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P-Wave Detection Alert System for Multi-Seismic Stations

Ahmed Abdelazim[1]*, Emad M. Zieur [2] , Adly S. Tag Eldien[2], Ali G. Hafez[1,3,4], M.Sami Soliman [1,4], Ahmaed Faried [1]

[1] Department of Seismology,National Resarch Institute of Astronomy and Geophysics,Helwan , Cairo, Egypt.
[2] Department of Electrical Engineering, Faculty of Engineering at Shoubra, Benha University, Cairo, Egypt.
[3] Resarch and Development Divisio, LTLab ,Inc.,Fukuoka,Japan.
[4] Department of Communication and Computer Engineering, Faculty of Engineering,Nahda University in Beni Suef, Beni Suef, Egypt.
[*] Corresponding Author.
E-mail: abdelaziem@nriag.sci.eg , emadzieur2010@gmail.com, adlymerg@yahoo.com,aligamal@itlab.com,mahoud.salam@nriag.sci.eg.geo_eagle@live.com

Abstract: This paper proposes an automatic P-wave picking algorithm based on discrete wavelet transform (DWT). This algorithm is applied to multi-station seismic data from the Egyptian National Seismic Network (ENSN) to enhance the accuracy and reliability of P-wave detection. The real-time detection of P-waves suggests a focus on practical applications for implementing earthquake early warning (EEW) systems. The integration of this algorithm into the system generates an event report and sends it via email, containing all the stations that recorded this event within the sub-network. The proposed algorithm has the major advantage of providing accurate P-wave arrival times with minimal processing time. In addition, this algorithm can detect even the smallest events, such as micro-earthquakes, due to different frequency sub-band analyses of discrete wavelet transform (DWT) with varying thresholds for every station. These features might be suitable for developing an Earthquake Early Warning (EEW) system. In a challenging test environment, the system achieved a remarkable 95.97% detection rate with minimal false alarms in the Cairo subnetwork, 80.88% in the Red Sea subnetwork, and 94.2% in the North Coast subnetwork.

Keywords : Automatic Detection P-wave, Real-time monitoring, Earthquake Early Warning System, Egyptian National Seismic Network, DWT

1. INTRODUCTION

Seismic networks have the primary purpose of locating earthquakes and determining their magnitude. The process of deciding earthquake location usually requires a minimum of three stations. These networks range from small mining networks that detect micro-earthquakes to global networks that record worldwide seismic data. One special application of a seismic network is to create an Earthquake Early Warning (EEW) System. After a strong earthquake has occurred, the system can send an alarm a few seconds before the damaging wave [1]. The P-wave of an earthquake is the first wave to arrive at a seismometer and is responsible for the initial shaking felt during an earthquake, but this P-wave is not a destructive wave. The destructive waves are S-waves and surface waves (phases). These phases come after the P-wave onset in about two to a few tens of seconds, depending on the location of the epicenter of the earthquakes. In the face of powerful earthquakes, extracting critical information from seismic waves relies on the quick decision-making of analysts or the capabilities of automated software, as every second counts.

Automatic detection of P-wave arrival time is essential for calculating earthquake parameters and developing Earthquake Early Warning systems (EEW). Real-time monitoring requires automated algorithms, although manual inspection is the most precise method. There are many ways to detect P waves in seismic signals automatically. One of the most common methods is called Short-Term Average/Long-Term Average (STA/LTA) detection. This method compares the short-term average (STA) of the seismic signal with the long-term average (LTA) of the seismic signal. When STA exceeds LTA by a certain threshold, a P wave is detected[2][3][4]. The International Association for

Seismology and Physics of the Earth's Interior (IASPEI) has developed the STA/LTA algorithm for real-time earthquake detection and acquisition. It has become a popular algorithm, although it can give false alarms from other transient signals caused by human activity or natural phenomena when tested on real-time data. Other algorithms, such as short quadratic Fourier transform (STFT), DWT, and maximum overlap DWT (MODWT) have been developed and tested to detect P-wave arrivals with high accuracy and few parameter settings[5][6][7][8][9][10][11][12]. However, these algorithms have only been tested with offline data. In recent years, significant technological advances and increased computing power have enabled the use of deep-learning models to analyze local earthquakes. These models have now reached a level of performance that is at least comparable to that of human analysts. Some noteworthy examples of such achievements include the work of [13][14][15][16][17] [18] [19] [20] [21] [22]. This information can then be used to issue early warnings to the public and authorities. Some research has used only the first 2-3 seconds of the P wave (Saad et al., 2021)[23][24].

The objective of the article is twofold. Firstly, it aims to develop an automated P-wave algorithm that will use Discrete Wavelet Transform (DWT) to process seismic waves. The algorithm will decompose the signals, denoise, and reconstruct them to obtain the wavelet coefficient. It will then establish thresholds within specific bands to improve the sensitivity of P-wave features and determine the arrival time in almost real time. This process will take place in three different sub-networks of the Egyptian National Seismic Network (ENSN). Secondly, the algorithm will notify analysts in ENSN via email. The email will contain the time of the event and the names of the stations that recorded it. The algorithm is structured to operate concurrently on multiple channels through multi-threading, thereby optimizing overall processing efficiency. To ensure accuracy, the results obtained from the algorithm will be cross-checked with the manual solution.

2 Wavelet Transform Analysis

Seismic P-wave signals are complex, non-stationary signals and contain a lot of noise. These signals have different frequencies that change over time, making it difficult to analyze and identify them accurately. To overcome this challenge, it is crucial to transform the signals, remove any noise interference, and separate the information from different frequencies. Wavelet transform analysis is a signal processing technique that decomposes a signal into a set of wavelet coefficients. Wavelets are small, oscillating functions that are localized in both time and frequency. This makes wavelet analysis well-suited for analyzing signals that contain transient features, such as P waves in seismic data[25]. In 1988, Daubechies developed a smoother orthonormal, compactly supported wavelet basis The wavelet theory has been applied to seismic signals through wavelet transform [26][27]. The Wavelet Transform decomposes a signal into basic functions at different timescales $\psi_{m,k}$(t).

$$\Psi_{m,k}(t) = \frac{1}{\sqrt{m}}\Psi\left(\frac{t-k}{m}\right) \qquad (1)$$

Where m and k are the scale and translation of the daughter wavelet, the term m−1/2 normalizes the energy for different scales, whereas the other terms define the width and translation of the wavelet. Each of these functions is tailored to capture specific frequencies and time intervals, much like how Fourier analysis uses sine waves of varying frequencies, amplitudes, and phases to represent signals[28][25].

2-1 Discrete-Time Wavelet Transform (DWT)

The Discrete Wavelet Transform (DWT) is a type of wavelet transform. The components represented here are sub-band compositions of the original signal that are localized around frequency bands instead of specific frequencies. This makes them a better representation of the signal compared to the Short-Time Fourier Transform (STFT) as they offer a more accurate representation of the signal along the time domain. This information was mentioned in a study by[9]. The coefficients at each scale are calculated using the hierarchal algorithm Obtain Scaling and Wavelet coefficient for stages 1 and 2, as shown in Figure 1. The coefficients can be used to derive multi-resolution components. as explained by [25]. The input vector, denoted by X, is transformed using scaling and wavelet filters, G(k/N) and H(k/N) respectively. The first stage of the transform yields two sets of coefficients: V1 representing the low-frequency content (approximation) and W1 representing the high-frequency content (detail). These coefficients are then used to calculate the multi-resolution components of the signal at different frequency bands. The equations for these calculations can be found in[25].

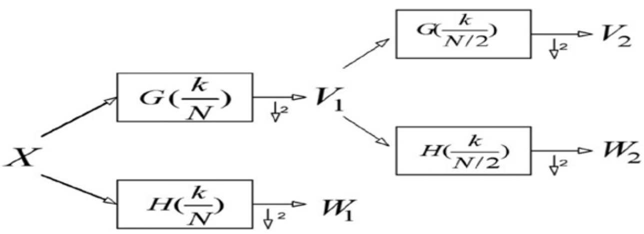

FIG 1 Utilizing the hierarchal Algorithm ObtainScalingandWaveletCoefficientsforStages.

3. Methodology

The software Python is used to connect to the main server to acquire seismic data. This section outlines the methodology for establishing a real-time connection between the ObsPy Python library and Ring Server to acquire seismic data from a network of seismic stations as shown in Figure 2. This method combines ObsPy for data retrieval and processing with real-time data access from the Ring Server by specifying the network code, station code, and channel code associated with the desired stations and setting the desired time window for data retrieval[29]. Next step After data retrieval by obspy, applied DWT, which essentially acts like a series of stacked high-pass and low-pass filters shown in Figure 3. This efficient technique allows us to split the signal into multiple frequency sub-bands, each capturing specific frequency ranges.

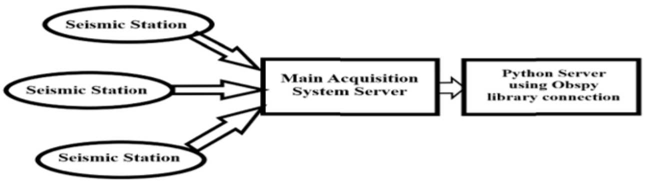

FIG 2 Connection between the Obspy python library and Ringsrever

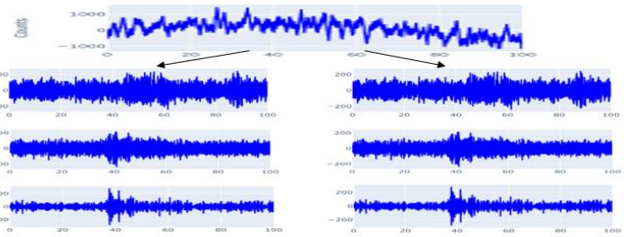

FIG 3 DWT acts as a series of high-pass and low-pass filters.

3.1 Wavelet-based P-Phase Detection Algorithm

The proposed algorithm uses the DWT decomposition of a seismic signal into five frequency ranges for vertical components for each station. DWT uses specialized mathematical functions called "wavelets" to analyze these high-frequency layers. These wavelets act like tiny detectors, searching for features in the signal that match their shape and scale (Daubechies5). The next step reconstruction signal from the third coefficient of high-frequency bands for each station (vertical components). After the step of reconstruction of the signal, this process involves several key steps: Statistical Feature Extraction: For each station, squared values of the third coefficient as shown in Figure 4, are utilized to capture noise levels, and highlight P-wave arrivals.

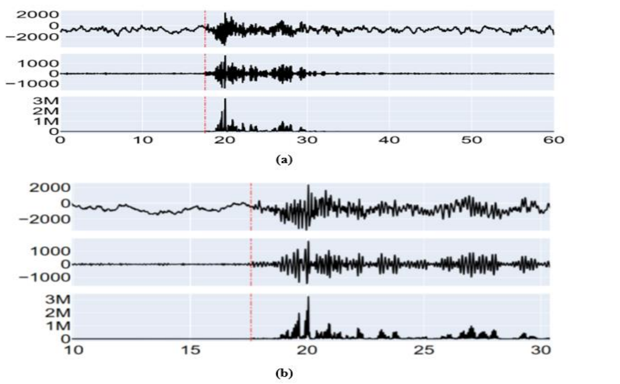

FIG 4 (a) squared value of the third coefficient and. (b) squared value of the third coefficient and zoomed window

The squaring step is crucial to ensure: (1) The noise level is significantly lower than the event level. (2) All the elements in this system have positive values. (3) Changes in amplitude are closely synchronized with the arrival of the p-wave. (4) The increase in amplitude at arrival is very distinct, making it easy to determine the onset. After this step, the adjusted threshold for each station is calculated by summing the squared values of each window of 8 samples, representing the signal energy within those periods, as seismic data are continuously recorded in ENSN at 100 samples per second. The threshold was adapted for the stations to distinguish between background noise (low-amplitude vibrations) and actual seismic signals (larger amplitude ground shaking), defining the first change between high-amplitude and actual low-amplitude by red line value (Threshold), as shown in Figure 5. According to an earthquake data study from the ENSN, which includes weak and strong earthquakes recorded over the past 10 years, the average threshold for each monitoring station was established. It was found that if the powers within a continuous 0.32-second window exceed the set threshold, an event is declared for that particular station. Thresholding in real-time seismic data processing presents a trade-off. Lowering the threshold enhances the algorithm's ability to detect weak seismic signals but increases the risk of false alarms. Conversely, a higher threshold prioritizes warnings for strong events, making it suitable for the earthquake early warning (EEW) system.

Finally, the system triggers a network alarm when at least 4 stations located close together register an event within a predetermined time window. and sends e-mail notifications to the relevant personnel by **Python (pywhatkit Library)**, including the event time and station detectability information. The algorithm analyzes seismic data within a specific time window (T) to detect P-wave onsets within a chosen sub-network of the ENSN.

This window is calculated as the difference between the first and last station detection event times within the sub-network. Due to differences in expected arrival times, the P-wave detection time window (T) is set to 10 seconds in the Cairo subnetwork and 30 seconds in the other two.

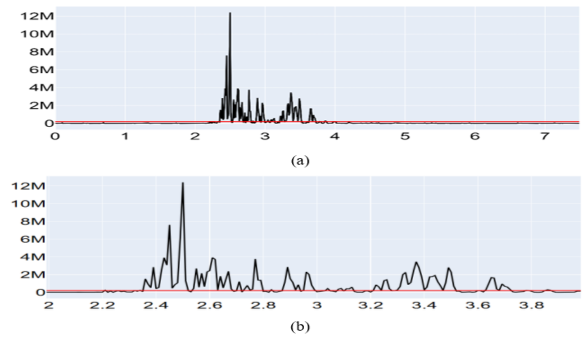

FIG 5 (a) Threshold of 8 samples. (b) Threshold zoomed window.

Key considerations for setting T:

Sub-network size: As the sub-network's geographic area expands, T needs to also increase to account for greater travel times of seismic waves. However, this enlargement of T also raises the likelihood of false alarms due to the increased potential for noise interference. Event magnitude: The velocity of P-waves remains constant regardless of event magnitude, so both weak and strong events are analyzed using the same T. Sensitivity trade-off: Detecting events requires careful consideration of the threshold used to declare an event. This threshold must balance sensitivity and accuracy, as lowering it can increase the detection of micro-tremors while also increasing the risk of false alarms. Therefore, selecting appropriate T and event detection thresholds is crucial to optimize the algorithm's sensitivity and avoid false alarms.

4. Real-time test results

The algorithms in the Figure 6 block diagram show the procedure of detecting the data and P-wave arrival picking. Were tested in real-time from 01-01-2023 to 31-10-2023 using seismic data from three subnetworks in ENSN (Cairo subnetwork, North Red Sea subnetwork, and North Coast subnetwork). The ENSN network consists of six subnetworks as illustrated in the provided Figure7 according to the seismic sources and the distribution of ENSN stations. Additionally, analyst-reviewed data was provided for comparison with the discrete wavelet detector.

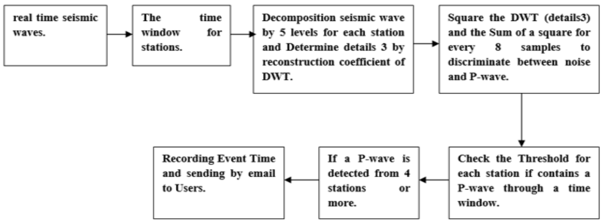

FIG 6 Block diagram showing the procedure of detecting P-wave arrival picking

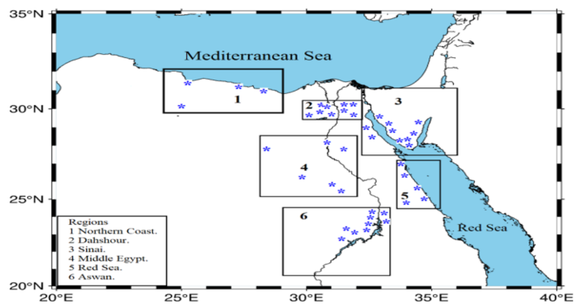

FIG 7 The Egyptian National Seismic Network is divided into six regional subnetworks.

4.1 Cairo subnetwork:

An algorithm was developed to detect P-waves in real-time monitored data from eight stations in **the Cairo subnetwork(HLW, KOT, SQR, MYD, NAT, RYAN, RAM, NBNS).** The algorithm successfully detected 143 out of 149 events, including local, and regional earthquakes and quarry blasts, resulting in a success rate of 95.97%. The system generated only six false positives in ten months. The P-wave arrival times deviated from manual picks by an average of 0.2-0.4 seconds. The algorithm detected an event with an Ml of 3.08 recorded by ENSN as shown in Figure 8, both the manual and automatic picking are demonstrated, with the bold line being the manual picks and the dashed line being the automatic picks illustrated in Figure 9. The example clearly shows that the error (difference between automatic and manual) can be neglected.

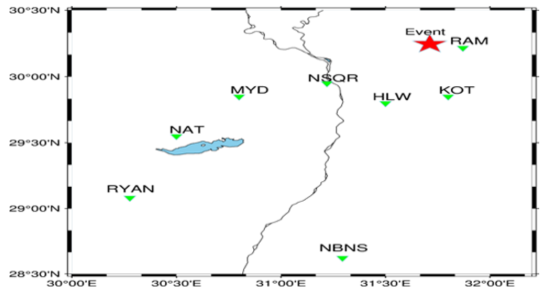

FIG 8 The event was recorded by ENSN And detected by Algorithm

4.2 North-Red Sea subnetwork:

An algorithm designed to detect P-waves in real-time monitored data from thirteen stations in the **North Red Sea subnetwork(TR1, TR2, KAT, BST, SUZ, RDS, ZAF, ZNM, GRB, HRG, NUB, DHB,)**. The algorithm detected 749 out of 926 events (80.88% success rate) recorded by ENSN for local, and regional earthquakes. Only 177 false positives were detected in ten months.

4.3 North-Coast subnetwork:

An algorithm designed to detect P-waves in real-time monitored data from nine stations in the **North-Coast subnetwork(SLM, FOKA, MATC, SWA, SBRA, NDB3, SMAT, BDR, HAMAM)**. The algorithm detected 130 out of 138 events (94.2% success rate) recorded by ENSN for local, and regional earthquakes. Only eight false positives were detected in ten months.

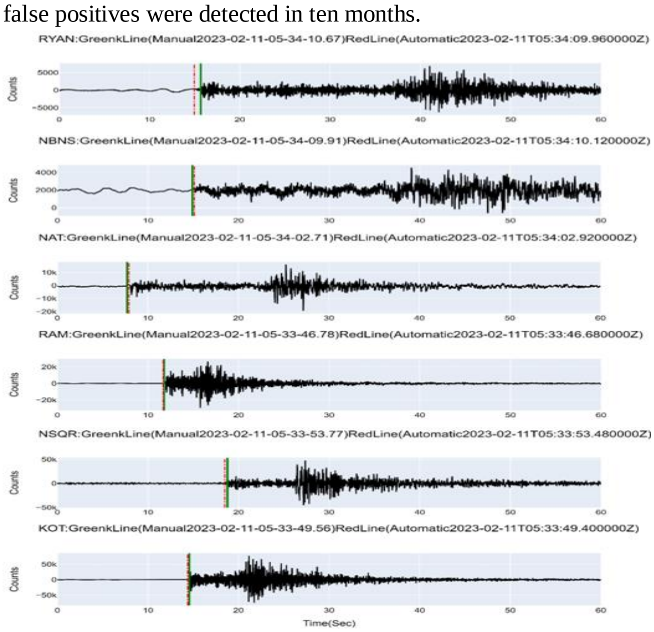

FIG 9. Differences between automated and manual solutions for a magnitude 3.08 local earthquake recorded within the Cairo subnetwork.

5. Conclusions

The algorithm was tested on real-time data from local and regional events on vertical component stations, and it accurately identified P-phase detections. The algorithm employs a three-step process: multi-resolution analysis, wavelet selection, and station-specific thresholding. The varying percentages in the three subnetworks can be attributed to differences in time windows and distances between stations in each subnetwork. Finally, the accuracy of the software's results was measured by comparing them with the picks of a human analyst, it can be used for routine analysis in the ENSN laboratory, and we can alert by e-mail and other different ways of communication.

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