Acoustic Pattern Recognition Based Digging Detection using Bayesian Network Classifier

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Article History Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 28 April 2021

Abstract: Events happening around us generate many sound signals. Some examples of these incidents are shooting in cities or forested areas, humans chopping wood in forested areas, calling for wild animals or chi birds, talking to vehicles driving in the forest or talking to people illegally crossing a safe border. In these incidents, it is very important to detect the mine activities and their locations, because they indicate illegal intrusion by laying mines or digging holes, placing animal traps in the forest, etc. This paper proposes a method to identify soil dig events in the presence of other forest noise. The sound signal for soil dig is collected by keeping the microphone at different distances from the sound source and digging. Signals were analyzed using spectrogram. A Bayesian Network Classifier is applied to classify the event.

Keywords: Digging detection, Bayesian Network Classifier, Machine Learning.

1. Introduction

In many cases, we need to continuously monitor sensitive areas (such as national borders, forests, military facilities, etc.). Intruders often use different methods to defeat surveillance, such as digging tunnels, through which they can enter protected areas, and bury mines. It also needs to be excavated to lay mines.

This paper presents method to determine soil excavation activities in noisy environments. Several techniques for training the system are proposed, such as envelope graph decision tree, spectrogram quantization method, and ANN [1, 2, 3, 4, 5].

Nakadai Kazuhiro et al. [6] has proposed footstep detection on the floor. Footsteps are low-frequency ground-borne sound. The author of the paper uses time domain, frequency spectrum, cepstrum and geometric features (position and velocity of the sound source) for classification. Support vector machine (SVM) [7] has been used for classification.

G.Dorantes-Méndez [8] proposed a technique for discovering the ability of time-varying autoregressive (TVAR) models to detect and provide estimates of small and rough cracks (thick cracks are discontinuous, short-lived, sudden Lung sounds) sound. For training and testing, multi-channel lung signals were collected at a sampling rate of 10kHz. These signals are low amplitude signals. Use the TVAR model to analyze the samples. The authors of the results section concluded that the time-varying autoregressive model is the correct choice to detect and provide an estimated number of fine cracks and coarse cracks, even if there are crack overlaps and cracks with an amplitude equal to 1.5 of the background standard deviation. Lung sounds. This article proposes a technique that can eliminate the large amount of noise caused by audible lung cracks.

Christer Ahlstrom et al. [9] proposed a third type of heart sound detection (usually heard in patients with heart failure). The third heart sound is difficult to hear and has a varying low amplitude signal. The author proposes an algorithm based on recursive time statistics to detect the third heart sound.

A.A. Maksutov et al. [10] proposed a probability model organized in the form of an acyclic graph. After briefly introducing the world of artificial neural networks (especially Bayesian methods), we next turn to the proof of the idea that Bayesian networks are not retrained, which is a practical use of neural networks in industry. The actual classification problem proved this hypothesis. Our goal is to build a Bayesian network that will classify the measured object and show that the network takes noise into consideration and will not be retrained.

A. Albu et al. [11] proposed stroke risk prediction and provided tools designed to help doctors make decisions. And compared two special methods (artificial neural network and naive Bayes classifier). The results show that these methods have similar performance and can provide valuable support for medical prediction.

I. R. S. Evangelista [12] developed a wireless sensor network that can use infrared sensors to detect insects and capture the flapping patterns of their wings, thereby remotely and independently monitoring insects in flight. The Bayesian classifier is used to predict the type of insect based on its wing beat frequency. The accuracy of classifying housefly data is 91.97%, and the accuracy of classifying mosquito data is 92.85%. The high demands and effective functions of this system have the potential for insect research for medical or agricultural applications.

Taking into account the aforementioned literature, the signals used for soil mining (described in the following sections) have been collected and analyzed to develop soil mining detection algorithms.

The paper is summarized as follows: The second part will introduce the experimental setup and signal data collection. The third part introduces signal analysis and feature recognition. The fourth part introduces feature recognition and feature description. The fifth part introduces the proposed algorithm design. Section VI introduces the results and conclusions.

2. Experimental setup:

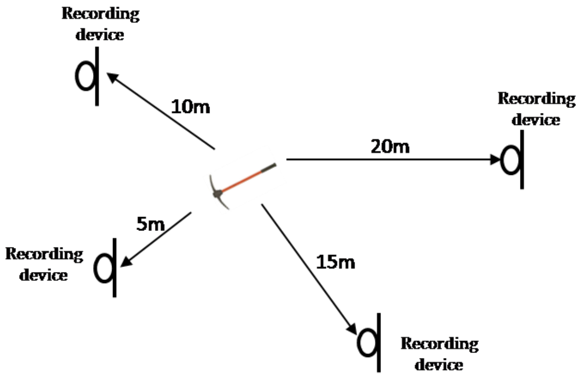


Figure 1: Experimental setup

The experimental setup consists of devices to record signal as well as detect the event. The figure 1 shows the setup to record and analyze the acoustic signals. The samples of signal collected with the hard soil, and wet soil.

The device use to record and detect the event (figure 2) consists of acoustic acquisition unit using microphone and signal conditioning. Additionally, a processor embed with algorithm is used to identify the event. Transmitter is used to send information of event to guards.

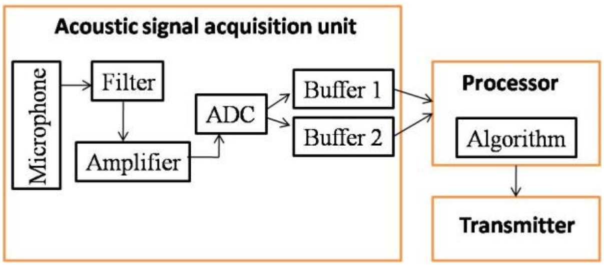
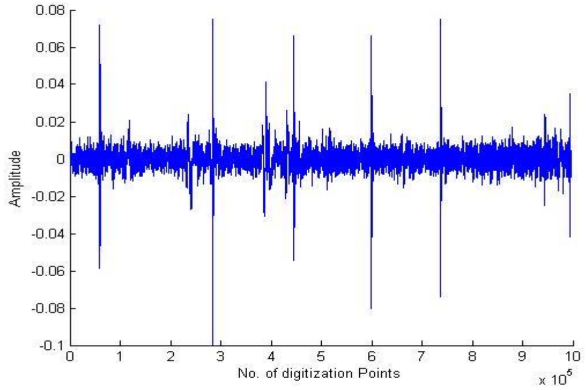


Figure 2: Block diagram of Detection Unit

3. Analysis of signals

A number of signals were collected and analyzed using the experimental setup. In all the collected signals 120 signals were used for analysis and other signals were used for random testing. The signals used in testing is not used for the training of system.

Figure 3, 4, 5, 6, and 7, shows the waveform and spectrogram of the excavated acoustic signal. A high amplitude indicates a blow on the ground. Each strike was extracted from the recorded signal.



3(a) Wave form of entire signal

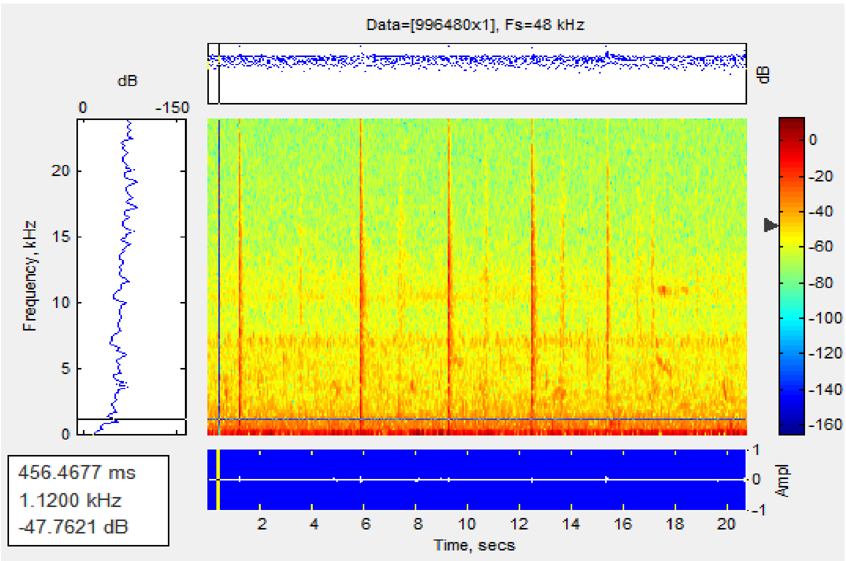


Figure 3: Spectrogram of entire signal

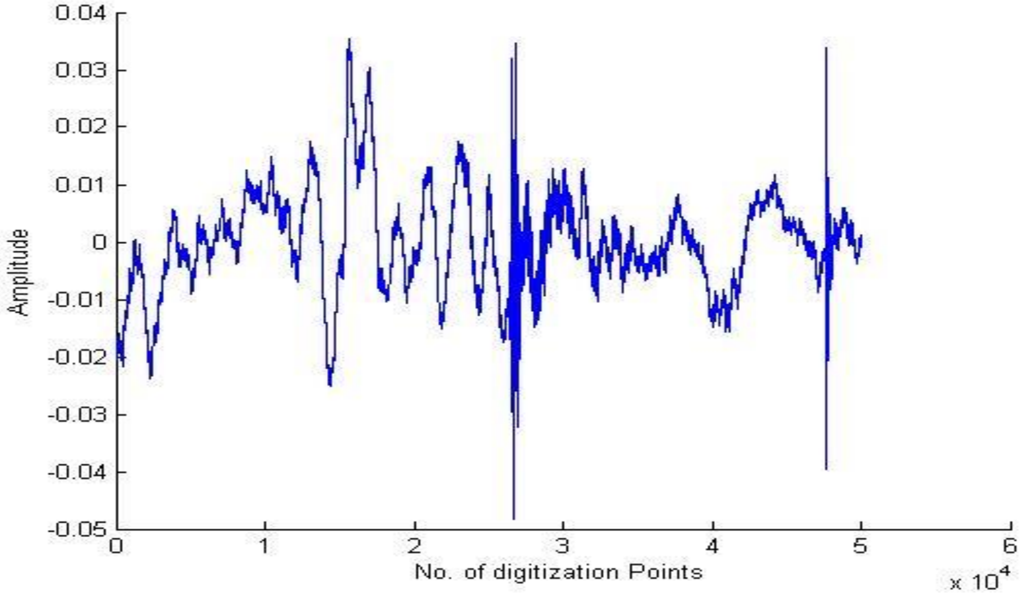


Figure 4: Wave form of single strike by pickaxe

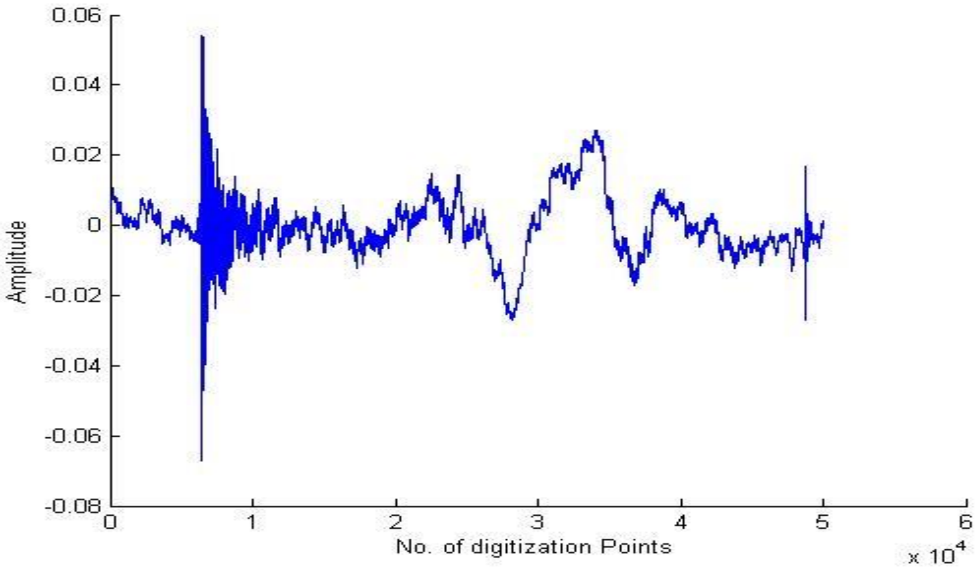


Figure 5: Wave form of single strike by hoe

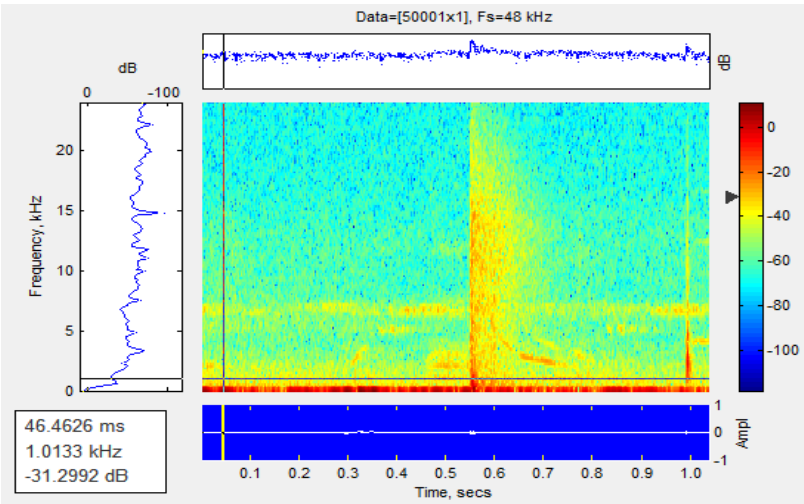


Figure 6: spectrogram of single strike by pickaxe

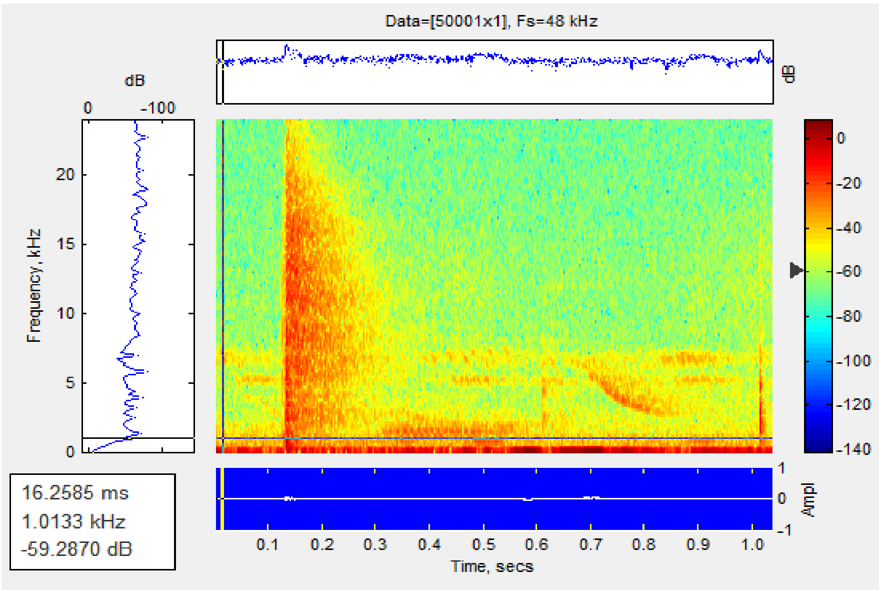


Figure 7: spectrogram of single strike by hoe

4. Algorithm for digging detection

After analyzing 80 acoustic signals in the time domain and frequency domain using MATLAB and literature survey methods, 10 parameters that help identify soil excavation events are determined. These parameters were used in Bayesian Network Classifier to identify soil excavation events.

Bayesian Network Classifier [11, 12]

Suppose we have data set denoted by X and we need a classifier that can correctly predict the class labels of new object $X_{(n+1)}$. We consider the attributes X= (X_1 , X_2 … , X_n) and the class C as random as a random variable. Now we need to estimate probability $P(c_j | X)$ that X belongs to a particular class. Further class c^* attached with X is the class where probability $P(c_j | X)$ is maximum.

$$c^* = \arg\max_{j=1\ldots m} P(c_j \mid X)$$

Here the class c^* is determined by the Bayes theorem as follows

$$P(C|X) = \frac{L(X|C)P(C)}{H(X)}$$

Where P(C) is the prior distribution of class C, *L(X|C)* is the likelihood function of observed data X and H(X) is a constant without C. Bayes theorem updates prior distribution on C in light of observed data and we get updated distribution for class C which is denoted by *P(C|X) i.e.* posterior distribution of C.

Now for classifying X to the class which has maximum posterior probability

$c^* = \arg\max P(c_j | X)$, we can define Bayes theorem as follows

$$P(c_j|X) = \frac{L(X|c_j)P(c_j)}{H(X)}$$

Since H (X) is a constant without C, we can define posterior distribution upto proportionality as

$$P(c_j|X) \; \alpha \; L(X|c_j)P(c_j)$$

So Bayesian classification rule will be defined more clearly as follows

$$c^* = \arg\max_{j=1\ldots m} P(c_j \mid X) = \arg\max L(X|c_j)P(c_j)$$

5. Result

With the help of a microphone sensor and a laptop, the algorithm was tested by digging the ground with a pickaxe. All three methods have been tested one by one. Table 1 shows the efficiency of the algorithm. The algorithm was also tested using the sound signals of tree felling and wood hammering.

	Bayesian Network Classifier
Accurate detection	89%
False positive	8%
False negative	11%

Table 1: Efficiency of algorithms

6. Conclusion

A soil mining detection algorithm is proposed. Under different soil and soil conditions, such as wet soil, hard soil, wet soil with gravel and hard soil with gravel, the sound signals used for soil excavation are recorded. The tool used for digging is a pickaxe. Analyze the signal in the time and frequency domains. 11 parameters are calculated for each signal. Three methods are used for event detection.

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