



Train Sound Level Detection System at Unmanned Railway Level Crossings

Vivek Singhal^{1*}, S.S. Jain² and Manoranjan Parida³

¹Associate Professor, Information Technology Department., JSS Academy of Technical Education, Noida-201301 Uttar Pradesh, India

²Professor, Transportation Engineering Group, Department of Civil Engineering & Associate Faculty, Center for Transportation Systems (CTRANS), IIT Roorkee, Roorkee-247667, Uttarakhand, India

³Professor, Transportation Engineering Group, Department of Civil Engineering & Associate Faculty CTRANS, IIT Roorkee, Roorkee-247667, Uttarakhand, India

Abstract

The study presents the development of a train sound level detection system for rail-road collision avoidance requirements using Mat lab 2013 and Java software. In this study, a new filtering strategy has been proposed to filter out the train sound from other surrounding noises using Mat lab 2013 software. The sound level i.e. between 0 to 65 dB has been filtered out using the system. The message warning alerts for train approach various positions of unmanned railway level crossings have been generated using this system. Time domain analysis resulted in rise of train sound than original composite signal with the approaching train. The maximum, minimum and mean sound pressure levels and bi-level measurements at different areas of crossing have been compared and analysed for both original composite and filtered train sound signal. The system detection probability has been found to be quite high (i.e. 95%) and false detection to be very low (5%). Therefore, the performance of the train sound level detection system has been found to be extremely high.

Keywords: Train, Sound, Detection, Road Vehicle-Train Collision, Unmanned Railway Level Crossing

1. Introduction

The road vehicle users are not able to detect the train sound level approaching the unmanned railway level crossings. The non-detection of the train sound level and unknowingness of the train may result in road drivers/pedestrians indulging in collisions with trains approaching the unmanned railway level crossings. The collisions at these unmanned railway level crossings lead to heavy loss of life and assets. As there is scarcity of the train sound level detection system to alert these road drivers, a computerized system application must be developed in order help the drivers/pedestrians to detect the train sound and avoid rail-road collisions.

* Corresponding author: Vivek Singhal (viveksinghal82@gmail.com)

1.1 Sound level terminology

1.1.1 Decibel (dB) scale

The decibel scale is a logarithmic unit scale, which helps in the train sound level measurement and defines a ratio. The power spectra are generally displayed in units of decibels. If P_1 is the power of one sound level and P_2 is the power of another sound level, then difference between two sound levels is given by Equation 1.

$$20 \log_{10} \frac{P_2}{P_1} \text{ dB} \quad (1)$$

1.1.2 Signal to Noise Ratio (SNR)

The SNR (according to Wikipedia, Skolnik (2001) and Richards (2005)) is the ratio of power of the original composite signal to the power of unwanted noise signal.

$$\text{SNR} = \frac{P_o}{P_n} = \left(\frac{A_o}{A_n} \right)^2 \quad (2)$$

where, P_o = Power of original composite signal, P_n = Power of noise signal, A_o = Root Mean Square (RMS) amplitude of composite signal and A_n = RMS amplitude of noise signal.

1.1.3 Noise filters

Filtering is a method of removal of the unwanted noise signal from the composite signal.

1.1.4 Noise filters design

There are two different and popular noises designs filters given as-

- Butterworth filters- The butterworth filter has equal frequency responses and easy backing for different frequencies.
- Equiripple filters- The filter describes the amplitude realization within the tolerant limit of frequency bands. The Equiripple filter minimizes the maximum amplitude of all ripple bands.

1.1.5 Noise filter types

The diverse types of filter available and are given as-

- Low-pass filter -Low pass filtering also called a high-cut or treble cut filter with cutoff frequency of 1 KHz. The transfer function of first order low pass filter (Kamenetsky) is given in Equation 3.

$$L(j\omega) = \frac{K}{1+j\omega} \quad (3)$$

where, K =Sensitivity or gain, τ = Time constant, $j\omega$ =Frequency response function and $L(j\omega)$ = Low pass filter

The low pass filter passes the noise signals having frequency lower than certain threshold frequency. It removes the noise signals with higher frequency than a threshold frequency. The filtering is also associated with filter design.

- High-pass filter -High pass filter also called low-cut filter or bass-cut filter (Chapter 7, Filters, Loading and Op-Amps). It removes the noise signals frequency with lower threshold frequency. Further, the certain threshold frequency and passes the noise signals with higher frequency than a threshold frequency as shown in Equation 4.

$$H(j\omega) = \frac{K\tau j\omega}{1+\tau j\omega} \quad (4)$$

where, K =Sensitivity or gain, τ = Time constant, $j\omega$ =Frequency response function and $H(j\omega)$ = High pass filter

- Band-Pass filter - Band pass filtering combines the low-pass and a high-pass filter. A band-pass filter passes the noise signal within a frequency range. The band pass filter discards the frequencies outside this frequency range. The band pass filter has a frequency response function (Chapter 7, Filters, Loading and Op-Amps) as shown in Eqn. (5).

$$BP(j\omega) = K \frac{1}{1+\tau_1 j\omega} \frac{\tau_2 j\omega}{1+\tau_2 j\omega} \quad (5)$$

where, K =Sensitivity or gain, τ_1 and τ_2 = Time constants, $j\omega$ =Frequency response function, $BP(j\omega)$ = Band s

- Band-Stop filter - Band stop or rejection filtering as opposed to band pass filtering removes the noise signal within a frequency range. The band stop filter discards the frequencies inside this range and is a combined low-pass and high-pass filter as shown in Figure 1.

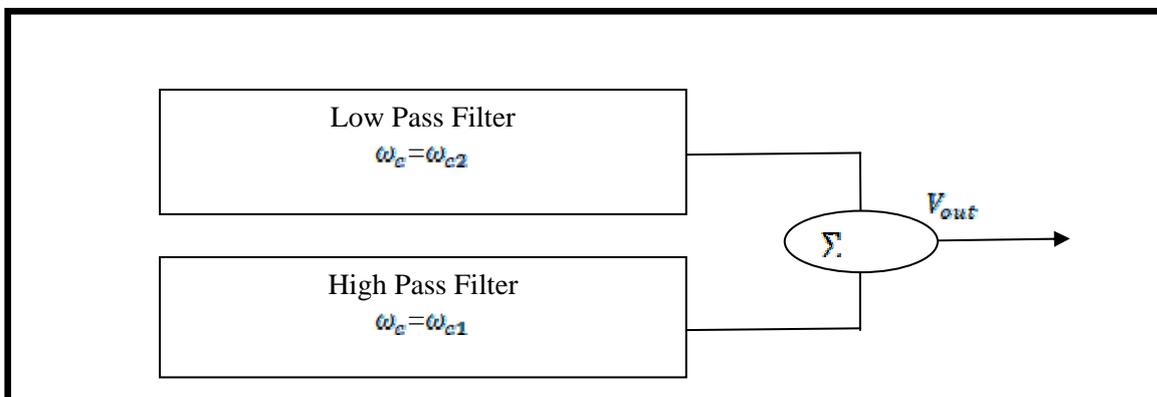


Figure 1: Band Stop or rejection filter

Source:<https://engineering.purdue.edu/ME365/Textbook/chapter7.pdf>

1.1.6 Fast Fourier Transform (FFT)

A sound signal is a collection of the sinusoids and cosines. FFT converts the sound signal samples into set of sinusoids and cosines i.e. converts the original composite signal into frequency domain. The basic FFT equation as given by Raginsky (2008) is given in Equation 6

$$X[k] = \sum_{n=0}^{N-1} x[n] \exp(-i 2 \pi [kn/N]) = \sum_{n=0}^{N-1} x[n] W_N^{nk} \quad (6)$$

Where, $X[k]$ = k^{th} harmonic ($k=0\dots N-1$)

$x[n]$ = n^{th} input sample ($n=0\dots N-1$),

W_N = Fourier-matrix

1.1.7 Amplitude and magnitude of signal

Amplitude is computation of train sound signal change over time. The peak-to-peak amplitude reveals the difference between highest and lowest amplitude value.

1.1.8 Sampling of sound signal

The sound signals that are not continuous and for sampling Zayed (1993), there is a requirement of signal to be non-continuous. Therefore, continuous wave signals are to be converted into discrete signals and also need to be sampled at sampling rate. The sampling is done by using the Nyquist frequency. The Nyquist frequency was given by the Shannon-Nyquist sampling theorem. The sampling is the done for FFT.

1.1.9 Power Spectral Density (PSD)

PSD is the Fourier transform of the autocorrelation function of a train sound signal. The PSD helps in displaying the continuous spectra. The PSD integrates the train sound frequency band over the power/frequency for the train sound signal. There is two types of PSD.

1. One-Sided PSD- A one-sided PSD defines the total signal power (in frequency interval) ranges to half of the Nyquist rate.
2. Two-Sided PSD- A two-sided PSD again defines the total signal power (in frequency interval) ranges to whole of the Nyquist rate.

Consider that a train sound wave with amplitude 'A' if mixed with other external noises at intermediate frequency and is fed into the intermediate frequency filter. It is assumed that frequency of the train sound wave is equivalent to frequency of intermediate frequency filter. There are different wavelet transforms available for computing probability of detection Singh et al.(1996).Therefore, by Rician distribution the output signal, the probability of signal detection is equivalent to the probability of R which exceeds the threshold voltage.

1.1.10 Probability of false alarm (P_{fa})

The false alarm event triggers when the train sound voltage is greater than a threshold voltage, V_t . The probability of false alarm is shown in Equation 7.

$$P_{fa} = Prob(V_{tv} < R < \infty) = \int_{V_{tv}}^{\infty} \frac{R}{\varphi_0} \exp \frac{-R^2}{2\varphi_0} dR = \exp \left(-\frac{V_{tv}^2}{2\varphi_0} \right) \quad (7)$$

where, φ_0 – Sound voltage variance

R – Amplitude of filter output

V_t – Threshold voltage

P_{fa} – Probability of false alarm

Probability of false alarm suggests that if “0” event is occurring then "1" is true.

2. Observed sound sources at unmanned railway level crossings

According to Cawser (2006), Deltarail (2012) and Rong et al. (2009) train produces many type of sounds i.e. whistle of train, traction (engines, fans, gears etc.) which is around 50 km/h (approx.), rolling sound ranging from 50 km/h to 270 km/h, (approx.) and aerodynamic effects from around 270 km/h. The contributor over the widest speed range is rolling sound. The sound sources observed at 19 unmanned railway level crossings are-

1. Approaching train sound
2. Road vehicle motor sound
3. Brick field emissions sound
4. Human talking sounds

The unmanned railway level crossings shown in Figure 2 shows the distance of road vehicles from unmanned railway level crossings (d_{car}), approaching train, SSD and road vehicle. The average sound pressure level in decibels have been observed to be minimum of 65 decibels and maximum of 75 decibels in area1($d_{car} < SSD$) and minimum of 75 decibels and maximum of 85 decibels in area2 ($d_{car} > SSD$) as shown in Figure 3.

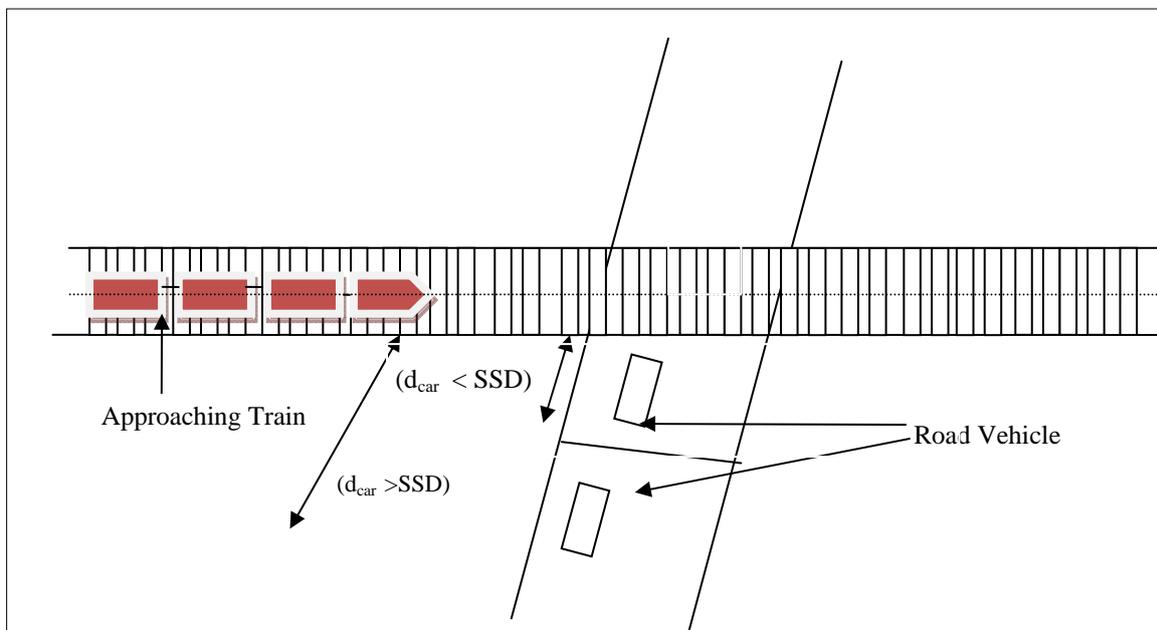


Figure 2: Unmanned railway level crossings showing d_{car} , approaching train, SSD and road vehicle

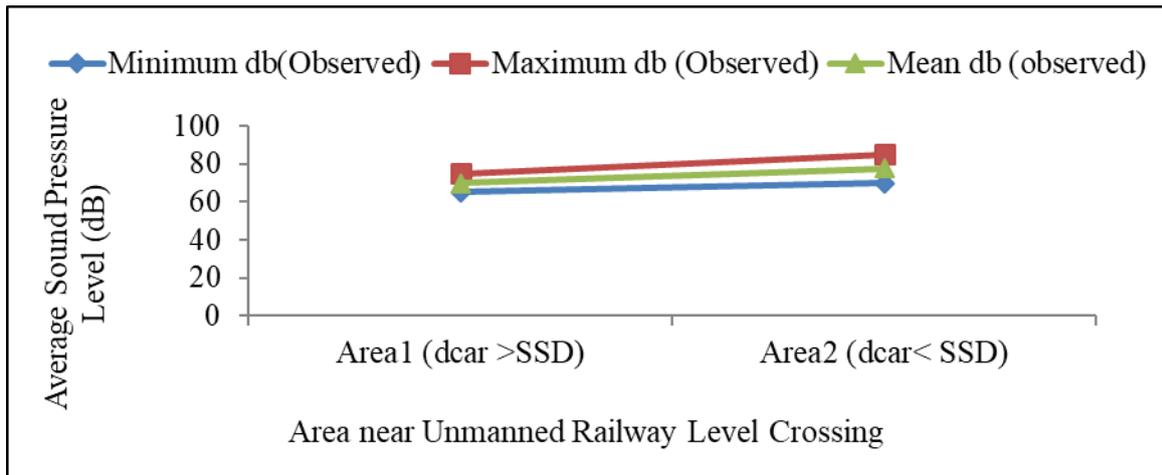


Figure 3: Area near unmanned railway level crossings with respect to average sound pressure level

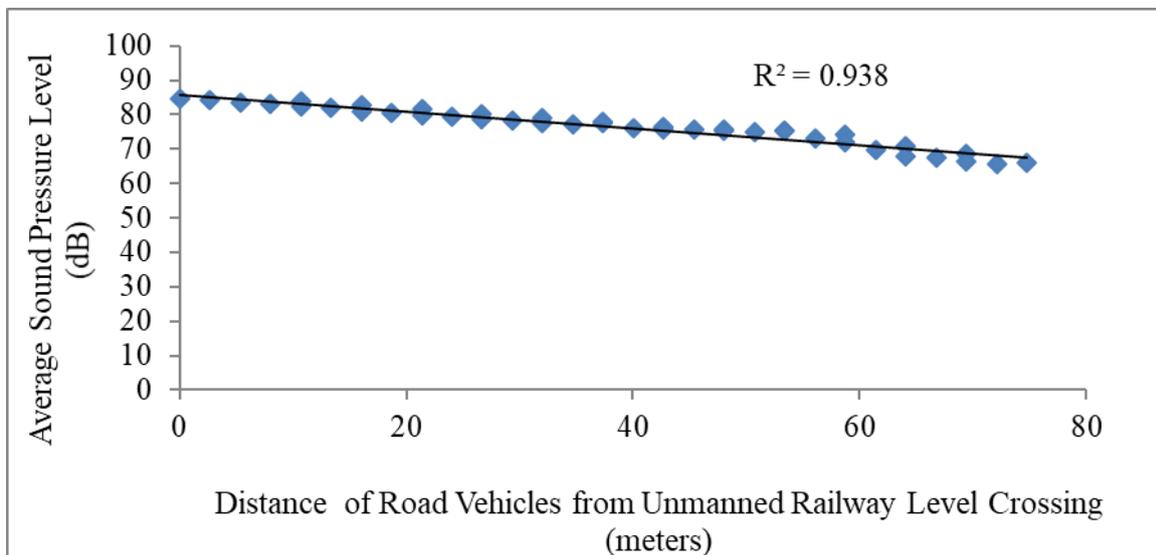


Figure 4: Average sound pressure level with respect to road distance from unmanned railway level crossing

The relationship between the average sound pressure level and distance from unmanned railway level crossings is shown in Figure 4. The train sound level varies inversely in relation with road distance from unmanned railway level crossing i.e. average sound pressure level decreases linearly with increase in the road distance from unmanned railway level crossing. Therefore, the relationship between average sound pressure level and road distance from unmanned railway level crossing is given in Equation 8.

$$\text{Average Sound Pressure Level} = -0.241 * d_{\text{car}} + 85.78 \quad (8)$$

3. Studies on train sound level detection

The train sound level detection system helps in providing how well the road vehicle user can detect the train sound approaching the unmanned railway level crossings. The train sound level detection studies done in India and abroad are briefly described as-

3.1 Work done in abroad

Gherassimoff (1930) developed a device for emitting an acoustic signal i.e. rail vibrations generated by the train rolling arrival at railway level crossings. The acoustic system was connected to the mechanical or electrical system with satisfactory performance.

AFTAC II (1997) model is the General Electric (GE)'s Frequency Modulation (FM) audio overlay technology for the train detection. The technology was suitable for saturated channel spectrum railway level crossing points. The model was completely in accordance with the FM Air Force Technical Applications Centre (AFTAC) requirements specification. The system was very much immune to different interferences and highly efficient. The system helped in the efficient train detection at railway level crossing using audio overlay.

Stephens (2001) developed an acoustic sensor based early warning system. The acoustic sensor attached to the rail tracks detected the sound generated from the railway environment. The sensors generated the audio warning on detection of the train sound. The audio warning signals were sent to the computer sound recognition system. Therefore, the train at the remote position could be stopped to avoid the collision.

Auriscchio (2003) study described a fuzzy based method for detecting and filtering out the unwanted noise signals around the railway level crossings. The railway sound from railway activities have been studied for Europe locations as studied by Pronello (2003) and Talotte et al. (2003) for Middle East locations.

Carvalho et al. (2005) developed a system to detect the approaching train for remote places using sonar sound detection method. Two scenarios were discussed in the study. Firstly, the magneto strictive transducer-based transmitter was connected to the rail. The receiver was further connected to the same rail. The transmitter emitted the signals and receiver again sensed the rail and cross-correlated the received signals from the transmitter. The method was again performed by coupling the transmitter and receiver in opposite direction rails. The cross-correlation tended to the highest value in this sound echo method and distance calculated by the echo of the signal was 6361 meters (approx.). The result also showed that, train reflectivity of the signal was very much erroneous and noisy. Therefore, the alternative method used was dependent on the spectrum modeling of sound vibrations created from the movement of approaching trains on the railroad systems. The similar train detection was also described by the Weeks (2006/07).

Dolan and Rainey (2005) studied about the collisions occurring when the train approached the railway level crossing. The road vehicles dependent on the train horns were not able to detect about the train distance from the railroad crossing. The study tried

to investigate the train horn sound levels that may help the road vehicles to detect the train location point. The adaptive method was used to collect the train horn sound from three test vehicles with 20 simple audio listeners. The result indicated that, train sound was minimum in no-sound condition with 1.8 decibel (dB) to 4.4 dB environment and was very high at 30-miles per hour. Further, the minimum Signal-to-Noise (S/N) ratios were determined for the detection of approaching train sounds at railway level crossings.

Mellesta et al. (2006) evaluated the train aero acoustic and rolling noise from high-speed approaching trains.

Anderson and Turpin (2009) discussed the railway activity and retrieved the train sound exposure at the locations of New Jersey, U.S.A.

Federal Railroad Administration (2009) presented about the acquisition of the approaching train horn sound at U.S.A. (San Jose and San Diego) railway level crossings. The train horn sound was heard from approximately 15-20 sec before the train reached the railway level crossing. The train distance from which the train horn detected was approximately ¼ mile. The average train horn sound pressure level was found to be 103 decibels (approx.) of the approaching trains at railway level crossings.

Alim et al. (2013) developed a train sound detection system for providing the safety at railway level crossing. A microphone was used to collect the approaching mixed sound signal i.e. train sound combined with other sounds at a predefined distance equal to the length of the train from the railway level crossing. The train sound feature extraction was done by Mel Frequency Cepstral Coefficient (MFCC). The Recurrent Neural Network (RNN) was used for train sound classification out of composite signal. Afterwards, the traffic lights were turned on with yellow colour in beginning and gradually turning red. An audio alarm was also activated until the train passed the railway level crossing. The results of MFCC using RNN are shown in Table 1 and shows that, the train sound when mixed with train sound was most sensitive (86.7%) and accurate (90%) compared to other mixed sounds. The misclassification rate was the lowest i.e. 10% again for the train sound mixed with train sound. The system was very much useful in avoiding the collision at railway level crossings.

Table 1: Performance of MFCC using RNN as a classifier

	Sensitivity (%)	Accuracy (%)	Misclassification rate (%)
Train + Aircraft	76.7	84.2	15.8
Train + Car	56.7	80.8	19.2
Train + Rain	86.7	90.0	10.0
Train + Thunder	60.0	85.0	15.0

Source: Alim et al. (2013)

Wave Train Systems (2015) developed a Mobile Train Detection System for European railway level crossing safety by the installation of acoustic detection sensors on the rail tracks. When the train approached near the acoustic detection sensor attached to the rail track, it detected the sound and vibrations of the train approaching near the railway level crossings and generated the signals. The signals activated the alert which was given to the

road users to avoid the collision with the train. The system was set up on both sides of the level crossings. The Mobile Train Detection System was proved to reduce the collisions and their consequences enormously.

3.2 Work done in India

Krishnakumar (2010) developed a train detection device called Train Proximity Detector. The system worked in three steps. In the first step, the sound and vibrations were retrieved using piezoelectric sensors placed at different positions on the railway track. In second step, signals were acquired and processed. Thereafter, the signal was amplified to a particular threshold level. Afterwards, the signals were analyzed and when the train was near to the unmanned railway level crossing an audio alert (i.e. siren) and visual warning (i.e. red flashing lights) was provided to the road vehicle user to retrieve back from the danger of an approaching train. The system was cost effective for its implementation on Indian unmanned railway level crossings. The system was found to be very much reliable for the train detection.

Kumar and Jain (2012) developed a train detection system called Rolling Noise Detection (RND). The study proposed the train rolling sound detection produced from approaching train near the unmanned railway level crossings produced at '0' m height from the railway track. The rolling sound propagation and vibration recording was also done before the arrival of train. The amplitude of the vibration signal wave increased with decrease in the train distance from unmanned railway level crossings.

Kumar and Jain (2013) proposed an acoustic signal computation dependent train detection system. The acoustic sound consisted of train wheels and rail track sounds. The study compared both sounds and detected the different train sounds before the train arrival for safety at level crossings. They again proposed the train sound rolling sound detection system to provide the safety for the train arrival.

4. Methodology of train sound level detection system

The proposed approach of the train sound level detection system at unmanned railway level crossings is developed using Java Swing software and database is prepared in Microsoft access 2007 database and module are described as shown in Figure 5.

1. Input Module- The composite sound signal is chosen having train sound signal and other noise, which is input to the train sound level detection system.
2. Filtering Module- The composite sound signal is filtered using the Band Stop and Equiripple filter.
3. Decision Module-The filtered train sound level average sound pressure level is checked in comparison to a particular threshold sound level.

4. **Output**
Module-The output module gives the message alerts about the approaching train on unmanned railway level crossing.

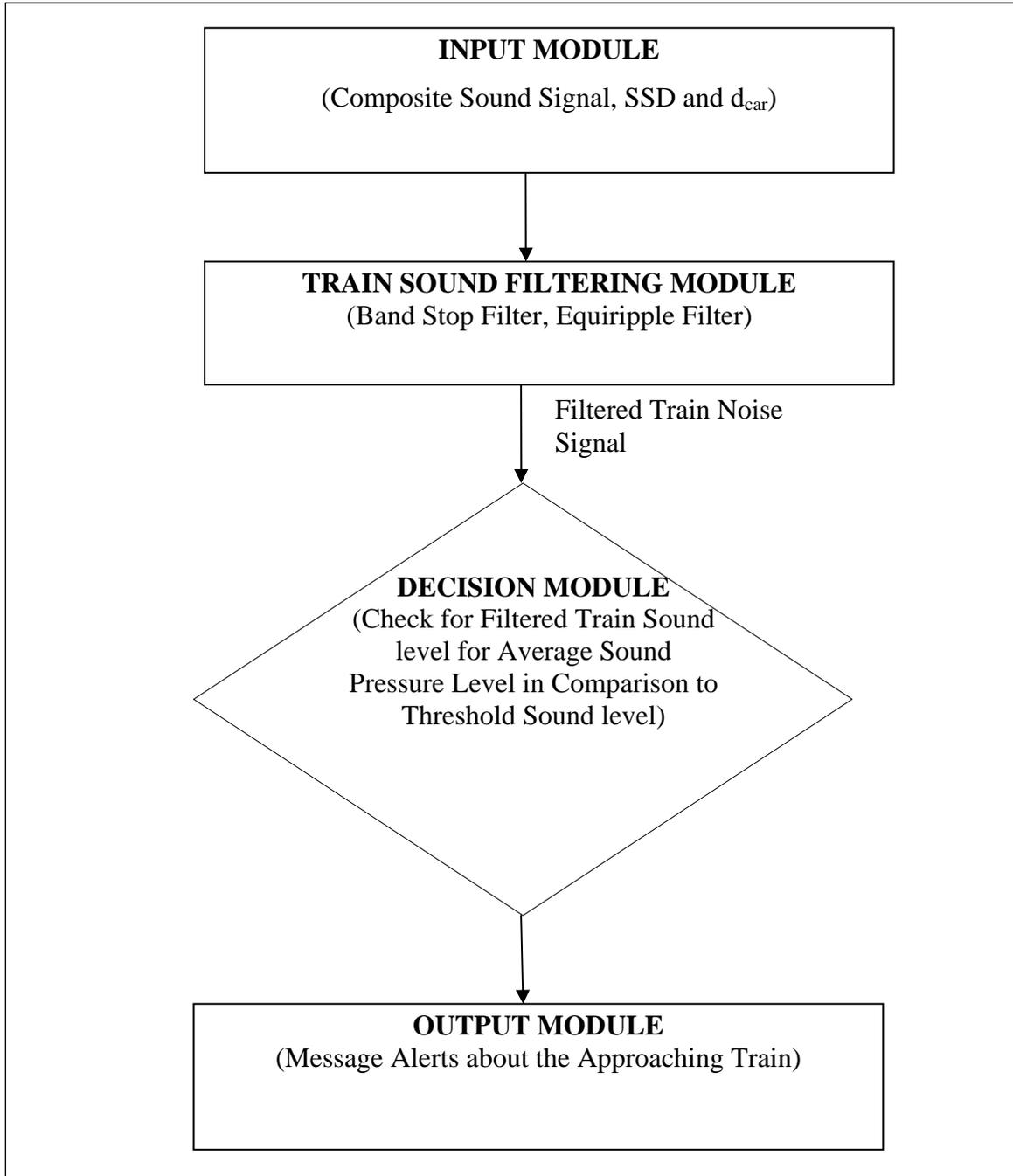


Figure 5: Proposed approach for train sound level detection

The algorithm is of train sound level detection system is given as-

1. Choose the composite signal ' S ' (i.e. combined train sound signal (S_T) with other noise signal (S_o)) collected is fed to the train sound level detection system (T_{NLDS})

$$T_{NLDS} \leftarrow S = S_T + S_o \quad (9)$$

$$T_{NLDS} \leftarrow f(SSD, d_{car}) \quad (10)$$

- Filter the 'S' train average sound pressure level ' S_{db} ' from other surrounding sounds using the Band Stop Filter and Equiripple Filter.

$$S_f \leftarrow \text{filt}_{bs}(S_{db}) \quad (11)$$

$$T_{NLDS} \leftarrow S_{db} \leftarrow \text{filt}_{ef}(S_f) \quad (12)$$

- If there is train sound available (i.e greater than zero decibels) and d_{car} is greater than SSD and S_{db} are greater than theshold values ' T_1 ' and ' T_2 '. The message alert ' MA ' on Human Machine Interface is given as:

While ($S_{db} \leq 0$ db)

```

{
If  $S_{db} > 0$  db
{
If  $d_{car} > SSD$ 
{
If  $S_{db} \geq T_1$ 
 $MA \leftarrow$  "Train is near to unmanned railway level crossing, please apply brakes"
Else
 $MA \leftarrow$  "Train in vicinity"
}
Else
{
If  $S_{db} \geq T_2$ 
 $MA \leftarrow$  "Please Stop fast as Train is near to unmanned Railway Level Crossing"
Else
 $MA \leftarrow$  "Train in vicinity"
}
}
Else
 $MA \leftarrow$  "No Train in vicinity of Crossing"
}
}

```

- Repeat the process until train passes the unmanned railway level crossing.

4.1 Filtering of train sound signal at unmanned railway level crossings

Filtering is applied to the original composite signal consisting of train sound level and other noise at 19 unmanned railway level crossings. The filter used here is band stop filter to retrieve the train sound from the original composite signal. Therefore, the response and design method used here is the Band stop method and Equiripple filter respectively. The observed sampling frequency (F_s) is the 44100 Hz. The stop band frequencies are - 9600 Hz and 12000 Hz, therefore noise level between 0 to 65 dB are stopped or rejected.

5. Results

5.1 Train sound level detection system output

The results of the train sound level detection for the safety at unmanned railway level crossings in India has been presented and database i.e. SSD, dcar and average sound pressure level can be visualized in train sound level detection system database in Figure 6. The three different types of the message alerts are being shown in Figure 7 a, b, c. The system has been tested on 19 unmanned railway level crossings of Shahdra-Shamli-Tapri railway route average sound level samples. Approximately, 43200 average sound pressure level samples per unmanned railway level crossing have been tested by the system.

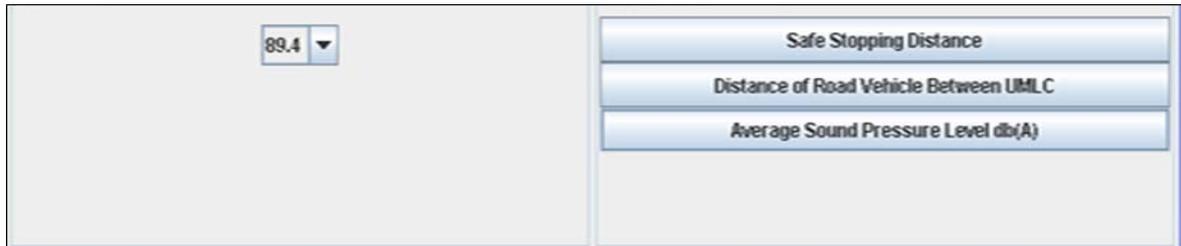


Figure 6: Train sound level detection system database output



Figure 7 (a): Train sound level detection system (alert 1)



Figure 7 (b): Train sound level detection system (alert 2)

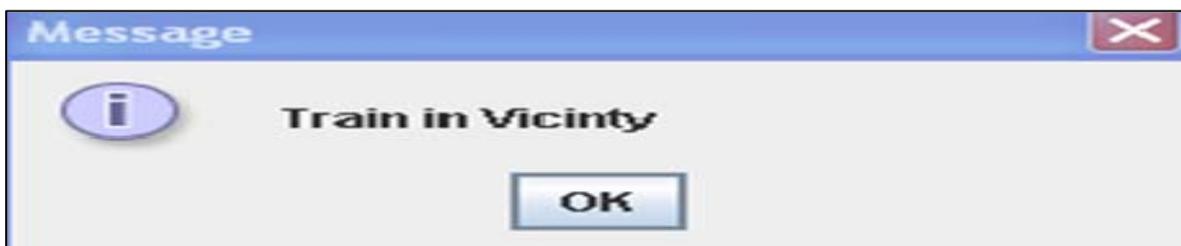


Figure 7 (c): Train sound level detection system (alert 3)

6. Simulation and analysis

6.1 Time domain representation analysis of sound signals

Time domain analysis refers to the variation of train sound signal amplitude or magnitude over time. The Figure 8 shows the time domain representation of the original composite signal containing the train sound signals with other noise signals collected from 19 unmanned railway level crossings. The Figure 9 shows the filtered train sound signal done using the band stop and Equiripple filter. The comparison of the sound signal statistics for original composite and filtered train sound signal from 19 unmanned railway level crossings are analyzed as-

- The maximum amplitude of the train sound signal is 1.7% greater than maximum amplitude of the composite signal.
- The minimum amplitude of train sound signal is 3.5% greater than minimum amplitude of the composite signal.
- The peak to peak amplitude of train sound signal in turn is 0.77% lower than peak to peak amplitude of the composite signal.
- The RMS of original composite signal is 1.25% higher than train sound signal.

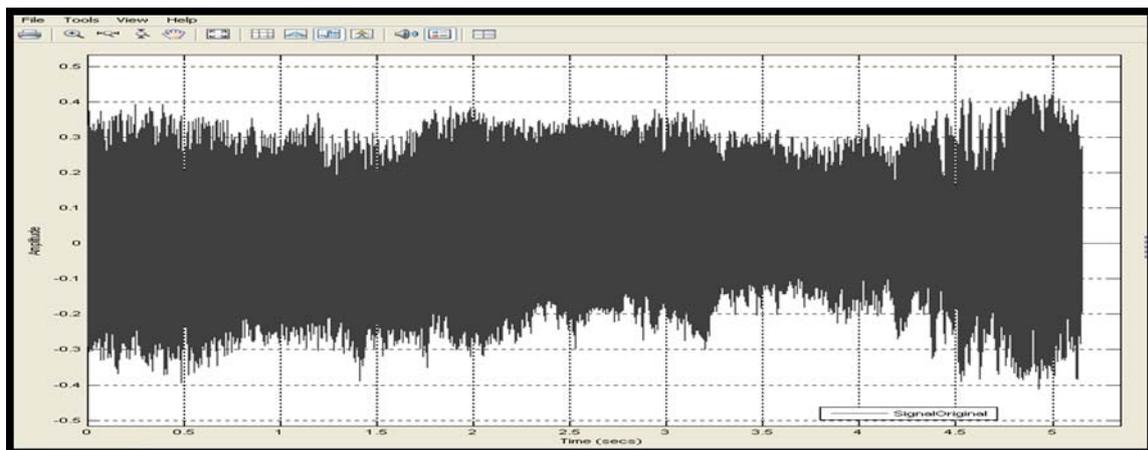


Figure 8: Time domain representation of composite sound signal

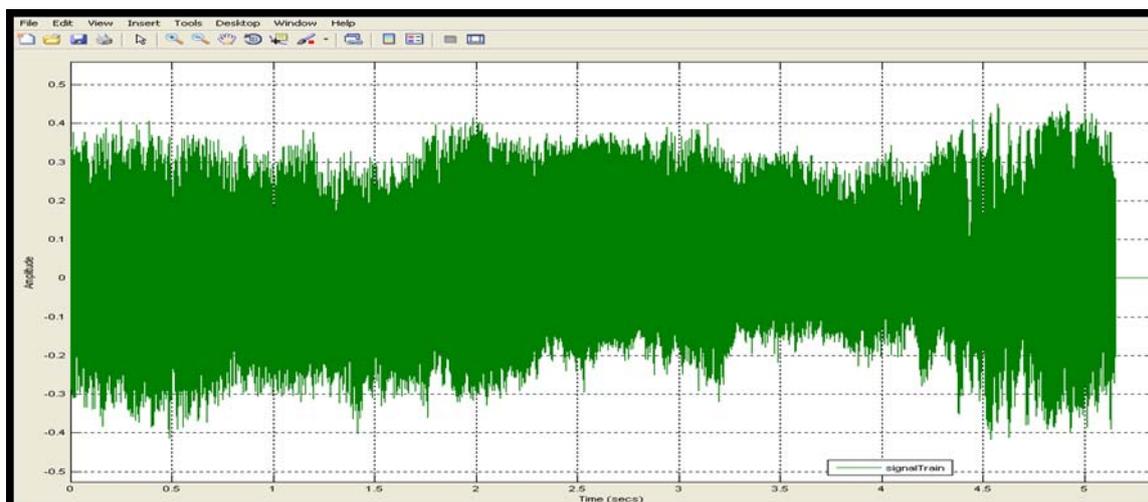


Figure 9: Time domain representation of train sound signal(filtered composite signal)

The comparison of the bi-level sound level measurements viz. transitions, overshoots/undershoots and cycles for original composite signal and filtered train sound signal for all unmanned railway level crossings as shown in Table 2. The comparison shows that, whether the train sound bi level measurements is higher (H) or lower (L) in comparison to the original composite signal. Table 2 also shows the (%) comparison between them. The bi-level measurements shows that measurements viz. high (mV), amplitude (mV), fall time (us), slew rate (V/ms) and duty cycle (%) and pulses of train sound signal are higher in comparison to the original composite signal. The high (mV) measurements of the train sound signal resulted to be the highest and the slew rate (v/ms) and duty cycle (%) has been observed to be the lowest rise in comparison to the original signal.

Table 2: Comparison of original composite sound signal and train sound peak value signal bilevel measurements

Bilevel Measurements	Train sound signal comparison to Original Composite Signal of Bilevel Measurements		
	Higher-H/ Lower-L	(% Higher /% lower)	
Transitions	High (mV)	H	226%
	Low (mV)	L	-67%
	Amplitude (mV)	H	98%
	+Edges	-	0 %
	+Rise Time (us)	H	78%
	+Slew rate (V/ms)	H	6%
	-Edges	-	0%
	Fall Time (us)	H	93%
	Slew rate (V/ms)	H	4%
Overshoot/ Undershoot	Preshoot (%)	L	-33%
	Overshoot (%)	L	-32%
	Undershoot (%)	L	-47%
	Preshoot (%)	L	-11%
	Overshoot (%)	L	-47 %
	Undershoot (%)	L	-10%
Cycles	Period (us)	-	0%
	Frequency (KHz)	-	0%
	Width (us)	L	-4%
	Pulses	-	0%
	Width (us)	L	-10%
	Duty Cycle (%)	H	4%

6.2 Detector performance analysis using Receiver Operating Characteristics (ROC) curves

The performance of train sound level detection system has been measured by ROC curves, which is a curve between ‘ P_d ’ and ‘ P_{fa} ’. Table 3 shows the probability of detection (P_d) (%) to be very high and the probability of false detection (P_{fa}) (%) is found to be low. Therefore, the performance of the train sound level detection system is

found to be very effective. The ROC Curve for the non-fluctuating coherent operating characteristic is shown in Figure 10.

Table 3: Train sound level detection system performance

Train Sound Signal Detection Performance	Probability of Detection (P_d)(%)	Probability of False Detection (P_{fa}) (%)
	95%	5%

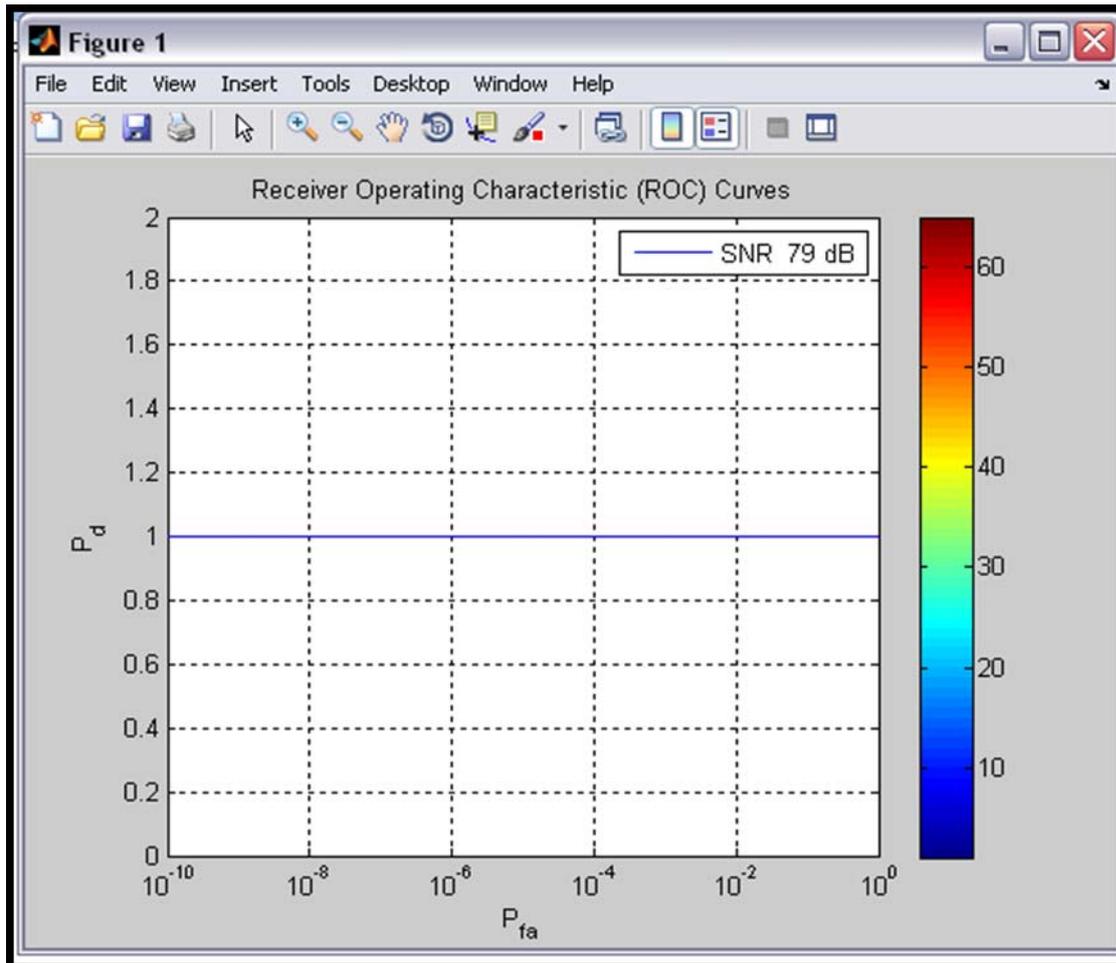


Figure 10: ROC curve for non fluctuating coherent operating characteristic

6.3 Train sound signal frequency domain analysis

The frequency (in Hertz) variation with average train sound pressure level has been observed to be at higher level. As shown in the Figure 11, the train is very near to the crossing. It is being observed to have 0-1000 Hz frequency and average sound pressure level remained at highest level in next 1000 Hz duration, when train crossed the unmanned railway level crossing. Further, it dropped and remained almost constant with only one spike at 2200 Hz.

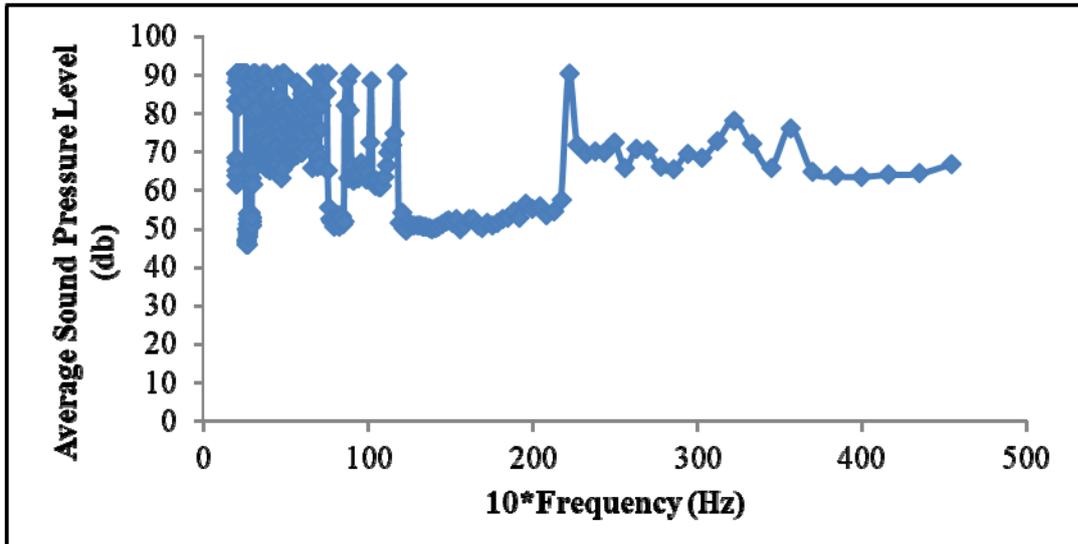


Figure 11: Frequency domain analysis of train sound signal

6.4 PSD analysis

PSD (Chapter 9, Power Spectral Density) is the Fourier transformation of a train sound signal. The PSD helps in displaying the continuous spectra. The PSD integrates the train sound frequency band over the power/frequency for the train sound signal. The period gram for the filtered train sound signal shows that, power frequency ranges from from -75 dB/Hz to highest -35 dB/Hz spike at 2000 Hz (approx.). The lowest spike is being observed to be at power frequency of-105 dB/Hz at 1400 Hz as shown in Figure 12.

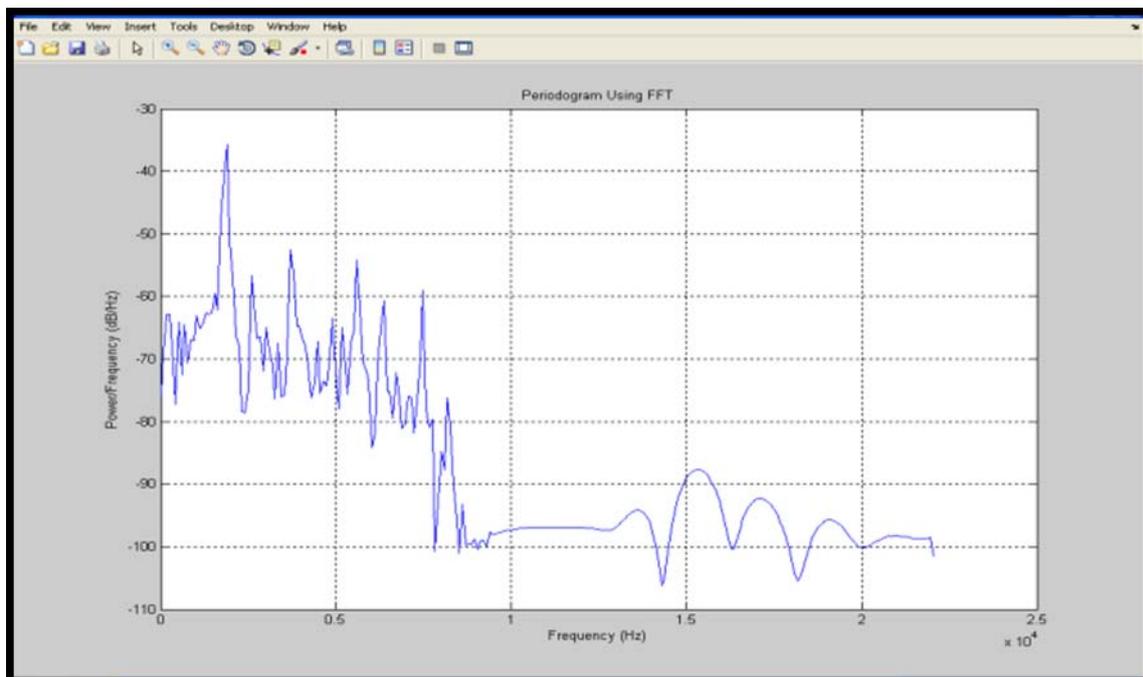


Figure 12: Filtered train sound PSD analysis

References

- AFTAC II (1997) "Train Detection-A New Generation of Audio Overlay Detection", *GE Transportation*, Chicago, IL 60661, pp.1-5.
- Auriscchio, G., Naso, D., Scalera, A. and Turchiano, B. (2003) "A Fuzzy Logic Based Filter for Spike-Noise Detection in Railways Monitoring Systems", *SMCia/03-Proceedings from the 2003 IEEE International Workshop on Soft Computing in Industrial Applications*, Binghamton, NewYork.
- Alim, S., Khair, N. Rashid, N., and Rahman, M. (2013) "Level Crossing Control: A Novel Method Using Sound Recognition", *Engineering Journal*, 17(3), pp.113-118
- Anderson, B.C. and Turpin, J.B. (2009), "Assessment of Railway Activity and Train Noise Exposure: A Teaneck, New Jersey, Case Study", New Brunswick, New Jersey.
- Carvalho, F. C., Martins, R. C. and Mário, S. N. (2005) "Remote Train Detection, Proceedings from the-Twelfth International Congress on Sound and Vibration, Lisbon, Portugal.
- Cawser, C. (2006) "IMAGINE WP 6 Railway Noise Default Directivity", *Memorandum IMA6MO- 060110-AEATUK01*.
- Dolan, T. G. and Rainey, J. E. (2005) "Audibility of Train Horns in Passenger Vehicles", *Human Factors*, 47(3), pp. 613-629.
- Federal Railroad Administration (2009) "Implementing Quiet Zones to Address Train Horn Noise", *Rail Road Controls Limited (RCL)*, Portland-Milwaukie, pp.1- 4
- Gherassimoff, N. (1930) "Automatic Train Signaling Device for Level Crossings", *US Patent Number 1775675*, pp. 1-5.
- Deltarail B.V.(2012) "Improved Methods for the Assessment of the Generic Impact of Noise in the Environment", *Project ID 50354*.
- Kumar, S. and Jain, K. Y. (2012) "Measurement of Noise by Sensor Technology for Automatic Level Crossings", *International Journal of Computer Science and Telecommunications*, 3(9), pp. 41-45.
- Kumar, S. and Jain, K. Y. (2013) "Comparison of Rolling Noise Detection Technique with GPS Detection System for Detection of Train," *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, 2(10), pp. 5125-5129.
- Krishnakumar, M. (2010) "Train Proximity Detector Developed", *School of Engineering, Amrita Vishwa Vidyapeettham*, pp.1-6
- Raginsky, M. (2008) "Lecture XI: The Fast Fourier Transform (FFT) Algorithm", *BME 171: Signals and Systems*, Duke University, pp. 1-13.
- Richards, M.A. (2005) "Fundamentals of Radar Signal Processing", In: McGraw-Hill (2nd eds.) *The Institution of Engineering and Technology*, NewYork.
- Rong, C., Ping, W., and Xiaoping, C. (2009) "Wheel/Rail Noise Generation Mechanisms and Its Control in High Speed Railway", *Eighth International Conference of Chinese Logistics and Transportation Professionals (ICCLTP)*, Chengdu, China.
- Singh, H., Meitzler, T., Karlsen, T., Sohn, G. and Gerhart, R. (1996) "Wavelet Transforms for Computing the Probability of Detection", *Infrared Imaging Systems: Design, Analysis, Modeling, and Testing VII*, 2743, pp. 302-310.
- Pronello, C. (2003) "The Measurement of Train Noise: A Case Study in Northern Italy", *Transportation Research Part D*, 8, pp. 113–128.
- Skolnik, M. (2001) *Introduction to Radar Systems*, New York, U.S.A.

- Stephens (2001) “Railway Hazard Acoustic Sensing, Locating, and Alarm System”, *US Patent-. US 6216985 B1*, pp. 1-11.
- Talotte, C., Gautier, P. E., Thompson, D. J. and Hanson, C. (2003) “Identification, Modelling and Reduction Potential of Railway Noise Sources: A Critical Survey”, *Journal of Sound and Vibration*, 267, pp. 447–468.
- Melletta, C., Le´tourneaux, F., Poisson and Talotte, C. (2006) “High Speed Train Noise Emission: Latest Investigation of the Aerodynamic/Rolling Noise Contribution”, *Journal of Sound and Vibration*, 293, pp. 535–546.
- Wave Train Systems (2015) “Railway Safety Systems for Level Crossings and Maintenance Activities”, pp.1-2.
- Wikipedia (2001) *The free Encyclopedia*, U.S.A.
- Weeks, M. (2006/07), “Train Detection System”, *Technical Report, University of Teesside*, 1996/7
- Zayed, A. (1993) *Advances in Shannon’s Sampling Theory*, U.S.A.

Acknowledgements

The MHRD fellowship provided by Indian Institute of Technology Roorkee, India to Mr. Vivek Singhal is gratefully acknowledged.