Buried Object Detection based on Acousto-seismic Method using Accelerometer and Neural Network

Setyabudi[1], Muhammad Rivai[1] and Ronny Mardiyanto[1]
[1]*Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia*

Keywords: Accelerometer, Acousto-Seismic Method, Buried Objects, Neural Network.

Abstract: A system for detecting buried objects is often needed for inspection, exploration and security purposes. This research has developed a system to detect buried objects based on the acousto-seismic principle. A sinusoidal signal is amplified by an audio amplifier to drive a subwoofer speaker to produce mechanical vibrations. The seismic vibrations propagating in the ground are measured by an accelerometer. The Fast Fourier Transform method converts vibrations in the time domain to the frequency domain. Neural Network algorithm is applied to distinguish these wave spectrums to determine buried objects. After testing in experiments, this system can distinguish between buried metal and non-metal objects. This system could also recognize the shallow buried objects with an accuracy rate of 86.6%. This method can be potentially developed to detect land mines both metal and non-metal materials.

1 INTRODUCTION

Buried object detections are often needed as an inspection and security machine. Metal detectors can detect objects within a certain distance both on the surface and inside the ground. Buried landmines with metal casings are often found in fields which can be dangerous to humans or animals around them. Metal detectors are generally only able to detect metal objects. In fact, many dangerous objects are covered by non-metal materials.

Several methods are applied to inspect buried objects. Radar-based noncontact displacement sensors can be used to detect buried landmines using seismic wave excitation (Martin et al., 2001). This system explores the elasticity characteristics of objects towards their environment. Detection of landmines can be carried out by capturing gamma rays emitted by hydrogen and nitrogen contained in the explosives (Yoshiyuki et al., 2007). The position of the buried object can be localized by the pendulum method to measure its acceleration (Maqsud and Daku, 2005). An acousto-seismic method has also been implemented in which buried objects have specific seismic (Rayleigh) wave responses in the time and frequency domains (Bulletti et al., 2010). Detection of land mines based on Time Reverse Acoustics can significantly improve the accuracy of the results (Sutin et al., 2005). The inspections of buried objects typically use low frequency mechanical vibrations of 5-100 Hz (Song et al., 2017).

In this research, a system has been designed and developed to detect buried objects based on the acousto-seismic method. Seismic vibration is generated by an acoustic signal produced by a subwoofer. The vibration that propagate on the ground is measured using micro-electro-mechanical systems (MEMS) accelerometers. Fast Fourier Transform (FFT) method converts vibrations in the time domain to the frequency domain. Neural Network algorithm will recognize the frequency spectrum pattern of the vibration in order to determine the buried object.

Setyabudi, ., Rivai, M. and Mardiyanto, R.
Buried Object Detection based on Acousto-seismic Method using Accelerometer and Neural Network.
DOI: 10.5220/0009882202520257
In *Proceedings of the 2nd International Conference on Applied Science, Engineering and Social Sciences (ICASESS 2019)*, pages 252-257
ISBN: 978-989-758-452-7

2 MATERIALS AND METHOD

The overall system of detection for buried objects is illustrated by Figure 1. This prototype is a wooden box with a size of 60cmx60cmx10cm containing 30 kg of sand. The 60 hertz sinusoidal signal is amplified by an audio amplifier to drive a 12-inch subwoofer speaker to produce mechanical vibrations of 125 dB. The subwoofer is located in a wooden box with a size of 60cmx45cmx100cm mounted on sand with a distance of 30 cm, as shown in Figure 2. The objects used in this study consisted of metal and non-metal objects buried 10 cm deep in sand including iron, aluminum, zinc, stainless steel, plastic, polyvinyl chloride (PVC), and acrylic, as shown in Figure 3.

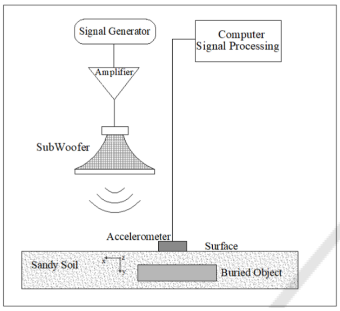

Figure 1: The overall system of detection for buried objects.

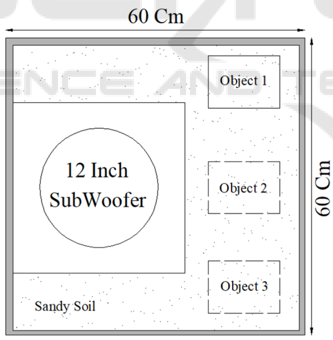

Figure 2: The layout of the buried object detection.

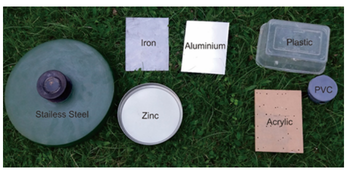

Figure 3: The buried objects used for the experiments.

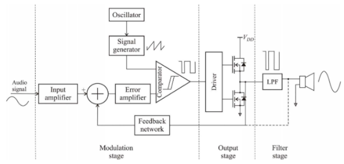

Figure 4: The architecture of switching power amplifier (Kovačević et al., 2018)

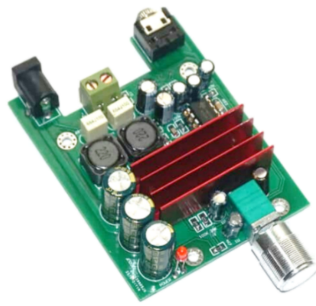

Figure 5: The MDL-049 TPA3116D2 amplifier module.

Class-D or switching power amplifier has a high power efficiency of more than 90% (Kovačević et al., 2018). This type of amplifier uses the Pulse Width Modulation (PWM) method as depicted in Figure 4. In this study, we use the MDL-049 TPA3116D2 subwoofer amplifier module as shown in Figure 5. This amplifier is a stereo digital amplifier that can drive speakers by 50 W per channel. This module is configured as a mono amplifier that can produce a power of 100 W to a 4 Ω speaker with the Bridge-Tied-Load method.

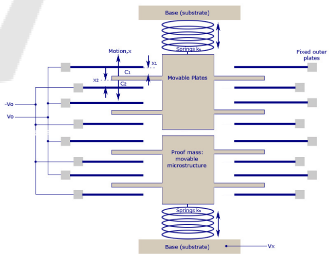

Figure 6: The working principle of MEMS accelerometer (John, 2011)

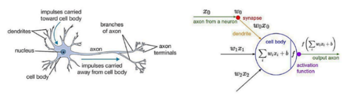

Figure 7: The neuron model.

Accelerometer is a sensor that can measure changes in speed. MEMS accelerometer is often used in many applications because of their compact size for three-dimensional space. This sensor can be used to measure vibrations that propagate on the ground or objects (Ardiansyah et al., 2018). The working principle of this sensor is based on changes in capacitance shown in Figure 6. The output voltage of the proof mass can be expressed as:

$$V_x = \frac{X}{d} V_0 \tag{1}$$

where x is the distance between the two plates of the internal capacitor, d is the change in distance between the plates, V_0 is the amplitude of the excitation voltage. By involving spring force, the output voltage will be proportional to the acceleration. In this study, the seismic vibrations are measured by ADXL335 analog accelerometer. This sensor operates at the voltage of 1.8–3.6V and the current consumption of 350μ. This device has a bandwidth of around 0.5-1600 hertz. The sensor signal is then digitized using an Arduino Nano microcontroller board.

The FFT method converts the signal in the time domain into a frequency domain. This frequency spectrum feature is often used for the identification of sounds produced by vibrating objects (Winjaya et al., 2017). Compared with Discrete Fourier Transform (DFT), the FFT has fewer total number of complex multiplies of (N/2) 2log (N) with N is the number of signal samples. In general, Fourier transform can be expressed as:

$$x[k] = \sum_{n=0}^{n-1} x[n] W_n^{kn} \tag{2}$$

$$W_n^{kn} = e^{-j2\pi kn/N} \tag{3}$$

where x [n] is a discrete signal in time domain, and x [k] is the frequency spectrum. In this study, the range of frequency spectrum is between 0-99 hertz with a step of 1 hertz. This spectrum is used as input for the Neural Network to recognize the vibrations.

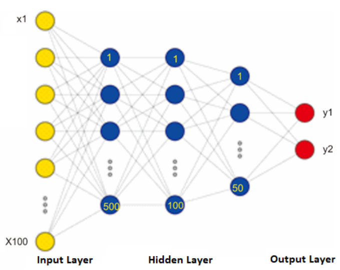

Figure 8: The Neural Network architecture used in the experiment.

Neural Network is a computational model inspired by human brain. The human brain has many neurons that are connected to each other. Figure 7 shows the model of a neuron cell. Using the logistic sigmoid function, a neuron model can be expressed by:

$$Z_j = \Sigma_i^3 (W_{j,i} X^1 + b_j) \tag{4}$$

$$O_j = \frac{1}{1 + e^{-azj}} \tag{5}$$

Neural Networks are widely used as artificial intelligence to identify patterns (Rivai and Tasripan, 2015), (Rivai et al., 2016), (Rivai et al., 2014). The Neural Network architecture used in this study is shown in Figure 8. The input layer consists of 100 nodes that correspond to the frequency spectrum of the acousto-seismic vibrations. The hidden layer consists of three layers, each of which consists of 500, 100, and 50 neurons. Meanwhile, the 2 neurons in the output layer represent the number of classes that will be recognized. The learning and running phases are accomplished by a computer using Python Programming Language.

3 RESULT AND DISCUSSIONS

The prototype of the system for detecting buried objects is shown in Figure 9. The experimental results of the frequency response without buried object is shown in Figure 10. Whereas, the frequency spectrum for buried metal and non-metal objects can be seen in Figure 11, and Figure 12, respectively. Bandwidth spectrum of buried objects is wider than that of without objects. There are also significant differences between the spectrum patterns of buried metal and non-metal objects.

The next experiment is the detection of buried metal and nonmetal objects using the Neural Network. In the training phase, the network uses pairs between 120 spectrum patterns of all metal objects for different positions and targets (Y1 = 1 and Y2 = 0), as well as pairs between 90 spectrum patterns of all nonmetal objects for different positions and targets (Y1 = 0 and Y2 = 1).

Figure 9: The prototype of the buried object detection system.

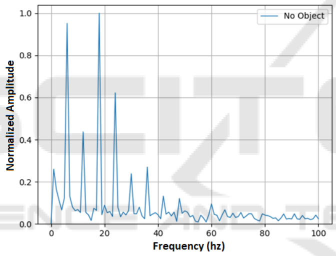

Figure 10: The spectrum of vibration without buried object.

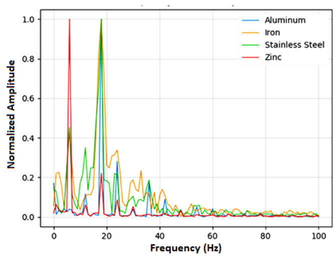

Figure 11: The spectrum of vibration with buried metal objects.

This training phase loss curve is shown in Figure 13. In the running phase, 35 spectrum patterns are tested online as shown in Table 1. The experimental results indicate that Neural Network could classify buried metal and non-metal objects with an identification level of 77%.

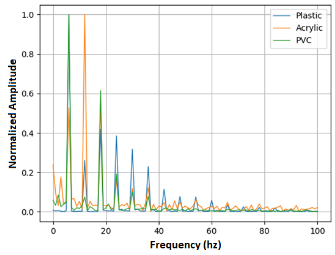

Figure 12: The spectrum of vibration with buried non-metal objects.

The next experiment is the detection of with and without buried objects. In the training phase, the network uses pairs between 100 spectrum patterns of without objects and targets (Y1 = 1 and Y2 = 0), as well as pairs between 210 spectrum patterns of all both metal and non-metal objects for different positions and targets (Y1 = 0 and Y2 = 1). This training phase loss curve is shown in Figure 14. In the running phase, 15 spectrum patterns are tested online as shown in Table 2. The experimental results indicate that Neural Network could determine the buried objects with a success rate of 86.6%. The similar results are obtained when this system is applied to identify buried objects for true field experiments, as shown in Figure 15.

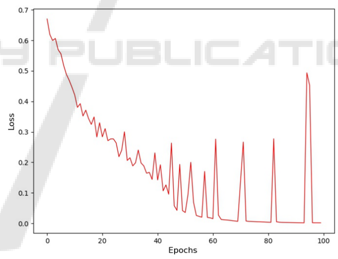

Figure 13: Loss curve of the Neural Network training phase to detect buried metal and non-metal objects.

Materials	No.	Category	Identification
Iron	1	Metal	Metal
	2	Metal	Metal
	3	Metal	Metal
	4	Metal	Non Metal
	5	Metal	Metal
Aluminum	1	Metal	Non Metal
	2	Metal	Metal
	3	Metal	Metal
	4	Metal	Metal
	5	Metal	Non-Metal
Stainless Steel	1	Metal	Metal
	2	Metal	Metal
	3	Metal	Non-Metal
	4	Metal	Metal
	5	Metal	Metal
Zinc	1	Metal	Metal
	2	Metal	Metal
	3	Metal	Non-Metal
	4	Metal	Non-Metal
	5	Metal	Metal
Plastic	1	Non-Metal	Non-Metal
	2	Non-Metal	Metal
	3	Non-Metal	Metal
	4	Non-Metal	Non-Metal
	5	Non-Metal	Non-Metal
PVC	1	Non-Metal	Non-Metal
	2	Non-Metal	Non-Metal
	3	Non-Metal	Non-Metal
	4	Non-Metal	Non-Metal
	5	Non-Metal	Non-Metal
Acrylic	1	Non-Metal	Non-Metal
	2	Non-Metal	Non-Metal
	3	Non-Metal	Non-Metal
	4	Non-Metal	Non-Metal
	5	Non-Metal	Non-Metal

Figure 14: Neural Network identification for buried metal and non-metal objects.

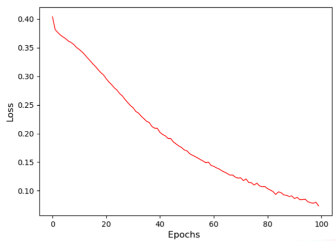

Figure 15: Loss curve of the Neural Network training phase to detect buried objects.

No.	Category	Identification
1	No Object	No Object
2	No Object	No Object
3	No Object	Object
4	No Object	No Object
5	No Object	No Object
6	No Object	No Object
7	No Object	No Object
8	Metal Object	Object
9	Metal Object	Object
10	Metal Object	Object
11	Metal Object	Object
12	Non-Metal Object	No Object
13	Non-Metal Object	Object
14	Non-Metal Object	Object
15	Non-Metal Object	Object

Figure 16: Neural Network identification for buried objects.

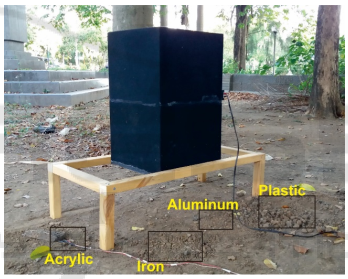

Figure 17: True field experiments for buried object identification

4 CONCLUSION

We have designed and realized a device to detect buried objects based on the acousto-seismic method. The 60 hertz sinusoidal signal is amplified by an audio amplifier to drive a 12-inch subwoofer speaker to produce mechanical vibrations of 125 dB. The seismic vibrations propagating in the ground are measured by the ADXL335 MEMS accelerometer. The FFT method converts vibrations in the time domain to the frequency domain. The Neural Network algorithm is applied to distinguish these wave spectrums to determine buried objects. The experimental results show that this system can distinguish between buried metal and non-metal objects with an identification rate of 77%. This system could also recognize the shallow buried objects with a success rate of 86.6%

REFERENCES

Ardiansyah, H., Rivai, M., and Nurabdi, L. (2018). Train arrival warning system at railroad crossing using accelerometer sensor and neural network. In *AIP Conference Proceedings*, page 040029–1.

Bulletti, A., Borgioli, G., Calzolai, M., Capineri, L., and Mazzoni, M. (2010). Acoustoseismic method for buried-object detection by means of surface-acceleration measurements and audio facilities. *IEEE Trans. Geosci. Remote Sens*, 48(8):3134.

John (2011). Mems accelerometer. `http://www.instrumentationtoday.com/mems-accelerometer/2011/08`. [Online; Accessed 23-June-2019].

Kovačević, S., Pešić-Brdjanin, T., and Galić, J. (2018). Class d audio amplifier with reduced distortion. *Int. Symp. Ind. Electron. INDEL.*

Maqsud, A. and Daku, B. (2005). Characterization of a mems accelerometer for an underground mine positioning system. In *Canadian Conference on Electrical and Computer Engineering*, page 2268.

Martin, J., Scott, W., and Larson, G. (2001). Experimental model for a seismic landmine detection system. *IEEE Transactions on Geoscience and Remote Sensing*, 39(6):1155.

Rivai, M., Arifin, A., and Agustin, E. (2016). Mixed vapour identification using partition column-qcms and artificial neural network. In *International Conference on Information, Communication Technology and System*, page 172.

Rivai, M., Talakua, E., and L. (2014). The implementation of preconcentrator in electronic nose system to identify low concentration of vapors using neural network method. *International Conference on Information, Communication Technology and System*, page 31.

Rivai, M. and Tasripan (2015). Fuel qualification using quartz sensors. *ARPN Journal of Engineering and Applied Sciences*, 10(16):6737.

Song, K., Tong, S., Ding, Z., and Dong, L. (2017). An electromagnetic feedback method to improve low-frequency response performance of geophone. In *Proc. IEEE Sensors*, page 5.

Sutin, A., Johnson, P., Tencate, J., and Sarvazyan, A. (2005). Land mine detection by time reversal acousto-seismic method time reversal acousto-seismic method for land mine detection. In *Proc. of Society of Photo-Optical Instrumentation Engineers*, page 706.

Winjaya, F., Rivai, M., and Purwanto, D. (2017). Identification of cracking sound during coffee roasting using neural network. *International Seminar on Intelligent Technology and Its Application*, page 271.

Yoshiyuki, T., Tsuyushi, M., Cheol, H., Seiji, S., Kiyosi, Y., Kai, M., and Teruhisa, T. (2007). Development of landmine detection system using scintillators by measuring radiations from landmine. *IEEE Nucl. Sci. Symp. Conf. Rec*, page 273.