ratio-based detection algorithms.

In a first step, Multi-Layer Perceptrons (MLPs) and Support Vector Machines (SVMs), trained in supervised mode, were tested. The sample data consisted of 2903 patterns extracted from records of the PVAQ station, one of the seismographic network's stations of the Institute of Meteorology of Portugal (IM). Records' spectral variations in time and characteristics were reflected in the input ANN patterns, as a set of values of power spectral density at selected frequencies. To ensure that all patterns of the sample data were within the range of variation of the training set, we used an algorithm to separate the universe of data by hyper-convex polyhedrons, determining in this manner a set of patterns that have a mandatory part of the training set. Additionally, an active learning strategy was conducted, by iteratively incorporating poorly classified cases in the training set. The proposed system best results, in terms of sensitivity and selectivity in the whole data ranged between 98% and 100%. These results compare very favourably with the ones obtained by the existing detection system, 50%, and with other approaches found in the literature.

Subsequently, the system was tested in continuous operation for unseen (out of sample) data, and the SVM detector obtained 97.7% and 98.7% of sensitivity and selectivity, respectively. The classifier presented 88.4% and 99.4% of sensitivity and selectivity when applied to data of a different seismic station of IM.

Due to the input features used, the average time taken for detection with this approach is in the order of 100 s. This is too long to be used in an early-warning system. In order to decrease this time, an alternative set of input features was tested. A similar performance was obtained, with a significant reduction in the average detection time (around 1.3 s). Additionally, it was experimentally proved that, whether off-line or in continuous operation, the best results are obtained when the SVM detector is trained with data originated from the respective seismic station.

1. Introduction

In the past decade, Computational Intelligence (CI) techniques have been applied in the area of seismology for several classes of problems: earthquake magnitude prediction [1,2], control and monitoring of civil engineering structures [3,4], discrimination between event types (earthquakes, explosions, volcanic, and underwater) [5,6], phase determination [7–9] and seismic imaging [10].

Although a significant amount of research has been devoted to automatic seismic detection algorithms, the majority of the systems employed in seismic centres are based on the short time average (STA)/long-time average (LTA) ratio and its variants [11]. These algorithms produce a significant number of false alarms and missing detections, therefore needing human supervision at all times. Thus, continuous research efforts are required aiming at highly reliable real time seismic event detectors to be applicable on continuous seismic data. A short summary of existing approaches to detect the P-phase onset is done below, where the accuracy figures obtained are highlighted, with a view to enable a comparison with the proposed methodology, described later on.

In terms of off-line approaches, i.e., methods that have been applied to a set of specific segments of seismic signals containing earthquakes, or just background noise, Dai and MacBeth [12] proposed a back-propagation neural network (BPNN) to identify P and S arrivals from three-component recordings of local earthquake data. The BPNN

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was trained by selecting trace segments of P and S waves and noise bursts, converted into an attribute space based on the degree of polarization (DOP). One thousand three hundred and sixty-three seismic records were used for training and validation. Compared with a manual analysis, this trained system correctly identified between 76.6% and 82.3% of the P arrivals, and between 60.5% and 62.6% of the S arrivals.

Gentili et al. [13] proposed a neural network system for P and S-picking and location of earthquakes. Their approach has been applied to 7108 seismograms corresponding to 1147 earthquakes occurred in Northeastern Italy in the period 2000–2003, with magnitude ranging from 0.6 to 5.6. Its results are compared with two sets of manual picks and with the picks performed by the existing seismic alert system. The P detection Recall values for the two systems are 0.93 and 0.80, considering the first database of manual picks, and 0.80 and 0.62, considering the second database, respectively.

Riggelsen and Ohrnberger [14] have applied a machine learning approach based on supervised learning and Dynamic Bayesian Networks (DBN). The methodology, which was introduced in [15], was applied for off-line detection of seismic events recorded in two stations, BOSA and LPAZ, belonging to the International Seismic Stations (IMS). A time–frequency decomposition provided the basis for the required signal characteristics needed in order to derive the features defining typical 'signal' and 'noise' patterns. Each pattern class is modelled by a DBN, specifying the interrelationships of the derived features in the time–frequency plane. Subsequently, the DBNs are trained using previously labelled segments of seismic data, using Generalized Expectation Maximization. For training the classifier for BOSA and LPAZ, 1 week of IMS data from July 2008 was used. A separate test-set (disjoint with the training set) was compiled from the data of the same week of July 2008. Sensitivity values in the range of 0.8–0.86, and Specificity values in the range of 0.84–0.97 were obtained. The range of the magnitude of the events considered was not specified.

Different approaches have also been applied to continuous seismograms, with different durations. Tiira [16] used artificial neural networks – MLPs – to detect the P-phase. Their inputs were 3 STA and 1 LTA values computed at seven different frequency bands, from 0.5 Hz to 3.4890 Hz. Separate detectors were trained for each one of three different seismic stations in Finland. The training data base was obtained from P-wave signals of 193 teleseismic events. The detection capability of the neural detector was tested using a voting system together with results from all three stations. Testing was performed by passing 10 consecutive days data (1–10 March, 1996) through the detectors. The number of seismic events marked by International Data Center was 657 (only events with distance $>20^{\circ}$ from the stations and magnitude greater than 3.5 have been used). The STA/LTA detector found 144, and the total number of detections was 941. The best neural network system found 25% more events than the LTA/STA detector and produced 50% less detections indicating smaller false alarm rates.

Botella et al. [17] have implemented a new earthquake detector, based on STA/LTA, applied to seismic signals pre-filtered using the discrete wavelet transform. They compared the performance of this algorithm against two well know detection algorithms: XRTP [18] and XDetect [19], using seismic data from the Local Seismic Network in the Province of Alicante (LSNPA) in Spain. The performance of their proposed algorithm was found to be dependent on the tuning parameters. Using seismic data of March 2001, and the detector tuned for high sensibility, the detection rate was 97.4% (in contrast with XRTP, which achieved 74.8%), but at the expense of a high false alarm ratio (72.8%). This value could be reduced to 40.6%, but with a detection rate of only 85.2%.

Beyreuther and Wassermann [20] proposed the use of Hidden Markov Modelling (HMM) to the detection of small to medium size earthquakes. The seismic signals were recorded with three stations of the Bavarian Earthquake Service. The performance of their algorithm was compared with a recursive LTA/STA detector, within a continuous one-month period. The detection rate was 81%, compared with 90%, for the LTA/STA, in a universe of 69 earthquakes. This approach was further developed in [21], and applied to a data set from the Swiss Seismological Survey in [22]. Although the performance of this approach cannot be directly compared with the results presented here, as only events close to the seismic station employed were considered, and only short sections of the continuous data set have been tested, the HMS detector was able, after re-training, to achieve 97% of correct detections in a universe of 206 seismic events, comprised of earthquakes, blasts and rockfalls.

Real-time seismic monitoring and earthquake early-warning system (EWS) must be capable of not only detecting a seismic event, but of producing estimates (with possible uncertainties) on the location and size of an earthquake beginning after a few seconds after the event is first detected. Thus, one key parameter of an EWS is time. The larger the time available before the catastrophic phenomenon hits the target, the more effective will be the countermeasures that can be taken [23]. The lead-time for EWS applications is of the order of a few seconds to a few tens of seconds depending on the target hypocentral distance.

There is always a trade-off between the warning time and the reliability of the earthquake information. For instance, the approach detailed in [24] is able to detect an earthquake within 0.2 s. But for 301 events inside the Irpinia Seismic Network, 104 outside, and 49 false events, their approach could not detect 19 and 28, respectively, and produced 10 event declarations, out of the 49 false events.

In the work hereby presented, we propose a seismic detection system, to be implemented at the seismic station, using computational intelligence models. This system should be able to distinguish segments of seismic records containing signals caused by local and regional earthquakes and explosions, from all other situations. The aim is to build classifiers that assign one of two classes to periods of the seismic record of pre-determined fixed duration: Class 1, local and regional earthquakes and explosions and Class 2, all the other possibilities.

The data used was collected from two seismic stations, located in the south/centre of Portugal: PVAQ,[1] located in Vaqueiros, Algarve (37°24.22′N, 07°43.04′W), and PESTR, located in Estremoz, in Central Alentejo (38°52.03′N, 07°35.41′W).

The structure of the paper is as follows. In Section 2, the procedures used in an early stage for data collection and feature extraction are described. The training methods used in the experiment are also indicated in this section. In Section 3 the trainings are described and the results analyzed. The performance of the classifier, in continuous operation, is discussed in Section 4. Section 5 deals with the time taken to detect an event. It is shown that using an alternative set of windows, similar accuracy performance can be obtained, with a significant reduction in detection time. Conclusions and future work are highlighted in Section 6.

2. Data and training methods

2.1. Input data

Non-stationary signals occur naturally in many real-world applications: examples include music, biomedical signals, radar, sonar and seismic waves. Time–frequency representations such as the

[1] In general, Portuguese seismic stations begin with a 'P', that stands for Portugal, followed by an abbreviation of the location name, in this case 'VAQ' stands for Vaqueiros