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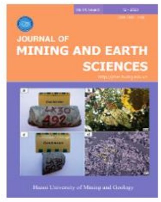

Data processing in blast-induced ground vibration measurement issue with Kalman filter

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ABSTRACT

Measurement data processing plays an important role in acquisition systems. Completely eliminating the error caused by noise is a difficult issue because correct data exists in noise. Besides, it is impossible to distinguish them clearly. For this reason, solutions to process and standardize data are always applied in the condition of paying close attention to the peculiarity and specific properties of the measured object and the factors affecting it. Blast-induced Ground Vibration wave data is one of the extremely important information in mining operations. It is used to evaluate the impact of the blasting on construction. Besides, it presents the efficiency of explosives as well as of the blasting and mining operation in general. For many particular cases, the physical and mechanical properties of the object to be broken (geological structure, physical and mechanical properties of the rock in the blasting area) are relatively image by knowing its waves. Furthermore, the parameters of the next blasting are also improved based on this data. Due to its important role, the requirement for automatic and highly accurate recording of blast-induced ground vibration data is an urgent issue in mining operations in Vietnam. In this paper, solutions to apply the Kalman filter to handle ground vibration wave data due to blasting were introduced. The work is done based on considering the properties and factors affecting the amplitude, frequency, and characteristics of ground vibration waves. Data is taken directly from the sensor without any processing. Therefore, it carries a lot of noise from many different causes such as the sensor structure, gravity, rock structure, the other sources of vibration at the same time, etc. The used sensor is a product of Nation Instrument (NI). The content of the article is the result of researching and building an automatic blast-induced ground vibration wave measuring device, which will be applied in the field of mining and quarrying in Vietnam.

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1. Introduction

Vibration waves are generated after each mining blast (Figure 1). The important information is wave amplitude, which represents the level of vibration of rock particles. It is a factor used to evaluate the impact, and the possibility of causing potential danger, or damage to the environment and surrounding structures. Also, the effectiveness of blasting can be judged by knowing it (Konya and Walter, 1991; Langefors and Kihlstrom, 1978). Therefore, monitoring the level of vibration is a mandatory requirement, especially when the blasting area is located near buildings or residential areas. This work has been carried out in Vietnam for a long time but has not been popularized due to equipment and cost limitations. According to the Vietnam standard stated in QCVN 01:2019/BCT (BCT, 2019), the standards for permissible distances for shock waves are given as follows (Table 1).

Vibration waves were recorded by a type of sensor called an accelerometer. The

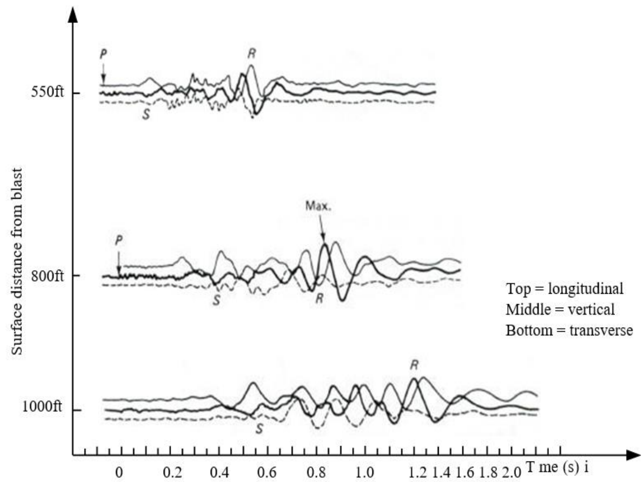


Figure 1. General form of blast-induced ground vibration time-history records.

Table 1. Permissible limits of impact of blast waves for blasting.

Type and method of blasting	Minimum radius of danger zone (m)	Minimum safe distance, m (for rock splash)
Blast-casting practice in opencast mines	Not less than 200 (2)	≥ 200 (2)
Secondary blasting on surface	Not less than 200	≥ 200
Blasting charge in small hole (d<75 mm)	According to design papers or approved construction method but mandatory, ≥200	≥ 200
Blasting to make small block caving pipe type	According to design papers, but mandatory ≥ 300	≥ 300
Blasting with the explosive charge in large hole (d>75 mm)	Not less than 400	≥ 400
Blasting with the large holes which made block caving bag	According to design papers	≥ 50
Secondary blasting excessively large boulders in underground	Not less than 50	≥ 100
Blasting with the small holes which made small block caving bag	According to design papers, but mandatory ≥10 (6)	
Blasting with the large holes which made large block caving bag		≥ 100
Blasting in the exploration activity	According to design papers, but mandatory ≥ 100	≥ 30

accelerometer operates based on the thin layer of silicon with condenser plates and is integrated as electronic chips. When the sensor chip is displaced according to the measuring object, the silicon layer is deformed (Figure 2a). That makes the two electrodes a variable capacitor (Figure 2b). It will change the balanced potential and causes an electric current to be generated. Measuring this current variation will determine the distance traveled by the sensor chip and its displacement acceleration. From there, the distance and acceleration of the measured object can be determined. A 3-axis accelerometer sensor chip is an integration of 3 silicon layers in the XYZ direction of the spatial coordinate system. Attach the sensor to the object, measure the signal level of the sensor in each direction, and then add it together according to formula 1, we will get the object's motion acceleration (Wearable Tech 101).

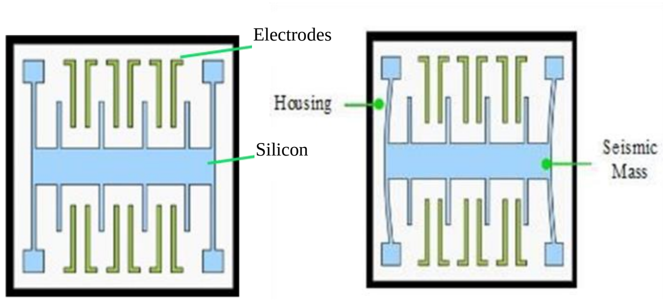
$$\vec{u} = \sqrt{\vec{u}_X + \vec{u}_Y + \vec{u}_Z} \qquad (1)$$

When a blast is done, it will create a vibration wave that propagates in the rock surrounding the blasting area. The particles vibrate in the space around it and are measured according to the LVT coordinate system (Figure 2c). The LVT coordinate system is an axis system in 3 directions of space, corresponding to the XYZ axis system. The total vibration calculated according to formula 1 is converted accordingly by formula 2:

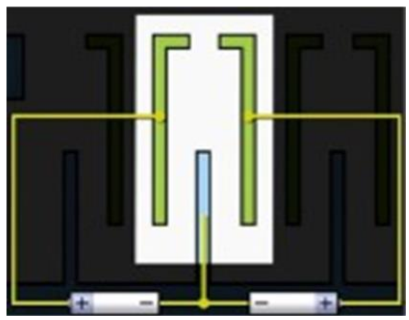
$$\vec{u} = \sqrt{\vec{u}_L + \vec{u}_Y + \vec{u}_Z} \qquad (2)$$

Collecting values obtained from the accelerometer to accurately describe the vibration waves is not a simple task. Data read directly from the sensor contains a lot of noise values. Two basic factors that greatly affect the measurement results are the gravitation and the elastic oscillation of the acceleration recording structure (the silicon layer). In fact, there are many types of accelerometers integrated microprocessors or FPGA circuits that help to eliminate these influencing factors. However, the sample rate of measured data depends on the speed of the microprocessor circuits (Dao et al., 2021). The vibration wave only lasts for a very short time (some seconds), so it requires a measuring device with a large sample rate to ensure accurate measurement data. Therefore, this research suggests a solution in which the base accelerometer sensor is used to record values. The sample results accept all noise values which will be removed by filtering techniques.

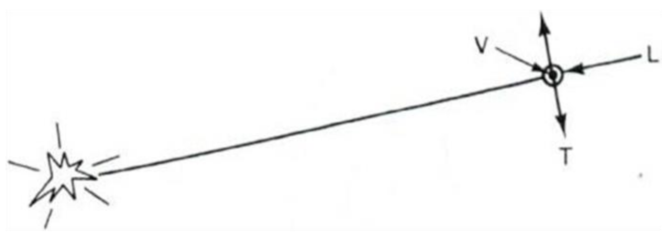
According to the theories of measurement and signal processing, the blasting shock wave is considered a nonlinear object. So, the processing of measurement data needs to apply complex technical solutions to nonlinear objects. So, the processing techniques will be more complex than for linear objects. The popular technique used recently is the Kalman Filter (KF). For nonlinear objects, this technique is called Extended Kalman Filter (EKF).



a. Displacement of the silicon layer when moving the accelerometer chip.



b. The method of converting the relative displacement level into an electrical signal.



c. Location of the vibration wave device.

Figure 2. The principle of accelerometer (Wearable Tech 101).

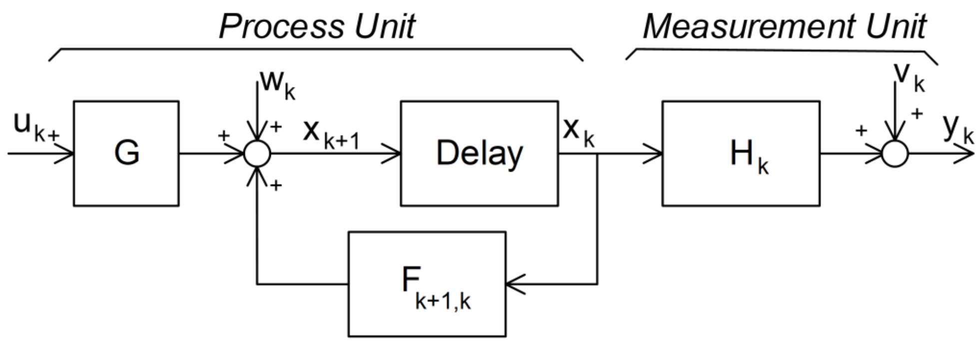


Figure 3. System state structure model.

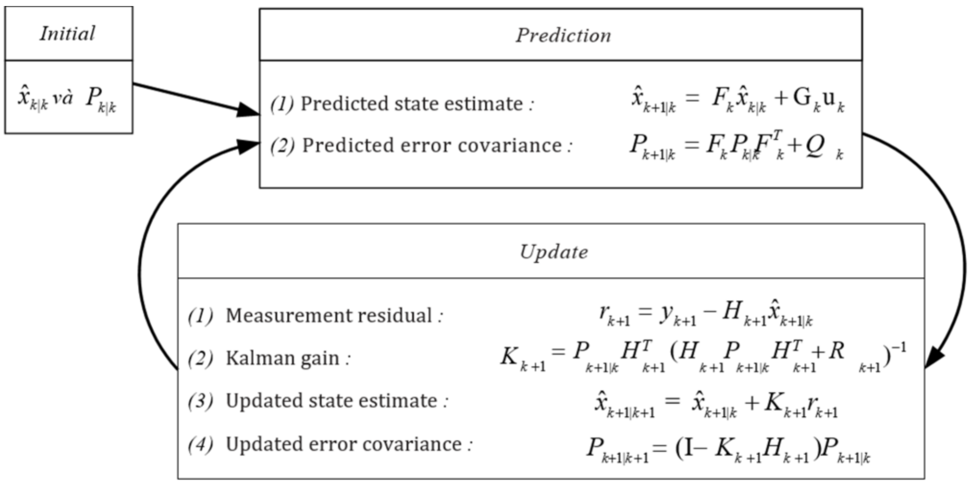


Figure 4. Data processing procedure of Kalman Filter (Kalman, 1960).

2. Theoretical basis of Kalman Filter and Extended Kalman Filter

2.1. Kalman Filter (KF)

The Kalman filter was first introduced by R.E. Kalman in 1960 (Kalman, 1960). The Kalman filter method is based on a recursive procedural data processing algorithm for discontinuous linear systems. Since, thanks to the advancement of computer science, this algorithm has been more and more perfected, developed, and widely used by scientists, especially in the two fields: navigation and positioning the displacement trajectory (Bishop and Welch, 1997; Haykin, 2001; Kim and Bang, 2018).

Assume that there is a linear system consisting of processing and measurement components. This system is affected by various noise sources and is modeled in Figure 3. We can build the following expression:

$$x_{k+1} = F_{k+1,k}.\, x_k + G.\, u_k + w_k \tag{3}$$

$$y_k = H_k.\, x_k + v_k \tag{4}$$

Where: $F_{k+1;k}$ - the transition matrix taking the state x_k from time k to time k + 1; the process noise w_k is assumed to be additive, white, and Gaussian, with zero mean and with covariance matrix; y_k - the observable at time k; H_k - the measurement matrix; The measurement noise v_k - assumed to be additive, white, and Gaussian, with zero mean and with a covariance matrix (Haykin, 2001).

Kalman algorithm is a method of performing the processing and measurement process simultaneously (Figure 3) to determine the optimal state for the system. The nature of the process is described as follows: when the system is linear, the observed data sets are the vectors y_1, y_2, ..., y_n. For each step k ($1 \le k \le n$), we will estimate the state x_i with the smallest mean error. The Kalman filter algorithm consists of two stages: Predict and Update (Figure 4).

2.2. Extent Kalman Filter (EKF)

Two conditions for applying the Kalman filter are: the system is linear and the model is nonlinear in fact. As a result, it is necessary to linearize the system in each stage. This solution is considered suitable because the Kalman filter is applied to the discrete system. Now, the Kalman filter is called the Extended Kalman Filter (EKF) (Kalman, 1960; Haykin, 2001). Thus, the system state k+1 (x_{k+1}) corresponding to the time t = i depends not only on the k state (x_k) (expression 3) but also on the time factor i. The state model is described as follows:

$$x_{k+1} = \mathrm{f}(\mathrm{k}, x_k) + w_k \tag{5}$$

$$y_k = \mathrm{h}(\mathrm{k}, x_k) + v_k \tag{6}$$

Where: w_k and v_k are independent, zero mean, Gaussian noise processes of covariance matrices Q_k and R_k.

The function $f(k,x_k)$ represents a time-varying nonlinear transition matrix function. Similarly, the function $h(k,x_k)$ represents a non-linear measurement matrix that can also vary with time.

Linearization of the state model is described in (5) and (6). At any time k, the state model estimates around that time are denoted by $\hat{x}_{k+1|k}$ and $\hat{x}_{k|k}$. It corresponds to the estimated state at the neighborhood of time k. After obtaining the linear model, the standard Kalman filter equations are applied. The linearization process goes through two basic steps: differential calculus of the functions $f(k,x_k)$ and $h(k,x_k)$ to get $F_{k+1|k}$ and H_k, then applying the Taylor series method of order 1 to get the approximation for the two functions $F(k,x_k)$ and $H(k,x_k)$ in terms of $\hat{x}_{k+1|k}$ and $\hat{x}_{k|k}$. The extended Kalman filter (EKF) algorithm is briefly described in Figure 5.

To meet the quality requirements of data, studies have shown that it is possible to use multi-loop EKF or combine the results of the forward filtering (from the beginning to the end) with the results of the inverse filtering. (last => beginning) when the amount of data is fixed. For instance, for a time-observable data set of N elements (N being deterministic and constant), the Kalman algorithm performs the procedure for estimating the system state at time k (xk): if k increases from 0=>N, it is called forward filter; if k decreases from N=>0, it is called backward filter (Haykin, 2001).

3. Recording data

The measured data were recorded at the open-pit mining area of Nui Beo coal mine in 2020. The site is located at Ha Tu Ward, Ha Long City, Quang Ninh. The measurement process was carried out with the staff of Cam Pha Mining Chemical Company. This is the agency tasked with monitoring ground vibrations caused by blasting mines at Nui Beo mine. Research equipment is always placed next to the standard equipment to have a calibration database (Figure 6).

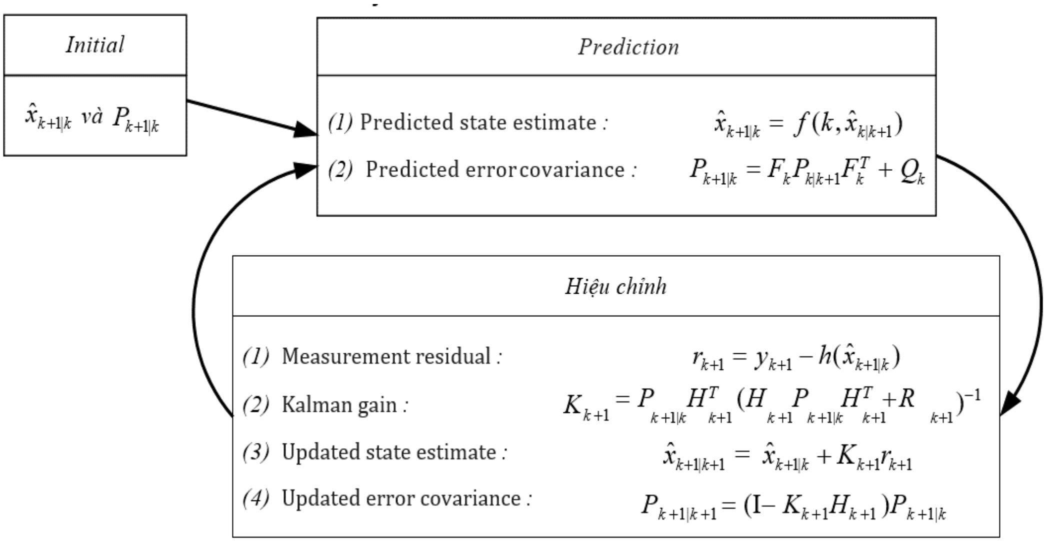


Figure 5. Data processing procedure of the Extended Kalman Filter (Haykin, 2001).

Figure 6. Recording data at Nui Beo coal mine.

4. Results of processing and evaluation

The data used in this study is blast-vibration data measured at the Nui Beo coal mine using the MyRio-1900 of Nation Instruments (NI). MyRio-1900 has a 3-axis accelerometer chip with 12-bit resolution and ±8 g measurement range (ADXL345 chip) (www.ni.com). Measurement data is recorded directly from the sensor data without any processing. Filtering techniques using the extended Kalman algorithm were performed on Matlab software with the following methods:

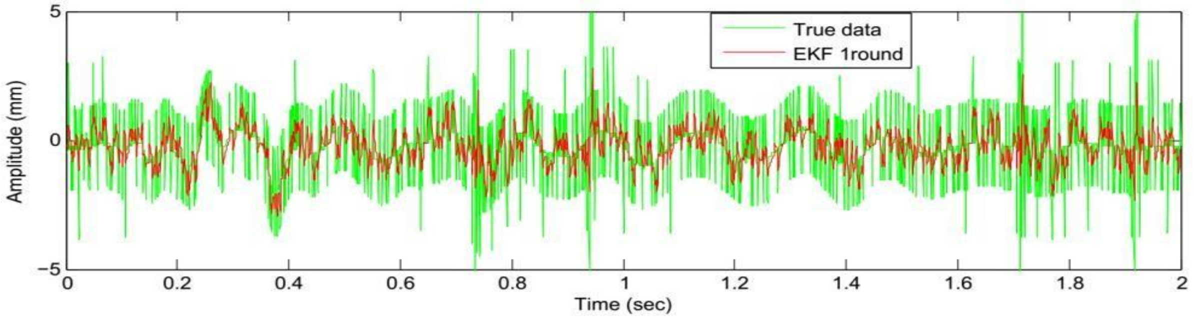
Method 1: Filter data once by EKF algorithm: from the recorded data, the EKF algorithm is applied to eliminate errors caused by noise. The result obtained is the data after filtering.

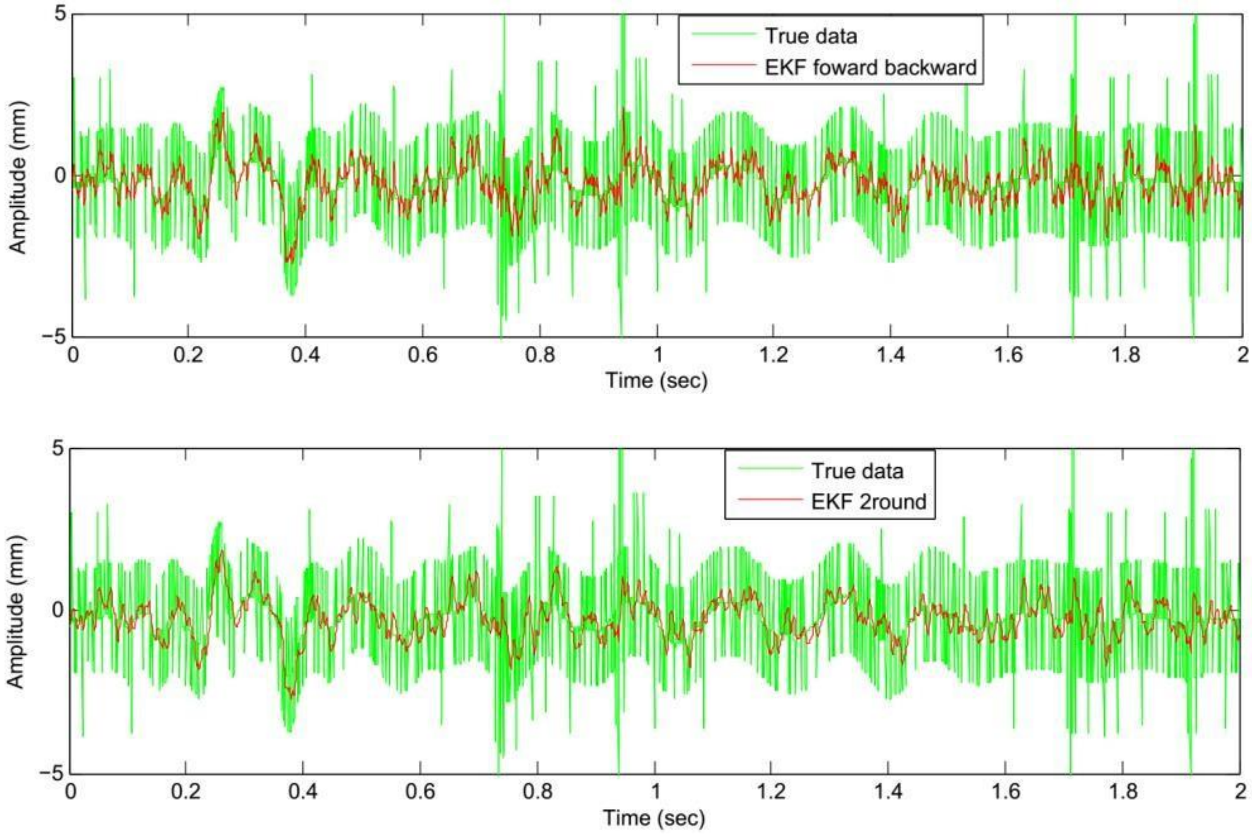
Method 2: Filter the data twice by EKF algorithm: from the recorded data, the EKF algorithm is applied to eliminate errors caused by noise. The received data after the first filter continues to be applied EKF algorithm once again to remove any noise components that may remain after the first time. The result obtained is the data after the second filtering.

Method 3: Filtering the combined data in the forward and reverse direction by the EKF algorithm is done as follows: from the original recorded data, apply the EKF algorithm to the elements in order from the first element to the end (forward); next, apply the EKF algorithm to the elements in order from the last element to the first (reverse). From the two results of forward and reverse filtering, the corresponding positions are averaged to determine the final data after the processing.

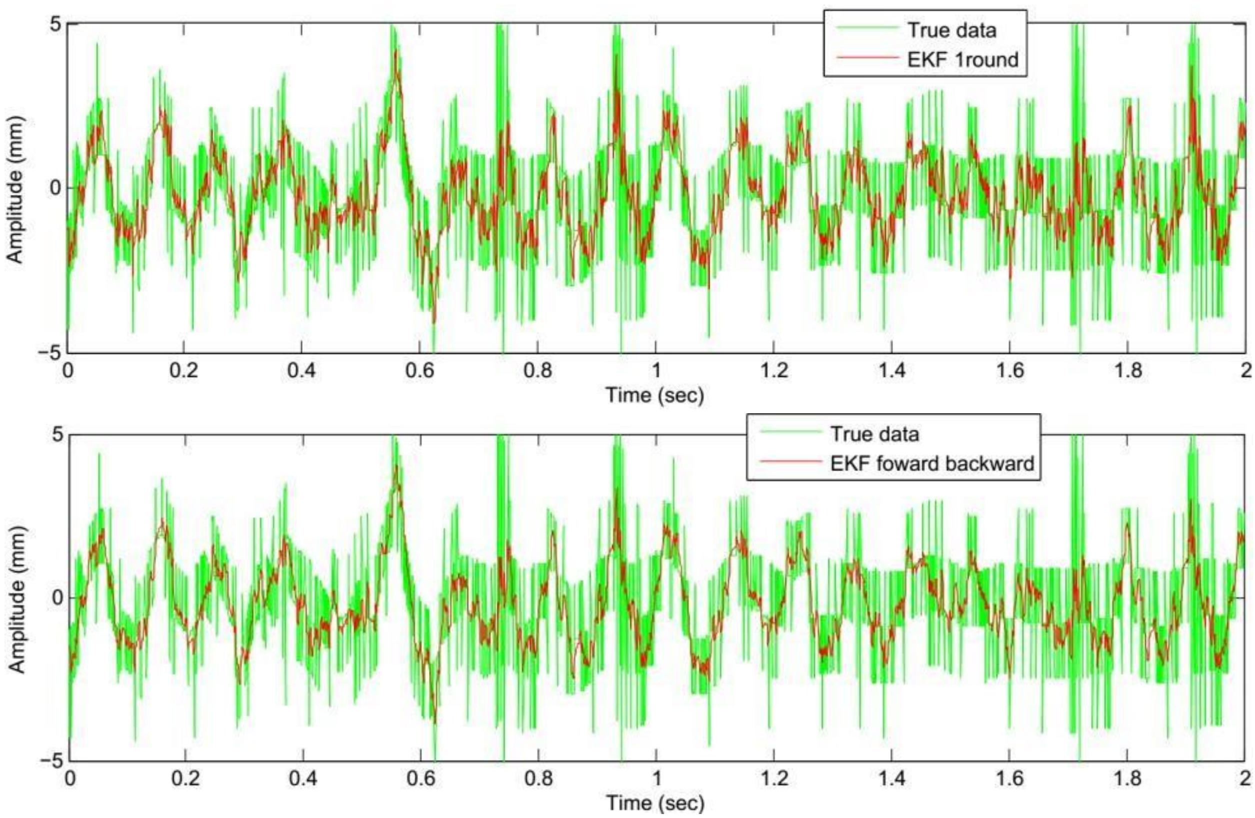
The results of data processing by each method are shown in Figures 6 and 7 for all 3 XYZ axes of the sensor. According to each axis, there are two groups of graphs described. The first group is the amplitude-time graphs. In which, the original (blue line) and the filtered (red line) are represented on the same coordinate system (Figure 7). The second group is the amplitude-frequency graphs of the original and filtered data that are represented separately on each graph (Figure 8).

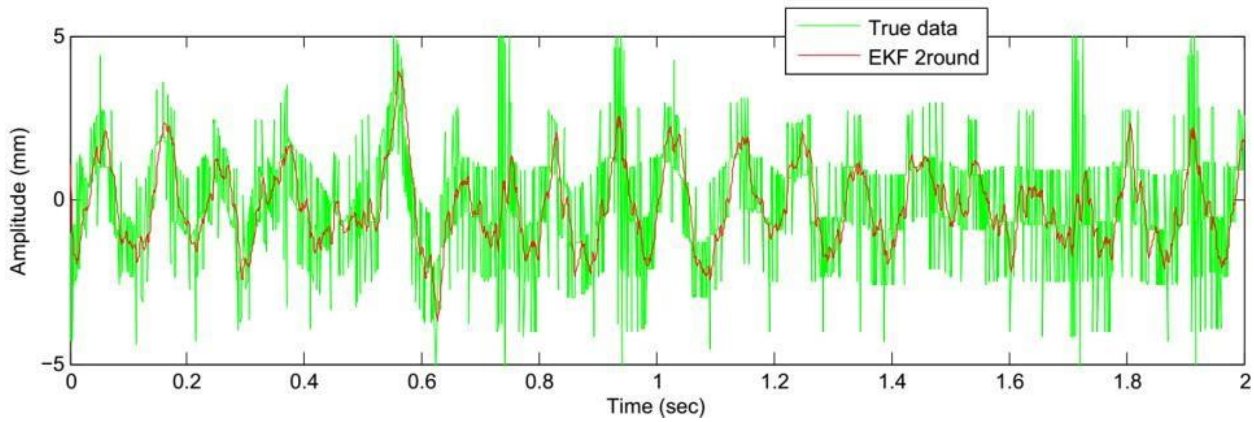
X axis



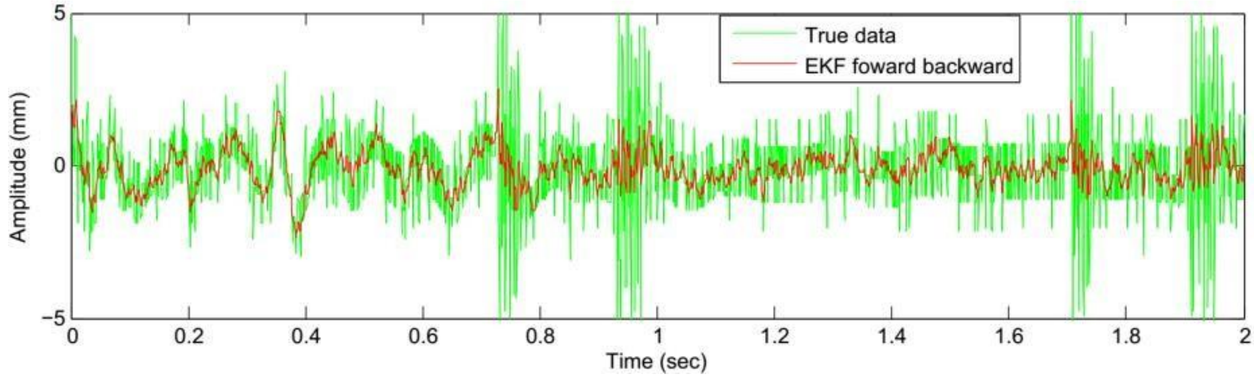

True data
EKF foward backward
Amplitude (mm)
Time (sec)
True data
EKF 2round
Amplitude (mm)
Time (sec)

Y axis


True data
EKF 1round
Amplitude (mm)
Time (sec)
True data
EKF foward backward
Amplitude (mm)
Time (sec)



Z axis



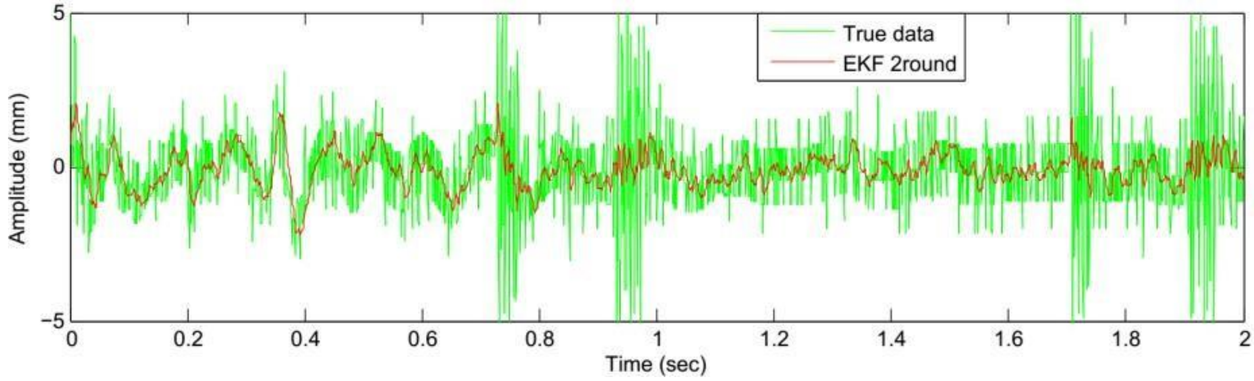
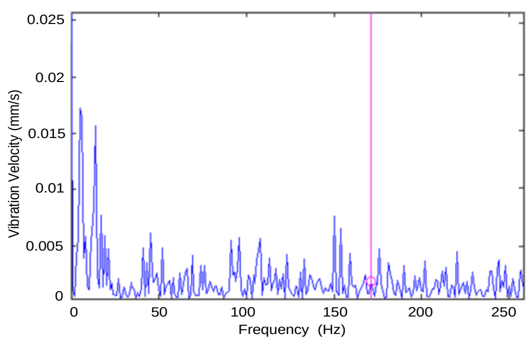
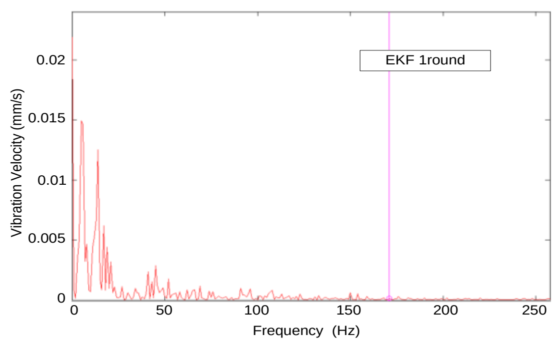
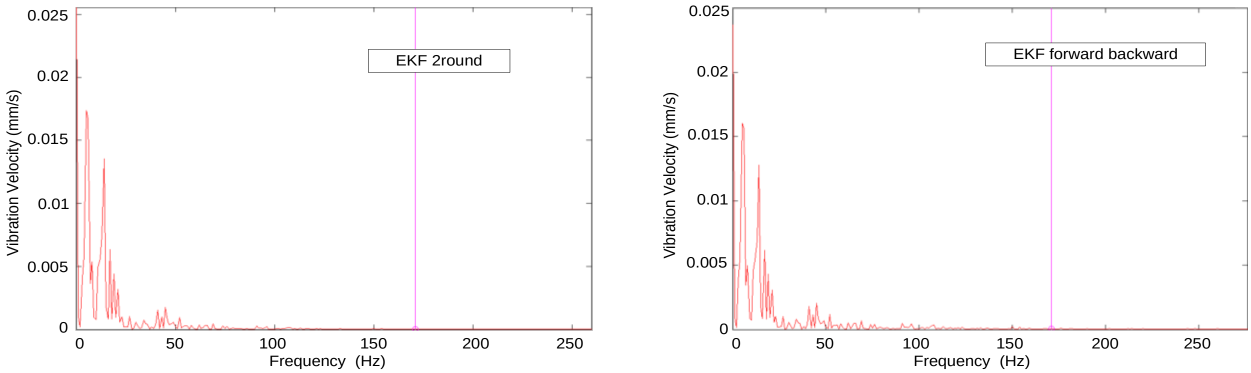


Figure 7. Vibration data processing results are analyzed by time.

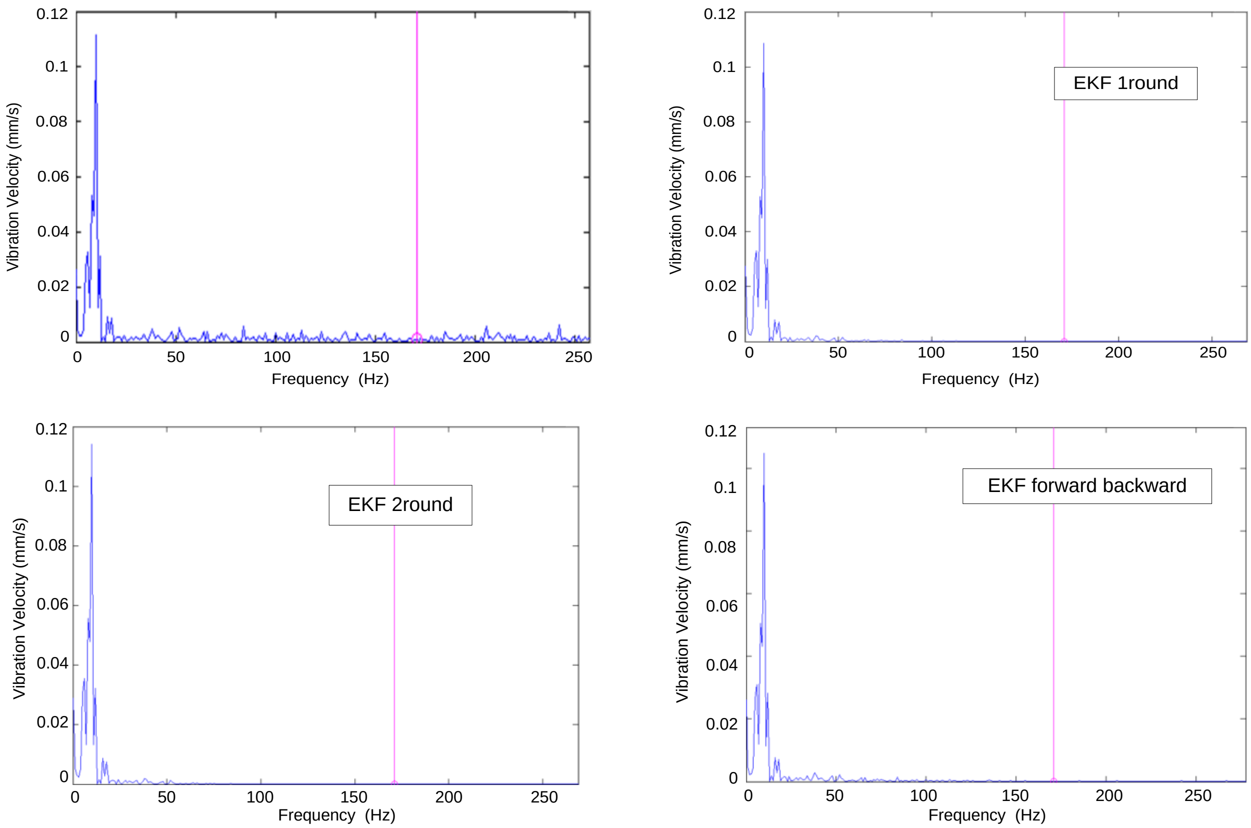
X axis



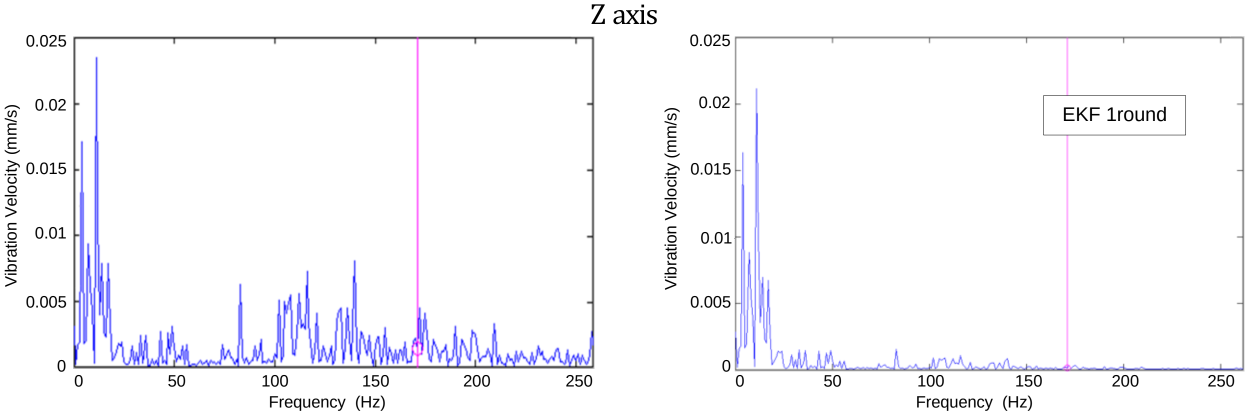



EKF 2round
EKF forward backward
Vibration Velocity (mm/s)
Frequency (Hz)

Y axis


EKF 1round
EKF 2round
EKF forward backward
Vibration Velocity (mm/s)
Frequency (Hz)

Z axis


EKF 1round
Vibration Velocity (mm/s)
Frequency (Hz)

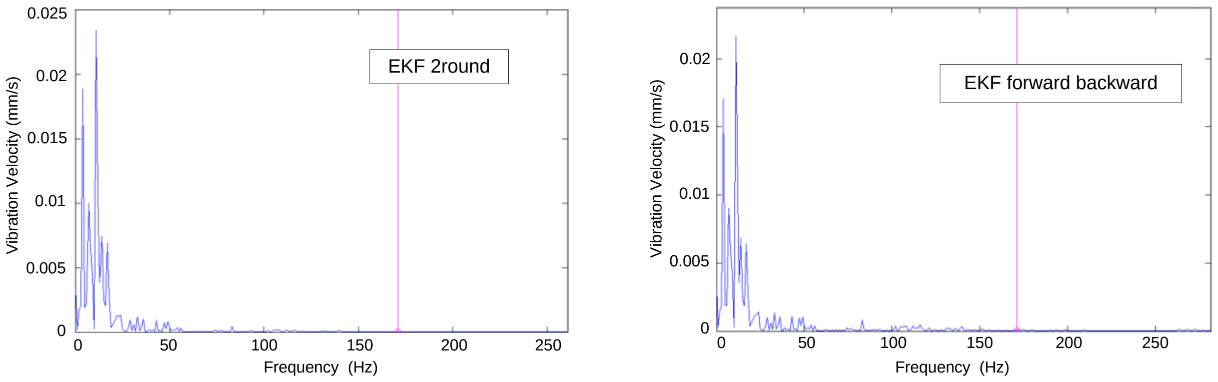


Figure 8. Vibration data processing results are analyzed by frequency.

In Figure 7, the red lines on the amplitude-time graphs with all three axes (X, Y, and Z) show that when the one-round EKF algorithm is used, the processed data still varies with high density. It means, there is a lot of unprocessed noise. The results were better with the EKF forward-backward solution. But, the solution using the 2-round EKF algorithm gives the best results to ensure the complete observation of the results, the amplitude-frequency graphs are shown in Figure 8. These graphs show that filtering with different techniques removes only high-frequency components without affecting the main frequency domain. In which, the 1-round EKF technique is still less effective than EKF forward-backward and 2-round EKF is the best. That confirms the effectiveness of combined filtering techniques.

5. Conclusions

From the analysis results, the study proposes to use a 2-round data filtering solution using the EKF algorithm.

Standardization of measurement data is the ultimate and the most important purpose for all data acquisition equipment in general and blast-induced ground vibration data acquisition device equipment in particular. Therefore, determining the data processing method plays a decisive role in building the structure and designing solutions for blast-induced ground vibration measurement equipment. The test results confirm the feasibility of the equipment construction target in Vietnamese conditions. More broadly, this result holds for data collection devices in all other areas. That shows the great significance of the research results.

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Contribution of authors

Hieu Dao - methodology, writing, review & editing; Loan Thanh Thi Pham - writing, review & editing, supervision.

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