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Enhancing manual *P*-phase arrival detection and automatic onset time picking in a noisy microseismic data in underground mines

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ABSTRACT

Accurate detection and picking of the *P*-phase onset time in noisy microseismic data from underground mines remains a big challenge. Reliable *P*-phase onset time picking is necessary for accurate source location needed for planning and rescue operations in the event of failures. In this paper, a new technique based on the discrete stationary wavelet transform (DSWT) and higher order statistics is proposed for processing noisy data from underground mines. The objectives of this method are to (i) improve manual detection and picking of *P*-phase onset; and (ii) provide an automatic means of detecting and picking *P*-phase onset time accurately. The DSWT is first used to filter the signal over several scales. The manual *P*-phase onset detection and picking are then obtained by computing the signal energy across selected scales with frequency bands that capture the signal of interest. The automatic *P*-phase onset, on the other hand, is achieved by using skewness- and kurtosis-based criterion applied to selected scales in a time-frequency domain. The method was tested using synthetic and field data from an underground limestone mine. Results were compared with results obtained by using the short-term to long-term average (STA/LTA) ratio and that by Reference Ge et al. (2009). The results show that the method provides a more reliable estimate of the *P*-phase onset arrival than the STA/LTA method when the signal to noise ratio is very low. Also, the results obtained from the field data matched accurately with the results from Reference Ge et al. (2009).

1. Introduction

The presence of stress fields produced as a result of the interaction between mine excavations and geological structures continue to present danger to underground workers and equipment. The microseismic monitoring technique (MMT) remains one of the major tools for improving the safety of personnel and equipment in underground mine operations. The technique provides an innovative way of monitoring activities associated with changes in stress fields which usually result in rockburst, coal bumps and the failure of the rock mass in underground mines. With the MMT, critical information such as event location, magnitude and source mechanisms can be obtained in real time. The obtained information can then be used in an effort to prevent, control and alert management of potential rock mass instabilities in the area of operation. Also, such information is important because it helps in the proper planning and rescue operations in the event of a failure.

A successful implementation of the MMT in the mining environment is however influenced by (1) planning and optimization of monitoring systems; (2) data processing; (3) event location, and (4) evaluating the location solutions [2]. The ability to pinpoint zones of instability in a monitoring area makes source location the most valuable feature of the microseismic technique. An accurate and stable source location depends on many factors. One of these factors is the quality of the data being used to determine the *P*-wave arrival time used in computing the source location [2,3]. The microseismic data recorded at mine sites is greatly affected by the presence of excessive background noise. The presence of such background noise make the analysis of acquired data very complex. The output signals of the systems used at mines are often buried by the surrounding noises, making it difficult to identify the actual arrival times of incoming signals [2]. Generally, acoustic emission/microseismic (AE/MS) signals are usually very weak, rendering data acquisition a challenge in a service environment that is generally very noisy. Identification of the actual signal of interest and the reduction of background noise are very demanding, nonetheless enormously vital for the effective application of the method [4]. The intricacies associated with mine

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microseismic data are usually due to other activities unrelated to the event under consideration. Additionally, a good portion of these signals may be caused by *S*-wave arrivals instead of *P*-wave arrivals as would normally be assumed. If these signals are used without discrimination, it will result in significant contamination of the database leading to the wrong source location. The Canadian experience of daily monitoring has shown that efficient monitoring is dependent on the ability to process microseismic data [2]. With these challenges in the mining environment, to be able to detect and pick accurately the first *P*-wave arrival requires a great deal of effort. Any technique used for performing this task, therefore, should factor in the special characteristics of this environment to achieve a good and reliable source location.

Again, due to the enormous volume of data collected per day, a pure manual analysis for the identification of the first *P*-phase arrival is time consuming and very stressful. The high level of background noise and the weak nature of the AE/MS data in the mining environment makes pure manual processing even more difficult. Also, human analysis is subjective. Therefore, there is a need to provide a more efficient, rapid, objective, and automatic means for improving both manual and automatic detection of the *P*-wave arrival onset to ensure a reliable source location estimate.

Among the many methods available for such processes, the classic STA/LTA by [5,6] is one of the most popular methods widely used in the field of seismology [7] and has also been employed by [8] in underground mines for the automatic detection of microseismic events. Beside the STA/LTA method, energy-based methods by [9,10] and the high order statistics (HOS) based methods by [7,11] have been widely reported. Ref. [12] noted that the methods based on HOS are most consistent and less affected by noise. They are also independent of signal-bandwidth. These qualities, therefore, makes the HOS-based methods appropriate techniques for the mine environment.

Also, techniques including the autoregressive (AR) and the wavelet transform (WT) methods have been extensively reported for detection and picking of *P*-phase arrivals. For instance, based on the Akaike information criterion (AIC) [13], researchers developed a procedure for the fitting of a locally stationary AR model to seismograms. They implemented this procedure in an online system called fast univariate case of minimum AIC method of AR model fitting. Ref. [14] proposed an autoregressive method that detects increases in the AR-model order due to the higher complexity of signals compared to preceding noise. Also, other applications of the AR and AIC models have been reported by [15–19]. Ref. [17] indicated that the AIC picker outperforms the STA/LTA picker in low signal to noise ratio (SNR) environment. Ref. [18], however, noted that the AIC method is sometimes affected by the SNR in the seismogram. There will always be global minimum in a given time window, and thus, the picker always pick onset time whether there is a true phase or not. On the other hand [20], employed the discrete wavelet transform (DWT) method to remove stationary noise at all stations in a network to assess its effect on the detection of seismic activities. Using this process to prefilter the signal, the authors noted that they achieved an increase in detection and a reduction in false alarm rate in comparison with two other detectors not using wavelet filters. Also, the authors indicated that no meaningful event was lost as a result of using this technique. The wavelet technique has also been used by many other authors to detect and pick the arrival of seismic phases successfully in the past. Ref. [21] demonstrated the use of the Haar wavelet in a discrete wavelet transformation as a tool for the time-scale representation of raw seismic data and identification of events of interest. Using the localization properties of the wavelet, the author extracted characteristics of importance (energy and predominant time scales), which were then examined for microseismic events detection. Also, Ref. [22] extracted key features from the discrete wavelet coefficients of a seismic record and then using the Bayes theorem provided a joint detection and classification of seismic events. A fundamental disadvantage of the traditional DWT is that it suffers from translation variant property. In other words, the DWT of a translated form of a signal $X(n)$ is in general not the translated form of the DWT of $X(n)$. Ref. [7] has noted that for best results, recent automatic pickers try to combine the advantages of different approaches.

In light of the advantages and disadvantages of the various methods coupled with limited applications in the mining industry, a new algorithm is proposed in this paper for processing noisy microseismic data in an underground mine. The proposed method is set out to achieve two main objectives: (i) improve manual identification/detection of the *P*-phase arrival in a noisy AE/MS data; and (ii) provide an automatic means of detecting and picking first *P*-phase arrival time accurately in a time-frequency domain. To aid in the manual detection of the first *P*-phase arrival, the data is filtered using the DSWT over several scales (levels) to extract features of interest. The DSWT has no translation of the signal and is obtained by modifying the original algorithm for the DWT [23]. By using selected scales, the *P*-phase arrival is accurately determined manually. The selected scales are then used for the automatic detection and arrival time picking of the first *P*-phase. The automatic picker is based on skewness and kurtosis criterion applied in a time-frequency domain. This approach ensures that the characteristics of the microseismic signal and the background noise are properly highlighted. In the sections that follows, the mathematical theorems underpinning the wavelet algorithm, the skewness and kurtosis-based criterions as implemented are presented. Also, results and discussions of the application of the method to synthetic data and actual noisy microseismic data from a limestone mine are provided. The results are then compared to the results obtained by using the STA/LTA method and the work by [1].

2. Brief mathematical background and theories

The following sections provide the basic mathematical expressions and theories employed in the study. Also, the advantages and disadvantages of the DWT method are highlighted to justify the choice of the DSWT.

2.1. Shift-invariance and the DWT

In signal processing applications, fast computation is key and the WT has shown a great amount of success in this direction [24]. Ref. [25] noted that the most widely used form of the WT families is the DWT. Ref. [21] on the other noted that for real-life problems involving time-varying frequencies, such as AE/MS signals, time-frequency analysis such as the WT are more reliable compared with an analysis in either time or frequency domain alone.

The DWT is mainly based on using low and high pass filters and downsampling. For the mathematical expressions and theory of the DWT, consider a two-channel orthogonal filter bank with analysis filters, $h_0[n]$, $h_1[n]$, and synthesis filters, $g_0[n]$, $g_1[n]$. The impulse responses of the analysis filters are the time-reversed versions of the synthesis filters. Where 0 represents the lowpass filter and 1 represents the highpass filter. From the equations provided by [20], the input signal for a j level decomposition process can be written as in Eqs. (1) and (2).

$$x[n] = \sum_{j=1}^{J}\sum_{k\in Z} X^{(j)}[2k+1]g_1^{(j)}[n-2^jk] + \sum_{k\in Z} X^{(J)}[2k]g_0^{(J)}[n-2^Jk] \qquad (1)$$