IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol. 10, Issue.3, March 2022 E-ISSN: 2347-2693

Llaima's Volcano Seismic Event Classification Using The Cross-Correlation Function

A. Atmani[1*], E.H. Ait Laasri[2], D. Agliz[3], E. Akhouayri[4]

[1,2,3]GEMS Laboratory, National School of Applied Sciences, Ibn Zohr University, Agadir, Morocco
[2,4]LETSMP Laboratory, Department of Physics, Faculty of Sciences, Ibn Zohr University, Agadir, Morocco

**Corresponding Author: a.atmani@uiz.ac.ma, Tel.: +212676935207*

DOI: https://doi.org/10.26438/ijcse/v10i3.17 | Available online at: www.ijcseonline.org

Received: 20/Feb/2022, Accepted: 15/Mar/2022, Published: 31/Mar/2022

***Abstract*—**Volcano seismic events are a source of great hazards implicating human lives and material damage. Consequently, continuous monitoring of this natural phenomenon is of great importance to reduce their dramatic effects on people and nearby economy. A seismic network is usually deployed around the crater to achieve this monitoring task. The different produced volcano seismic events (e.g., long period LP, tremor TR, volcano tectonic VT) are related to physical phenomenon (explosion, eruption, depressurization …etc) occurring at the source. The seismic network may also record seismic events that are not related to volcanoes such as tectonic events (TC) produced by geological faults. The first vital task in volcano monitoring is to recognize the source of each detected event. This task should be performed automatically due to the large amount of data recorded daily. In this work, we propose an easy and straightforward method to classify volcano seismic events using the cross-correlation function in time domain. We applied this method using three approaches. The application of these approaches to the seismic database of the Llaima volcano (Chile) gives good results, particularly the third approach that achieves a global accuracy of 92.7%.

***Keywords*—** Volcano seismic events, Classification, Cross-correlation, Time domain.

I. INTRODUCTION

Continuous seismic monitoring of active volcanoes is one of the most efficient methods to prevent their hazard. The main goals of this monitoring are :

- Understanding how they behave and detecting changes in their behavior. This can help researchers to identify different physical processes occurring inside the volcano such as explosions, rock fracturing, eruptions, and pressurization.
- Launching an early alarm when an eruption is about to occur identified by an increase in the number of shallow earthquakes. This also permits the local authorities to take the appropriate decision regarding the evacuation of people from the neighborhood regions.

The system insuring volcano seismic monitoring is necessarily a network constituted of numerous stations deployed around the volcano. Every station transmits its recorded signal to a central observatory where the different signals are retrieved, classified and stored for further analysis and processing. The transmission of the signals was achieved in the past by wires or radio link. It is actually achieved by IP or satellite communication. Every station is equipped with one or several sensors like seismometers which basically measure ground motion. After a preliminary phase of amplification and shaping of the analogical signal, the latter is transmitted using a radio link by modulating a carrier wave in older systems. However, in the newer systems, the signal is first digitized and then transmitted using an internet or a satellite connection. The received signals from the different stations are subjected to numerous processing in the central observatory. The first essential processing task is the classification of the events according to the physical phenomenon that occurs inside the volcano.

In the case of the Llaima volcano, whose data is used in this study, a permanent real time monitoring system of 9 stations provides continuous data streams that rapidly grow. This large volume of data requires efficient programs allowing the extraction of meaningful information. The monitoring system belongs to Chile state agency, namely, *Observatorio Vulcanológico de los Andes Sur* (OVDAS). The time required by the processing task is also a critical parameter due to necessity of an almost real time reply expected in such systems to emit an early alarm. The classification task of volcano seismic events has been addressed using different techniques. Some of them use artificial and neural networks after a preliminary phase of signal features extraction [1],[2],[3],[4],[5],[6],[7],[8],[9],[10],[11],[12]. According to the previous mentioned researches, the feature extraction phase needed in the artificial neural network methods is mandatory [13],[14],[15],[16], meanwhile, it is tricky and affects significantly the classification result. Other studies prefer using simple and most straightforward techniques. One of these interesting techniques that recently attracts researcher attentions is based on the so called cross-correlation function [17]. One of the recent studies applies this technique to classify the Llaima volcano seismic events [18]. The authors have used the normalized cross-correlation function in the time-frequency domain. The obtained classification results are encouraging. However, one of the disadvantages of this approach is time and memory consuming. The idea behind this current work is to apply the cross-correlation function to the data of the same volcano, but in the time domain. Indeed, the authors have not investigated the cross correlation in the time domain, yet, it is more uncomplicated and can significantly reduce the calculation. To obtain the best classification result with low complexity, we have examined three approaches. The application of the method to the volcano database demonstrates that the global accuracy can reach 92,7%.

This paper is organized as follows : Section II is devoted to the previous related work. Section III presents the dataset used in this work and a brief description of its seismic event classes. In Section IV, we introduce the Maximum Normalized Cross Correlation (MNCC) function as a mathematical tool used to evaluate similarity between seismic events. Section V presents the MNCC matrix. In section VI the MNCC matrix is calculated for the Llaima volcano data. Section VII discuses the three examined MNCC-based approaches and the obtained results. We finally conclude this work in Section VIII.

II. RELATED WORK

The cross-correlation is actually used in various fields of research related to signal processing. In a previous study, we have employed the cross-correlation function for detecting weak seismic events in a noisy signal [19]. It also can be used to improve hypocenters of earthquakes and provide reliable P- and S-arrival time information [20]. In addition, it has been used to improve the accuracy of the so-called "Failure Forecast Method" [21]. Furthermore, the cross-correlation ability to detect resemblance between signals allows detecting, locating and identifying aftershocks events of an earthquake or a nuclear explosion [22]. In the field of image processing, the cross-correlation function has been used to detect dissimilarity between original and fake images for example when using a watermarking technique [23].

III. VOLCANO SEISMIC EVENT DATABASE DESCRIPTION

Llaima is known as one of the biggest and most dangerous volcanoes in Chile. It is precisely located at the Araucanía region (38◦ 41' S , 71◦ 44' W) in the southern Andes. Llaima is monitored by nine seismic stations (Figure 1).

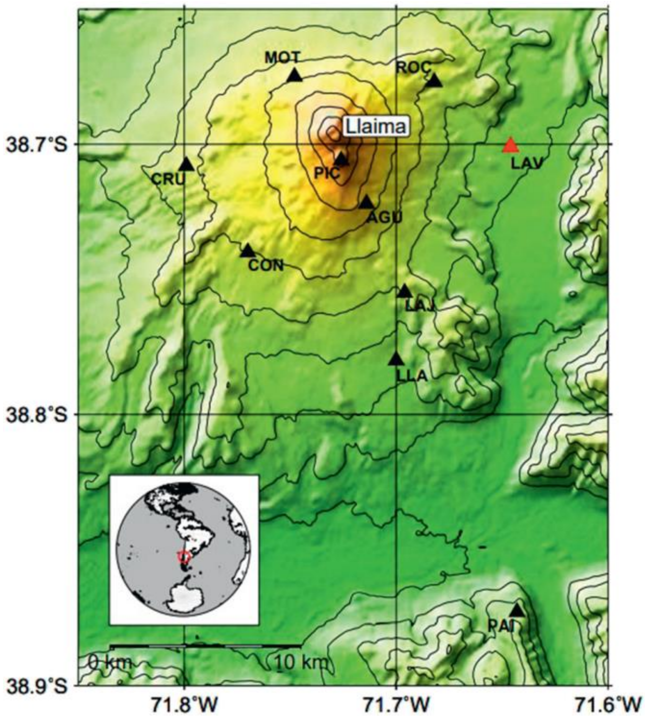

Figure 1. Llaima volcano and its seismic monitoring network

The events used in this study were recorded by the Z-vertical component of the LAV station (marked by a red triangle in the figure), during the period between 2010 and 2016 [24]. The signals are digitized using 100 Hz sample frequency. To keep just the useful frequency range for Llaima events, a numerical *l0th* order Butterworth bandpass filter between 1 and 10 Hz is used. A last phase of normalization by their maximum values is performed on the signals before classifying them manually by the OVDAS experts into the four classes : Long Period (LP), Tremor (TR), Volcano-Tectonic (VT), and Tectonic (TC), as shown in Table 1.

Table 1. Number of events per class in the Llaima volcano seismic database.

Class	LP	TR	VT	TC
Number of events	1310	490	304	1488

- VT class is generated by rock fracturing inside the volcanic structures. Its source mecanism is similar to that of earthquakes, hence the name "tectonic".
- LP class events are associated to the movement of magmatic and hydrothermal fluids inside the volcano. These events play an important role in predicting a possible volcanic eruption.
- TR class is produced by different processes such as long-lived resonance due to extended flow of magma movement through cracks. It generates continuous or a sequence of transient high-amplitude signals similar to those generated by LP. They present duration generally longer than LP.
- TC class contains events which are not related to volcanic activity. These events are generated by the

dynamic of the geological faults. According to the location of their epicenter, TC events can be local, regional or distant. The farther the TC event is, the lower the frequency content is. This fact is due to the filtering effect of the structure and physical properties of the earth medium through which the seismic waves propagate. Moreover, the TC events can be confused with those of LP or VT depending on the epicenter-station distance.

IV. Cross-correlation function in time domain

To estimate the degree of similarity between two signals *u(t)* and *v(t)*, we use the Maximum Normalized Cross Correlation (MNCC) function as defined in [25]:

$$MNCC_{uv} = \frac{max(|R_{uv}(k)|)}{\sqrt{R_{uu}(0)R_{vv}(0)}}$$

$R_{uv}(k)$ is the cross-correlation function of the sampled signals *u(m)* and *v(m)* deduced from the continuous signals *u(t)* and *v(t)*, respectively:

$$R_{uv}(k) = \frac{1}{M}\sum_{m=1}^{M} u(m)v(m-k)$$

M is the number of samples, and *k* is a delay introduced on the *v(m)* signal with respect to the *u(m)* one.

$R_{uu}(0)$ is the autocorrelation of the signal *u(m)* at zero delay. It gives an estimate of the energy contained in the signal *u(m)*.

V. MNCC matrix structure

To visually notify any similarity between events of the same class and any dissimilarity between events of different classes, we represent the maximum normalized cross-correlation MNCC matrix of Liaima volcano seismic database as a heat map form (figure 2). The obtained matrix is symmetrical, where the element of coordinates (*i*,*j*) represents the MNCC between the event *i* and the event *j*. The more the events *i* and *j* are correlated, the more the color of the corresponding point in the heat map turns towards red. This may be the case of two events belonging to the same class. At the opposite, the more the events *i* and *j* are uncorrelated, the more the color of the corresponding point in the heat map turns towards blue. This may be the case of two events belonging to different classes.

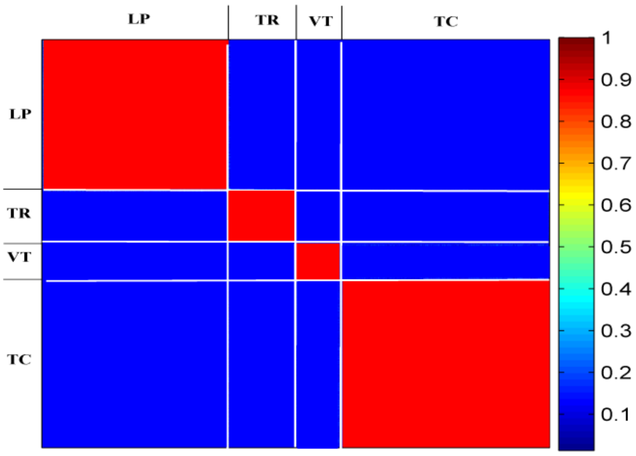

Figure 2. MNCC Matrix appearance when the four class events are perfectly classified.

VI. Determination of the MNCC matrix for the Laima seismic volcano database

The application of the MNCC method to the Laima seismic volcano database gives the matrix showed in figure 3. The latter demonstrates a possible separation of the first three classes LP, TR and VT. Table 2 shows the MNCC global average values in the sixteen areas of the figure 3. The diagonal of the latter contain relatively higher values (marked in green in the table 2) than the other cells, except the TC class. These relatively significant values can be explained by the fact that two events of the same class are more correlated than two events belonging to different classes. So, we can consider a possibility of applying the MNCC for identification of the three classes (LP, TR and VT) of Llaima volcano seismic events. Contrary, the recognition of the fourth class (TC) events cannot be guaranteed as the MNCC is not able to distinguish between its events and those of the other classes. This can be explained by the diversity of the source effects characterizing the tectonic (TC) events, in one hand. In the other hand, it is due to the geology structures and physical properties of the earth medium through which their seismic waves propagate. Finally, we notice that the TR and VT classes are well discriminated as shown by the color of their intersection in the figure 1, and the weak value of their MNCC average in table 2.

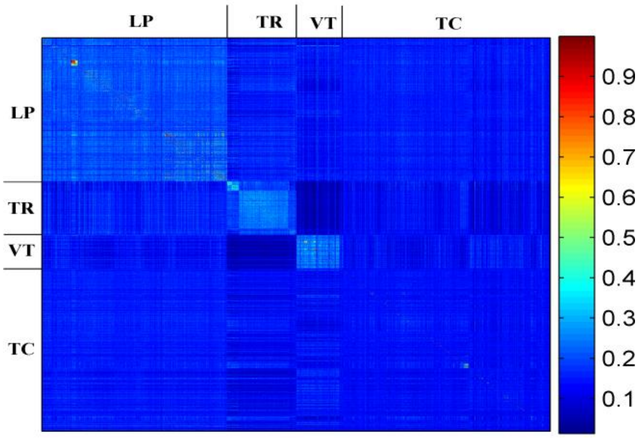

Figure 3. Matrix of the MNCC related to the Llaima seismic volcano database

Table 2. Average of the MNCC values obtained between each pair of classes.

	LP	TR	VT	TC
LP	0,21	0,15	0,14	0,15
TR	0,15	0,22	0,07	0,13
VT	0,14	0,07	0,23	0,13
TC	0,15	0,13	0,13	0,13

VII. Classification Approaches

In order to automatically classify the seismic events of the Liaima volcano seismic database into four predefined classes LP, TR, VT and TC using MNCC, we propose to represent each class by a set of selected events, called "Class template". These templates are determined and then used in three different approaches :

A. First approach

To determine the template, we first calculate the mean of MNCC values of each event with all events of the same class. Then, the template of the class is the event giving the maximum MNCC mean value. This template is supposed to have resemblance with the maximum number of the events in its class. Once the template is determined, it can be correlated with each new incoming event to predict to which class it belongs. This class corresponds to the highest MNCC value with its template.

The application of this method to the Llaima volcano seismic database leads to the confusion matrix shown in figure 4, which indicates the number of the correctly classified and the misclassified events of each class. The columns define the target classes, whereas the rows indicate the predicted classes. The diagonal correspond to the agreement and the other cells indicate the misclassified events.

Predicted class \ Target class	LP	TR	VT	TC
LP	969	46	16	408
TC	153	441	0	329
VT	20	1	203	220
TR	168	2	85	531

Figure 4. Confusion matrix obtained using the first approach

To analyze the classifier efficiency according to the first approach, we have established its performance evaluation as shown in table 3. We notice the highest accuracy of the classifier regarding the two classes VT (90,5%) and TR (85,2%). We also note the weak values of the majority of the performances for the TC class compared to the other classes leading to a global accuracy of 59,7%.

Table 3. Performance evaluation of the classifier according to the first approach

	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)	Error (%)
LP	74	79,40	67,34	77,42	22,58
TR	90	84,46	47,78	85,22	14,78
VT	66,8	92,67	45,72	90,48	9,52
TC	35,7	87,88	67,56	66,26	33,74

Evaluating the effectiveness of this classifier for only the three first classes (LP, TR and VT) without the TC, leads to the confusion matrix shown in figure 5 and the performance evaluation represented in table 4.

Predicted class \ Target Class	LP	TR	VT
LP	1094	46	23
TR	163	441	0
VT	53	3	281

Figure 5. Confusion matrix obtained without TC class, according to the first approach.

We observe a significant improvement in all performances relatively to the table 3 providing a global accuracy that reaches 86,3%.

Table 4. Performance evaluation of the classifier without TC class, according to the first approach.

	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)	Error (%)
LP	83,51	91,31	94,07	86,45	13,55
TR	90,00	89,90	73,01	89,92	10,08
VT	92,43	96,89	83,38	96,25	3,75

B. Second approach

Although the previous template seems to be qualitatively adapted to the desired classification task, it has the disadvantage of being based only on the maximum value of MNCC mean. Indeed, the chosen template may only be relatively well correlated with few events, which makes the average MNCC important, even if it is not correlated with the other events. In such a case, the template does not represent the whole class. In order to improve the classification result, we introduce, in the second approach, the standard deviation parameter in order to select a more adequate template. To do so, the events of each class are classified in a decay order in term of their mean MNCC. Then, as a template, we choose among the first thirty events the one with the smallest standard deviation.

The obtained classification result using this new template is given in figure 6 and the table 5.

Predicted class	Target Class: LP	TR	VT
LP	1123	28	19
TR	117	460	0
VT	70	2	285

Figure 6. Confusion matrix obtained without TC class, according to the second approach.

Table 5. Performance evaluation of the classifier without TC class, according to the second approach.

	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)	Error (%)
LP	85,73	94,08	95,98	88,88	11,12
TR	93,88	92,75	79,72	93,01	6,99
VT	93,75	96,00	79,83	95,67	4,33

As shown by the confusion matrix, the obtained classification results using this new template are better than those obtained using the previous template. This can be proven by the increase in the number of correctly classified events and the decrease in the number of misclassified events of each class. The analysis of the results provided by table 5 shows an improvement of all classifier performances for the LP and TR classes, but we can notice a light lose of precision and accuracy for the VT class. Nevertheless, the global accuracy improved to 88,8%, indicating that the second approach is more efficient than the first one.

C. Third approach

To further improve the classification accuracy, we have performed more tests to find a more representing template. A new idea is to take into account five events which have the smallest standard deviation among the thirty ones having the highest MNCC average.

In this case, each class is represented by five templates. To predict the class of each new incoming event, the classifier correlates the five templates of each class with the event to obtain five MNCC values for each class. The five values are then averaged for each class and the event is attributed to the class with the maximum MNCC mean.

Applying the third approach to the Llaima volcano seismic database produces the confusion matrix as indicated in figure 7. The latter shows a better distinction among the three classes LP, TR and VT. The number of correctly classified events is generally increased while the number of misclassified events is decreased compared to the previously results obtained using the second approach (figure 6).

Predicted class	Target Class: LP	TR	VT
LP	1194	16	20
TR	60	472	0
VT	56	2	284

Figure 7. Confusion matrix obtained without TC class, according to the third approach.

Table 7 summaries the main measures of the performance evaluation of the classifier according to the third approach. The results obtained show a further enhancement of all the classifier performance parameters. We particularly highlight the accuracy which achieves best results leading to the least error among the three approaches. The global accuracy rises to 92,7%, making the classifier more efficient to identify the events of the three classes LP, TR and VT. We can however notice a slight decrease in the sensitivity value for the VT class which does not affect the robustness of the classifier.

Table 7. Performance evaluation of the classifier without TC class, according to the third approach.

	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)	Error (%)
LP	91,15	95,47	97,07	92,78	7,22
TR	96,33	96,28	88,72	96,29	3,71
VT	93,42	96,78	83,04	96,29	3,71

VIII. CONCLUSION

Seismic monitoring becomes one of the most efficient methods to survey and monitor active volcanoes all around the world. The issue which arises is that the recorded signals can be produced by different sources. Identification of the source of each signal is the first step before any other processing. In this study, we have proposed a simple but fairly effective method to classify volcano seismic events using the cross-correlation function in time domain. Three approaches have been studied to improve the classification result. To examine the classifier performance, real data produced by Llaima (Chile) volcano are used. The principal results are summarized below :

- The tectonic events (TC) are not well identified by this method. A global accuracy of about 60% was reached by the first approach.
- Excluding the TC events improves the global accuracy to 86,3% using the first approach.
- Using the second approach, a global accuracy of 88,8% is achieved without the TC class.
- The application of the third approach further increases the global accuracy to 92,7%.

The obtained results demonstrate the ability of MNCC in the time domain to classify volcano seismic events, yet its simplicity and low computation complexity compared to the same method in the time-frequency domain. The effectiveness of this method can be explained by the fact that volcano signals may show resemblance due to similar propagation path between the source and the recording station. Whereas, MNCC in time domain is not very efficient to recognize tectonic events which are poorly correlated because of the diversity of their sources and propagation paths.

REFERENCES

[1] S. Scarpetta, F. Giudicepietro, E. Ezin, S. Petrosino, E. Del Pezzo, M. Martini, M. Marinaro, "*Automatic classification of seismic signals at Mt. Vesuvius volcano, Italy, using neural networks*", Bulletin of the Seismological Society of America, Vol. **95**, No. **1**, pp. **185**–**196**, **2005**.

[2] H. Langer, S. Falsaperla, T. Powell, G. Thompson, "*Automatic classification and a posteriori analysis of seismic event identification at Soufrière hills volcano, Montserrat*", Journal of Volcanology and Geothermal Research **153** (**1**–**2** SPEC. ISS.), **1**–**10**, **2006**.

[3] M. Masotti, S. Falsaperla, H. Langer, S. Spampinato, R. Campanini, "*Application of support vector machine to the classification of volcanic tremor at Etna, Italy*", Geophysical Research Letters, **33**, **L20304**, **2006**.

[4] M. Titos, A. Bueno, L. Garcia, & C. Benitez, "*A Deep Neural Networks Approach to Automatic Recognition Systems for Volcano-Seismic Events*", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, **11**(**5**), **1533-1544**, **2018**.

[5] M. Malfante, M. D. Mura, J.-P. Métaxian, J. Mars, O. Macedo, A. Inza. "*Machine Learning for Volcano-Seismic Signals: Challenges and Perspectives*", IEEE Signal Processing Magazine, Institute of Electrical and Electronics Engineers, **35** (**2**), pp.**20** – **30**, **2018**.

[6] J.P. Canário , R.F. de Mello , M. Curilem , F. Huenupan , R.A. Rios, "*In-Depth Comparison of Deep Artificial Neural Network Architectures on Seismic Events Classification*", Journal of Volcanology and Geothermal Research, volume **30**, **105627**, **2020**.

[7] M. Titos, A. Bueno, L. Garcia, M. C. Benitez, & J. Ibanez, "*Detection and Classification of Continuous Volcano-Seismic Signals With Recurrent Neural Networks*" IEEE Transactions on Geoscience and Remote Sensing, volume **57**, Issue **4**, pp.**1936**–**1948**, **2018**.

[8] M. Titos, A. Bueno, L. Garcia, C. Benitez, & J. C. Segura, "*Classification of Isolated Volcano-Seismic Events Based on Inductive Transfer Learning*" IEEE Geoscience and Remote Sensing Letters, vol. **17,** Issue. **5**, pp.**869**–**873**, **2019**.

[9] A. Salazar, R. Arroyo, N. Perez, & D. Benitez, "*Deep-Learning for Volcanic Seismic Events Classification*", In the Proceedings of the 2020 IEEE Colombian Conference on Applications of Computational Intelligence (IEEE ColCACI 2020), **2020**.

[10] M. Lopez-Perez, L. Garcia, C. Benitez, & R. Molina, "*A Contribution to Deep Learning Approaches for Automatic Classification of Volcano-Seismic Events: Deep Gaussian Processes*", IEEE Transactions on Geoscience and Remote Sensing, Vol. **59**, Issue. **5**, pp. **3875** - **3890**, **2020**.

[11] P. Venegas, N. Perez, D. S. Benitez, R. Lara-Cueva, & M. Ruiz, "*Building Machine Learning Models for Long-Period and Volcano-Tectonic Event Classification*", In the Proceedings of the 2019 IEEE CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON 2019), Chile, pp. **1-6**, **2019**.

[12] R. Carnel, "*Characterization of volcanic regimes and identification of significant transitions using geophysical data: a review*", Bulletin of Volcanology, 76(8), pp. **1-22**, **2014**.

[13] K. Mohabkumar, K. Sangeetha, "*A Study on Earthquake Pediction Using Neural Network Algorithms*", International Journal of Computer Sciences and Engineering. Vol. **6**, Issue.**10**, **2018**.

[14] P. Venegas, N. Perez, D. Benitez, R. Lara-Cueva, & M. Ruiz, "*Combining Filter-Based Feature Selection Methods and Gaussian Mixture Model for the Classification of Seismic Events From Cotopaxi Volcano*", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Vol. **12**, **Issue. 6**, pp. **1991** - **2003**, **2019**.

[15] R. Soto, F. Huenupan, P. Meza, M. Curilem, & L. Franco, "*Spectro-temporal features applied to the automatic classification of volcanic seismic events*", Journal of Volcanology and Geothermal Research, **358**, pp.**194**–**206**, **2018**.

[16] N. Perez, P. Venegas, D. Benitez, F. Grijalva, R. Lara, & M. Ruiz, "*Benchmarking Seismic-Based Feature Groups to Classify the Cotopaxi Volcanic Activity*", IEEE Geoscience and Remote Sensing Letters, Vol. **19**, pp.**1**–**5**, **2020**.

[17] T. Permana, T. Nishimura, H. Nakahara and N. Shapiro, "*Classification of volcanic tremors and earthquakes based on seismic correlation: application at Sakurajima volcano, Japan*" Geophysical Journal International, **229**, pp. **1077**–**1097**, **2022**.

[18] M. Curilem, R.F. de Mello, F. Huenupan, C. San Martin, L. Franco, E. Hernández, R.A. Rios. "*Discriminating seismic events of the Llaima volcano (Chile) based on spectrogram cross-correlations*", Journal of Volcanology and Geothermal Research **367**, pp.**63**–**78**, **2018**.

[19] E. H. Ait Laasri, E. Akhouayri, D. Agliz, A. Atmani, "*Automatic detection and picking of P-wave arrival in locally stationary noise using cross-correlation*", Digital Signal Processing, Vol. **26**, pp. **87- 100**, **2014**.

[20] F. Wagner, A. Tryggvason, R. Roberts and O. Gudmundsson. "*Processing automatic seismic event detections: an iterative sorting algorithm improving earthquake hypocentres using interevent cross-correlation*", Geophysical Journal International. **219**, pp. **1268**–**1280**, **2019**.

[21] R.O. Salvage, J.W. Neuberg. "*Using a cross correlation technique to refine the accuracy of the Failure Forecast Method: Application to Soufrière Hills volcano, Montserrat*", Journal of Volcanology and Geothermal Research **324**, pp.**118**–**133**, **2016**.

[22] D. P. Schaff, W.-Y. Kim, P. G. Richards, E. Jo, and Y. Ryoo, "*Using Waveform Cross Correlation for Detection, Location, and Identification of Aftershocks of the 2017 Nuclear Explosion at the North Korea Test Site*", Seismological Research Letters, Vol. **89**, Number **6** pp. **2113-2119**, **2018**.

[23] F. R. Suratwala, S. G. Kejgir, "*A Robust Multi-Channel Digital Image Watermarking Technique with SVD, DWT, DCT*", International Journal of Computer Sciences and Engineering. Vol. **7**, Issue.**5**, **2019**.

[24] J. P. Canario, R. Mello, M. Curilem, F. Huenupan , and R. Rios, "*Llaima Volcano Dataset: In-Depth Comparison of Deep Artificial Neural Network Architectures on Seismic Events Classification*", *Data in Brief*, **30**, **105627**, **2020**.

[25] E.H. Ait Laasri, A. Atmani, D. Agliz, E. Akhouayri, "*Application of Cross-Correlation to Seismic Signal Database of Agadir*", International Journal of Computer Sciences and Engineering. Vol. **9**, Issue.**6**, **2021**.

AUTHORS PROFILE

A. Atmani is an assistant professor of electrical engineering at Ibn Zohr University, Agadir, Morocco. He has obtained his thesis in seismic instrumentation and signal processing at Ibn Zohr University, Morocco. He had developed a low cost portable system which can be used to perform several tasks, including seismic prospection, microzination, seismic background acquisition and processing. His present research interests include seismic background noise processing, seismic exploration and impact of seismic events on the structures.

E. H. Ait Laasri is a professor of Electronics at Ibn Zohr University, Agadir, Morocco. His research interests lay in the field of instrumentation and signal processing, especially seismic signal processing. During his thesis, he had developed a real time system for managing the seismic local network of Agadir (Morocco). In which system he had implemented several complex software packages for automatic and interactive analysis of seismic data. These programs are developed based on both classical processing methods and artificial intelligence techniques. His current research focuses on improving seismic signal detection algorithms, event classification and phase picking schemes.

D. Agliz is currently a full Professor of Physics at National School of Applied Sciences, Ibn Zohr University, Agadir, Morocco. He received his PhD in Physics in 1987 at University of Rennes I, France, where he also received his master's degree in Physics in 1984, and state doctorate in 1997. Since then he has carried out research in seismic signal processing. He joined the seismic signal research team in 2000. His recent work has focused on seismic signal processing including background noise processing, classification, detection and structure modal analysis.

E.S. Akhouayri is a full Professor of signal processing and instrumentation at the Faculty of Sciences, Ibn Zohr University, Agadir, Morocco. He received his state doctorate in seismic signal processing and instrumentation at Ibn Zohr University in 2002, and his doctorate in electronics at Cadi Ayad University in 1989, where he also received his Master's degree in Physics in 1986. He has been responsible for Agadir seismic network since 2000. He has carried out many researches in this field. His current research interests include seismic signal processing and instrumentation.

