# Signature Matching for Seismic Signal Identification

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doi: https://doi.org/10.21467/proceedings.114.17

## Abstract

Seismic signals can be classified as natural or manmade by matching signature of similar events that have occurred in the past. Waveform matching techniques can be effectively used for discrimination since the events with similar location and focal mechanism have similar waveform irrespective of magnitude. The seismic signals are inherently non-stationary in nature. The analysis of such signals can be best achieved in multiresolution framework by resolving the signal using continuous wavelet transform (CWT) in time-frequency plane. In this paper similarity testing and classification of nuclear explosion and earthquake are exploited with correlation, continuous wavelet transform, cross-wavelet transform and wavelet coherence (WC) of P phase of seismogram. Clustering of seismic signals continuous wavelet spectra is performed using maximum covariance analysis. The proposed classifier has an average classification accuracy of 94%.

**Keywords:** Correlation, Continuous wavelet transform, Wavelet coherence, Maximum covariance analysis.

## 1 Introduction

The seismic signal comes from earthquake, nuclear explosion, mining explosion or rock bursts. Seismic signal classification is necessary for seismic monitoring or to identify the source that generates the signal. The seismic signal properties such as amplitude, frequency content, energy in different phases depends upon location, source etc. Traditionally, an analyst classifies events by visual inspection. This is a time-consuming procedure that necessitates a considerable amount of knowledge and experience. Automatic seismic signal classification is important due to large amounts of data obtained continuously. An automatic classifier would raise the first alert and provide support to analyst. To monitor nuclear testing, we need to segregate earthquake signals from that of nuclear explosion. The North Korea conducted five nuclear tests in 2006, 2009, 2013 and twice in 2016, the seismogram of nuclear explosion recorded at MDJ station china is shown in Fig. 1.

Presently nuclear explosion can be identified using different parameters such as event location. If a event occurred at aseismic region or known test site it may be nuclear explosion event. If the estimated depth of event is less than 10 km with high confidence then the event may be classified as nuclear explosion. Explosion is point phenomenon and radiates equal energy in all directions and generates P-waves and poor S waves. Earthquake occurs at fault slips and radiates different energy in different direction depending on fault plane. The P wave have less energy compared to S waves in earthquake. So, the P/S amplitude ratio can be used for event discrimination. The P/S spectral ratio is used for event discrimination [1]. The regional phases $P_n$, Pg, Sn and Lg spectra are calculated at different stations. The P/S spectral ratios Pg/Lg, Pn/Lg and $P_n$/S calculated and network averaged spectra is used for discriminating nuclear explosion and earthquake signals. It is difficult to detect S phase of a waveform hence these methods are indeterminate.

The possibility to identify nuclear explosion using questionable waveform alone is long goal; However, many researchers used template matching method using cross-correlation for discriminating earthquake and nuclear explosion. [2]–[5] In this method the templates of earthquakes and nuclear explosion are chosen



Proceedings DOI: 10.21467/proceedings.114; Series: AIJR Proceedings; ISSN: 2582-3922; ISBN: 978-81-947843-8-8

from past events by human perception. Template must have higher signal-to-noise ratio. The array based cross correlation and multi-channel correlation is used for event detection. The limitation of this method is that the correlation is affected by micro seismic noise which varies with time. To mitigate the effect of noise the correlation is performed at different frequency bands in time domain.

Automatic detection of seismic events using multi-channel correlation and classification using Hidden Markov Models at seismic array stations is proposed in [6]. Different time and frequency-based features are extracted from seismic signal and classified using neural network [7], [8], support vector machine [9], [10] and random forest classifier [11]. Real-time earthquake or noise signal classification using machine learning techniques for earthquake early-warning system is presented in [12]. Machine learning and empirical mode decomposition are used for the classification of multi-channel volcano-seismic events [13].

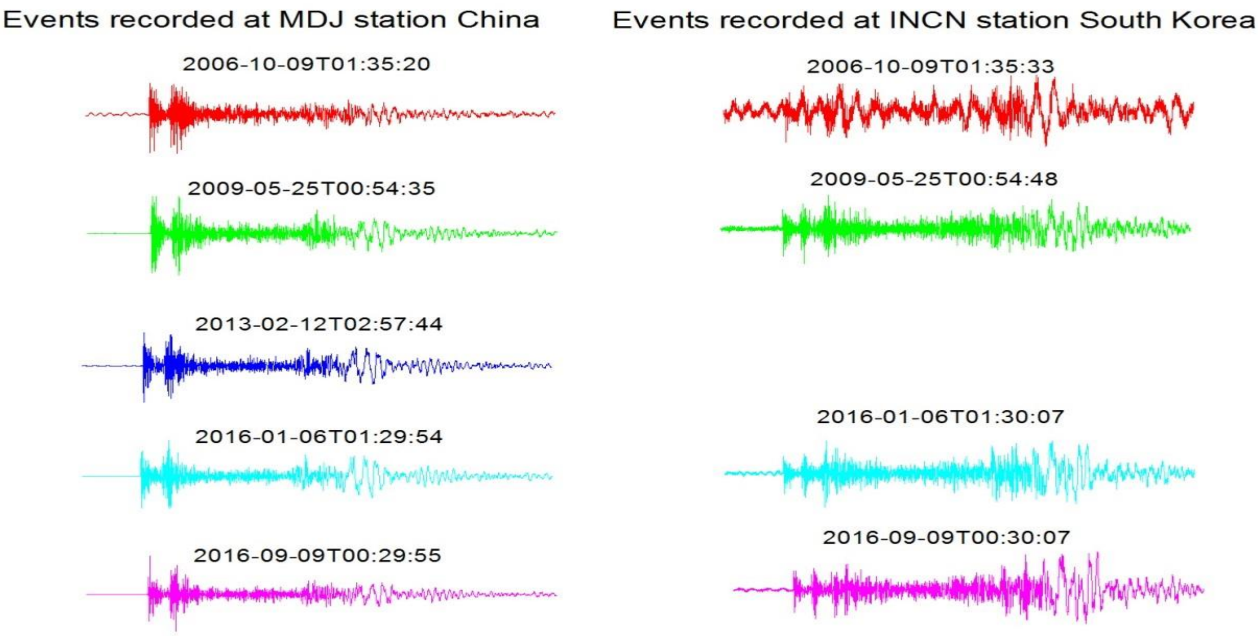


Fig. 1. Nuclear Explosion Events recorded at MDJ and INCN station of GSN

However, nowadays Wavelet based techniques are used to discriminate earthquake and nuclear explosion [14]. The wavelet transform technique is a band pass filtering of signal at different center frequencies at various scales. For a nonstationary seismic signal, the wavelet coherence method [15]– [18] can be used for template matching. In this paper various wavelet based methods are discussed and subsequently the appropriate method is used to identify nuclear explosion and earthquake.

## 2 Data

The seismic events used for classification are taken from Mudanjiang, China (MDJ) and Inchon, South Korea (INCN) stations of global seismogram network(GSN) stations. These events cover a 3-degree radius around North Korean nuclear test site Pungye Re (41.5° N, 129.1° E). For a period between 1 Jan, 2000 to 31 March, 2017, there were 149 events for this region shown in Fig. 2. There are 5 nuclear explosions events indicated as red star and remaining earthquake events indicated in blue circles occurred at different regions within 300 km radius of nuclear test site of North Korea. The events selected for this study are given in Table II. For these 16 seismic event's vertical component (BHZ) data was available at MDJ and INCN stations downloaded from IRIS website
[19].

# 3 Methods

## 3.1 Cross correlation to discriminate earthquake and nuclear explosion

The degree of similarity between seismograms is calculated using cross-correlation coefficients. An observed seismogram is a convolution of the source term, path effects, site effects and instrumental responses [20]. As a result, earthquake pairs with a high cross-correlation coefficient are assumed to have the same focal mechanisms and hypocenters. The template for cross-correlation is chosen from region of interest by human perception. Synthetic template is created for aseismic region.

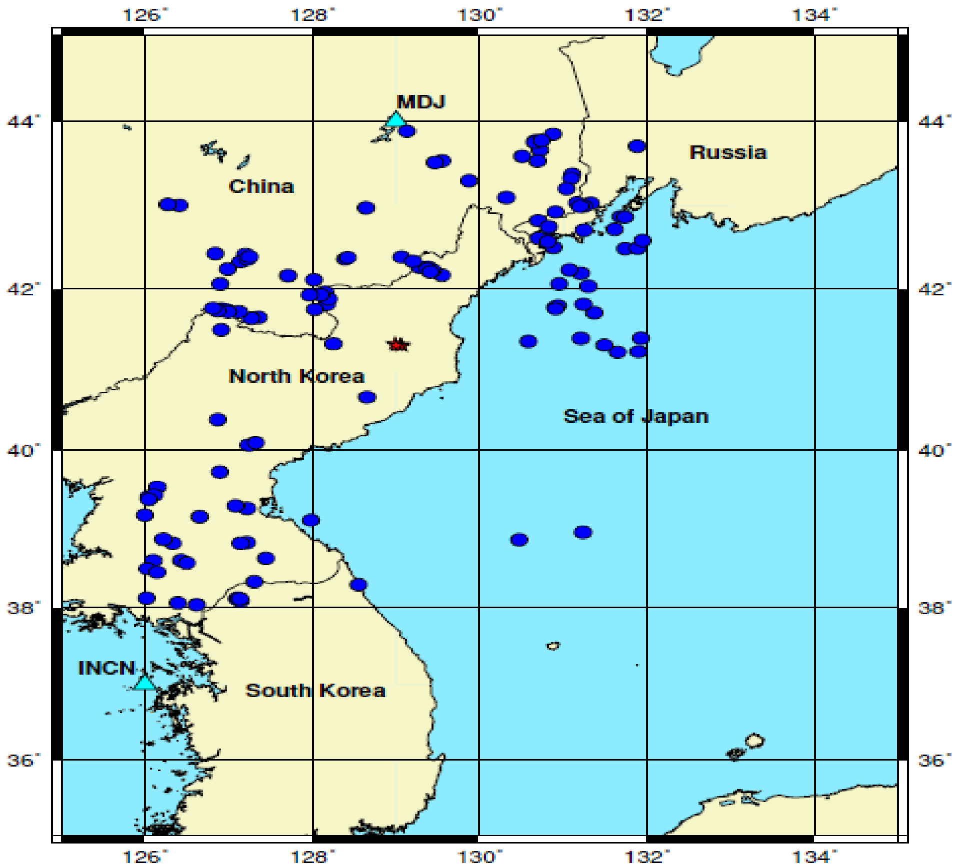


Fig. 2. Location Map of Region of Study

Similar earthquakes are clustered into groups by researchers [5]. A waveform correlation method for identifying quarry explosion [2] is done by selecting master events from different mines. They used a p-wave data segments recorded at 13- element array, this method successfully resolves two sources regions. Similar earthquakes do not necessarily have to have equal magnitudes, and the difference in location is permitted to some extent. Different cross-correlation thresholds are used to judge the similarity between waveforms depending on the desired target.


ISBN: 978-81-947843-8-8
ISSN: 2582-3922

TABLE I LIST OF EVENTS

| Event No. | Date | Time | Latitude | Longitude | Depth | Magnitude | Event Location Name | Distance (Km) | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | MDJ | INCN |
| 1 | 13/02/2000 | 2:57:07 | 42.863 | 131.68 | 501.5 | 6 | E. Russia-N.E. China Border Reg. | 258 | 736 |
| 2 | 08/09/2000 | 14:18:21 | 41.766 | 130.897 | 582.3 | 4.9 | North Korea | 335 | 600 |
| 3 | 16/04/2002 | 22:52:38 | 40.658 | 128.652 | 10 | 4.6 | North Korea | 447 | 394 |
| 4 | 28/06/2002 | 17:19:30 | 43.763 | 130.665 | 568 | 7.3 | E. Russia-N.E. China Border Reg. | 129 | 777 |
| 5 | 15/08/2004 | 15:36:56 | 43.3722 | 131.1058 | 544.6 | 4.6 | E. Russia-N.E. China Border Reg. | 185 | 756 |
| 6 | 16/12/2004 | 18:59:12 | 41.9181 | 127.968 | 10 | 4 | North Korea | 327 | 507 |
| 7* | 09/10/2006 | 1:35:27 | 41.3107 | 129.0552 | 0 | 4.3 | North Korea | 370 | 474 |
| 8 | 19/05/2008 | 10:08:36 | 42.4852 | 131.882 | 515.6 | 5.7 | E. Russia-N.E. China Border Reg. | 301 | 714 |
| 9 | 18/04/2009 | 3:56:31 | 42.815 | 130.6949 | 568 | 4.9 | E. Russia-N.E. China Border Reg. | 220 | 686 |
| 10* | 25/05/2009 | 0:54:42 | 41.2937 | 129.0699 | 0 | 4.7 | North Korea | 372 | 473 |
| 11 | 10/08/2009 | 12:42:53 | 43.5291 | 130.6883 | 575.5 | 4.8 | E. Russia-N.E. China Border Reg. | 150 | 755 |
| 12 | 18/02/2010 | 1:13:18 | 42.6027 | 130.6993 | 573.7 | 6.9 | E. Russia-N.E. China Border Reg. | 242 | 666 |
| 13 | 21/02/2010 | 7:29:08 | 42.4952 | 130.8793 | 561.5 | 4.5 | E. Russia-N.E. China Border Reg. | 258 | 665 |
| 14 | 10/05/2011 | 15:26:05 | 43.3199 | 131.0913 | 554.9 | 5.7 | E. Russia-N.E. China Border Reg. | 189 | 751 |
| 15* | 06/01/2016 | 1:30:01 | 41.2996 | 129.0467 | 0 | 5.1 | North Korea | 371 | 473 |
| 16* | 09/09/2016 | 0:30:02 | 41.3228 | 128.9866 | 0 | 5.3 | North Korea | 371 | 473 |

Nuclear explosion events are indicated by * symbol with event number.

The correlation for two time series x and y can be defined as inner product of x and time shifted version of y at each time instant. In seismology we often use correlation to clustering of similar events or detection of repeated events in past time series of seismic data. A normalized cross-correlation coefficient is used to determine the similarity between two signals. The normalized cross-correlation is obtained by dividing crosscorrelation by the square root of product of energy of x and
y.

$$\rho = max \frac{< x, y(t-\tau) >}{< x, x >^{0.5} < y, y >^{0.5}} \quad (1)$$

### 3.2 Continuous Wavelet Transform (CWT)

Fourier transform is used to represent signal in frequency domain. Fourier transform gives information about frequencies present in signal. The basis function used for Fourier transform has infinite duration. This is useful in stationary signal having the same frequency content at all time. But it fails to differentiate between two signals having same frequency content but the frequencies occur at different times. The Short Time Fourier Transform provides time localization using windowed Fourier transform. The analyzing time window for STFT is fixed so it does not provide compact support. Wavelet is small wave which has finite duration. Wavelet transform gives timefrequency localization of signal using compact basis function. Seismic signal is of non-stationary nature. The time–frequency representation such as wavelet transform of seismic signal gives more information to analyze the seismic signal. If the wavelet function $\psi \in L^2(R)$ meets the following criteria, it is called mother wavelet [21].

1) Zero Mean

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \quad (2)$$

2) Finite Energy

$$\int_{-\infty}^{+\infty} |\psi(t)|^2 \, dt < \infty \quad (3)$$

3) Admissibility Condition

$$0 < C_\psi = \int_{-\infty}^{+\infty} \frac{|\psi(w)|}{|w|} \, dw < \infty \quad (4)$$

A wavelet function may be real or complex. By scaling and translating the mother wavelet, a family of wavelet functions is obtained.

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}} \psi(\frac{t-\tau}{s}) \quad (5)$$

Where, s is scaling parameter that controls width of wavelet (s¿1 stretching and s¡1 compression) and is translation parameter controlling location of wavelet.

The complex Morlet wavelet also called modulated Gaussian is chosen as analyzing function for seismic data. The complex Morlet wavelet is symmetrical, non-orthogonal. This complex wavelet function provides amplitude and phase information, making it better suited to capturing oscillatory behavior in data. Morlet wavelet is crude wavelet defined by mathematical expression:

$$\psi_0(\eta) = \pi - 1/4ei\omega 0\eta e - \eta^2/2 \quad (6)$$

Where non-dimensional frequency $\omega_0 = 6$ is taken to satisfy admissibility condition.

Correlating *psis,tau* at different scales and shifting along the signal's length at each instant of time yields wavelet transform coefficients. CWT of $x(t) \in L_2(R)$ is function of two variables,

$$W_{x,\psi_{(\tau,s)}}(\tau, s) = \int_{-\infty}^{+\infty} x(t) \, \frac{1}{\sqrt{|s|}} \psi^*(\frac{t-\tau}{s})dt \quad (s,\tau)\epsilon, s \neq 0$$

(7)


ISBN: 978-81-947843-8-8 ISSN: 2582-3922

In discrete form, CWT of time series ($x_n, n = 1 \cdots N$) having equal time interval $\delta t$ is defined as convolution of $x_n$ with scaled and normalized wavelet function [16].

$$W_n^X(s) = \sqrt{\frac{\delta t}{s}} \sum_{n'=1}^{N} x_{n'} \psi_0 \left[ (n' - n) \frac{\delta t}{s} \right] \quad (8)$$

### 3.3 C. Cross wavelet transform (XWT)

The cross-wavelet transform of two-time series $x(t)$ and $y(t)$, is defined as

$$W_{xy} = W_x W_y^* \quad (9)$$

Where, $W_x$ and $W_y$ are continuous wavelet transform of $x(t)$ and $y(t)$ respectively. $W_y^*$ denotes complex conjugate of $W_y$. Cross-wavelet power is $|W_{xy}|$.

$$\left(XWP\right)_{xy} = |W_{xy}| \quad (10)$$

The wavelet power spectrum gives local variance of time series at each time and frequency. Similarly, the cross-wavelet power spectrum provides local covariance of time series. So, crosswavelet power is measure of common power in time series.

*D. Complex Wavelet Coherency* Complex wavelet coherency is defined as

$$\rho_{xy} = \frac{S(W_{xy})}{[S(|W_x|^2)S(|W_y|^2)]^{1/2}} \quad (11)$$

Where S denotes smoothing operator in both time and scale. In polar form, $\varrho_{xy} = |\varrho_{xy}| e^{i\varphi_{xy}}$. The absolute value of complex wavelet coherency is called wavelet coherency and denoted by $R_{xy}$,

$$R_{xy} = \frac{S(W_{xy})}{[S(|W_x|^2)S(|W_y|^2)]^{1/2}} \qquad 0 < R_{xy} < 1 \quad (12)$$

The angle $\varphi_{xy}$ of the wavelet complex coherency is called the phase-difference i.e.

$$\phi_{xy} = arctan \left[ \frac{\Im(S(W_{xy}))}{\Re(S(W_{xy}))} \right] \quad (13)$$

### 3.4 E. Maximum Covariance Analysis (MCA) method

The wavelet transform has been widely used in time series analysis. Wavelet analysis decomposes time series into timefrequency plane. The wavelet cross spectral analysis used to find association between two time series. In our problem to classify earthquake and nuclear explosion wavelet coherence and wavelet cross-spectrum are used to identify and characterize common patterns in time series. Classification of timeseries using wavelet or cross-wavelet is complex problem. To classify time series hierarchical clustering is used in timefrequency plane. The matrix of dissimilarity is constructed to compare wavelet spectra. Maximum covariance analysis (MCA), a multivariate approach for comparing Spatiotemporal fields, compares wavelet spectra.

MCA is also called singular value decomposition (SVD). Between each pair of wavelet spectra $W_i$ and $W_j$, we compute the covariance matrix $R_{ij}$ [22].

$$Rij = WiWjT \quad (14)$$

where, $W_j^T$ represents transpose of $W_j$. On $R_{ij}$, the singular value decomposition is used.

$$R_{ij} = U\Gamma V^T \quad (15)$$

The matrix U and $V^T$ are orthogonal and contain singular vectors of $W_i$ and $W_j$, respectively. Γ is a diagonal matrix whose diagonal elements are singular values in descending order. Each singular value corresponds to common patterns of decreasing importance between the two spectra. The SVD finds an orthonormal basis for each spectrum, determined by their respective singular vectors maximizing their mutual covariance.

The leading patterns are obtained by projecting the wavelet spectrum onto its respective singular vectors,

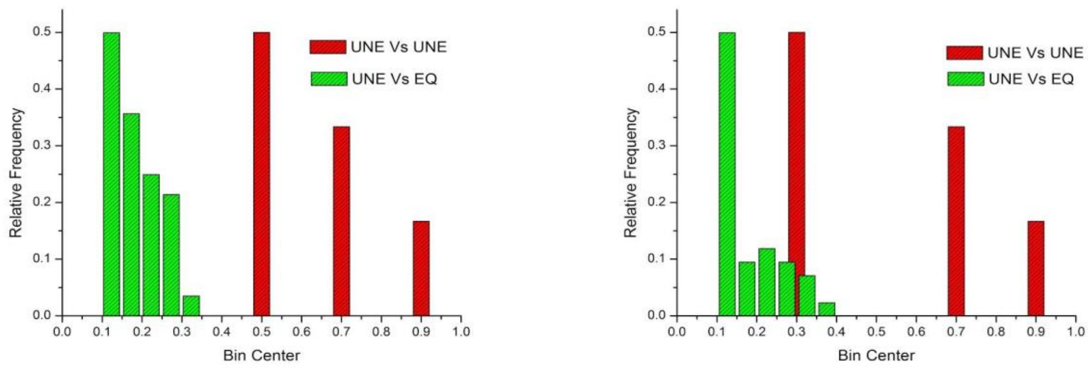


Fig. 3. Histogram of cross correlation coefficient at MDJ station (left) and INCN station (right)

with F being the maximum frequency common to both spectra, and show how respective frequency patterns evolve over time.

$f$=$F$

$L^k_i(t)$ = X $U^k \times W_i(f,t)$

$f$=1

(16)

$f$=$F$

$L^k_j(t)$ = X $U^k \times W_j(f,t)$

$f$=1

With a given number of leading patterns, N, it is possible to reconstruct the initial wavelet spectra using the relationship:

$k$=$N$

$WiN$ = X $Uk \times Lki$

$k$=1

$k$=$N$

$WjN$ = X $Uk \times Lkj$ (17)

$k$=1

The leading patterns and singular vectors obtained by the MCA over a given number of axes are compared to determine the distance between two wavelet spectra.By calculating the angle between each pair of consecutive segments, this metric compares two vectors.

$$D(L_i^k, L_j^k) = \sum_{t=1}^{N-1} tan^{-1}\left[\left|\left(L_i^k(t) - L_j^k(t)\right)\right| - \left|\left(L_i^k(t+1) - L_j^k(t+1)\right)\right|\right. \quad (18)$$

$L^k_i(t)$ and $L^k_j(t)$ are $k^{th}$ pair of leading pattern for $W_i$ and $W_j$, having vector length n. The sum of angles obtained between each pair of leading patterns and singular vectors is a comparable metric. The distance was then calculated as a weighted average of the distances between each pair of singular vectors, with leading patterns held. We calculate the distance $DT(i,j)$ between wavelet spectra i and j using the formula:

$$DT(i,j) = \frac{\sum_{k=1}^{k=K} w_k \times \left(D(L_i^k, L_j^k) + D(U_i^k, V_j^k)\right)}{\sum_{k=1}^{k=K} w_k} \quad (19)$$

Where, weights ($w_k$) are set equal to the sum of covariance explained by each axis ($wk$). The distance matrix suitable for cluster analysis is filled with distance DT(i,j). This distance matrix DT(i,j) is used for the hierarchical clustering of Nuclear explosions and earthquakes.

## 4 Results

### 4.1 Waveform matching for seismic signal identification

*1) Waveform Cross-correlation:* Cross correlation between P-wave signatures in the waveform of earthquakes with nuclear explosions vis-a-vis the same between earthquakes/ nuclear explosions with themselves is examined. The 2006 nuclear explosion is said to be possibly fizzle. Shown in Fig. 1, although the seismogram of nuclear explosion is similar in nature, the cross-correlation coefficient of a 8 seconds (1 sec before onset and 7 sec after onset) P phase of nuclear explosion conducted in 2006 with other nuclear explosion events is low for data recorded at both MDJ and INCN. Fig. 3 shows histogram for all combinations of cross correlation coefficients of nuclear explosion vs nuclear explosion (UNEUNE) and earthquakes vs nuclear explosion (UNE-EQ) pairs at MDJ and INCN stations. It can be seen that cross correlation of nuclear explosions with themselves is generally high. The most of event pairs of earthquake and nuclear explosion have low cross correlation coefficient at both stations. The nuclear explosion events can be discriminated at MDJ station by keeping cross correlation coefficient threshold of 0.45. There is overlapping between cross correlation coefficients of UNEUNE and UNE-EQ at INCN hence the nuclear explosion and earthquakes cannot be discriminated at INCN. The crosscorrelation coefficient is affected by SNR ratio. Hence we need to apply band pass filter to obtain high SNR to perform crosscorrelation. Here we cannot differentiate events using crosscorrelation based statistics. Thus, such a correlation based classifier is unreliable for single station. Thus, there is a need to build a reliable classifier.

*2) Classification based on Cross-Wavelet Transform (XWT):* The cross-wavelet spectra of P phase (from onset to 20 sec) of nuclear explosion 2006-09-09 and 2016-01-06 is shown in Fig. 4. The Common power between two events is concentrated around 2-5 Hz for 0-3s to 8-12s.

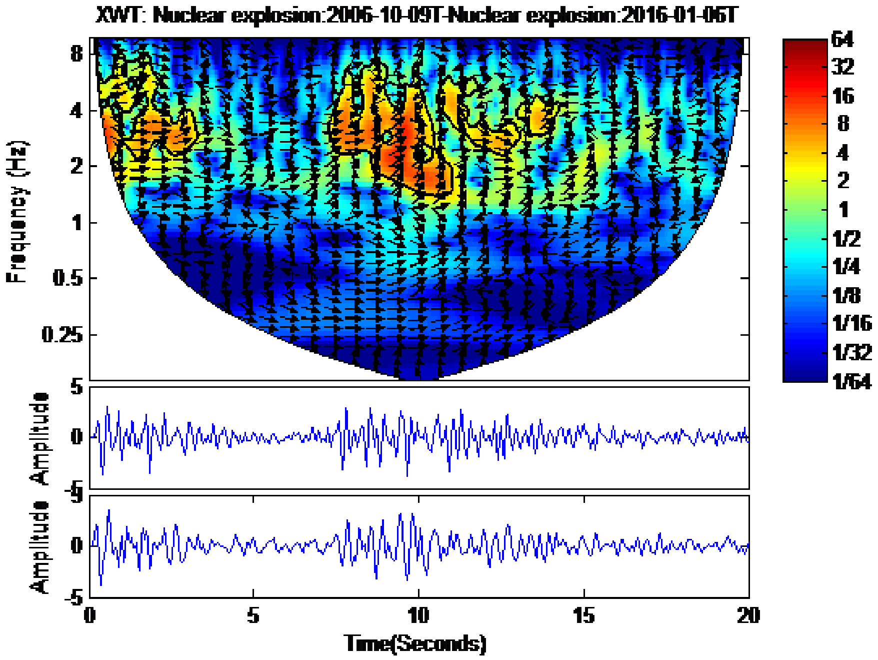


Fig. 4. Cross-wavelet spectrum of P phase onset to 20 sec of seismogram of nuclear explosion conducted on 2006-10-9 and 2016-01-06 recorded at MDJ station. The bottom waveforms shows normalized P phase of nuclear explosion seismograms of 2006-10-9 and 2016-01-06 respectively

3) *Wavelet transform Coherence:* Wavelet coherence is to find lead-lag relationship in time series or In above Fig. 1 seismograms of nuclear explosion events 2006-10-06 and 201601-06 looks similar in nature but cross-correlation between two events is low at both MDJ and INCN station. This indicates the two events are not similar. Wavelet coherence gives correlation between two time series at different scales. Wavelet coherence is not affected by the noise and hence doesn't require any filter; whereas correlation is affected by noise and requires filter. Wavelet Coherence of nuclear explosion 2006-09-09 and 201601-06 at MDJ and INCN station is shown in Fig.5 and Fig. 6 respectively. It is difficult to find common patterns in two time series using naked eye. Color representation of wavelet coherence makes it easy to find patterns. In below Fig. 5 and Fig. 6 the correlation at each frequency band can be found visually. The red color indicates 1(high correlation) while blue color indicates 0 (no correlation). Thus wavelet coherence plot gives better visualization of common patterns in both events localized in time-frequency plane.

4) *Classification Based on Continuous Wavelet Transform(CWT):* Time-frequency analysis of nuclear explosion seismogram conducted by North Korea on 9 Oct, 2006 is shown in Fig. 7. For this analysis; broadband high gain vertical sensor data recorded at MDJ station China of GSN network (sampling frequency of 20 samples per second) is used. Morlet wavelet with a dimensionless frequency ($\omega_0$= 6) and total 74 scales (from 0.1 to 6.7806) with 12 octaves per scale is taken for decomposition. Resulting wavelet power spectrum shows the change in frequency content of seismogram signal with time. As shown in Fig. 7, color map ranges from blue to red where Blue represents low power and red represents high power. It can be seen that for nuclear explosion, significant

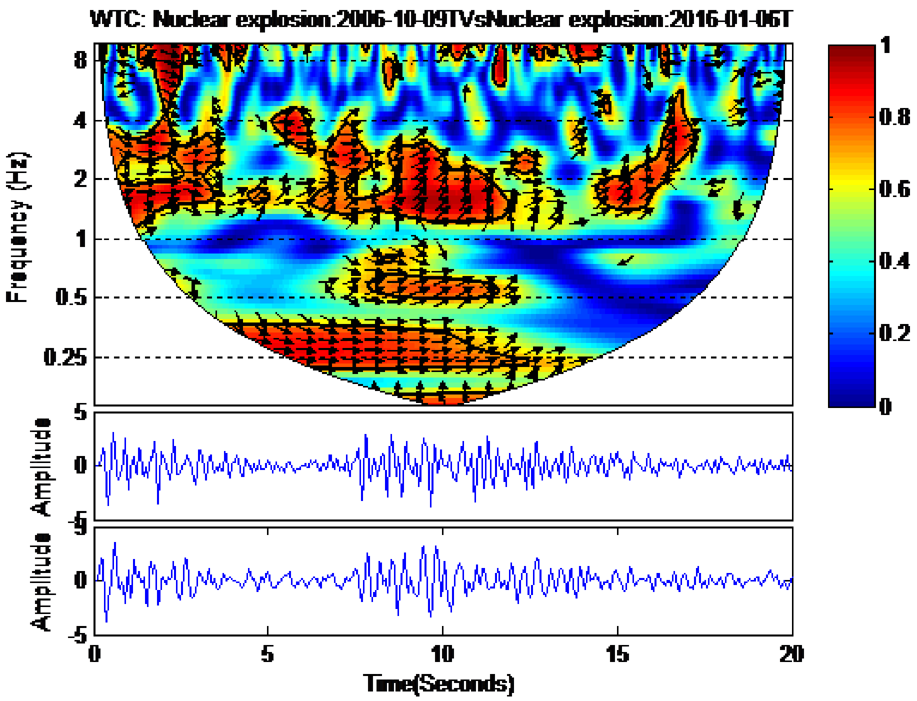


Fig. 5. Wavelet coherence of P phase from onset to 20 sec of nuclear explosion 2006-10-09 and 2016-01-06 recorded at MDJ station china. The red color indicates the high correlation between two nuclear explosions.


Proceedings DOI: 10.21467/proceedings.114
ISBN: 978-81-947843-8-8
Series: AIJR Proceedings
ISSN: 2582-3922

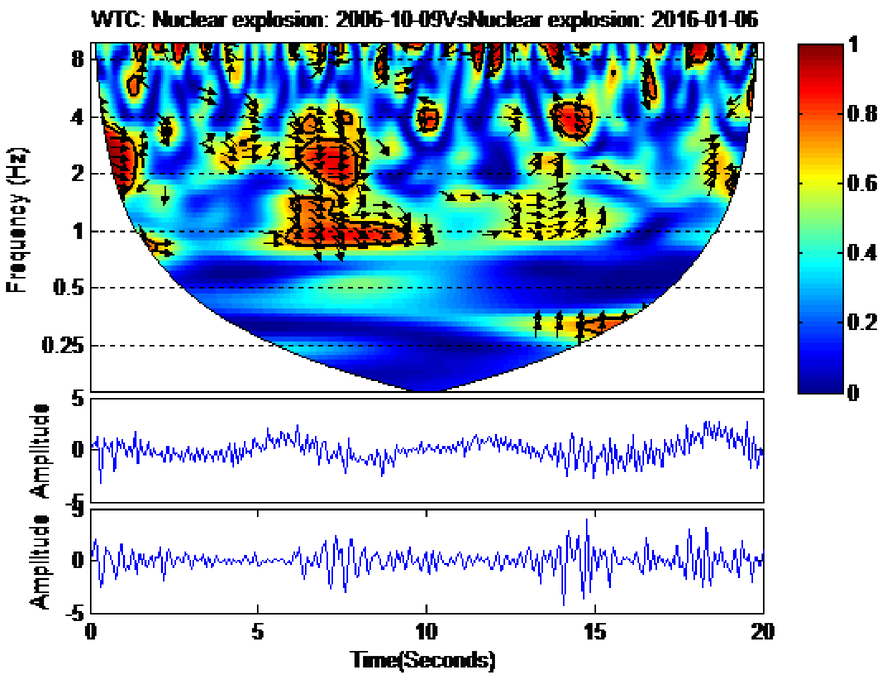


Fig. 6. Wavelet coherence of P phase from onset to 20 sec of nuclear explosion 2006-10-09 and 2016-01-06 recorded at INCN station. The red color indicates the high correlation between two nuclear explosions.

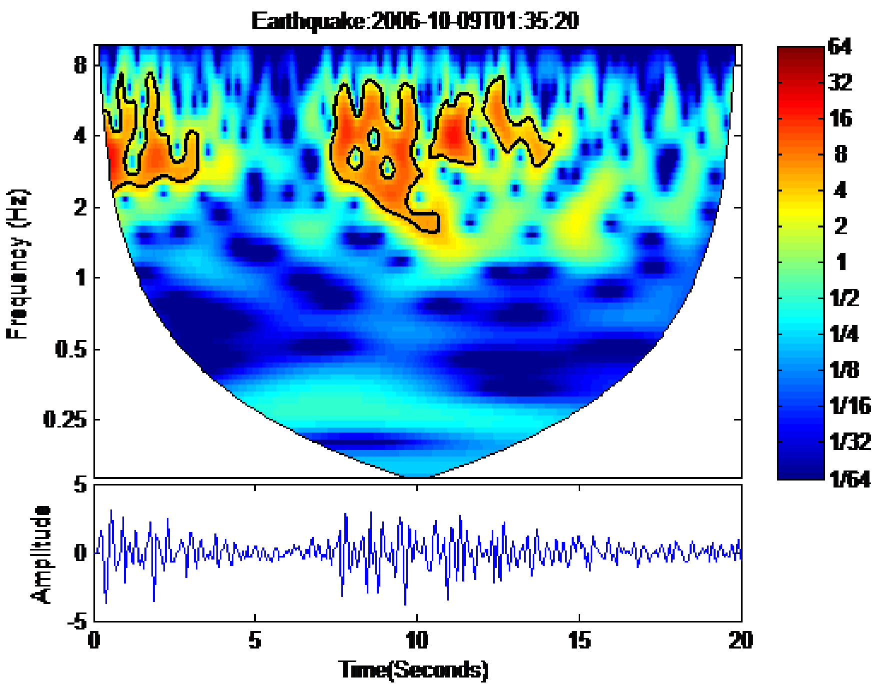


Fig. 7. Wavelet power spectrum of P phase from onset to 20 seconds of seismogram of Nuclear explosion conducted by North Korea on 2006-10-09 recorded at MDJ station. The color-map of wavelet power spectrum is shown right where blue indicates low power and red indicates high power. The 5% significance level against red noise is shown by thick black contour. The cone of influence i.e. region affected by edge effects is shown in thick black line amount of energy is concentrated in frequency band of 1 Hz to 8 Hz.

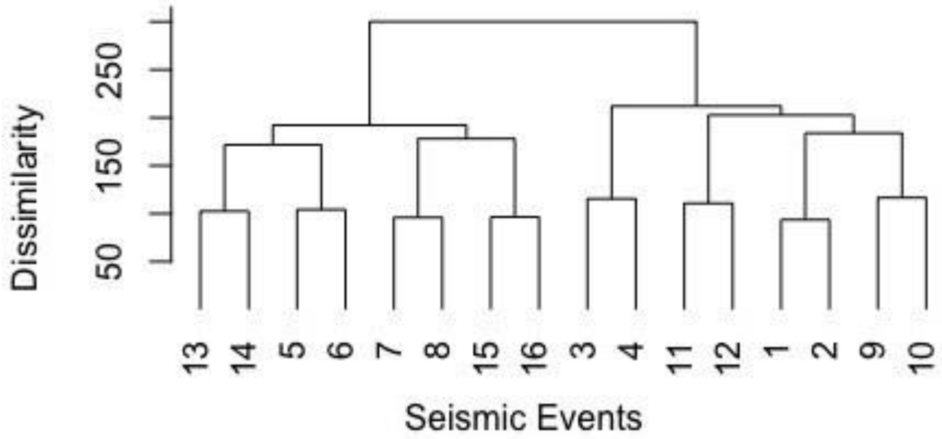


Fig. 8. Clustering of Earthquake and nuclear explosion events

The CWT plot gives better visualization of energy distribution of signal in time-frequency plane. Further, CWT is performed for both earthquake as well as nuclear explosion events. The objective is to classify earthquake and nuclear explosions based on wavelet magnitude spectrum. The dissimilarity between multiple wavelet spectra is computed using maximum covariance analysis method explained above. The hierarchical clustering of nuclear explosions and earthquakes is done using Ward method shown in Fig. 8. It shows the nuclear explosion events and earthquakes are classified correctly but the earthquake event 8 is wrongly classified as nuclear explosion. The closest events are nuclear explosion event 7 and earthquake event 8. Clustering achieved a classification accuracy of 94%.

## 5 Conclusion

The proposed method cross-wavelet transform and wavelet coherence gives covariance and correlation between two-time series. These methods can be powerful discriminator of nuclear explosion and earthquake at single station. The clustering of seismic events using CWT is done without extracting any features from CWT. The cross-wavelet based methods are good for discriminating earthquakes and nuclear explosion. The preprocessing such as filtering is not required which is tough job to select frequency band to increase signal to noise ratio. This method can be used for online classification but the onset of the incoming events is detected accurately.

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