Application of Cross-Correlation to Seismic Signal Database of Agadir

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Abstract— The Agadir seismic database is fed by a local seismic network of five stations. The latter belongs to the national seismic network of Morocco. Three types of seismic events are recorded on daily basis: earthquakes, quarry blasts, and other undesired seismic events which are considered as noise. A quantity of data is currently available. The aim of this study is to highlight the degree of similarity that may exist between these different seismic events. This similarity could help in many studies including classification of these seismic events. The cross-correlation function, commonly used in signal theory, is used to quantify this similarity and compare the obtained results. The cross-correlation function is firstly applied to synthetic signals to clearly demonstrate its behavior versus signal parameter variation, and then to real seismic signals. The obtained results show that quarry blast signals are more correlated than those of earthquakes. This is explained by different factors. This relative correlation that exists between quarry blast signals may be exploited to develop an identification task.

Keywords—Cross-correlation, Seismic signal, Similarity, Classification.

I. INTRODUCTION

Seismic signal recording is so important as its analysis reveals important information about the structure and physical properties of the earth medium through which the seismic waves propagate. In addition, seismic signals carry wealthy information about their sources. Due to its importance, seismic signal is recorded using large sensor network composed of many stations covering few kilometers to a couple of hundred kilometers. In the past, seismic signals are transmitted in real time by wire or radio link to a central recording system where all data is recorded with central timing. This enabled very accurate relative timing between stations, and therefore also made it possible to make more accurate locations of local Nowadays, with the earthquakes. evolution of communication capabilities, there exist seismic networks that cover the whole world [1]. Seismic networks can now be local, regional or global.

The three main purposes of seismic networks are: early seismic alarm triggering, accurate determination of earthquake locations, and research on the interior of the Earth. However, seismic networks could serve for other missions such as detection of nuclear explosions and their location (CTBTO) [1].

In all applications, one crucial and generally faced issue is how to identify automatically the source of the different recorded signals. Indeed, seismic sensors can sense any ground vibration regardless of its source. Consequently, a signal classification task is necessary to help identifying the source of each detected signal. Many approaches have been tested in the literature [2-9].

The aim of this paper is to reveal the degree of similarity existing among seismic signals of the same and different sources, which have been recorded by the seismic network of Agadir. This is in order to investigate at which extent the similarity between signals of the same source or dissimilarity between signals of different sources could be used to develop a classification task.

To quantify the similarity between signals, it is necessary to use a mathematical tool which makes it possible to compare signals and measure the degree of their resemblance or correlation. In this study the crosscorrelation function, commonly used in signal processing, is employed [10]

It should be noted that the applicability of cross-correlation detectors in seismic monitoring systems is so far restricted to only some regions where aftershock sequences and repeating seismicity occur. The main idea behind this work is to further investigate the cross-correlation in order to extend its applicability to other seismic networks and other tasks such as classification.

The rest of this paper is organized as follows. Section II is devoted to the previous related work. Section III explains the mathematical background of the cross-correlation function and its properties. Section IV treats its numerical estimators. In section V, the biased estimator is applied to synthetic signals. Section VI demonstrates the obtained

results on real seismic signals. Section VII concludes research work with future directions.

II. RELATED WORK

Nowadays, cross-correlation function has become very useful in many disciplines. For instance, it plays a central role in many practical applications in seismology [11-13]. Due to the effectiveness of the function to measure resemblance between signals, it is used in many studies for detecting known signals. Nowadays, the cross-correlation technique is becoming a standard method for detecting seismic signals of repeating sources [14-25]. In a previous study, we have also employed the cross-correlation function for detecting seismic event of low magnitude [26].

III. CROSS-CORRELATION FUNCTION

A. Definition

The cross-correlation function $R_{xy}(\tau)$ is defined as the integral of the product between a signal x(t) and a second signal y(t) shifted by τ [9]:

$$R_{xy}(\tau) = \int_{-\infty}^{+\infty} x(t) y^*(t-\tau) dt$$

where y^* denotes the complex conjugate of y. τ is known as lag.

 $R_{xy}(\tau)$ allows measuring the degree of similarity or mutual dependence between two signals x(t) and y(t) even if they are delayed. In the particular case where y(t) = x(t), we obtain the so-called autocorrelation function of the signal which compares the signal x(t) with its delayed copy $x(t-\tau)$:

$$R_{XX}(\tau) = \int_{-\infty}^{+\infty} x(t) x^* (t-\tau) dt$$

B. Properties

The maximum of $R_{xy}(\tau)$ is located at the lag τ corresponding to the maximum of similarity between the two signals. Two illustrations are given in figure 1, where two signals are compared with their delayed copies. In the first case, the two signals are delayed by $\tau_0=20$ samples, whereas in the second case, they are delayed by $\tau_0=10$ samples.

It can be seen that the cross-correlation function of each signal with its shifted version has a very well defined maximum at the lag corresponding to the delay between the two signals:

$$\tau_{delay} = \arg \max(R_{xy}(\tau))$$

The maximum (or minimum if the signals are negatively correlated) of the cross-correlation function indicates the point in time where the signals are best aligned.



Figure 1. Appearance of the cross-correlation function maximum at the position corresponding to the shift between the two signals.

 $R_{xy}(\tau)$ and $R_{yx}(\tau)$ do not generally produce the same results. However, one can write for real signals:

$$R_{yx}(\tau) = R_{xy}(-\tau)$$

Delaying y(t) with respect to x(t) with a value of τ is equivalent to advancing the signal x(t) with respect to y(t). Indeed, with a change of variables, it is easy to prove:

$$R_{xy}(-\tau) = \int_{-\infty}^{+\infty} x(t)y(t+\tau)dt = \int_{-\infty}^{+\infty} x(u-\tau)y(u)du = R_{yx}(\tau)$$

With $u=t+\tau$

- If the two signals are periodic with the same period, the cross-correlation function is also periodic with the same period.
- Cauchy-Schwartz inequality:

$$\left|R_{xy}(\tau)\right| \le \sqrt{R_{xx}(0)R_{yy}(0)}$$

C. Normalized cross-correlation (NCC) From the cauchy-schwartz inequality, we have:

$$\rho_{xy}(\tau) = \frac{R_{xy}(\tau)}{\sqrt{R_{xx}(0)R_{yy}(0)}} \le 1$$

If the normalized cross-correlation function NCC tends to unity, we say that the signals x(t) and y(t) are correlated. On the contrary, if NCC equals zero for any value of τ , x(t)and y(t) are uncorrelated.

IV. NUMERICAL ESTIMATION OF CROSS-CORRELATION

The theoretical expression of the cross-correlation function supposes a temporal signal of infinite duration. However, practice imposes the representation of the studied signal over a limited temporal duration. This consists in multiplying the signal by a time window that cancels the signal outside the calculation time interval.

A. Biased estimate

The numerical calculation of the cross-correlation is done by replacing the integral by the sum and the continuous signals by their sampled values x(n) and y(n):

$$R_{xy}^{b}[k] = \frac{1}{N} \sum_{n=0}^{N-1} x[n+k] y * [n] \qquad k_{\min} \le k \le k_{\max}$$

This function provides a biased estimate of the crosscorrelation due to limited length N of the two signals. Indeed, the fact of shifting the signal in the crosscorrelation operation poses that the number of samples involved in the sum decreases as the shift (lag k) increases. The consequence of this choice is that the summations corresponding to a high value of k are made on a few samples, but are always divided by the total number of samples N; this results in a diminution of the correlation function amplitude as k increases. We can write:

$$R_{xy}[k] = \frac{1}{N} \sum_{n=0}^{N-1} x[n+k] y^{*}[n] = \frac{1}{N} \sum_{n=0}^{N-1-|k|} x[n+k] y^{*}[n]$$

To illustrate this phenomenon, consider two constant signals, x(n) and y(n), of 5V amplitude, each acquired over 10 samples (figure 2). Since the signals are identical, the cross-correlation function should be constant and equal to:

$$R_{xy}^{b}[k] = \frac{1}{N} \sum_{n=0}^{N-1} x[n+k]y[n] = \frac{1}{10} \cdot 10 \cdot 5^{2} = 25 \quad \forall k$$

However this value is obtained only for k=0 (no shift) when all samples are involved in the sum computation (figure 2). The more k increases, the less the samples on which the sum is performed, leading to a diminution of the cross-correlation function amplitude.



B. Unbiased estimate

To avoid biasing the results by using the previous estimator which does not take into account the finite duration of the signals, the modified cross-correlation function below can be used:

$$R_{xy}^{u}[k] = \frac{1}{N - |k|} \sum_{n=0}^{N-1-|k|} x[n+k]y*[n] \quad 0 \le k \le N-1$$

By a simple change of variable, we deduce:

$$R_{xy}^{u}[-k] = \frac{1}{N - |k|} \sum_{n=0}^{N - |k|} x[n]y * [n+k]$$

In this estimate, the division is made on the number of samples involved in the sum calculation and not all of the samples. Figure 3 shows the results of applying the unbiased estimate to the previous signals.



Relying on what shown in figure 3, we can see that the obtained results are accurate. However, this is not always the case because the unbiased estimator does not really solve the problem as not all signal samples are used in computation, but instead it just divides by the number of used samples. Consequently, the greater the lag k, the less

reliable become the obtained cross-correlation values.

In Figure 4, the same processing is carried out in the case of a sinusoidal signal. We notice that both estimators give erroneous values especially at the extremities (large values of k). This is the classic problem with numerical analysis since, in practice, only finite duration is taken into account. It should be noted that the biased estimator is the most employed because the summations are given lower weights as they become less reliable with increasing k.



In this study, we have chosen the biased estimator to calculate the similarity degree between seismic signals. This choice is based on the fact that this estimator does not alter the desired maximum value of the cross-correlation function. We then define the maximum of the normalized cross-correlation MNCC of two signals by the ratio:

$$MNCC = \max(|\rho_{xy}(k)|) = \frac{\max(R_{xy}^{b}(k)|)}{\sqrt{R_{xx}^{b}(0)R_{yy}^{b}(0)}} \le 1$$

where $R_{xy}^{b}(k)$ is the biased cross-correlation estimator. max $(|R_{yy}^{b}(k)|)$ is its absolute maximum value.

 $R_{xx}^{b}(0)$ et $R_{yy}^{b}(0)$ are autocorrelation values at the zero delay for the two signals x(n) and y(n).

We always have : $0 \le MNCC \le 1$

- MNCC = 1 for x(n) and y(n) totally correlated.
- MNCC = 0 for x(n) and y(n) totally independent or uncorrelated.

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V. APPLICATION TO SYNTHETIC SIGNALS

In this section we apply the cross-correlation function to simple periodic synthetic signals to clearly demonstrate its behavior versus signal parameter variation. All the signal parameters are evaluated: amplitude, frequency, phase as well as shapes (sinusoidal, square, triangular).

A. Case of signals with different amplitudes

Figure 5 illustrates that MNCC is not sensible to signal amplitude variation. Indeed, we notice that the MNCC achieves its maximal value and does not vary when we change the amplitude ratio between the two signals. The same results are obtained using periodic signal of different shapes: sinusoidal, triangular and square.



Figure 5. Demonstration of amplitude effect on the MNCC using three periodic signals of different shapes

B. Case of signals with different frequencies

In figure 6, we demonstrate how the MNCC is very sensible to signal frequency variation. Indeed, we notice that when we change the frequency, MNCC decreases rapidly. The obtained results are the same for the four shapes: sinusoidal, triangular and square.

C. Case of signals with different shapes

Figure 7 shows that modifying only the shape of a signal does not greatly influence the value of MNCC (the variations at the edges are due to the estimator).

D. Case of signals with different phases

Figure 8 illustrates that MNCC is not very sensible to the phase changes.







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From these illustrations, we can conclude that the only parameter that influences significantly the MNCC is frequency. That is, if two signals have different frequencies, they will be classified as independent.

VI. APPLICATION TO SEISMIC SIGNALS

A. Seismic database of Agadir

The seismic database of Agadir is fed by a network of five stations. Each station consists of a vertical-component short-period seismometer. Every detected signal is saved with a pre/post-signal seismic background noise. The recorded signal is identified by its name in the following format: hhmmssjj.MMS. The pairs of characters represent respectively from left to right: Hours, Minutes, Seconds, Day, Month and the last digit identifies the station (CGH: 1, AFL: 2, FSA: 3, DKD: 4, YBT: 5).

The employed detector is the well-known STA/LTA energy-based detector [27]. This detector triggers whenever sufficient signal energy is encountered. Consequently, signals of different sources are recorded on a daily basis. These include:

- Earthquake sources

- quarry blast sources

- Noise sources which regroup all undesired sources such as ocean swells and urban activities.

Figure 9 illustrates examples of recorded seismograms which are generated by different sources.

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Figure 9. Examples of recorded seismograms at the Agadir seismic database, which are generated by different sources.

B. Application of MNCC to seismic signals

To investigate at which extent the MNCC could be used to classify seismic signals, it is applied to the previously recorded earthquake and quarry blast signals. We will take into account all possible arrangement, i.e., signals of the same source recorded by several stations and signals of different sources recorded by the same or different stations. The calculation window is chosen rectangular.

1) Correlation between earthquake signals

The first experiment was performed on a dataset of 128 earthquake seismograms. The MNCC of the whole dataset is calculated in a form of a matrix, in which the MNCC between two seismograms i and j is stored at position (i,j). This matrix is then transformed into a colormap, where red colors are used to represent greater values and blue colors represent lower values (fig. 10). The interpretation of this colormap is straightforward. One should expect the maximum value of MNCC in the diagonal as it corresponds to the auto-correlation of the seismograms. Moreover, as the seismograms are sorted by their names, the MNCC matrix is organized as shown in figure 11. An event corresponds to an earthquake occurrence which could be detected by several stations. Note that not all seismic events are recorded by the five stations; an event could be detected in only one station.

Figure 10 shows that the MNCC values are quite low to what can be expected, especially since these events belong to the same class 'earthquake'. This is not always true if we consider some events that show good correlation (MNCC= 0.8). For example, figure 12 shows one of these events, which recorded by four stations (1, 2, 4 et 5). As can be deduced from MNCC values, the four seismograms show a non negligible similarity. This can be attributed to the fact that they are generated by the same earthquake source. Nevertheless, this assumption might be discarded because of the results shown in figure 13. The latter demonstrates that signals of the same event recorded by two different stations could be weak correlated. This demonstrates the significant degree at which a signal could

be altered by the propagation path. Our interpretation of the obtained correlation in figure 12 is that it could be attributed to an effect of source-station distance. We believe that the further away the seismic source is from stations, the more likely its recorded signals are correlated. This leads us to talk about the notion of seismic network resolution. We think that a source-station distance equals to at least ten times the size of the network will allow a good correlation for an event recorded by the network. The idea behind this assumption is that, in this case, the propagation paths could be considered approximately similar for all stations.









Figure 12: Examples of MNCC between signals recorded at four stations (1, 2, 4 et 5) and generated by the same earthquake source.

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Figure 13. Examples of MNCC between two signals recorded at two stations and generated by the same earthquake source.

Figure 14 demonstrates another example of correlation in the case of different events recorded by the same station. We see that the values of the MNCC are less significant than those relating to events generated by the same source and recorded by several stations.

2) Correlation between quarry blast signals

It is essential to know that this type of event is generated by sources on the surface. The energy deployed is less than that of earthquake sources. These sources generate essentially surface waves with low energy and short duration. To be detected, their sources should be generally close to the station.

Figure 15 shows the MNCC matrix generated using a dataset of 102 quarry blast seismograms. From the first view, we can notice a more significant correlation between quarry blast events compared with earthquake ones. This noticeable correlation is not restricted to only seismograms of the same event, but it is extended to seismogram of different events. For example, figures 15 and 16 show that relatively significant values of MNCC could be obtained for signals recorded by the same station even if they are generated by different sources.

This could be interpreted by the fact that quarry blasts are often exploded on the same location approximately (compared to the expanse of the recorded network). In addition, the employed explosive is the same with equal quantity. Therefore, one can accept the assumption that two different explosions may generate similar signals. The lower MNCC values obtained in figure 16 could be related to the different paths traversed by the wave to achieve each station.







3) Correlation between earthquake and quarry blast signals

The last experiment carried out in this study consists in analyzing the correlation between seismograms of the two classes: earthquake and quarry blast. To do so the two previous datasets are used. Figure 17 demonstrates the obtained MNCC matrix. Each matrix row designates the MNCC between an earthquake seismogram and all quarry blast ones. As expected, the obtained correlation is generally weak except in some rarely cases. It is also important to note that when an earthquake is correlated with a quarry blast at some degree, it very often shows the same correlation degree with the majority of the remaining quarry blast seismograms.

MNCC 11464518.063 11265020.063 0.5 0.5 0.40 -0.5 -0.5 11265020.062 11464518.062 0.5 0.5 0.50 -0.5 -0.4 100 100 11382630.063 11464548.063 0.5 0.30 -0.5 -1 č 100 60 80 120 20 <u>4</u>0 60 80 100 Time (s) Time (s)





Figure 16. Examples of MNCC between two signals recorded at two stations (3 and 2) and generated by the same quarry blast source.

VII. CONCLUSION AND FUTURE SCOPE

In this work, we have highlighted the correlation degree between seismic signals recorded by the local seismic network of Agadir. This is with the aim of investigating the possible similarity that may exist between signals of the same source type. This similarity could help in many studies including classification.



Figure 17. MNCC matrix using 128 earthquake and 102 quarry blast seismograms

- Simplify the concept of the correlation commonly used in signal theory.
- Practicing on synthetic signals, which reveal the relevant signal parameters that influence the cross-correlation. It turns out that frequency is the vital parameter. Thus the spectral content of the seismic phases and the filtering due to the propagation path will be mainly responsible for the weak MNCC values obtained.
- Earthquake signals are not very often correlated even if they are produced by the same event. This could be attributed to the propagation path effect on the signal.
- Quarry blast signals are more correlated then earthquake ones even for different events recorded by the same station. This could be interpreted by using the same type and quantity of explosive, and the propagation path could also be approximately similar if these explosions are occurred at the same location.
- From these results, we think that a method based on MNCC could be developed to identify quarry blast events and assign them to known mines. That is, for each mine, template signals can be selected from previously recorded signals, which can be compared with each new detected signal using MNCC. However, this may not be possible for earthquake events as the obtained MNCC values are generally weak and could not be used to identify them.
- Highlight the complexity of seismic signals. The latter is a convolution of several different functions: source function, propagation path function, site function and seismometer function. Modification of one function could lead to a different signal, making MNCC not an efficient tool for classification. In other word, each function could be considered as a filter which alters the signal spectrum and thus MNCC.

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