Algorithms for Detecting P-Waves and Earthquake Magnitude Estimation: Initial Literature Review Findings

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ABSTRACT

Earthquake Early Warning System (EEWS) plays a major role during an earthquake in alerting the public and authorities to take appropriate safety measures during an earthquake. Generally, EEWSs use three types of algorithms to generate alerts during an earthquake; namely: source-based, ground motion or wavefield-based and on-site-based approaches. However, source-based algorithms are commonly used in most of EEWSs worldwide. A source-based EEWS uses a particular time frame of the P-wave of an earthquake to estimate the source parameters such as magnitude and the location of that earthquake with the support of P-wave detection and earthquake magnitude and location estimation algorithms. As the initial step of a research project which aims to explore the best use of P-waves to generate earthquake alerts, this Work in Progress paper (WiPe) presents the initial partial findings from an ongoing literature review on exploring the algorithms used for P-wave detection and earthquake magnitude estimation.

Keywords

Earthquake Early Warning, P-waves, Magnitude Estimation, EEW algorithms

INTRODUCTION

Earthquake Early Warning (EEW) algorithms adopted by the various systems globally can be categorised into three main types: source-based, ground motion or wavefield-based and on-site-based algorithms (R. M. Allen & Melgar, 2019). Each of these has its strengths and weaknesses. To overcome the weaknesses and utilise the strengths of these different types of systems, researchers have explored developing hybrid systems – systems that use more than one type of algorithm for generating EEW (Kodera, 2018; Peng et al., 2020).

An ongoing work In New Zealand, a research project led by the Crisis Response and Integrated Simulation Science Laboratory (CRISiSLab) of the Joint Centre for Disaster Research (JCDR), Massey University, is currently studying innovative approaches to Earthquake Early Warning System[1] (EEWS) including using low-cost sensors and decentralised approaches. They have implemented a unique EEW network architecture using the PLUM (Propagation of Local Undamped Motion) based algorithm at the sensor nodes to detect earthquakes (Prasanna et al., 2022). However, the PLUM algorithm has limitations, as the algorithm is mostly limited to a 30-kilometre radius which only can give a 10-second warning time (Prasanna et al., 2022). Having a 10-second warning time can be beneficial to the areas near the epicentre but providing 10 seconds of warning time for the areas far from the epicentre is not sufficient since a longer warning window can be provided to those areas at the moment of detecting an earthquake.

To overcome this key limitation with EEW algorithms, a novel hybrid EEWS has been proposed for low-cost MEMS-based sensors which use the PLUM approach to generate a warning to the areas near the epicentre and a more traditional source-based method to generate warnings to the areas far from the epicentre with increased warning time through exploring the feasibility of implementing a P-wave detector to detect the P-waves[2] and predict the earthquake's magnitude at the sensor node itself. This could benefit the EEWS to disseminate the alerts to the end-users with the earthquake's magnitude and help the EEWS dynamically change the alerting region according to the predicted magnitude to reduce the number of false alerts. However, when exploring literature related to P-wave-based detection and warning, it is evident that detecting P-waves in real-time and estimating the magnitude of an earthquake using the characteristics of the P-waves create significant challenges which lead to inaccuracies. Therefore, it is important to analyse the P-wave-based approaches carefully to overcome these challenges to gain the end-user trust toward EEW.

Even though there are several algorithms for detecting P-waves and estimating the earthquake's magnitude using the P-waves, there is no literature discussing the different algorithms used for EEWS in terms of their processing time, reliability and accuracy. As a first step toward reviewing the pros and cons of each EEW algorithm, the P-wave detection algorithms and earthquake magnitude prediction algorithms should be clearly understood. Therefore, towards generating such a comprehensive understanding of the use of P-waves for EEWS, this Work in Progress paper (WiPe) reviews present and past literature on P-wave detection algorithms and their applications for earthquake detection. Identifying the different approaches carried out toward generating EEW will be helpful for researchers in the future to develop more appropriate and robust algorithms for their EEWS.

The paper is structured as follows. The paper starts by providing a background on earthquake early warning, Then the paper presents the methodology for conducting the proposed literature review. This will be followed by the initial findings of the literature review. Finally, the paper concludes with the next steps of the research.

BACKGROUND

Throughout history, disasters have created devastating consequences to people and infrastructures (Coppola, 2007). Earthquake is one that poses a serious threat to areas near major active faults on land or offshore subduction zones (Adhikari et al., 2018). Compared to other hazards such as cyclones and tsunamis, earthquakes cannot be predicted hours in advance where they can only be detected in the event of an earthquake: earthquake detection and warnings happen within seconds. This makes building an EEWS challenging due to the short period between the detection of an earthquake event and its forthcoming destructive impact (Fischer et al., 2012). Two facts enable the operation of EEWSs (i) the information travelling over communication networks moves faster than seismic

[1] A system of accelerometers, seismometers, communication, computers, and alarms that are devised for notifying regions of a substantial earthquake while it is in progress.

[2] Primary waves are a type of body waves that are generated at first during the earthquake and travel faster compared to any other seismic waves.

waves - P-waves (primary or pressure waves) and S-waves[3] (secondary or shear waves), and (ii) the most damage during an earthquake occur with S-waves which arrive later than P-waves (Fischer et al., 2012). To generate alerts, EEWSs use a network of sensors distributed in a geographical area to detect earthquakes and transmit alerts in real-time. Generally, the early warning window can be a few seconds to tens of seconds depending on the specific geometry of the earthquake and the stations used in EEWS (Y. M. Wu & Zhao, 2006).

During the last three decades, many high-end EEWSs have evolved and operated in several countries or regions worldwide including Japan, Taiwan, Mexico, South Korea, China and USA (Y. Wang et al., 2020). Even though these systems have improved significantly, become more robust, and have shown better results in detecting earthquakes, exorbitant costs associated with building modern-day high-end EEWS can make it impractical and less affordable not only for developing countries but even for developed countries (Prasanna et al., 2022). For example, the ShakeAlert EEWS in the USA is currently implemented only in three states namely California, Oregon, and Washington and the implementation costs approximately 100 million USD (Brooks et al., 2021). The high financial costs associated with current EEWSs and the latest technical advances in sensor technology have steered researchers to investigate low-cost EEWSs to detect earthquakes (Lin et al., 2012). There have been several research conducted in developing EEWSs using low-cost Micro-electromechanical systems (MEMS) based sensors. Examples of systems that use low-cost MEMS-based sensors include those in Taiwan (Lin et al., 2012), California (Clayton et al., 2015), China (Peng et al., 2013), Iceland (*TurnKey Earthquake Early Warning*, 2020) and New Zealand (R. M. Allen & Stogaitis, 2022; Prasanna et al., 2022).

When it comes to EEW algorithms, source-based algorithms detect the earthquake and disseminate the alert to EEW stakeholders with detailed information about the detected earthquake. These algorithms typically use a few seconds of P-wave data (0.5–4 s) from 2 to 6 sensors close to the epicentre to detect an earthquake and characterise the location, origin time, and magnitude by employing an appropriate ground motion prediction equation (GMPE) (R. M. Allen & Melgar, 2019). Ground motion and wavefield-based algorithms became popular due to their robustness and fast processing time. They do not estimate the source parameters of an earthquake (Hoshiba, 2013; Hoshiba & Aoki, 2015; Kodera, 2018). Thus, they avoid vulnerabilities of the source-based algorithms (Hoshiba, 2021). The core idea of these algorithms is the use of the present state of ground shaking and knowledge of propagation physics in a concise time to forecast the likely evolution of ground motion intensity in the future (R. M. Allen & Melgar, 2019). On-site-based algorithms detect an earthquake using a single station using a simple ground motion threshold to generate an alarm or warning (R. M. Allen & Melgar, 2019; Bindi et al., 2015; Picozzi, Emolo, et al., 2015). However, few improved on-site-based algorithms can detect P-waves and generate an alert when the intensity of the following S-wave is predicted to be destructive (R. M. Allen & Melgar, 2019). Generally, source-based algorithms take a longer time to detect an earthquake compared to other types of algorithms due to their source parameter estimation (R. M. Allen & Melgar, 2019). Therefore, almost all the EEWSs that adopted the source-based algorithms generate only alerts to areas far from the epicentre whereas on-site algorithms were adopted for alerting the areas near to the epicentre (D.-Y. Chen et al., 2015; C. Y. Wang et al., 2022). However, adopting on-site-based algorithms for generating alerts resulted in a higher number of false alerts (R. M. Allen & Melgar, 2019). Ground motion-based algorithms became popular recently due to their robustness and fast processing time (Prasanna et al., 2022). These types of algorithms are becoming suitable for alerting regions near the epicentre. However, it can be used to alert only a defined distance. For example, for the PLUM-based ground motion approach, it is 30 km (Kodera et al., 2018).

METHOD

To explore the different algorithms used for EEW, relevant articles were collected from the databases Scopus and Web of Science using a keyword search on 17 May 2022. Articles published since 2000 were considered for the search because a scan of existing literature showed that there was not much literature related to EEW before then. To review the different algorithms used for P-wave detection and earthquake magnitude estimation, "earthquake early warning" and "p-detector" were used as the primary keyword to answer the questions. In addition to that, "earthquake warning" and "earthquake detection" were used as alternatives to "earthquake early warning". Similarly, "p-wave", "s-wave", "p-phase", "s-phase" were used as alternatives to "p-detector". Peer-reviewed academic publications available online in a full-text format and relevant to the research aims are only included in the search, and publications in languages other than English; grey literature, such as government or industry reports; and non-academic research are excluded from the search. The initial search produced 491 relevant articles. Duplicates from the Initial results were removed and filtered further if they had the following content.

[3] Secondary or shear waves arrive following the P-waves during the earthquake and these are more destructive compared to P-waves.

- Algorithms which are not related to generating EEW.
- Evaluating and assessing the performance of the EEW algorithms.
- Algorithms related to structural monitoring and civil engineering.
- Algorithms not related to ground motion sensors, such as Optical fibres, Distributed Acoustic Sensing, GPS sensors, Gravity strain meters, GNSS sensors, and Transoceanic smart cables.
- Algorithms are only related to earthquake location estimations, calculating site factors, and reducing power consumption.
- Articles only discuss the EEW implementation and not the detection algorithm.

After filtering the articles, 144 articles were selected for review. Figure 1 illustrates the number of papers returned at each step following the filtering process.

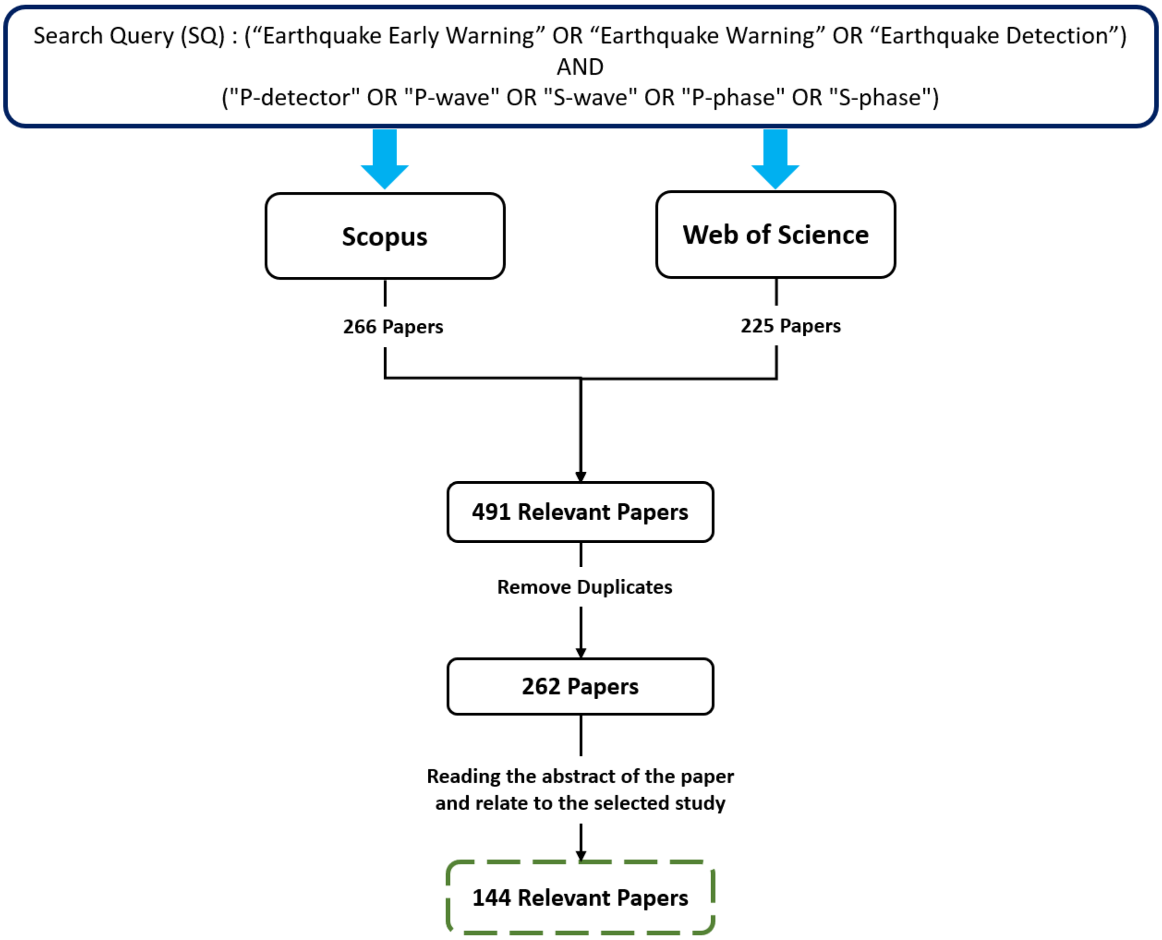

Figure 1. Flow diagram for the article filtration.

The relevant data from the selected articles are extracted by introducing a qualitative systematic review process where the research evidence is searched systematically from the primary qualitative studies and the findings are merged. Analysed information added to a Microsoft excel sheet by creating a table in an organised manner. Summary of the selected 144 articles made available upon request for the readers who are interested.

FINDINGS

Analysis of the 144 articles reveals the different P-wave detection approaches, earthquake magnitude prediction techniques implemented worldwide, and the contextual differences between using such algorithms and the technologies used. The first sub-section discusses the various P-wave detection techniques adopted by different EEWSs. This will be followed by a discussion on the earthquake magnitude estimation algorithms.

P-Wave Detection Algorithms

Firstly, the literature on P-wave detectors was explored where different algorithms are proposed for the automatic detection of real-time P-wave arrivals. From the literature, the most commonly used method for detecting the P-waves is the Short-Term Average/Long-Term Average (STA/LTA) method (Ding et al., 2017; Peng et al., 2017; Qingkai & Ming, 2012; Y.-M. Wu & Mittal, 2021). STA/LTA was introduced by Allen (R. v. Allen, 1978) for automatically detecting the P-waves in seismology. The STA/LTA is the most used algorithm in weak motion. It has two moving windows namely: the STA window and the LTA window. It calculates the sum of the absolute value of STA and LTA amplitudes. The STA/LTA ratio is then calculated, and when it exceeds a predefined threshold, the phase of the P-wave is identified. (Khalqillah et al., 2018). Even though STA/LTA algorithm has been adopted by several EEW implementations, STA/LTA algorithm is prone to result in false alerts due to the high background noise of the seismic instruments (Bose et al., 2020). This led researchers to implement different algorithms to detect P-waves with a minimal number of errors. The following table (Table 1) summarises different P-wave detection approaches attempted by researchers to detect P-waves during an earthquake.

Table 1. Summary of the approaches implemented for detecting P-waves during an earthquake.

Authors	Title of the Article	Approach in detecting P-waves
Küperkoch et al., 2010	Automated determination of P-phase arrival times at regional and local distances using higher order statistics.	Identification of the P-phase is done by applying Akaike Information Criterion to the characteristic function. The accurate P-wave arrival time is determined using a pragmatic picking algorithm on the recalculated characteristic function. Also, a Jackknife procedure and an envelope function analysis are applied to the characteristic function to reduce the false P-phase picks.
Hafez et al., 2010	Clear P-wave arrival of weak events and automatic onset determination using wavelet filter banks.	Automatic P-wave arrival detection of local events using wavelet transformation. The proposed algorithm is independent of the nature of the noise at the site and the type of seismometer used.
Qingkai & Ming, 2012	Evaluation of earthquake signal characteristics for early warning.	This approach uses a modified STA/LTA method to detect P-waves. This approach eliminates the impacts of spike-type noise and small pulse-type noise prior to the commencement of the P-wave from the usual STA/LTA approach by adding two new parameters.
Bhardwaj et al., 2013	Root sum of squares cumulative velocity: An attribute for earthquake early warning.	P-wave is detected by computing two parameters namely: Root Sum of Squares Cumulative Velocity (RSSCV) and Cumulative Absolute Velocity (CAV), and compared with predetermined threshold values.
Baillard et al., 2014	An Automatic Kurtosis-Based P - and S -Phase Picker Designed for Local Seismic Networks.	A new kurtosis-based technique for automatically selecting P-phase and S-phase arrivals and easy to implement with high picking accuracy.
Bogiatzis & Ishii, 2015	Continuous wavelet decomposition algorithms for automatic detection of compressional- and shear-wave arrival times.	This method uses the continuous wavelet transformation of the waveform where P-waves are identified by calculating the wavelet coefficients using the vertical component of the ground motion recording.

Z. Wang & Zhao, 2017	Automatic event detection and picking of P, S seismic phases for earthquake early warning and application for the 2008 Wenchuan earthquake.	This approach uses combination of high-precision algorithms to detect phases of P and S-waves. First, an amplification coefficient is introduced to the STA/LTA characteristic function for a better detection of the P and S-phases. Along with that, higher order statistics and the Akaike information criterion function have been utilised to narrow the signal and lock more accurately on the arrival time of the P and S-phases.
Kwon et al., 2018	A new P-Wave detector via moving empirical cumulative distribution function.	This method is based on the shape of the absolute-valued signal's moving empirical cumulative distribution function (MECDF) in a moving window. It uses one fewer window than the STA/LTA approach, which removes the load of window length optimisation while maintaining a comparable level of performance.
Z. Li et al., 2018	Machine Learning Seismic Wave Discrimination: Application to Earthquake Early Warning.	A machine learning based method It uses Trained Generative Adversarial Network (GAN) to detect P-waves.
Kodera, 2018	Real-Time Detection of Rupture Development: Earthquake Early Warning Using P Waves from Growing Ruptures.	This approach uses simple polarisation analysis technique to detect P and S-waves.
Dokht et al., 2019	Seismic event and phase detection using time-frequency representation and convolutional neural networks.	A machine learning based method. Using a deep convolutional network (ConvNet), a generalised model has been created to enhance the ability to distinguish between earthquake and noise recordings. P and S waves are separated from one another, and their approximate arrival times are calculated using a secondary network that employs the main seismic arrivals' wavelet transform.
Mousavi et al., 2020	Earthquake transformer—an attentive deep-learning model for simultaneous earthquake detection and phase picking.	A machine learning based method. It uses a global deep learning model for detecting earthquakes and picking the phases of P and S waves at the same time.
Walter et al., 2020	easyQuake: Putting machine learning to work for your regional seismic network or local earthquake study.	A machine learning based method. This approach uses an associator and a phase picker driven by machine learning to detect the arrival of P-waves.
Tous et al., 2020	Deep neural networks for earthquake detection and source region estimation in north-central Venezuela.	A machine learning based method. P-wave earthquake detection and source region estimate using a deep convolutional neural network called UPC-UCV (Universitat Politecnica de Catalunya-Universidad Central de Venezuela), using single-station three-channel signal windows.
Bose et al., 2020	Framework for Automated Earthquake Event Detection Based on Denoising by Adaptive Filter.	An Enhanced Variable Step-Size Least Mean Square (EVSSLMS) technique for P-wave detection. The EVSSLMS algorithm is used in the proposed event detection strategy to denoise the seismic data before the usual STA/LTA technique is used to detect the arrival of the P-wave.

Sugondo & Machbub, 2021	P-Wave detection using deep learning in time and frequency domain for imbalanced dataset.	A machine learning based method. The Synthetic Minority Oversampling Technique (SMOTE) approach to detect P-waves is proposed using deep learning with time domain and frequency domain as inputs.
Lapins et al., 2021	A Little Data Goes a Long Way: Automating Seismic Phase Arrival Picking at Nabro Volcano with Transfer Learning.	A machine learning based method. Using the data from the Nabro volcano, a technique known as transfer learning was used to create a deep learning model for automating phase arrival detection for P-waves using a limited amount of training data.
Saad & Chen, 2021	Earthquake Detection and P-Wave Arrival Time Picking Using Capsule Neural Network.	A machine learning based method It uses a capsule neural network (CapsNet) to identify and detect P-waves during an earthquake automatically.
Yanwei et al., 2021	Deep learning for P-wave arrival picking in earthquake early warning.	A machine learning based method Convolution neural network-based automatic algorithm (DPick) was created and trained to detect P-waves.
Liu, Li, et al., 2022	Discrimination between Earthquake P Waves and Microtremors via a Generative Adversarial Network.	A machine learning based method Generative adversarial network (GAN) for detecting P -waves and microtremors from the training set obtained from JAPAN.
W. Zhu et al., 2022	An End-To-End Earthquake Detection Method for Joint Phase Picking and Association Using Deep Learning.	A machine learning based method A neural network design for processing seismic waveforms from several stations that were captured using a seismic network which proves that the end-to-end method can successfully detect P- and S-wave arrivals and accomplish precise earthquake detection.
Liu, Song, et al., 2022	Seismic Event Identification Based on a Generative Adversarial Network and Support Vector Machine.	A machine learning based method A hybrid model based on a generative adversarial network (GAN) and a support vector machine (SVM) is introduced for the purpose of detecting P-waves and differentiating between earthquakes and microtremors.
D'Angelo et al., 2022	A new picking algorithm based on the variance piecewise constant models.	It uses the variance piecewise constant models of the earthquake waveform to detect P and S-wave automatically.
Khan & Kwon, 2022	P-Detector: Real-Time P-Wave Detection in a Seismic Waveform Recorded on a Low-Cost MEMS Accelerometer Using Deep Learning.	A machine learning based method It uses a deep learning model that can detect P-waves in noisy environments.
Yamada & Mori, 2022)	P-wave picking for earthquake early warning: Refinement of a Tpd method.	A refinement algorithm called Tpd method is used to determine the P-wave arrival time accurately.
Wibowo et al., 2022	Earthquake Early Warning System Using Ncheck and Hard-Shared Orthogonal Multitarget Regression on Deep Learning.	A machine learning based method. It uses an algorithm called Ncheck for picking the p-arrival on a multi-station waveform by handling the noise.

As captured in Table 1, it can be clearly seen that, the number of attempts in detecting P-wave have increased over the past years. There are several approaches in detecting P-waves based on the mathematical equations (statistics) where the skewness, kurtosis and frequency changes of moving seismic windows were analysed for detecting P-waves (Baillard et al., 2014; Kodera, 2018; Küperkoch et al., 2010; Kwon et al., 2018; Yamada & Mori, 2022). Some researchers have tried wavelet transformation to detect P-waves. Usage of wavelet transformation shows that P-wave can be detected clearly even in a weak seismic event (Bogiatzis & Ishii, 2015; Hafez et al., 2010). As discussed, STA/LTA has shown issues in detecting P-waves in noisy environment. To overcome this issue, some researchers have tried improving the method by modifying or adding new parameters to the algorithm to eliminate the effects of noise (Qingkai & Ming, 2012; Z. Wang & Zhao, 2017). However, with the increased processing power of the computers, machine learning became one of the main tools in detecting P-waves. There are a significant number of articles show that researchers are more focussing on machine learning techniques to detect P-waves where every year the number of papers published on machine learning based P-wave detection are increasing (Bose et al., 2020; Dokht et al., 2019; Khan & Kwon, 2022; Lapins et al., 2021; Z. Li et al., 2018; Liu, Li, et al., 2022; Liu, Song, et al., 2022; Mousavi et al., 2020; Saad & Chen, 2021; Sugondo & Machbub, 2021; Tous et al., 2020; Walter et al., 2020; Wibowo et al., 2022; Yanwei et al., 2021; W. Zhu et al., 2022).

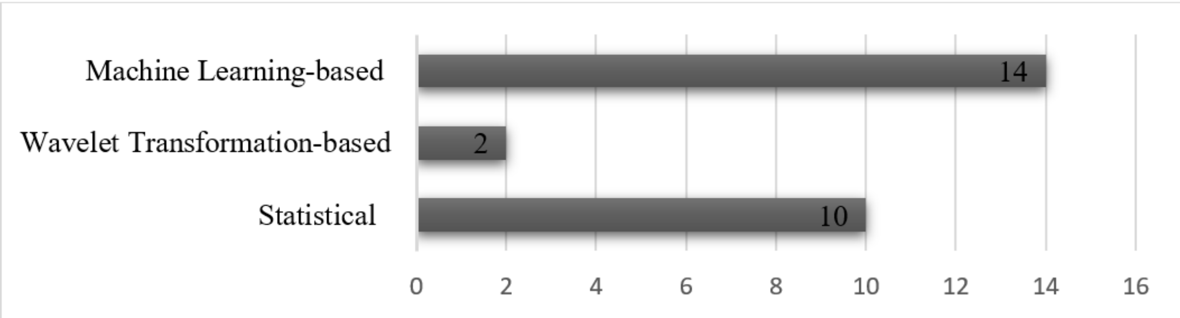

Figure 2. Number articles published in P-wave detection according to the type of approach

Analysis of different algorithms used for P-wave detection and the number of articles published in three different approaches (Figure 2) shows that the evolution of the algorithms started from statistical equations related to the skewness, kurtosis and frequency change of the seismic wave and moved towards machine learning-based techniques over the years. Having discussed the P-wave detection algorithms implemented by different researchers, the next section discusses the algorithms which can predict an earthquake's magnitude using a time window of a detected P-wave.

Algorithms for Estimating an Earthquake's Magnitude

As previously mentioned, estimating an earthquake's magnitude at the first instance of P-wave detection could assist the EEWS to provide alerts to end users with the earthquake's magnitude and it will help in dynamically changing the alerting zones according to the expected magnitude. The literature on techniques used to predict the magnitude of an earthquake has been explored. Generally, in most of the algorithms, an earthquake's magnitude is predicted by analysing a 0.5-4 second time window of the detected P-waves (R. M. Allen & Melgar, 2019). The common technique used in many EEWS implementations is to determine the earthquake's magnitude from the time parameter(τ_c) and Peak displacement Amplitude (P_d) (Linear regression model) (Alcik et al., 2011; D. Y. Chen et al., 2017; Hsiao et al., 2011; Kuyuk & Allen, 2013; Nazeri et al., 2017; Park et al., 2010; Peng et al., 2013; Peng, Yang, Xue, et al., 2014; Peng, Yang, Zheng, et al., 2014; Pinsky, 2017; Romeu Petit et al., 2016; Sasani et al., 2018; Sheen et al., 2014; Tusa et al., 2017; Vallianatos et al., 2021; W. Wang et al., 2009; Y. Wang et al., 2021; Y. M. Wu et al., 2007; Y. M. Wu & Zhao, 2006; Y.-M. Wu, 2017). Several studies indicate that magnitude estimation of S-wave tends to saturate when using such a short time window of P-wave where earthquakes are significantly large and have long rupture durations (M > 6) (Hoshiba et al., 2011; Rydelek & Horiuchi, 2006). To overcome the saturation issues related to the linear regression model, different approaches were implemented by researchers to predict an earthquake's magnitude. The following table (Table 2) summarises the different earthquake magnitude prediction algorithms attempted by researchers.

Table 2. Summary of the approaches implemented for predicting an earthquake's magnitude during an earthquake

Authors	Title of the Article	Approach in Estimating Earthquake Magnitude
R. M. Allen & Kanamori, 2003	The potential for earthquake early warning in Southern California.	It uses the frequency content of the P-waves to determine earthquake's magnitude before any damaging ground motion occurs.
Odaka et al., 2003	A new method of quickly estimating epicentral distance and magnitude from a single seismic record.	It calculates the magnitude of an earthquake from the maximum amplitude measured during a specified short time window following the arrival of the P-wave using an empirical magnitude-amplitude relationship.
Simons et al., 2006	Automatic detection and rapid determination of earthquake magnitude by wavelet multiscale analysis of the primary arrival.	It uses the discrete wavelet transform-based method to analyse the waveform and calculate the final magnitude of an earthquake from the first few seconds of the P wave.
Y. M. Wu & Zhao, 2006	Magnitude estimation using the first three seconds P-wave amplitude in earthquake early warning.	Peak amplitude of displacement (Pd) in the first three seconds after the arrival of the P wave is used for the estimation of the earthquake's magnitude.
Lancieri & Zollo, 2008	A Bayesian approach to the real-time estimation of magnitude from the early P and S wave displacement peaks. Click or tap here to enter text.	It uses the early P and S wave displacement peaks along with the Bayesian probabilistic approach for the real-time estimation of earthquake's magnitude.
Qingkai & Ming, 2012	Evaluation of earthquake signal characteristics for early warning.	It uses stepwise regression analysis of 12 kinds of parameters from the first 3 seconds of the P-wave to estimate the epicentral distance and magnitude of the earthquake.
Kuyuk & Allen, 2013	A global approach to provide magnitude estimates for earthquake early warning alerts.	It determines the earthquake's magnitude using the global scaling relation between Pd (Peak amplitude of displacement) of the P-wave window and magnitude of an earthquake.
Reddy & Nair, 2013	The efficacy of support vector machines (SVM) in robust determination of earthquake early warning magnitudes in central Japan.	This method uses an improved wavelet transformation-based earthquake magnitude prediction approach to estimate an earthquake's magnitude accurately.
J. Li et al., 2013	Continuous estimates on the earthquake early warning magnitude by use of the near-field acceleration records.	It uses the statistical analysis method to determine the earthquake's magnitude by measuring the acceleration, displacement, and effective peak acceleration in each seismic record within a certain time after P wave arrival.
Hloupis & Vallianatos, 2013	Wavelet-based rapid estimation of earthquake magnitude oriented to early warning.	It uses a wavelet-based algorithm for estimating the earthquake magnitude.
Heidari et al., 2013	Magnitude-scaling relations using period parameters τc and τpmax, for tehran region, Iran.	It determines the magnitude of an earthquake by combining and using the period parameters τpmax and τc from the vertical and horizontal components of a P wave's first three seconds.
Meier et al., 2015	The Gutenberg algorithm: Evolutionary Bayesian magnitude estimates for earthquake early warning with a filter bank.	It uses the broadband frequency information of seismic signals in a probabilistic algorithm to estimate the earthquake magnitude.

Picozzi, Colombelli, et al., 2015	A Threshold-Based Earthquake Early-Warning System for Offshore Events in Southern Iberia.	It calculates the Pd (Peak amplitude of displacement) of the P-wave window and uses log Pd vs PGV (Peak Ground Velocity) empirical relationship to predict the earthquake's magnitude.
Hloupis & Vallianatos, 2015	Wavelet-Based Methods for Rapid Calculations of Magnitude and Epicentral Distance: An Application to Earthquake Early Warning System.	It determines an earthquake's magnitude and estimate its epicentre using wavelet transform (WT) as a processing method. Wavelet coefficients used to characterize the seismogram of the P-wave portion are used for earthquake's magnitude and location estimation.
Yang & Motosaka, 2015	Ground motion estimation using front site wave form data based on RVM for earthquake early warning.	A machine learning-based method. It uses five input variables observed in the P-wave (earthquake PGA, PGD, pulse rise time, average period and the Vp max/Ap max ratio) in a relevant vector machine (RVM) to estimate the magnitude of an earthquake.
Atefi et al., 2017	Rapid estimation of earthquake magnitude by a new wavelet-based proxy.	It uses a wavelet-based scale regression of log (λlog) value extracted from the P-wave window for predicting earthquake's magnitude.
Noda & Ellsworth, 2017	Determination of earthquake magnitude for early warning from the time dependence of P-wave amplitudes.	It calculates the displacement of the P-wave before the arrival of the peak amplitude and uses the built relationship between the earthquake magnitude (M) and P-wave displacement to estimate the earthquake's magnitude.
Lizurek et al., 2017	Fast Moment Magnitude Determination from P-wave Trains for Bucharest Rapid Early Warning System (BREWS).	It uses P-wave spectral levels to determine the earthquake's magnitude.
Cuéllar et al., 2018	An earthquake early warning algorithm based on the P-wave energy released in the ts–tp interval.	To estimate the magnitude threshold, the P-wave coda's energy on the vertical component during the tS - tP period is measured.
Z. Wang & Zhao, 2018	A new Mw estimation parameter for use in earthquake early warning systems.	It calculates the initial P-wave window's squared displacement integral (ID2) to estimate earthquake's magnitude.
Ochoa et al., 2018	Fast magnitude determination using a single seismological station record implementing machine learning techniques.	A machine learning-based approach. It uses only five seconds of signal from a single three component seismic station's P wave to derive the earthquake's magnitude (Ml) using the Support Vector Machine Regression (SVMR) algorithm.
J. Zhu et al., 2021	Magnitude Estimation for Earthquake Early Warning Using a Deep Convolutional Neural Network.	A machine learning-based approach. An advanced model for magnitude prediction that employs the 3-seconds of P-wave data into a deep convolutional neural network for earthquake magnitude estimation.

Zhang et al., 2021	Real-Time Earthquake Early Warning with Deep Learning: Application to the 2016 M 6.0 Central Apennines, Italy Earthquake.	A machine learning-based approach. A deep learning technique that analyses continuous seismic waveform streams to simultaneously detect earthquakes and estimate their source properties such as earthquake's magnitude and location using fully convolutional networks.
Abdalzaher et al., 2022	A Deep Learning Model for Earthquake parameters Observation in IoT System-based Earthquake Early Warning.	A machine learning-based approach. A deep learning model based on integrating autoencoder (AE) and convolutional neural network (CNN) is presented (3S-AE-CNN) for a rapid determination of an earthquake's magnitude and location after three seconds from the beginning of the P-wave.
J. Zhu et al., 2022	Magnitude Estimation for Earthquake Early Warning with Multiple Parameter Inputs and a Support Vector Machine.	A machine learning-based approach. To estimate earthquake magnitudes, it uses a variety of parameter inputs, including the support vector machine magnitude estimation (SVM-M) model.

From the above table (Table 2) it can be clearly seen that the number of attempts in predicting the magnitude of an earthquake have increased over the years. As mentioned, almost all the algorithms analyse the characteristics of a P-wave in a particular time window to predict the magnitude of an earthquake. However, similar to the P-wave detection algorithms, the evolution of the magnitude estimation algorithms started from linear regression models where the magnitude of an earthquake estimated by forming a correlation between the parameters of the detected P-wave time window and historical earthquakes' magnitude, and moved towards machine learning-based techniques over the years. Analysis of different earthquake magnitude estimation approaches show that an earthquake's magnitude can be estimated successfully.

NEXT STEPS AND FUTURE WORK

From the above analysis, it is evident that the implementation of the P-wave based EEWS is achievable. Therefore, in order to select an appropriate P-wave detector, as a next step, experiments will be conducted to identify an appropriate lightweight and easy-to-implement detection algorithm to detect the P-waves. This is important since the low-cost MEMS-based sensors used in our CRISiSLab EEW network only possess limited processing power and memory. While selecting an appropriate P-wave detector, experiments will be designed in such a way that the P-wave detectors will be ranked according to the processing time of the algorithm. It is crucial to keep the processing time to be minimal so that the warning time can be maximised. Furthermore, the detection error will also be compared between the P-wave detectors before making the selection. In addition to that, the performance of the algorithm in a noisy environment will be analysed, because according to the literature, P-wave detectors produce inaccurate results in noisy environments. Finally, the algorithms will be tested in the sensor environment, for example, algorithms which perform well only in the sensors that are installed in the boreholes (Kodera, 2018) will not be a feasible option to implement since the sensors installed in the CRISiSLab EEW network are surface-based stations which are installed in homes belonging to members of the public. Therefore, the P-wave detector will only be selected after having considered the above-mentioned criteria.

After selecting the appropriate P-wave detection algorithm, our next phase of work will be identifying the appropriate earthquake magnitude estimator which can use the characteristics of the P-wave. For that, an in-depth comparison and analysis of the magnitude predictors will be conducted. To select the most suitable magnitude estimator, the complexity of the algorithm will be reviewed in terms of the processing time and estimation error. As mentioned, earlier, due to the limited processing power and memory of the low-cost MEMS sensors used in the CRISiSLab EEWS, the most appropriate method to estimate the earthquake's magnitude needs to be simple and easy to implement. Also, the methods will be analysed and the one with the least estimation error will get selected. In addition to that, the selected magnitude estimator will be tested with complex scenarios related to large earthquakes (M > 6) where the possible entanglement of P-wave and S-waves will occur as the earthquake size increases. Such P and S wave collisions could lead to detection errors and may result in false alerts. However, such challenges will be overcome by including aleatory and epistemic uncertainties of seismic waveforms from large-magnitude earthquakes. The selected earthquake magnitude predictor should satisfy all the above-mentioned factors.

After identifying the appropriate P-wave detector and earthquake magnitude predictor suitable to be used along with the PLUM-based approach, the plan is to compare the results with the previous work carried out on P-wave-based EEW approaches in other parts of the world. In this stage, the plan is to evaluate the results about the processing speed, estimation error and warning time by using appropriate evaluation procedures and engaging with international experts. Also, a comprehensive systematic literature review on the EEW algorithms will be submitted to a journal.

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