International Journal of Earth, Energy and Environmental Sciences
ISSN: 2517-942X
Vol:1, No:5, 2007

A New Approaches for Seismic Signals Discrimination

M. Benbrahim, K. Benjelloun, A. Ibenbrahim, M. Kasmi, and E. Ardil

Abstract**—**The automatic discrimination of seismic signals is an important practical goal for the earth-science observatories due to the large amount of information that they receive continuously. An essential discrimination task is to allocate the incoming signal to a group associated with the kind of physical phenomena producing it. In this paper, we present new techniques for seismic signals classification: local, regional and global discrimination. These techniques were tested on seismic signals from the data base of the National Geophysical Institute of the Centre National pour la Recherche Scientifique et Technique (Morocco) by using the Moroccan software for seismic signals analysis.

Keywords**—**Seismic signals, local discrimination, regional discrimination, global discrimination, Moroccan software for seismic signals analysis.

I. Introduction

As the earthquakes, a chemical explosion, an underground nuclear explosion, a volcanic eruption or generally any event that can generate vibrations of the soil creates seismic signals that propagate in the ground. In order to be a monitoring tool, a seismic network must be able to identify the source of different seismic signals. This task consists to discriminate between different events: local earthquakes, far earthquakes, chemical explosions, nuclear explosions, etc. The manual discrimination of digital records is a difficult task that demands considerable efforts and costs. In this sense, several works have been developed to automate the discrimination task.

In this paper, we present three techniques for the classification of seismic signals: local, regional and global discrimination. These techniques are based on a modular system composed by three blocs (see Fig. 1): 1) representation, 2) Dimensionality reduction and 3) Classification.

In the experimental tests, we have used the seismic data base of the of the National Geophysical Institute of the Centre National pour la Recherche Scientifique et Technique (Morocco) and the Moroccan software for seismic signals Analysis (**MSSSA**) [4].

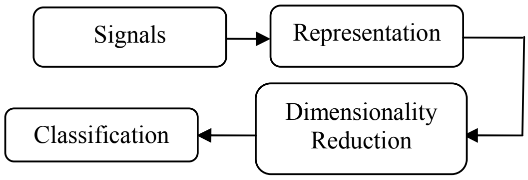

Fig. 1 Modular system

II. Seismic Signals Representations

The choice of the representation is an important parameter that it must be chosen carefully in order to increase the classification performances. It consists to define a representation space permitting the extraction of the pertinent information.

For seismic signals, all previous works have highlighted that a representation space, where the power, the frequency and the time are present, is an adequate space. We can replace the frequency parameter by the scale parameter that permits a multiresolution analysis of the signal.

A. Time and Frequency Representations

The **time representation** is the natural form to represent a signal deriving from a given phenomena. It is not necessary to use any mathematical tool to perform it and we can have some information about signal from it. However, it is not adapted for the automatic classification.

The **frequency representation** is an alternative for the temporal representation of looking at a signal. It consists to represent the frequency content of the signal via the Fourier transform. In the seismic signals case, the frequency contents and all the statistic properties change with the time. Consequently, for the events with weak signal noise ratio, the classification based on the Fourier transform can give wrong results. Moreover, this representation limits the generalization of the automatic classification system for other classes where frequency content is similar.

B. Time-Frequency Representations

In order to overcome the limits posed by the temporal and the frequency representations, the use of a **time-frequency representation** (**TFR**) provides localized information in time and frequency simultaneously. This representation gives a natural description for the non stationary signals such as the seismic signals. Indeed, TFRs characterize signals over a time-frequency plane. They thus combine time-domain and

This work was supported by PROTARS III (CNRST, Rabat, Morocco) under Grant D48.

M. Benbrahim and K. Benjelloun are with Automatic laboratory in the Ecole Mohammadia d'Ingénieurs, Rabat, Morocco (corresponding author to provide phone: 212-63631938; fax: 212-35602684; e-mail: benbrahim10@yahoo.fr).

A. Ibenbrahim and M. Kasmi are with National Geophysical Institute in the Centre National pour la Recherche Scientifique et Technique, Rabat, Morocco.

E. Ardil is with Department of Computer Engineering, Trakya University, Edirne, Turkey.

frequency domain analyses to yield a potentially more revealing picture of the temporal localization of a signal's spectral components.

Several TFRs exist in the literature. However, there is not any universal solution for all signals, and by consequent, we must necessary to do a choice based on the mathematical properties of the representation and it's utility for a given signal. In the experimental part of this paper, we use the spectrogram, the Wigner-Ville and the smoothed pseudo Wigner-Ville representations [1].

C. *Time-Scale Representations*

The techniques based on windowed Fourier transform represent inaccurate and inefficient methods of time-frequency localization, as they impose a fix size of the analysis window.

A direct way to overcome the problems with a fixed window size is to use a **time-scale representation** (**TSR**). As the TFRs, the TSRs can be divided in linear and quadratic representations. For the linear case, we find the wavelets and for the quadratic case, the affine class is the most important class of the covariant TFRs [1].

For the continuous wavelet transform, there are two popular functions: the Mexican hat wavelet and the Morlet wavelet [2]. The first is a real function and because it is the second derivative of the Gaussian function, it is most adapted to detect discontinuities in signals. The second wavelet is complex valued, enabling one to extract information about the amplitude and phase of the signal being analyzed [3].

For the seismic signals (multi component and non stationary signals), in order to profit of the intrinsic properties of the Mexican hat wavelet and Morlet wavelet, another new complex wavelet called the Ben wavelet was designed [5].

III. Dimensionality Reduction

The bi-dimensional representations of seismic signals by TFRs and TSRs give high dimensional images. For a system of automatic classification, in order to eliminate the problems due to high dimensional data such as the curse of dimensionality [6], the dimensionality stage must be integrated in the system.

For the case of seismic signals, the dimension of the bi-dimensional representations is variable in the temporal axe because the length of time of the seismic events is variable. In the precedents works, in order to obtain images with the same length, the method used consists to clip the signal. But it is possible to loose the pertinent information in the ignored part. To overcome this problem, we use a new algorithm based on the combination of the random projection (**RP**) and the two dimensional principal component analysis (**2DPCA**).

A. *Random Projection*

In RP, the original d-dimensional data is projected to a k-dimensional (k<<d) subspace through the origin, using a random k×d matrix *R* whose columns have unit lengths. Using matrix notations where $X_{d\times N}$ is the original set of N d-dimensional observations,

$$X^{RP}_{k\times N} = R_{k\times d} X_{d\times N} \quad (2)$$

is the projection of the data onto a lower k-dimensional subspace. The key idea of random mapping arises from the Johnson-Lindenstrauss lemma [7]: If points in a vector space are projected onto a randomly selected subspace of suitable high dimension, then the distances between the points are approximately preserved.

B. *Two Dimensional Principal Component Analysis*

Principal component analysis (**PCA**) is a widely used dimensionality reduction technique in data analysis. Its popularity comes from two important properties. First, it is the optimal (in terms of mean squared error) linear scheme for compressing a set of high dimensional vectors into a set of lower dimensional vectors and reconstructing [8]. Second, the model parameters can be computed directly from the data. Indeed, dimensionality reduction by PCA consists of projecting data onto a subspace spanned by the most important eigenvectors:

$$X^{PCA}_{k\times N} = E^{T}_{d\times k} X_{d\times N} \quad (3)$$

where the $E^{T}_{d\times k}$ is the transpose of the d×k matrix $E_{d\times k}$ that contains the k eigenvectors corresponding to the k largest eigenvalues of the data covariance matrix.

The application of the PCA for images is computationally very expensive and there is a loosing of the bi-dimensional structure of the initial images. To overcome these problems, Yang et al [9] was introduced the 2DPCA that consists to apply the PCA directly on images by using the image covariance matrix. Wang et al [10] were demonstrated that 2DPCA is equivalent to PCA applied to line-base images. For this reason, the proposed 2DPCA is considered as row-oriented and denoted by 2DPCARO. In order to have a 2DPCA column-oriented, we can apply the 2DPCA to the images transpose of the matrices. We denote this 2DPCA by 2DPCACO.

In order to have a bi-dimensional and bidirectional PCA (**2D2DPCA**), we can do the projection in the both directions:

$$X^{2D2DPCA} = W^{T}_{2dpcaco} X W_{2dpcaro} \quad (4)$$

where $W_{2dpcaro}$ and $W_{2dpcaco}$ are, respectively, the image covariance matrix and the transpose image covariance matrix.

C. *Algorithm*

In order to reduce the dimensions of TFRs and TSRs images of seismic signals, we propose the following algorithm:

- **Step1**: Normalization of the TFR or TSR images of the training base;
- **Step2**: Reduction of dimensionality of each image of the training base by random projection in order to have images of the same dimension;
- **Step3**: Find the 2DPCARO ;
- **Step4**: Find the 2DPCACO;

- **Step5**: Reduction of the image test by the RP;
- **Step6**: Apply the 2D2DPCA to the resultant image of the step 5.

IV. Classification

For our knowledge, in the literature, there aren't any parametric methods that are multi- (source, representations, strategies, experts) for the classification of seismic signals. In this paragraph, we propose three methods for doing this task.

A. Local Discrimination

The local discrimination consists of doing a classification of seismic signals for each seismic station independently of the others stations of the seismological network. In order to increase the reliability of the classification, we use a system mono source and multi-(representations, strategies and experts). (see Fig. 2).

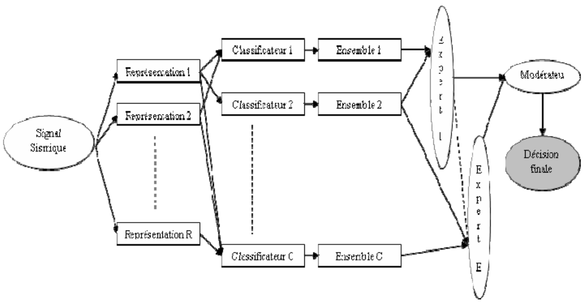

Fig. 2 Scheme of the local discrimination

B. Regional Discrimination

Always the manager of a seismological network divides the network in geographical regions composed by a number of stations in order to reduce the false alarms and to increase the reliability of the detection system. The same approach can be used to improve the results of the local discrimination. For this reason, we propose the scheme given by the Fig. 3 that is multi-(source, representations, strategies and experts).

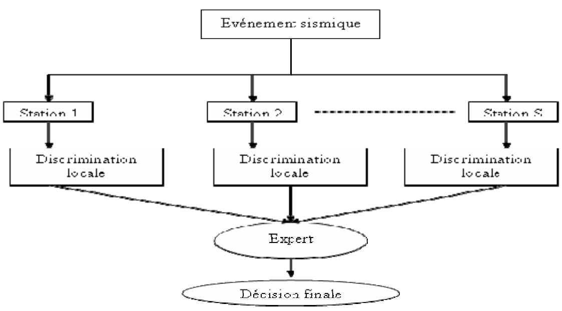

Fig. 3 Scheme of the regional discrimination

The approach of the regional discrimination described above is based on a static choice of the number of stations independently of the epicenter of the event. If we can locate automatically the event, instead to use a static region, we can form virtual region according to some rules defined by the manger en dependence with the epicenter of the event. We call this scheme dynamical regional discrimination to differentiate with the precedent scheme called static regional discrimination.

C. Global Discrimination

The global discrimination permit to profit of the two precedent approaches for giving the final decision. (see Fig. 4). Thus all the activated stations of the seismological network and all the prior knowledges are used.

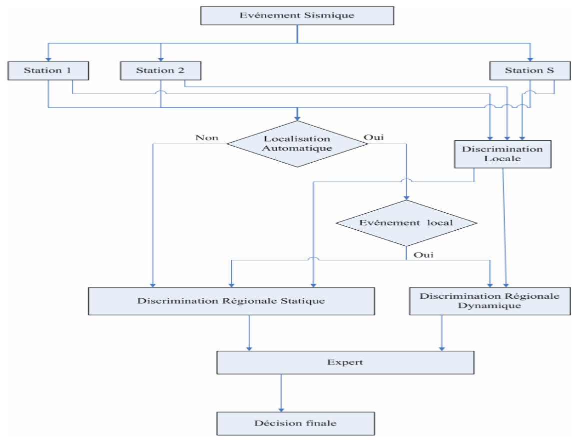

Fig. 4 Scheme of the global discrimination

V. Experimental Results

A. Local Discrimination

To demonstrate the performances of the local discrimination, we propose to use a data base composed of 130 signals where 50 corresponds to chemical explosions, and 50 corresponds to local earthquakes and 30 for far earthquakes. 100 signals were used for the training process (40 for explosions, 40 for local earthquakes and 20 for far earthquakes) and 30 signals for the test process (1/3 for each type). We use five representations: spectrogram, Wigner-Ville, smoothed pseudo Wigner-Ville, Scalograms of the Morlet and the Ben wavelets. For the dimensionality reduction, we use the algorithm described previously and for the classification, we use a multilayer perceptron neural network trained by Rprop algorithm and architecture 30-302 for the time-frequency representations and 24-30-2 for the time scale representations. The other parameters are 0.001 for the learning rate and error goal, 0.95 for the moment term, 1000 for the maximal iteration number and the sigmoid for the activation functions. For the experts, we use the majority, the unanimity and the threshold (80%) voting for the classification of class type. For the measure type, we use the sum and the product. The software used is the MSSSA Thus, for a mean of the results of 100 tests we obtain the Table I.

TABLE I
RESULTS FOR THE LOCAL DISCRIMINATION

Expert	Error %	Reject %
Majority	3.66	1.80
Unanimity	0.033	28.2
Threshold 80%	0.93	12.53
Sum	5.46	0
Product	5.96	0

The results of the table above permit to conclude that the combination of several classifiers improved the performance of one classifier of type classes for which the minimal error obtained is 5.15%. However, for the majority, unanimity and threshold voting cases, there is a percentage of signals rejected that must to be classified manually or by other classifier. We also note that the increase of the reliability of the classification system implies automatically the increase of the reject rate (compare the results of the unanimity vote with the majority vote), this is due to the error/reject dilemma [11].

B. Regional Discrimination

In order to explain the utility of the regional discrimination, we consider three signals corresponding to a far earthquake event (file :Es0206-2005-05-01 19:05:38 in the data base) . This event was be recorded by three stations CZD, MIF and ZFT of the region 5 in the Moroccan seismological network. The others stations of this regions were be inactivated. We do a local discrimination for each station using the unanimity, the majority and the threshold (80%) voting for the combination and the same classifier used in precedent example with the same parameters and the training data base. For the regional discrimination, we use the majority voting for the expert. Thus for 5 tests, we obtain the Table II where C, F and R design respectively Correct, False and Reject and T designs test.

TABLE II
RESULTS FOR THE REGIONAL DISCRIMINATION

Method\Test	T1	T2	T3	T4	T5
Unanimity - CZD	C	C	C	C	C
Unanimity - MIF	F	C	F	F	F
Unanimity - ZFT	C	C	C	C	C
Majority - Regional	**C**	**C**	**C**	**C**	**C**
Majority - CZD	C	C	C	C	C
Majority - MIF	F	C	F	F	F
Majority - ZFT	C	C	C	C	C
Majority - Regional	**C**	**C**	**C**	**C**	**C**
Threshold - CZD	C	C	C	C	C
Threshold - MIF	F	C	F	F	F
Threshold - ZFT	C	C	C	C	C
Majority - Regional	**C**	**C**	**C**	**C**	**C**

We note that for the station MIF and for the tests 1, 3, 4 and 5 the local discrimination give false result whereas the regional discrimination with majority voting as expert give a correct decision. Thus, we can improve the discrimination task by using the regional discrimination.

C. Global Discrimination

For the global discrimination, we can give the same discussion as the regional discrimination but in this case we consider the regional discrimination instead the local discrimination in Table II.

VI. CONCLUSION

With this paper, we presented three approaches for the discrimination of seismic signals. The first technique is the local discrimination that can be used for one station independently of the others stations of the network. The second approach is the regional discrimination that can be used for a number of stations that compose a static or dynamic regional seismological network. Finally, the third approach concerns the global discrimination where all the decision of the stations can be used to obtain the final decision. The experimental tests using the Moroccan software for seismic signals analysis give some examples of the utility of these approaches

REFERENCES

[1] P. Flandrin, "Temps-fréquence", Academic Press, 1998.
[2] I. Daubechies, "Ten lectures on wavelets", SIAM, Philadelphia, Pa, 1992.
[3] C. Torrence and G. P. Compo, "A practical guide to wavelet analysis" Bull. Amer. Meteor. Soc, vol. 79, pp. 61-78, 1998.
[4] M. Benbrahim, K. Benjelloun, A. Ibenbrahim, A. El mouraouah, M. Kasmi and A. Birouk, "The Moroccan Software for Seismic Signals Analysis", Technical report, National Geophysical Institute, CNRST, Morocco, 2006.
[5] M. Benbrahim, K. Benjelloun, A. Ibenbrahim and A. Daoudi, "Classification of Non Stationary Signals using Ben Wavelet and Artificial Neural Networks" *International Journal of Signal Processing.*, vol. 2,no. 1, pp. 34–38, 2005.
[6] R. Bellman, "Adaptive control processes: A guided tour" Princeton University Press, Princeton, 1961.
[7] W.B. Johnson and J. Lindenstrauss, "Extensions of Lipshitz mapping into Hilbert space" In Conference in modern analysis and probability, volume 26 of Contemporary Mathematics, Amer. Math. Soc, pp. 189-206, 1984.
[8] I. T. Jolliffe, "Principal component analysis", Springer-Verlag, 1986.R. W. Lucky, "Automatic equalization for digital communication," *Bell Syst. Tech. J.*, vol. 44, no. 4, pp. 547–588, Apr. 1965.
[9] J. Yang, D. Zhang, A. F. Frangi and J-Y Yang, "Two-dimensional pca: new approach to appearance-based face representation and recognition", IEEE trans on Pattern Analysis and Machine Intelligence, vol. 26, no. 1, pp. 131-137, 2004.
[10] L. Wang, X. Wang, X. Zhang and J. Feng, "The equivalence of two dimensional pca to line-based pca", Pattern Recognition Letters, vol. 26, no. 1, pp 57-60, 2005.
[11] L. K. Hansen and C. Liisberg and P. Salamon, "The Error-Reject Tradeoff", Open Systems & Information Dynamics, vol. 4, no. 2, pp 159-184, 1997.