

# Acoustic Signal Classification for Deforestation Monitoring: Tree Cutting Problem

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## Abstract

This paper deals with tree cutting real-world problem, causing significant damages to forests. The sensing and classification of acoustic signal emitted during tree cutting, is used to extract information of tree cutting events using sensors. Detecting the acoustic signal due to saw scratching power level in presence of ambiance noise and the other choral noise sources is a major issue in a forest environment. An acoustic sensor experimental setup is established for capturing the acoustic signal generated due to cross cut sawing with varying distances. Based on the experimental analysis, saw scratching acoustic signal is found with appropriate for tree cutting detection. The acoustic signal pre-processing is performed with the help of a SNR algorithm. The extraction of features in frequency space is done by using modified MFCC and spectral features extraction. Modified MFCC feature based dynamic time warping (MDTW) and spectral feature based Gauss-Bayesian classifier (SGBC) are used and compared.

**Keywords:** Tree cutting; Acoustic signal; Spectral features; Octave filter analysis; MDTW; SGBC

## Introduction

In India, most of the lumberjacks work using manual tools like axes and hand saws. Owing to the inherent complexity and variability of the sawing process, the acoustic signals of the tree cutting process are usually combined with wood fiber breakage signals and polluted by environmental noise which makes it very difficult for detection. One of the main reasons for difficult pattern analysis of the tree cutting event is due to wood fiber and process of saw scratching. The noise level and the event signal spectral characteristics are closely related, as the signal quality degrades significantly with increase in the noise level. The acoustic signals generated due to saw movement on bole, has a close to sinusoidal oscillation pattern in time domain. An important concern associated with the acoustic signal emitted due to tree cutting process is the analysis or interpretation of the signal due to the randomness of the acoustic signal emission process. Saw scratching acoustic signal contains different frequencies and thus substantial mathematical classification are required for describing and categorize it accurately. The traditional tree cutting event acoustic pattern, obtained with a saw scratching designed for two men, is shown in the Figures 1 and 2. The presence of noise in such an environment makes event detection a tedious work. Research work on the analysis of tree chopping signature detection is limited. This paper presents a study on the detection of tree chopping signature from the acoustic signal. A features based statistical signal processing technique is proposed to identify the tree cutting signature from the recorded acoustic signal. The event source is acoustic vibration produced due to the saw scratching through the bowl. Microphones, used for detecting acoustic signature in the forest were low cost and required less power, resulting in the extended monitoring period. The Proposed work specifically focuses on detection of the scratching acoustic vibration as an event. Acoustic signature of these sound sources can be distinguished by using statistical pattern recognition technique. Proposed statistical mechanism can be used at different levels of complexity which are developed to recognize the sound signal in the presence of forest clutter.

## Organization of the Paper

Section 2 reviews related work on feature extraction and scratching pattern classification. Section 3 describes the system description and

formulates the problem. Section 4 describes the proposed approach. The result and discussion is presented in section 5. Finally paper is concluded in Section 6.

## Related Work

A wood and steel material impacted sound synthesis model proposed. The author established a relation between the synthesis

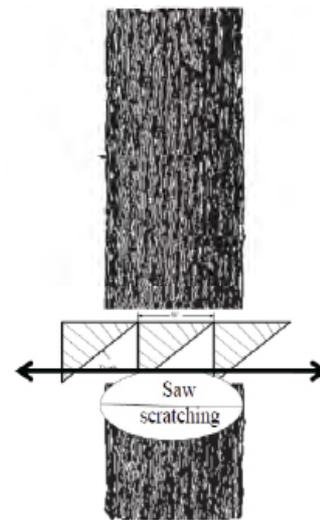


Figure 1: Experiment set up of saw scratching on bole in forest.

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parameter and the physical parameters of sound identify the spectral characteristics of impact sound to be broad band. The proposed model established a relationship between the geometry of the structure and the type of impact influence the spectral bandwidth [1]. An experimental study of the friction noise, between two rough and dry flat surfaces [2]. The effect of surface roughness on frequency of frictional sound generated in dry flat-flat sliding contact. Sound was measured by a microphone, placed at about 30 cm away from the rubbed specimens and data was acquired with a sampling frequency of 50 kHz on a personal computer. The peak frequency shift caused by the varied roughness of the surfaces was monitored in the proposed approach [3]. Very recently physical source filter model, which is suitable for real-time implementation. The associated sounds are captured with lower values for surface roughness with the evocation of an extremely smooth surface along with rougher surface [4]. A new system that allows for intuitive control of an additive sound synthesis of sonic feature from perceptually model. The objective is to reduce the dimensionality of the parameter synthesis space by finding a compact representation of the time varying amplitude matrix. The proposed system allows for adaptable and imbedded control of signal generation. It provides the user with continuous control over a sound directly analyzed from recordings. The proposed algorithm is devised to analysis a paradigm well-suited for a machine learning approach for non-linear mapping problem. The scheme successfully reduces the dimensionality of the synthesis parameter space, while preserving the auditory quality of the re-synthesis. This system yields various original audio and musical applications [5]. A method for incorporating the expressivity of human performance into real-time computational audio generation for games and other immersive environments. They presented new methods for human performers to control computational audio by using a model of a squeaky door as a case study. The author presented a new approach to the design of computational audio models, which aims to incorporate human expressivity through performance. This involves a different way of abstracting the core signal-processing components, focusing on perceptual features rather than varying parameters derived from physical behaviour [6]. Identification of object to surface properties to be the most important parameters for intelligent robotic grasping. They proposed a novel algorithm to identify surface frictional property and classify object surfaces based on identified frictional property. The scheme was able to achieve a classification accuracy of about 87% in distinguishing twelve different surfaces. For measuring the friction force and the normal force while sliding an object on a non-flat surface [7]. An experimental set up to measure the dependence friction noise versus the nominal contact area. The normal load and the sliding velocity were maintained constant while the nominal contact area was varied over two orders of magnitude. The experimental finding can be summarized for the object involved in producing the friction sound: Two solids,

one sliding and one vibrating surface. In the linear regime, the radiated acoustic power is proportional to the vibration energy. Interestingly the internal damping of the resonator is maximum when the regime is most linear [8]. The essential elements of signal processing and pattern recognition applied for the analysis of Acoustic Emission (AE) data from different materials, structures and processes. Signal processing and pattern recognition are extensively used in AE data evaluation in order to discriminate relevant from non-relevant indications, characterize the source of emission and correlate with the associated failure mechanism. The author trained Back Propagation Neural Network to achieve a 100% recognition rate [9]. The sounds produced during any activity carry information about what is occurring. The idea is to use classification algorithm based on template matching, with templates obtained from peaks in the acoustic power signals to present recognition results on an alphabetic and a word database. The microphone used was a laptop PC Mic-333 and audio was captured in a quiet environment on an Asus Eee PC 701 (Intel HD audio) with running audacity under Ubuntu Linux, at a modest sample rate of 16 kHz, with 8 bits per sample, and saved to a file in WAV format [10]. In one of the early works investigated the early physiological changes of pine trees following infection with the pine wood nematode. The author indicated that the timing of abnormal cavitation development very clearly nematode-infected trees [11]. The most common areas where NDT methods are frequently used in the forest industry. A comprehensive overview of the most widely used non-destructive testing techniques in the forest products industry is presented while focusing on the methods feasible to assess the integrity of built in wooden member [12].

## System Description and Problem Formulation

Experiments were performed with a Tascam handheld device and the acoustic signal was captured via mono head-mounted microphones at 44.1 kHz sampling frequency. Cool edit software was used for dividing small sections of the recorded acoustic signals. A condenser Omni-directional microphone was used for the experiments in Indian forests. In an alternate setup with a set of different hardware, specifically PCB130D20 cardioids directional microphone pre-amp interface to a laptop. Ten seconds segment samples of the acoustic signal were also collected [13-15]. A two handed cross-cut saw is often used by the feller for tree chopping, as such the same was used in the experiments. The scratching of saw, perpendicularly on the bole, generated acoustic signal and was captured with the help of the hardware described above (Figure 1).

The tree cutting process involves, structure vibration and acoustic emission of the cutting tool saw blade. Each sound frequency is associated with a particular mode of vibration of the saw blade. These modes and their frequencies are established from sand patterns which are obtained by exciting the rim of the stationary, saw when clamped horizontally. Vibration in a moving saw is evidently excited by flow of air past the moving teeth. This flow was investigated by testing models in a water channel. Modifications of tooth shape were tried out with a view to prevent excitation, and thus eliminating discrete noise.

The sawing power  $P_s$  is defined as the multiplication sawing force  $F_s$  and sawing speed  $V_s$ :

$$L=20\log(P_s/P_0)$$

$$F_s=H_s*V_s*T_s$$

$H_s$ =Harmonic produces during sawing.

$V_s$ =Velocity of sawing.

$T_s$ =Contact teeth during sawing.

The interaction force carries relevant perceptual information



Figure 2: Saw scratching on bole.

related to scratching interaction between wood fiber and saw teeth. The signal formed due to interaction force, considered a series of interaction amplitudes in time domain.

$$f[t] = \sum_n A^n \phi^n (t - T^n)$$

$A^n$ =amplitude,  $T^n$ =time positions and  $\phi^n$ =interaction factor of  $n^{\text{th}}$  interaction.

$$\Delta_r^n = (T^{n+1} - T^n)$$

The forces were a series of interaction events signal described as:

The process is repeated every time the cuts overlap briefly. On every occasion when the cuts overlap and a small cut is making tracks small waves in the structure that are redeveloping with each consequent pass of the tool. It is considered the dominant mechanism of AE in saw tooth scratching operations. It can be assumed that scratching acoustic signal of tree cutting is vastly different and is thus separated to recognize the specific problem to identify parameters for detecting scratching tree cutting pattern using those parameters.

## Proposed Approach

### Data collection and pre-processing

Experiments were performed with a Tascam handheld device at Rukhad forest in the Madhya Pradesh, India. Acoustic signals were captured via mono head-mounted microphones, to 44.1 kHz sampling frequency. The microphone used was condenser Omni-directional type. The tree cutting process is shown in Figure 2, where two men are cutting a tree into sections using a crosscut saw.

The signal to noise ratio (SNR) plays a vital role in the data pre-processing. The SNR algorithm uses the short frames of the energy of the background noise to identify the event samples in the captured acoustic signal. The SNR is analyzed to obtain the shape information of the acoustic event signal. An optimized non-Gaussian distribution of the input signal is used to improve the performance of the classification algorithm. The pre-processing process result in a data set obtained using spectral and modified Mel-filter cepstral coefficient (MMFCC). The data set is divided into two subsets. The first subset is cepstral coefficient and the second subset has spectral features.

#### Algorithm: Signal Pre-processing

Input: [Signals, Fs]=wavread (input.wav), n=Number of samples in given signal, Frame\_Size=882; Over\_lapp=256; Step\_Size=Frame\_Size-Over\_lapp; Number\_of\_frames=((n-Frame\_Size)/Step\_Size)+1; **Output:** Output Signal (Sm)

PRE\_STE=0.25

High\_SNR=10

Low\_SNR=02

For signal S (time 10 sec)

F [] =Frame the signal in length 20 ms

N=Samp\_frequency\* F\_Length

For each Fi

Calculate\_STE<sub>i</sub> =  $\frac{1}{N} \sum_{i=0}^{N-1} |S_i(i)w(N-1-i)|^2$

Calculate\_STE<sub>i</sub>=log(STE<sub>i</sub>/PRE\_STE)

For each frame in F

If (High\_SNR>SNR<sub>i</sub>>LOW\_SNR &&High\_SNR>SNR<sub>i</sub>+1>LOW\_SNR)

Frame\_List [] =i;

Start\_Frame=min (Frame\_List [])

End\_Frame=min (Frame\_List [])

Frame\_threshold=Start\_Frame\*250;

If (End\_Frame<=Frame\_threshold)

Start\_sample\_point=Start\_Frame\*Frame\_length;

End\_sample\_point=End\_Frame\*Frame\_length;

Form Start\_sample\_point to End\_sample\_point

S<sub>m</sub> =S<sub>n</sub>

Return S<sub>m</sub>

### Measured saw scratching acoustic signal

Figure 3 shows the sawing fricative acoustic signal, received signals with a distance of fifteen meter between the emission and reception (E-R). The acoustic measurements were made in the presence of bird chirping and wind noise. The acoustic emitter and receiver microphone were placed 5 m, 10 m and 15 m apart. The S/N ratio was quite low and can be visually analyzed from Figure 3a. As evident from the Figure 3c the signal has low signal to noise ratio i.e., 6 dB and as show in the spectrogram of the signal the noise can be easily discriminated in the time and frequency domain especially for high bandwidth signal. As shown in the Figure 3c, the scratching pattern can be certainly discriminated in the frequency domain especially for high bandwidth signals.

### Feature extraction and classification

Acoustic features were extracted in time and spectral domain. For the feature extraction of the saw scratching signal the signal is divided into short frames at short time energy in the time domain. The step of the algorithm is:

1. A FFT of the identified framed is performed.
2. The spectral features, specifically Spectral Centroid, Spectral Spread, Spectral Roll off, Spectral Entropy and Sub band Energy are extracted in spectral domain.
3. An Octave filter analysis is performed for identifying the dominant spectral energy band present in the saw scratching signal.
4. On the basis of octave analysis, a modified Mel- Scaled filter band is obtained and is shown in Figure 4.

On a time frame of 20 msec and overlapping of 10 msec, frame

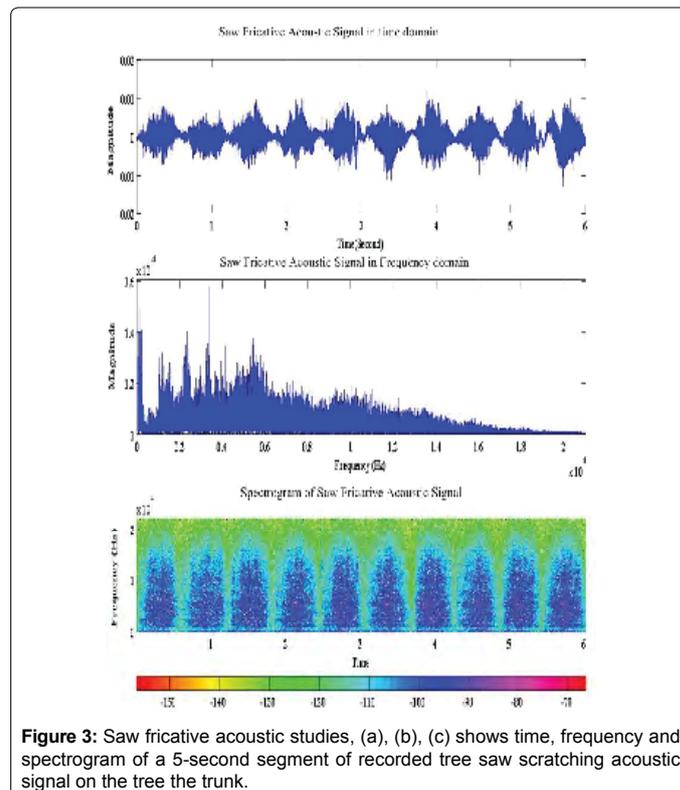


Figure 3: Saw fricative acoustic studies, (a), (b), (c) shows time, frequency and spectrogram of a 5-second segment of recorded tree saw scratching acoustic signal on the tree trunk.

by frame feature extraction was performed using short - Time Fourier Transform (STFT). A centroid of the frame is a measure of the average frequency divided by sum of the amplitude. As shown in the Figure 5, the brightness of a saw scratching acoustic signal is measured by spectral centroid. It is evaluated for the magnitude of center of gravity using FFT. Spread of the spectrum around its mean value is defined as the spectral spread variation. Spectral roll-off is correlated with the harmonic cutting frequency and it is estimation where 85% of the signal energy below this cut of frequency. Band energy per frame shows spectral pattern between 4000 to 12000 Hz signal amplitude (Figure 6).

For each  $F_i=1$ : number of frames

$$\text{Calculate\_DFT} = M_i[k] = \sum_{j=0}^{m-1} S[j]e^{-j(2\pi/m)km}$$

$$\text{Feature (i,1)=Spectral\_Centroid} = \frac{\sum_{i=1}^N M_i f_i}{\sum_{i=1}^N M_i}$$

$$\text{Feature (i,2)=Spectral\_Spread} = \sqrt{\frac{1}{N} \sum_{i=1}^N (M_i)^2}$$

$$\text{Feature (i,3) Spectral\_Roll\_off} = 0.85 * \sum_{i=1}^n M_i(i)$$

$$\text{Feature (i,4) Spectral\_Entropy} = -\sum_{i=1}^N p(M_i) \log_2 p(M_i)$$

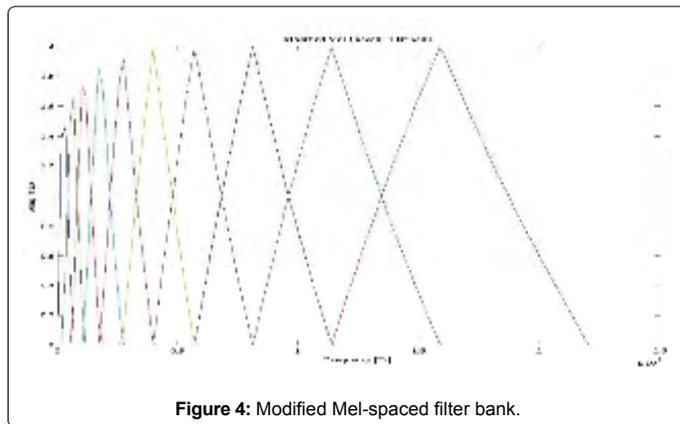


Figure 4: Modified Mel-spaced filter bank.

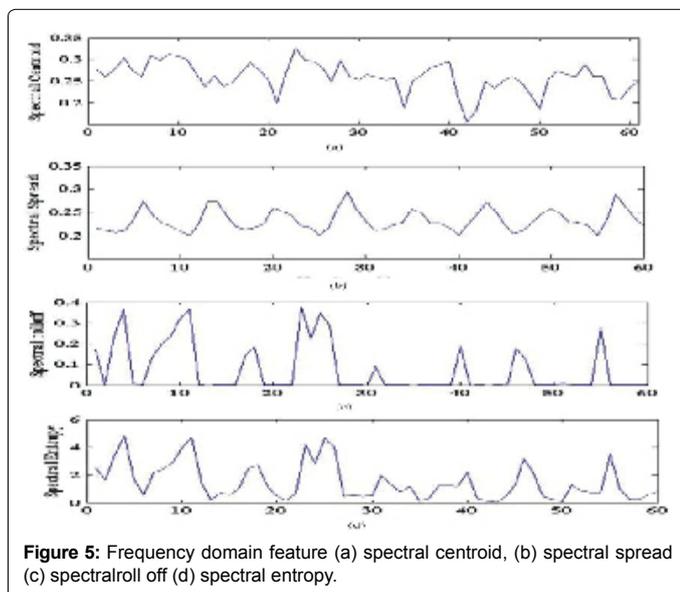


Figure 5: Frequency domain feature (a) spectral centroid, (b) spectral spread (c) spectralroll off (d) spectral entropy.

$$\text{Feature (i,5) Sub\_band\_Energy} = \log \left( \sum_{L_j}^{H_j} M_i(\omega_j) \right)$$

$$\text{Sigma} = \sqrt{\frac{\sum (x-m)^2}{n}}$$

SC (NN, 1)=sigma of Feature (1: number of frames, Feature (1))

SS (NN, 2)=sigma of Feature (1: number of frames, Feature (2))

SR (NN, 3)=sigma of Feature (1: number of frames, Feature (3))

SE (NN, 4)=sigma of Feature (1: number of frames, Feature (4))

SBE (NN, 5)=sigma of Feature (1: number of frames, Feature (5))

Return;

Sigma [feature vector number] [SC, SS, SR, SE, SBE]

**Algorithm: Modified MFCC Feature Extraction**

**Input:** Signal=Sm; m=Number of samples in given signal, Frame\_Size=882; Over\_lapp=256; Step\_Size=Frame\_Size-Over\_lapp; Number\_of\_frames=((m-Frame\_Size)/Step\_Size)+1; Input frame=Frame signal\*Hamming (Frame\_Size); **Output:** Modified MFCC feature vector code book

For each sample i

For each frame j in sample i

Calculate Log filter bank coefficient using modified Mel-scale

$$\log\_filter = \log \sum_{k=0}^{k/2} M_i(k) F_{Mel}(k, g)$$

Calculate cepstral coefficient using discrete cosine transform.

$$CC = (2/N)^{1/2} \sum_{i=0}^{N-1} A(i) \cdot \cos \left[ \frac{\pi \mu}{2N} (2i+1) \right] * f_i$$

Calculate modified cepstral coefficient as feature vector

$$MMFCC(v) = CC(v+\alpha) \text{ End}$$

Code Book ()

For each MMFCC feature vector

Make code book

$$\frac{1}{m} \sum_{j=1}^m MMFCC(i, j)$$

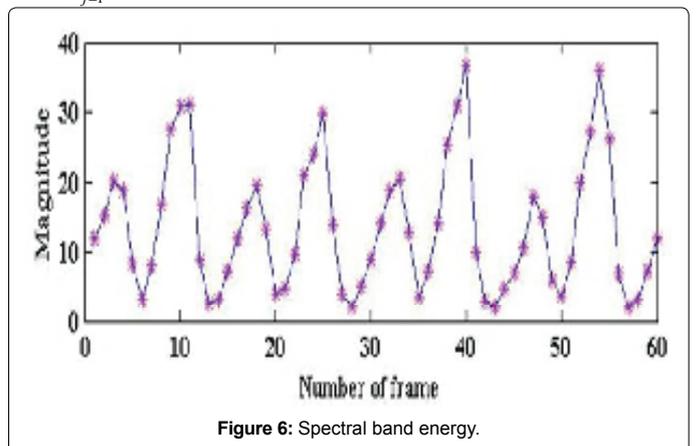


Figure 6: Spectral band energy.

Where  $i$  is the component of each vector,  $m$  is the number of vectors in the cluster (Figure 7).

**Algorithm: SGBC Classifier**

**Input:** Inputs sigma matrix calculated from spectral features

**Output:** Matched Samples results

**Calculate**

Mean  $m$  of [SC, SS, SR, SE, SBE]

Where  $i=1$  to 5

And  $C$  co-variance matrix of was standard deviation of feature vector

For each feature  $i$

For each  $j$  1 to 5

$$C(i,j) = 1/n - 1(X(i,j) - \mu_i)$$

For each  $i$  (feature vector)

For each  $j$  1 to 5

$$P(X; m, C) = \frac{1}{2\pi^{k/2} |C|^{1/2}} e^{- (X - m)^T C^{-1} (X - m)}$$

Bayesian Decision

$$P(D/T) = \frac{P(T/D)P(D)}{P(T/D)P(D) + P(T/D)P(D)}$$

Return;

Algorithm: DTWM Classifier

**Input:** Code book from modified MFCC

**Output:** Matching result matrix

For  $l$ : length of training model

Calculate time warping distances using

$$Dist(M, N) = \frac{\sum_{s=1}^v d(L_s, w_s)}{\sum_{s=1}^v w_s}$$

End

Matching = min (Dist)

**Results and Discussion**

The acoustic signals generated due to saw scratching on a bole, was obtained from the experiment performed in an Indian forest. A data set of such acoustic signals was created for analyzing the performance of the proposed algorithms. The master data set was divided into two equal parts. The first half of the data set was used to train the model while other half was used for evaluating the proposed algorithms. The master data set originally had 300 saw scratching samples out of which 200 samples were captured with Tascam hand held recorder with varying distance and rest the 100 samples were captured by a laptop recording setup at a 10 meter distance. The analysis for the DTWM SGBC is presented in the following subsections.

**Octave analysis of saw scratching on bole**

Practical ways to measure the spectrum of acoustic signal incorporate a mix of the original signal filter bank to split into a number

of frequency bands. Each group is defined by two corner frequencies; high frequency and low frequency  $\sqrt{f_{hi} \cdot f_{lo}}$ .

The difference of the two frequencies is called bandwidth and is denoted by  $\Delta f$ . The octave band is given by  $f_c = \sqrt{f_{hi} \cdot f_{lo}}$ .

Where range  $F = [200\ 325\ 560, 1000\ 1250\ 3015, 4000\ 5000\ 6300, 7000\ 8000\ 9050, 10000\ 11000\ 12000, 13150\ 14000\ 15000]$ . For the octave analysis of saw scratching on bole, the RMS power is computed in each band. As shown in the Figure 8 the RMS energy in 200 to 5000 Hz has lower band of (-85 dB) 5000 to 10000 Hz (-85 to -75 dB). However, the pattern shows a growth and rises up to 10000 to 15000 Hz with a peak intensity of (-75 to -65 dB) (Figure 9).

**Modified Mel-spaced filter bank**

An acoustic signal masks other signals and the same can be viewed in Figure 10a. This technique of masking of the signal is known as frequency masking. Since the saw scratching acoustic has a low RMS energy, the frequency masking technique can be efficiently applied in octave analysis. Figure 10 shows the frequency masking nature of the power spectral and as shown in the Figure 10a signal spectral energy is masked with the background. Thus, the application of the modified MFCC results in a visible power spectrum and is shown in Figure 10b for the close analysis of the frequency energy band octave filter approach is used shown in Figure 8. After analysis frequency band energy modification in the Mel-scale filter band is proposed as shown in Figure 9. Power in modified spectral shown in the Figure 10 bottoms.

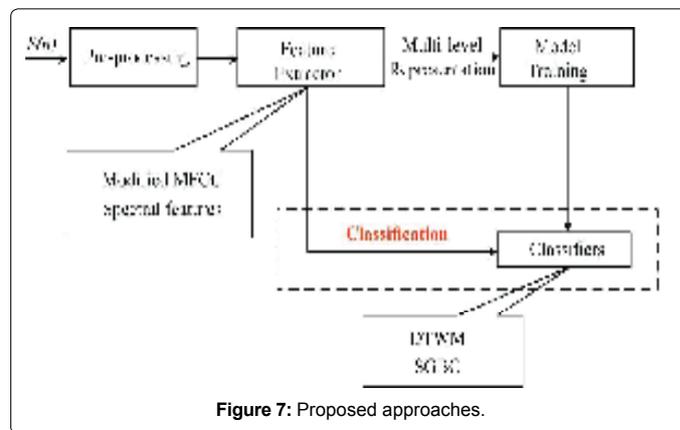


Figure 7: Proposed approaches.

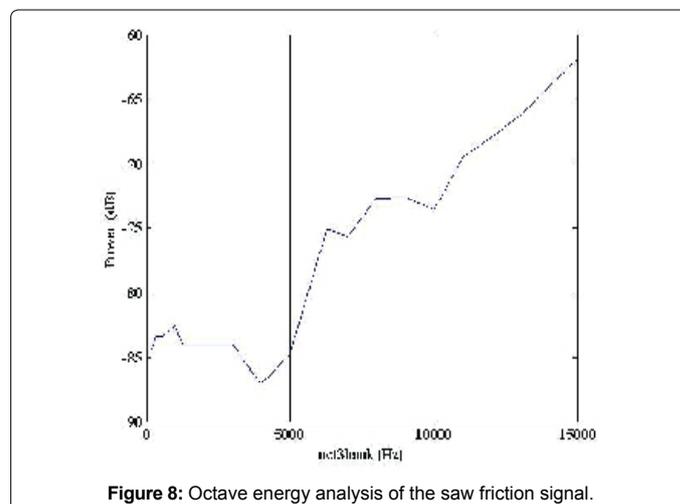


Figure 8: Octave energy analysis of the saw friction signal.

Feature extraction was done using Modified MFCC.VQLBG Vector quantization using the Linde-Buzo-Gray algorithm applied to extract the required features. For classification of the given data dynamic time warping technique was used. We classified the event with ambient noise and clutter. Results show the realization of the devious signal with varying signal to noise ratio and a decrease in classification rates drops (Figure 11). Saw scratching through tree trunk acoustic emission

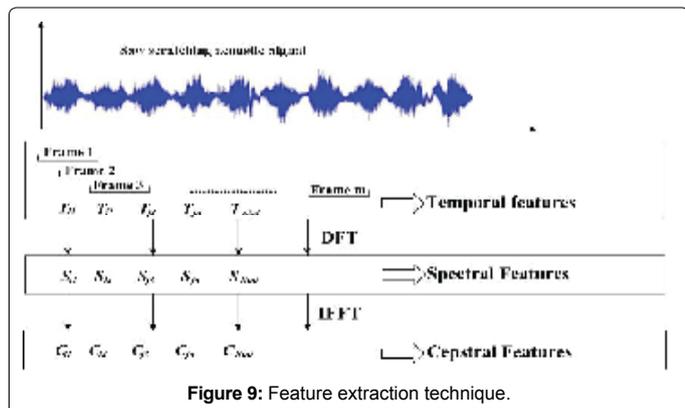


Figure 9: Feature extraction technique.

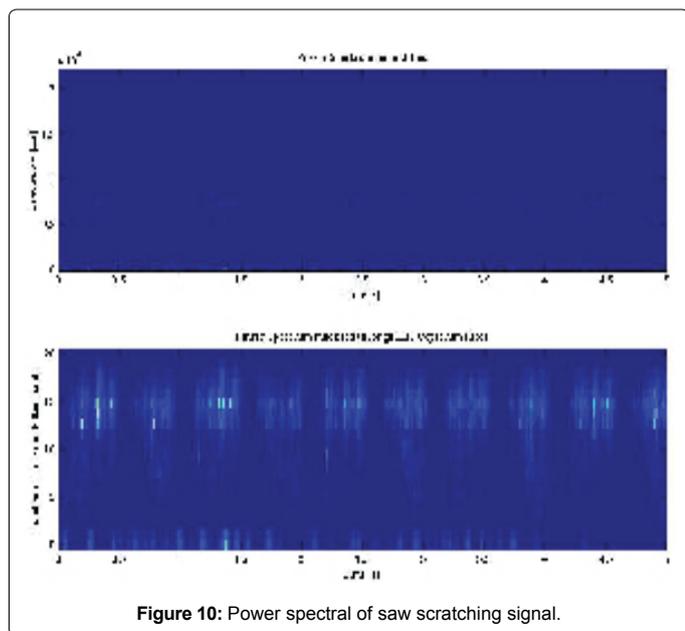


Figure 10: Power spectral of saw scratching signal.

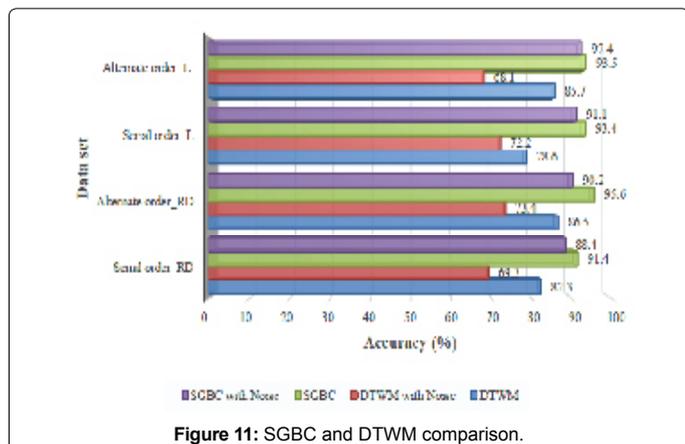


Figure 11: SGBC and DTWM comparison.

monitoring is promising up to 83.27%, for 10-meter distance with noise, and the presence of clutter relatively low 70.75% classification rates using DTWM. The SBGC algorithm gives average accuracy 93.47% for clean signals and 90.52% for noise mixed signals. This work only considers the saw scratching through tree trunk for tree cutting detection along with material characteristics.

## Conclusion

An acoustic sensor based experimental setup is established on cross cut sawing acoustic signal varying distances. Two classification algorithms, dynamic time warping (DTW) combined with modified MFCC (DTWM) features and spectral features based Gauss Bayesian classifier (SGBC) are proposed and compared. SGBC has accuracy slightly better than DTWM. These techniques present a relationship between the characteristic shapes of acoustic emission signal in frequency domain with relevant time. Results show that the spectral distribution has a significant dependence on the time during saw scratching on wood fiber. A detailed analysis shows that the acoustic emission due to saw movement on the bole is accurately classified by the proposed algorithms. It is observed that the performance of DTWM gets reduce in the presence of various clutter. Also the experimental analysis reveals that the acoustic pressure variation, due to the saw scratching on the bole, has spectral variation. The scratching acoustic emission pattern reduced false alarm and provided ambient noise immunity. Due to lack of bench mark data in this area, we could not perform comparisons.

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