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Automatic detection of tree cutting in forests using acoustic properties

Sheikh Fahad Ahmad *, Deepak Kumar Singh

Department of Computer Science & Engineering, BBD University, Lucknow, India
Jaipuriya Institute of Management, Lucknow, India

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ABSTRACT

Deforestation is cutting trees of forests on a huge scale, often resulting in loss of habitat of millions of wild animals. About 30% of earths land is still covered with forests but due to deforestation we are losing them at the rate of about half the size of England per year. In forests, tree cutting activities are illegal but due to shortage of manpower and other resources, governments are not very successful in curbing this menace. One way to stop this is to detect the tree cutting process in an early stage so that timely measures can be taken to stop the same. The simplest method of early detection of tree cutting is to regularly monitor the forest area either manually or using some automatic techniques. As tree cutting generates lot of noise, it can be detected by regularly monitoring the acoustic signals inside the forest. An acoustic signature can provide valuable information about the activities of any intruder inside the forest. This paper proposes an algorithm for automatic detection of tree cutting in forest. The proposed algorithm is based on distance between parameters, along with K-means clustering, GMM and PCA for comparison. The efficiency of proposed algorithm is 92%.

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1. Introduction

A research by the International Union of Forest Research Organisations published in the Hindustan Times says that India is placed on third position for illegally importing logged timber in the world. With a yearly import estimation of over Rs. 40 billion, India represents nearly one tenth of the worldwide illicit trading of wood.

A report published in (Brack, 2006) discharged in continuous worldwide gathering of United Nations Convention on Biological Diversity (CBD) in Cancun, Mexico (CBD, 2016), reveals that around 33% of tropical wood traded all over the world may originate from unlawful conversion of the forest land. In this gathering, 167 countries discussed about global mechanisms for the protection of biodiversity of the planet.

As indicated by the report (CBD, 2016), 42% of the aggregate round wood and sawn wood traded all over the world, with a yearly estimation of Rs. 427 billion, is harvested illicitly. Some Amazon and South East Asian countries like Russia, Brazil, Indonesia, Cambodia, Burma and Papua New Guinea are top producers in illegal timber trade. China tops the list in illicit trading of wood with an import value of Rs. 223 billion annually. The report also reveals that Vietnam is the second largest importer of timber trade with an annual value of Rs. 52 billion. Illicit tree cutting and importing is the major reason of deforestation globally which hurts the earth and making misfortune for the administration exchequers. Illicit wood trade imperils organic assorted variety and irritates environmental change. As per a study, in some parts of the world, illegal wood trade leads to organized forest crimes. Additionally, illegal wood trade is also a source of finance in crimes and enmities.

Because of the requirement of timber, some developed nations have put legitimate checks on timber trade. This lead the timber trade move to business sectors in countries like India and China, due to the reason that in these countries less strict rules for timber trade are set up, a report reveals. In a span of seven years (2006–2013), the import value of unlawful wood items from India, Vietnam and republic of China expanded by almost 49%. Whereas for US and Europe, the volume of illegal wood trade sliced by almost 33% and 50% respectively (Brack, 2006), where very stringent rules and laws for timber trade have been set in the previous couple of years.

Tropical forests and Russia are the sources from where China imports unlawful timber while for India the significant volume of

* Corresponding author.
E-mail address: er.fahad@gmail.com (S.F. Ahmad).

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illicit timber comes from Southeast Asian countries. "Given their gigantic local places of wood trade and China's extensive ability to manufacture wood items, it becomes amazingly hard to significantly diminish unlawful logging and trade at the worldwide platform without drawing in these two nations," reveals a study (CBD, 2016).

Woods produce water supplies, biodiversity, pharmaceuticals, reused supplements for farming and surge counteractive action, and are key to the change towards a Green Economy with regards to reasonable improvement and destitution destruction. By far most of deforestation and illicit logging happens in some of the central African and Southeast Asian countries and also in the Amazon Basin's tropical forests. Ongoing investigations into the degree of unlawful logging gauge that illicit logging represents almost 50%–90% in tropical nations and around 15%–30% worldwide. In the interim, the financial estimation of worldwide unlawful logging, which includes handling, is evaluated to 30–100 billion US Dollars, which is almost 10%–30%. The issue of this level illicit logging must be dealt very seriously as it exhausts the forest assets. The probability of accurately estimating illicit logging is very strenuous because 65% or more of all logging activities is conducted illegally in the most vulnerable forest areas. Illegal logging exercises have additionally now and again drew in viciousness, dangers, kills and even abominations against forest living individuals (Brack, 2006).

The work is organized as follows: Literature survey is done in Section 2 and overall sound recognition methodology is presented in Section 3. Collection and analysis of tree cutting signals and parameter extraction is discussed in Sections 4 and 5 respectively. Section 6 deals with the algorithms for tree cutting detection while Section 7 deals with the proposed distance based approach for the detection of tree cutting. Results are presented in 8th section and we finally conclude in section.

2. Literature review

Although many researchers are working on acoustic signal processing, but still detection of tree cutting through acoustic signal is done by very few researchers. This review also presents summary of algorithms used for acoustic signal recognition and detection. Despite the fact that observing the woods from illicit logging by the sound acknowledgment is one of a kind, we have as of late gone through a work named as "Forest Watcher", which is a checking framework to counteract forest annihilation (Miroslav et al., xxxx) and it's firmly identified with our study. It comprises of almost 200 remote sensors which conceal the woods territory of approximately 200 ha. We did not discover any work of this framework in business utilization yet. G. Sharma et al. (Sharma et al., 2016; Sharma, 2018) gave a measurable solution for detecting tree cutting using acoustic signals which was observed by saw scratching through a bole. The noise was separated from acoustic signals using Signal-to-noised (SNR) based algorithm.

Automatically recognizing the sound for the people with Hearing defect (Yoo and Yook, 2008) is one of the numerous tasks on scene which uses sound identification as a mean for handling audio signals. In this paper, the authors gave a framework which helps hearing hindered people by recognizing some straightforward mechanical sounds, for example, telephone sounds, doorbells, alarms and so forth. The spectral peaks of such sounds are clearly distinct. The authors gave another strategy for recognizing audio signals called as NPDR (normalized peak domination ratio) whose tiny structure can make it fit into a wrist watch. One more research project (Mitsubishi Research Institute, 2019) from Mitsubishi Research Institute can recognize seven sorts of sound signals, for example, a chime ringing, hand clap etc with a precision of 80% or more. This Framework uses an array of microphone and a personal computer to process sound signals. It also recognizes the sound and even tries to find the relative position of the source of sound. Peter J and Menevver K in (2011) presented a way for automatically detecting and recognizing tonal bird sounds in environments with too much noise. They used GMM for modeling 165 bird tones. Their model detected bird tonal components with high accuracy rates.

Hidayati et al. (2009) analyzed the sound of crying infant. First, the authors used acoustic feature characteristics which are recognized using the sound formants and sound pitch. After this, they have used K-means clustering for clustering feature vectors (acoustic) in order to determine the different classes of sound signals. P. Sharma in (2017) proposed an efficient SNR based algorithm which is used for deriving different attributes in a speech sound for different tasks in the recognition of speech. The authors used a method which consists of two stages. The first stage involves learning various dictionaries for every speech entity and the second stage involves using of a sparse solver to obtain sparse features. Winursito et al. (2018) presented the mix of two methods, i.e. MFCC – Mel Frequency Cepstral Coefficients which is adopted for extracting sound features and PCA – Principal Component Analysis for improving preciseness in the Indonesian speech recognition system. This combination formed matrix data which was later reduced using PCA. After this, the outcome of the reduction data of PCA is processed by K-Nearest Neighbor (KNN) approach.

Mohanapriya et al. (2014) presented a model for recognizing environmental sounds. The research comprises of the following steps: 1. collecting the sound signals, 2. extracting the crucial features, 3. making clusters of identical features, 4. classifying the features. The authors then extracted the coefficients of Mel frequency cepstrum which are used for making the clusters by GMM. Further, these features are classified and the environmental audio scene is identified using the Neural Network.

3. Sound recognition method

The acoustic signals of tree cutting by axe have been recorded in forest as well as downloaded from some online repositories such as www.sounddog.com and www.freesound.org. From these acoustic signals, a master database is designed which contains the extracted important features. This designed database is further broken in 2 parts, 1st part is used for training purpose and 2nd part is used for testing purpose. The overall proposed methodology is depicted in Fig. 1.

As shown in Fig. 1, first block of capturing acoustic signal comprise of audio signal recording devices, which can record signal without compression in wav format. Laptop is also used for recording audio signals.

Second block is used for noise removal using signal analysis software. Third block is used to calculate parameter extraction using MATLAB. Fourth block is used for classification by implementation of algorithms.

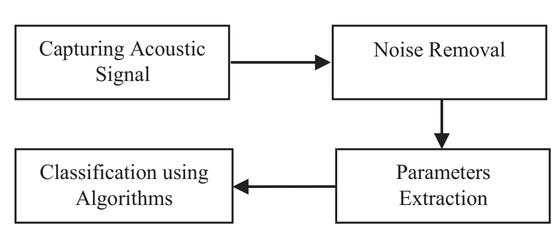

Fig. 1. Overall proposed methodology.

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4. Collection & analysis of tree cutting signals

The focus of research is to recognize tree cutting signal by axe in presence of forest clutter. For that purpose 60 signals of tree cutting by axe were recorded in forest. For testing with other similar signals 60 signals of balloon burst, hand clap, hammering and digging were also collected, so that false positive and negative can be calculated.

All signals were distributed among 5 different classes i.e. class 1 for tree cutting signals, class 2 for balloon burst sounds, class 3 for clap sounds, class 4 for digging sounds and class 5 for hammer sounds. Further, these signals were divided in 2 sets; the 1st set is comprised of 80 signals while the 2nd set has another 40 signals and both set contains sounds from each of the 5 classes. 1st set is selected for analysis and training the system and the second set is reserved for testing purposes. Figs. 2–4 shows the waveforms and spectrograms of airborne acoustic signals of tree cutting. Axe strikes on the tree are depicted by high amplitudes. In spectrogram red color shows higher signal intensity, yellow color shows intensity lower then red signal. Peak of signal shows strength of signal, which goes high for each strike of axe, and then slowly get weaker. The panel in left side of spectrogram shows frequency of signal at selected points.

Every recorded signal contains many axe strikes on tree. So we have extracted every single strike from the signal and then analyzed it for signature identification. Figs. 2a.a and 2b is showing waveform and spectrogram of signal for 11 s respectively. Spikes show the strike by axe on the tree. 4 strikes have occurred in the duration of 11 s. Each strike is in red color, it means the signal have high amplitude at each strike. Figs. 3a,b are showing waveform and spectrogram of single strike of axe on green wood and Fig. 4a,b are showing waveform and spectrogram of single strike of axe on dry wood. Amplitude, intensity and frequency of signal are high during strike. The pattern of strike can also be observed in the spectrogram.

5. Parameter extraction

After analysis of 80 acoustic signals in time domain as well as in frequency domain using the literature survey (Chu et al., 2015; Wei et al., 2010; Zhan et al., 2012; Ye et al., 2014; Yan et al., 2014), we identified a total of 10 parameters which can prove to be helpful for recognizing the tree cutting events. Tables 1 and 2 provides list of selected parameters.

The tree cutting signals were divided in frames. The size of each frame was 10 ms. Fig. 5 shows division of signal into frames. The

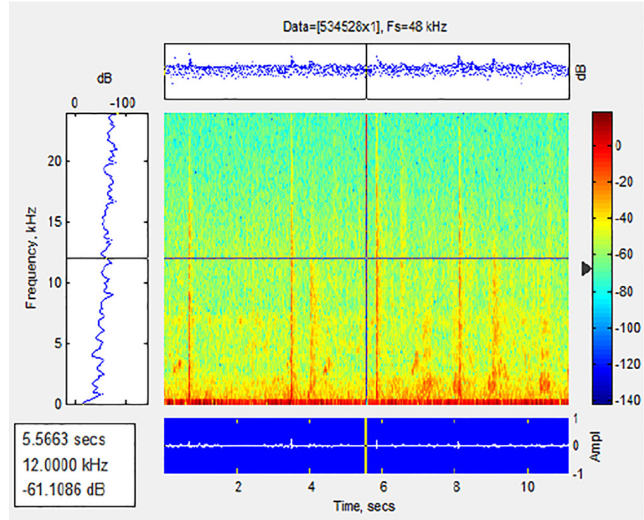

Fig. 2b. Spectogram of 11 sec signal (strike by axe).

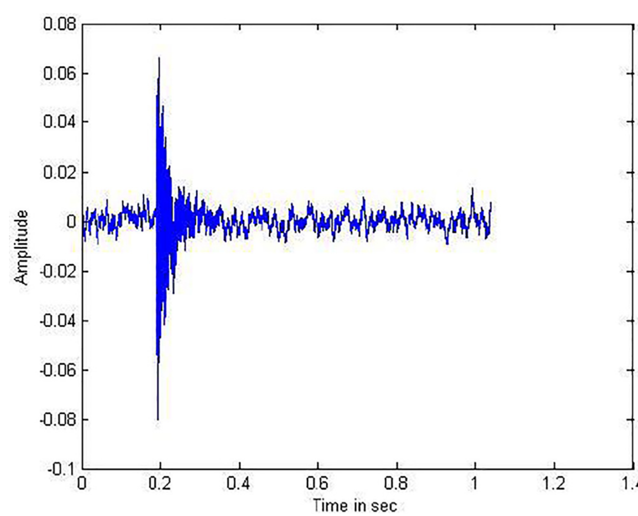

Fig. 3a. Waveform of single strike by axe on green wood.

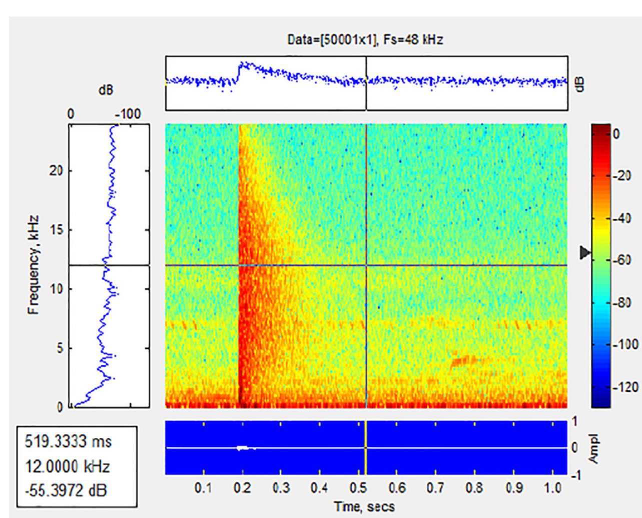

Fig. 3b. Spectogram of single strike by axe on green wood.

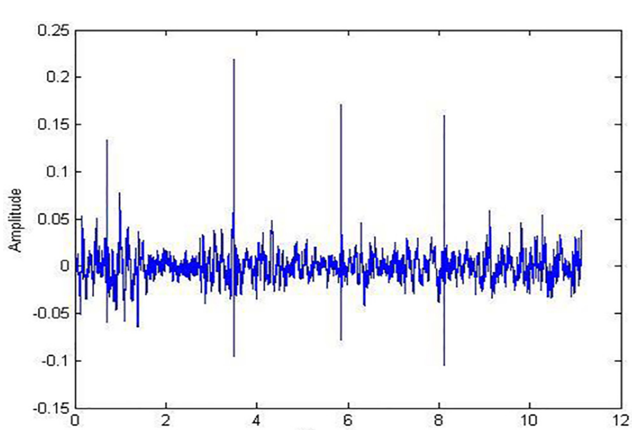

Fig. 2a. Waveform of 11 sec signal (strike by axe).

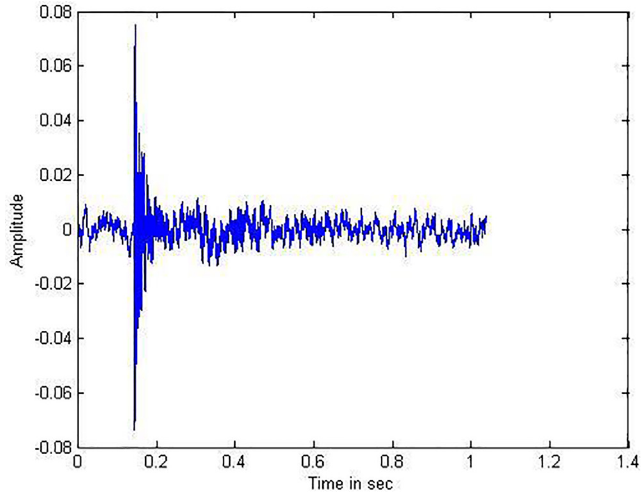

Fig. 4a. Waveform of single strike by axe on dry wood.

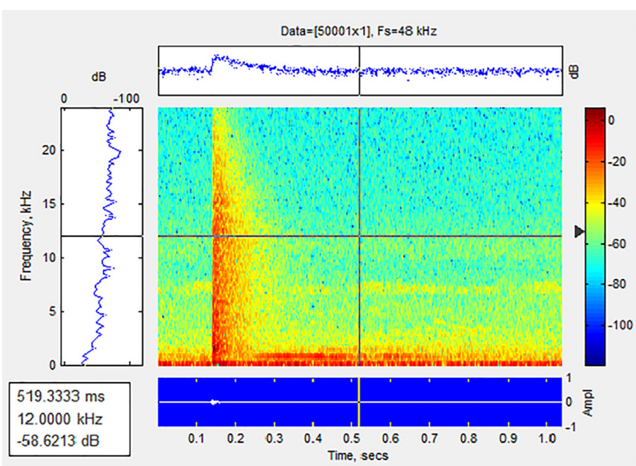

Fig. 4b. Spectogram of single strike by axe on dry wood.

Table 1
Temporal Features.

S. No.	Parameter	Description
Temporal features		
1.	Standard Deviation	How much a group of data is deviated from its mean. $\sigma = \sqrt{\left\{ \left(\frac{1}{N}\right) \sum_{i=1}^{N} (xi - \mu)^2 \right\}}$
2.	Min peak	Min peak is used to define the lowest threshold borderline of signals.
3.	Root-mean-square (RMS)	RMS value indicates the signal loudness or intensity. $\boldsymbol{x_{rms}} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2}$
4.	Max peak	Max peak defines the maximum threshold borderline of the signals
5.	ZCR – Zero crossing rate	It counts the number of times amplitude cuts the 0 mark in any time interval. $Z_t = \frac{1}{2} \sum_{n=1}^{N} \lvert sign(x[n]) - sign(x[n-1]) \rvert$

values of parameters for each frame were stored in the master database. This database is used as master database to train the system.

Table 2
Spatial Features.

S. No.	Parameter	Description
Spectral features		
1.	Spectral Centroid	Magnitude spectrum's gravity center of the short-time fourier transforms. $C_t = \frac{\sum_{n=1}^{N} n \cdot \lvert M_t[n] \rvert^2}{\sum_{n=1}^{N} \lvert M_t[n] \rvert^2}$ Here $M_t[n]$ represents Fourier transform's magnitude at the frequency n and the frame t.
2.	Spectral Rolloff	Spectral rolloff is the point under which the concentration of magnitude distribution is 85%. $\sum_{n=1}^{R_t} M_t[n] = \sum_{n=1}^{N} M_t[n] \times 0.85$
3.	Spectral Crest Factor	This value is the parameter of a certain waveform which shows the ratio of peak amplitude to its RMS energy. $\frac{\max_{n \in B_k} \{M_t[n]\}}{\frac{\sum_{n=1}^{N} M_t[n]}{N_k}}$
4.	Spectral Flux	This value is calculated by taking the square of the difference between two consecutive magnitudes of spectral distributions $F_t = \sum_{n=1}^{N} (N_t[n] - N_{t-1}[n])^2$
5.	Spectral Entropy	This value shows whether or not there are predominant peaks. $H(x) = -\sum_{i=1}^{N} p(x_i) \log_2 p(x_i)$

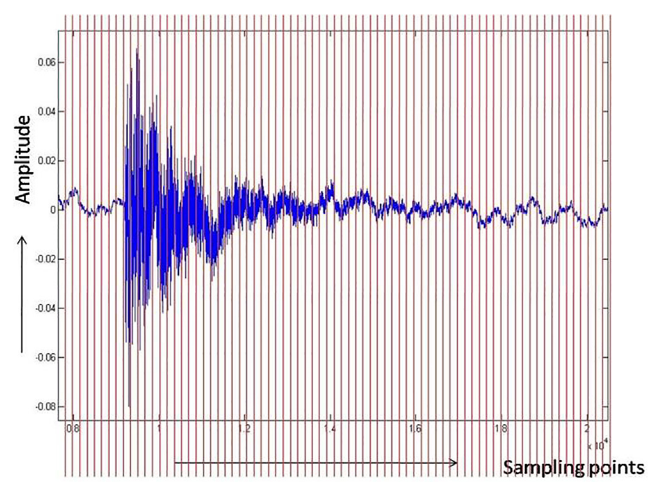

Fig. 5. Framing of Signal.

6. Algorithms for tree cutting detection

Three different algorithms were used for detection of the tree cutting event:

Algorithm 1: GMM – Gaussian mixture model
Algorithm 2: K-means Clustering
Algorithm 3: PCA – Principal Component Analysis

6.1. Algorithm 1 – Gaussian mixture model

GMM can be described as a function of probable parameterized density and it is expressed as the Gaussian Distributions' weighted sum (Yunqi and Yibiao, 2014; Linyun et al., 2014). This model is usually employed in classifying and/or recognizing speech signals. Iterative Expectation-Maximization (Nguyen and Wu, 2013) method is used to calculate the GMM parameters from the training data.

6.1.1. Expectation-maximization algorithm

An iterative technique used to create clusters of similar classes. In the first step i.e. "Expectation" step, it uses the mean vectors and covariance matrices and then calculates the probability that each data point belonging to each cluster.

In the second step i.e. "Maximization" step, this algorithm re-estimates the means and the covariance matrix of each cluster based on the probabilities previously estimated.

6.1.2. Initializing the algorithm

During the Initialization, this algorithm selects data points randomly for using it as the initial means, and then it tries to equalize the covariance matrix of each cluster to the covariance matrix of the full training set. Each and every cluster is assigned equal "prior probability".

6.1.3. Expectation

During the Expectation step, some crucial calculations are done. These calculations are based on the possibility that every point of data is related to each cluster. Each Gaussian component is defined as:

$$G_k = \frac{1}{(2\pi)^{n/2}|V_k|^{0.5}} e^{[-0.5(X-M_k)^T V_k^{-1}(X-M_k)]}$$

here M_k represents the Gaussian's mean and V_k represents the Gaussian's covariance matrix.

6.1.4. Maximization:

This process is used to re-calculate the mean and variances of data sets to create more accurate clusters.

6.2. Algorithm 2 – K means clustering

This learning technique is an unsupervised technique (Juanying and Shuai, 2010). In this technique, n number of objects are clustered into k number of partitions, where $n > k$. This algorithm works just like the EM algorithm. In this technique, n objects are classified into k groups (Boutsidis et al., 2015; Kunhui et al., 2014).

6.3. Algorithm 3 – principal component analysis

PCA is used to identify data patterns. It expresses the data in such a way so as to feature its likenesses and contrasts (Duo et al., 2014; Rujirakul et al., 2013). Since data patterns are difficult to find in high dimensional data, PCA is an incredible technique for data analysis. After finding pattern in data, it can be compressed without losing any information (Dakui et al., 2013).

As the signal is linear, PCA is suitable for analysis. PCA is based on the mathematical calculations of Eigen values and eigenvectors. The eigenvectors of the data are the principal components. For this experimentation 10 feature vectors were taken for testing.

After the creation of master database of feature vectors, algorithm for testing is needed.

7. Proposed approach

Distance based methodologies are used to figure out how the two samples are relatively close to each other. There are various distance based approaches, like Bhattacharyya distance, Mahalanobis distance, Hellinger distance etc.

Bhattacharyya distance, Mahalanobis distance are the measurement of similarity between two data sets. These distances show the closeness of a sample to the other sample. The presented methodology is also based on distance between samples. This algorithm calculates the difference or variation b/w the stored parameters and new sample.

A master database is created which contains the values of 10 parameters (described in Tables 1 and 2) and then a minimal variation is estimated for matching. Whenever any new signal is arrived, this technique calculates the values of those 10 parameters for this signal and then it calculates the variation b/w the stored values of the master database and the new calculated values.

Steps of the proposed algorithm are as under:
Step 1: Recording of signal for 5 sec
Step 2: Divide signal in frames
Step 3: Calculation of parameter
Step 4: Calculating distance (D) between new parameters and master database
  $D(p, q) = (\sqrt{(\mathrm{sum}((q_i - p_i)^2)})$ Where i = 1. . .... . .n
  $p = [p_0, p_1, p_2..p_n]$, parameter calculated for new signal and
  $q = [q_1, q_2, ...qn]$ parameter stored in master database
Step 5: If (D (p, q) < y)
  count_i = count_i + 1;

where y is the maximum difference between parameters. count_i is the number of counts, and increases when parameters matched for each frame.

Step 6: Calculating the matching percentage

If matching percentage is more than 80, then tree cutting is recognized.

8. Results

We implemented and tested all the four algorithms, i.e. K means clustering, PCA, GMM and proposed algorithm, in dense forest and open forest.

Fig. 6 shows a scenario of dense forest, in which tree in blue color with axe indicate the tree cutting event, and red color sensor boards are tied on trees. These sensor boards recognize the tree cutting event using algorithms one by one.

The efficiency of algorithms is calculated according to the percentage of successful events detection out of total events occurred,

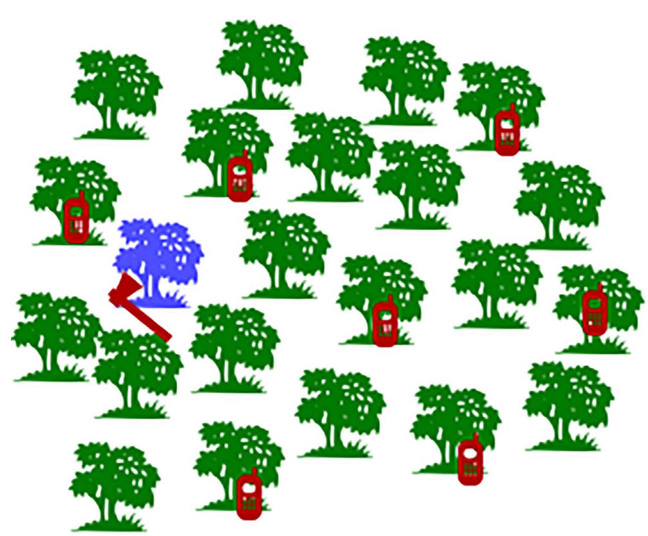

Fig. 6. Dense Forest.

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as shown in Table 3. To check false positive and false negative recognition, the algorithms were also passed through the acoustic signals of balloon burst, hand clap, hammer and digging.

Fig. 7 shows scenario of open forest, notations are same as dense forest. The only difference is the distance between the trees. The efficiency of algorithms in open forest is shown in Table 4.

Since the sensor boards are widely distributed in open forests, they are not able to capture signals perfectly; thus resulting in low efficiency.

Many authors have proposed algorithms for tree cutting detection with varying results. Table 5 shows the efficiency of those algorithms. It can be noted from the table that the distance based algorithm proposed in this paper has an efficiency of 92% which is clearly better than other algorithms.

Table 3
Efficiency of Algorithms in dense forest.

	K Means Clustering	GMM	PCA	Proposed algorithm
Tree cutting detection	83%	86%	83%	92%
False positive recognition	16%	11%	13%	5%
False negative recognition	17%	14%	17%	8%

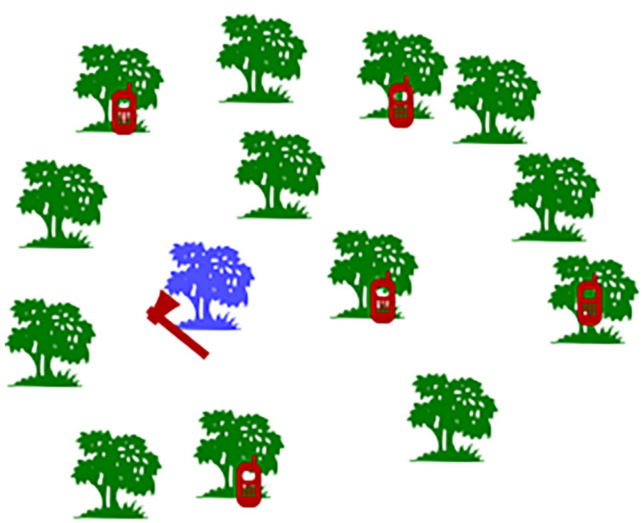

Fig. 7. Open Forest.

Table 4
Efficiency of Algorithms in open forest.

	K Means Clustering	GMM	PCA	Proposed algorithm
Tree cutting detection	68%	65%	74%	76%
False positive recognition	35%	28%	21%	21%
False negative recognition	32%	35%	26%	24%

Table 5
Efficiency of other Tree Cutting algorithms.

S. No	Author	Algorithm	Efficiency
1	Iosif Mporas (2016)	Wood Logging Identifier	77–78%
2	Sharma G (2018)	Dynamic Time Warping combined with modified MFCC (DTWM)	83.2%
3	Sharma G (2018)	Spectral features based Gauss Bayesian classifier (SGBC)	90.5%
4	Tang et al., 2012	Audio Recognition of chainsaw	65–75%

9. Conclusion

Tree cutting and smuggling is a big problem. It is dangerous for society and environment. People use to cut trees in forest to make their residences. There are manual approaches available to catch tree cutters. This paper presented technological solution to catch tree cutting event through acoustic signal processing. The paper has described feature extraction parameters. The three algorithms namely GMM, K Means clustering and PCA have been implemented for tree cutting recognition. There is a distance based algorithm proposed for better efficiency. All algorithms were tested and efficiency has been calculated. According to results, efficiency of distance based proposed algorithm is better than existing algorithms.

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