Exploration Seismology and Disaster Management using DSP

Application Assignment Report
Evaluation Component 5 : Group 24

EE338 : Digital Signal Processing
Indian Institute of Technology, Bombay
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1 Abstract

It is well known that Digital Signal Processing (DSP) plays an essential role in many applications of science and engineering disciplines, including seismology, sonar, radar, and communications. Interestingly, oil and gas are still considered to be extremely important natural resources for human beings, with many beneficial applications. In order to extract oil from beneath the earth, we need to first estimate as accurate as possible an image of the subsurface. This can be done by listening to the echo caused by artificial earthquakes via a surveying method known as seismic exploration. The process generally requires acquisition, processing, and interpretation of seismic data, where DSP plays a vital role in estimating seismic subsurface images.

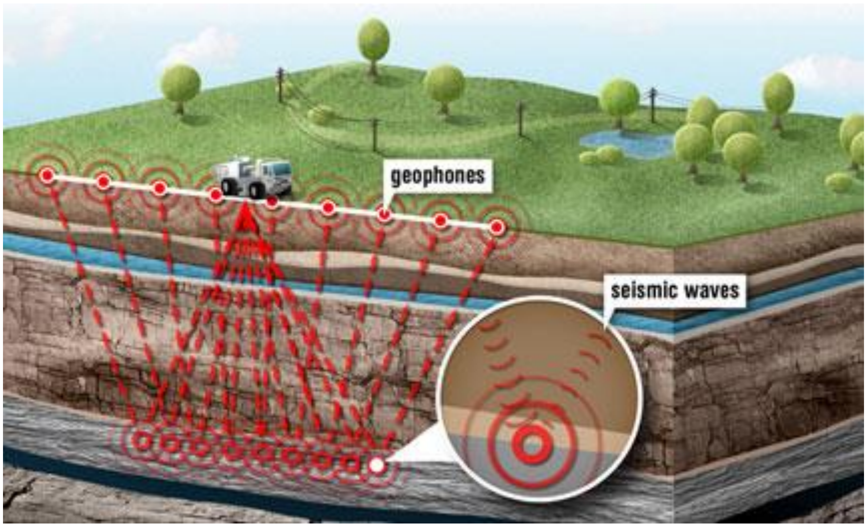

Figure 1 : seismic technology for oil and gas exploration (picture credits – EarthSky)

Using similar techniques, we also plan to work towards the detection of minor seismic events (such as avalanches, rockfalls and landslides), which would be helpful in disaster management and damage mitigation. The main challenge is the high noise in seismic signals. Therefore seismic data processing involves quite a lot of signal preprocessing. We plan on using the concepts taught in the course EE338: Digital Signal Processing and learnt from the references for driving the project towards completion.

2 Problem Statement for Application Assignment

The problem statement as given to us is reproduced below –

This assignment will be carried out by the students of the class, group-wise, in the groups of students already formed in the class. The aim of this assignment, is to explore one application using the ideas of Digital Signal Processing – and to present the concept and realization in as complete a form, as the team finds feasible, with the time and resources available to the team members. Some credit in the assignment is reserved for a definite capacity for contribution through the application, to the 'Atmanirbhar Bharat' or 'Self-Reliant India' initiative.

The assignment is as follows: Assume that a world renowned company/ organization, involved in the manufacture of Digital Signal Processors/ Microcontrollers/ FPGAs, has announced that it will support groups of people who build applications, which employ concepts of Digital Signal Processing, around their Digital Signal Processors/ Microcontrollers/ FPGAs, and present a reasonably convincing product plan for the 'Atmanirbhar Bharat' National Initiative. Your team (group) is interested in availing of this opportunity – and will make a product presentation in this regard for consideration for support.

The considerations that will be used to evaluate the product or application are:

i. The technical feasibility of what is proposed.
ii. The national need/ social need recognized for conception of the product and addressed, for the 'Atmanirbhar Bharat' National Initiative, in the product.
iii. Keep in mind the cost sensitivity of the product for wider use in India, while addressing a social need that can make a difference to the large population of India.
iv. The manner in which it is presented in the Application Online Exhibition and Presentation, planned in November 2020.
v. The attainment of the team, as far as comprehension of the design, the concepts of Digital Signal Processing involved and realization of the idea, are concerned.

2.1 Project's relevance to the problem statement with focus on the Atmanirbhar Bharat Mission

India was the third-largest importer of crude oil in 2018. It spent an estimated ₹ 8.81 lakh crore to import crude oil in 2018-19. Unarguably, oil and natural gas are the most important natural resources, they are, even today the primary source for fulfilling the energy requirements of a country. Having a larger supply by discovering new oil wells will make India more self-reliant and will help save the country huge amounts of foreign currency. Since the principles used in seismic exploration can be extended to the early detection of minor seismic events; we plan to explore the application of Digital Signal Processing in Disaster Management to give early warnings which can help us avoid loss of life and property due to events like landslides, avalanches and minor seismic shocks.

Thus we have tried to solve a national need, in terms of energy security and saving of valuable foreign exchange currency, through the use of DSP techniques for mapping the subsurface features of the earth which are of great importance in oil and gas and other natural resources exploration. Similarly the second part of our project, use of DSP techniques in disaster management and seismic event detection, aims to solve a social need. Landslides and rockfalls along highways and railways in the monsoon months are a common phenomenon in various parts of India such as in the northern and northeastern Himalayan states, and also the Western Ghats. These often cause loss of life and damage to property, and their early detection might save a lot of valuable time in rescue operations and also prevent further damage.

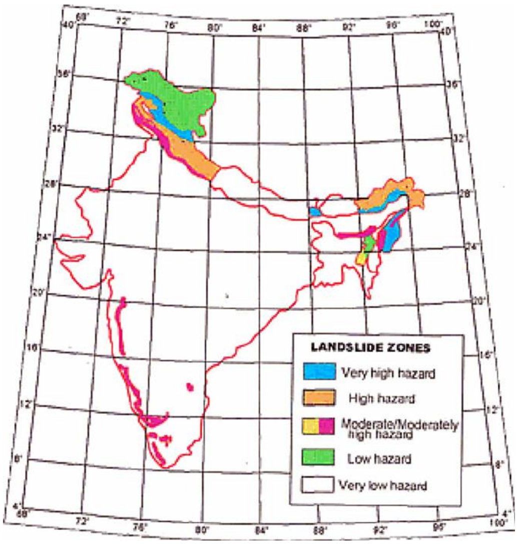

Figure 2 : Areas prone to landslides in Inda (picture credits - Geological Survey of India)

We have tried to implement a real time seismic alert system through the use of digital signal processing techniques, and have tried to cover as many actual implementation details as possible in the given time. We believe it should be technically and economically feasible to setup such a system in practice, which could be of great utility to the people at large.

3 A Primer on Seismic Theory

3.1 Introduction to Geophones

Oil and Natural Gas are found thousands of kilometers below the Earth surface (sometimes below the ocean bed too!). They exist only in certain locations depending on the seismic history of the region. For this purpose, the geological strata below the ground need to be imaged using a technique like *reflection seismology*. Reflection Seismology involves creating and propagating artificial seismic waves through the ground and analysing the reflections obtained from various parts below the earth.

However, this acquired seismic data does not make much sense unless it is processed using some concepts of Digital Signal Processing (like window filtering). Seismic Data is one of the most challenging data to deal with because of the high amount of noise contained in the data (sometimes close to 75% too). Therefore, we need to be careful with analysis of this data and use sophisticated noise removal and signal amplitude enhancement techniques here.

Large Scale Geophysical and Geological surveys are constructed before an oil well is drilled. Petroleum and Natural Gas are such an important natural resource that presence and absence of these can make or break a country's economy. It is often a driving force to other commodity prices too. A large scale of source and receiver senor arrays are carefully engineered to ensure that the least amount of noise is involved in the data acquisition process; we also need to ensure that the source produces waves of adequate power in a large frequency range (seismic activity is generally localized to quite low frequencies, around a few tens of hertz). The detectors used for seismic wave detection are called as *geophones*. The moving coil geophone is the most common form of geophone that is used for practical purposes. It is composed of two systems, a mechanical subsystem followed by an electrical subsystem.

Let input the geophone be $x_1(t)$, $x_2(t)$ *be* the input to the electrical subsystem fed from the mechanical subsystem, let $r_g(t)$ the final output from the geophone. Both these subsystems can be modelled as LTI systems with the following differential equations, the mechanical subsystem is modelled as:

$$x_2'' + 2h_0 w_0 x_2' + w_0^2 x_2 = x_1$$

w_0 is the natural frequency and h_0 is the geophone damping constant. The electrical LTI system is characterized by:

$$r_g = \Lambda x_2'$$

Λ is the transduction constant of the geophone system. The geophone system is a cascade of the above mentioned LTI systems (in order).

The analog transfer function of the overall system is:

$$H(s) = \frac{\Lambda s}{s^2 + 2h_0 w_0 s + w_0^2}$$

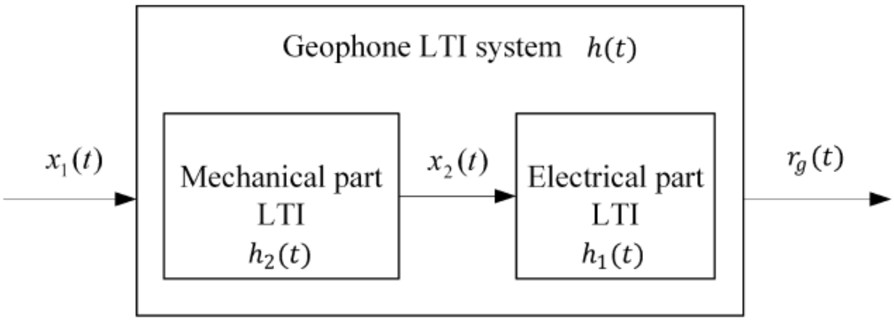

Figure 3 : Block diagram showing the geophone LTI system (Figure used from Advanced Digital Signal Processing on Seismic Data)

Digital Seismic Amplifiers are on the data collected from the geophones; these typically consist of four stages which are mentioned below:

1) Pre- Amplifiers: The signal is amplified by a constant value.
2) Anti-Alias Filters or Pre-Filters: These are lowpass filter which remove frequencies above the Nyquist frequency to prevent aliasing of any kind.
3) Multiplexers
4) Analog-to-Digital Converter (ADC): The signal is samples at a particular frequency and the signal output value is quantized, the output values are stored in binary format.

A basic flowchart of the Digital Amplifier System is:

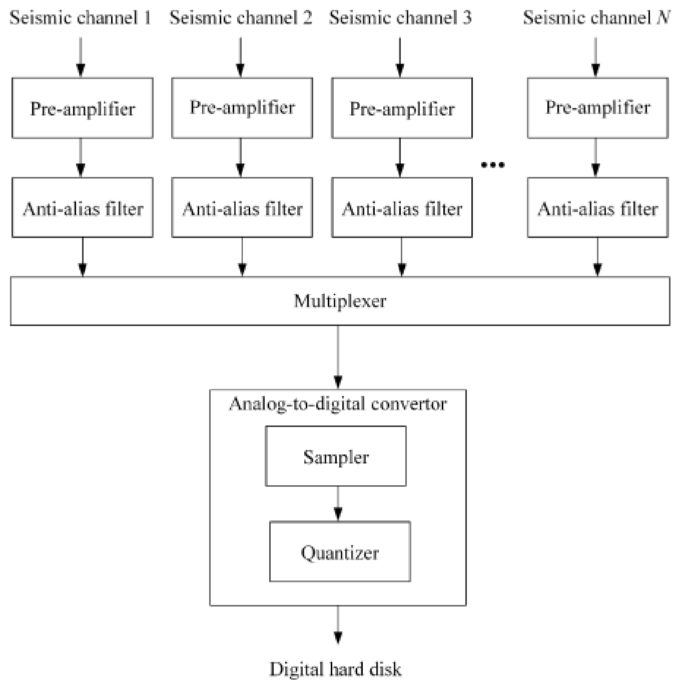

Figure 4 : Schematic Diagram of a typical Digital Seismic Amplifier (Figure used from Advanced Digital Signal Processing on Seismic Data)

Seismic Data is stored in standard 'seismic' formats like SEG-Y or Seismic Unix Format. These files almost always contain a detailed header at the top giving details about the parameters used while acquisition of the seismic data. E.g.: It contains information like the receiver *stacking chart* which to say in simple words contains information about the receiver and source location in the system.

3.2 Seismic Data Processing

It is important to note that the signal stored itself contains some inherent noise and non-uniformities. This is easily modelled using the Seismic convolution model by Robinson and Trietel in 2000. This is quite a simple model but is used commonly even today due to its ability to encapsulate different situations in a simple way.

$$g[n] = r[n] * \omega[n] + n_r[n]$$

r[n] is the reflectivity function of the earth; w[n] is the input wavelet. n_r is the additive noise to the system. To simplify the calculations, the additive noise can be assumed to be White Gaussian noise.

The aim of Seismic Data Processing is to successfully estimate w[n] given g[n]. Three primary stages are involved in Seismic Data Processing. These are:

1) Deconvolution: To increase the vertical resolution of the seismic data
2) Stacking: to increase the signal to noise ratio (SNR) of the seismic data
3) Migrating: to increase the horizontal resolution of the seismic data

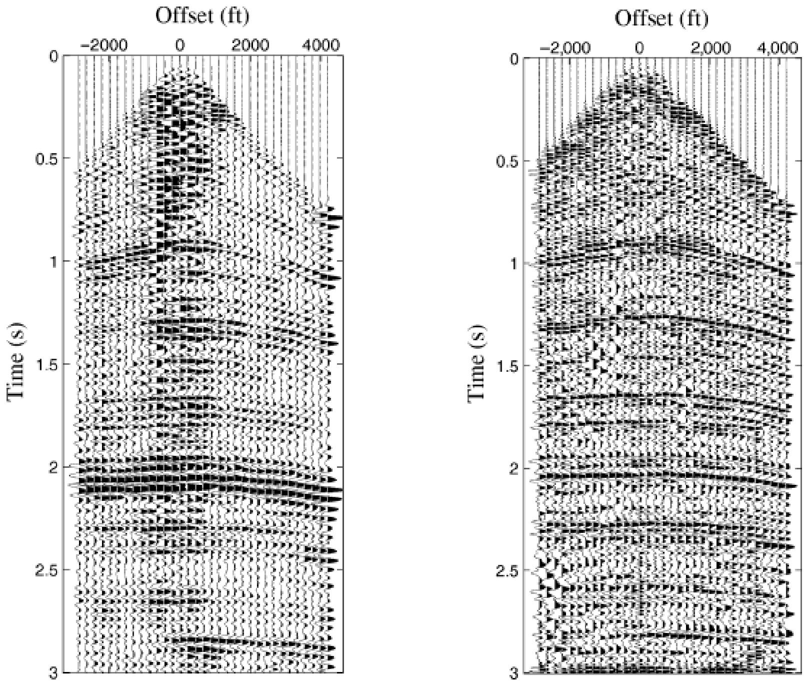

Figure 5 : A seismic data shot before (left) and after deconvolution process (right). Location and time are on the axes. The darkness on the graph is proportional to the magnitude of the seismic signal (Figure used from Advanced Digital Signal Processing on Seismic Data)

Finally, image processing algorithms (that are primarily based on Digital Signal Processing) are used to interpret the seismic data to know all about what's inside the earth, information like rock structure, layer structures (called stratigraphy) and rock age. It is also important to understand the local rock properties (whether it's limestone, sandstone, carbonates etc.) and the presence of particular tectonic plates and fault lines.

3.3 Seismic Waves

These are waves of energy that travel through Earth's layers, and are a result of earthquakes, magma movement, large landslides and man-made explosions that give out low-frequency acoustic energy.

We now discuss the types of seismic waves as these will be instrumental in our understanding of exploration seismology and disaster management and the discussions on how to improve them.

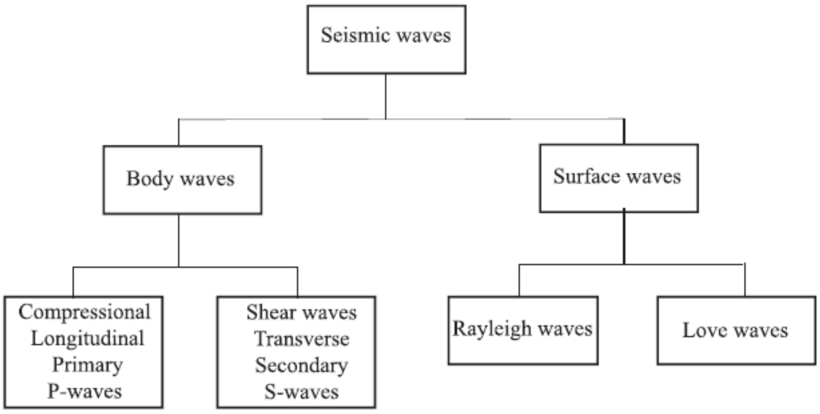

Figure 6 : Flowchart mentioning the types of Seismic Waves (Figure used from Advanced Digital Signal Processing on Seismic Data)

Body Waves: These are seismic waves that can travel through the body of the medium, i.e. they can travel through the internal volume of an elastic solid. On basis of the direction of particle oscillation, body waves are further classified into:

Compressional Longitudinal Primary (P Waves): They travel by compressional strain in the direction of the wave travel (or energy travel). Particle motion is oscillation about a fixed point along the direction of wave propagation. They are the fastest types of seismic waves and are the first to reach any point away from the epicenter.

Shear Transverse Secondary (S Waves): They propagate by shear strain in direction perpendicular to the direction of wave propagation. Individual particles oscillate about a fixed point in direction perpendicular to the direction of wave or energy transmission. They travel slower than P Waves but faster than surface waves.

Surface Waves: They are also called as boundary waves. These are seismic waves where the energy travels along the surface of a bounded elastic solid (along the Earth's boundary). The further classification of surface waves is non-trivial and we would skip it for this project. As such, Rayleigh waves are the ones which are commonly observed and used for various applications, so knowing about Love waves wouldn't hinder one's ability to understand the matter of this project.

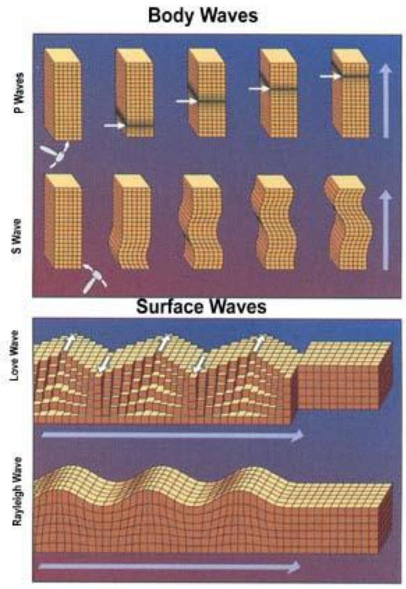

Figure 7 : Types of Seismic Waves (picture credits – US Geological Survey)

3.4 Attenuation in Seismic Waves

Attenuation means loss of amplitude or loss of energy of a wave. Attenuation is a big challenge in seismic data analysis, the waves travel hundreds of kilometres on the boundary or inside the earth surface which leads to huge decay in their amplitude value. The SNR ratio also lowers quite a lot which makes it difficult for us to make sensible and concrete conclusions from the data. Attenuation needs to be cared for whenever we are formulating a strategy for seismic data analysis.

4 Processing Seismic Signals using DSP

Concepts like 1D Discrete Time Fourier Transform, z-transform, convolution are commonly used on the seismic data too. These have been studied and used extensively during the course EE338- Digital Signal Processing. Thus, we do not explicitly write how to calculate them. Instead we discuss some new concepts which we did not learn during the course but are instrumental in seismic data analysis and processing.

4.1 2D Discrete Time Fourier Transform

Let $g[n_t, n_x]$ be a seismic record of size N_t x N_x. Its 2d DTFT is given by:

$$G(n_\omega, n_k) = \sum_{nt=0}^{Nt-1} \sum_{nx=0}^{Nx-1} g[nt, nx] \exp(-j2\pi(n_\omega nt - n_k\, nx)/\mathrm{NtNx})$$

The inverse 2D Fourier transform is defined as:

$$g[nt, nx] = \left(\sum_{nw=0}^{Nt-1} \sum_{nk=0}^{Nx-1} G(n_\omega, n_k) \exp(j2\pi(n_\omega nt - n_k\, nx)/\mathrm{NtNx})\right)/\mathrm{NtNx}$$

An example of 2D Fourier transform is:

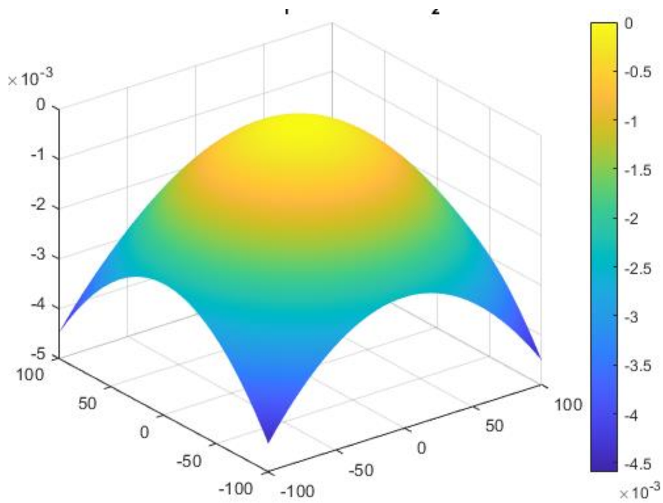

Figure 8 : An example of 2D Fourier transform. Image is taken from an assignment solution of the course CS 663 - Fundamentals of Digital Image Processing (at IITB)

This transform is extensively used in the field of Image Processing and Data Analysis in general.

4.2 Radon Transform (Discrete)

The Radon Transform has attracted attention of seismologists for its effectiveness in the analysis of seismic data. It is much more complicated to understand, thus we will just observe the formulae for discrete radon transforms and understand when to use it. Whenever required we will use it via a programming language like MATLAB, so the exact implementation details may not be sought right now. At this stage, we may consider it as a black-box.

The formulae for the radon transform (discrete) are:

$$u[n_q, n_\tau] = \sum_{n_x} g[n_x, n_t = n_\tau + n_q \phi[n_x], n_t = n_\tau + n_q \phi[n_x]],$$

$$\hat{g}[n_x, n_t] = \sum_{n_q} u[n_q, n_\tau = n_t - n_q \phi[n_x]].$$

$\Phi(x)$ is the function of offset parameter x and the summation (or integration) path. The analog counterpart of the radon transform is also manifested similarly. Let's visualize what the radon transform means physically.

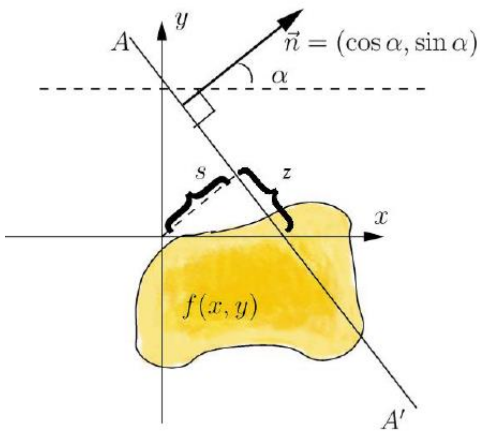

Figure 9 : Radon Transform or Tomographic Projection (Source: Wikipedia)

Imagine a line was drawn through the 2D image in a certain direction α, and we integrate the intensity values along that line. Now we repeat this for lines parallel to the original one but at different offsets. Each such summation produces a 'bin' of the 'tomographic projection'. The collection of bins forms a 1D array which is called the tomographic projection or the Radon transform of the object in the direction α.

4.3 Filtering the Seismic Signals

Seismic waves are generally quite low frequency waves, noise from sources such as ground drilling is of a frequency around a few kilo hertz. To filter out the noise low pass filters or band pass filters of required specifications are used. Depending on the resources one is willing to spend and the accuracy one requires, he may choose to make a Butterworth, Chebyshev or Elliptic filter. The procedure of making these filters was seen in great detail in the filter design assignment of this course.

For seismic applications windowing (FIR) filters are quite common. Hamming, Blackmann and Hann windows are commonly used, a specific choice among these depends on the particular requirement and the situation.

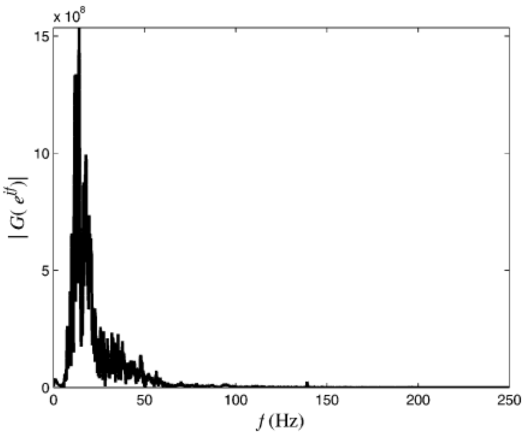

Figure 10 : Magnitude of the fourier transform of a seismic wave, note the high spectral content at lower frequencies (Figure used from Advanced DSP on Seismic Data)

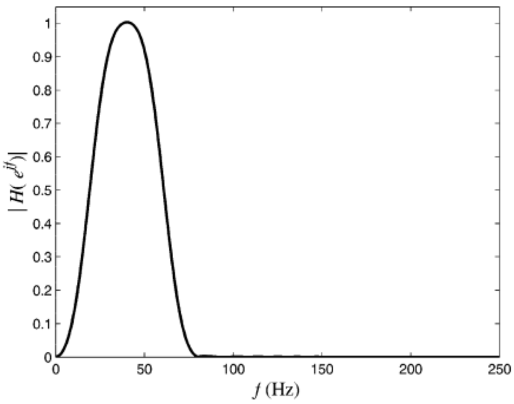

Figure 11 : Magnitude of the Frequency response of the filter (Figure used from Advanced DSP on Seismic Data)

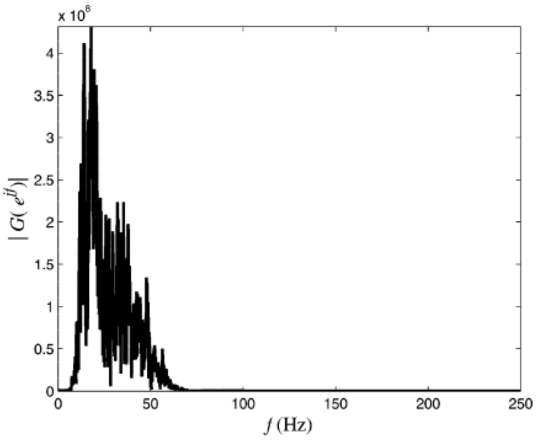

Figure 12 : Magnitude of the Fourier Transform after the wave is passed throught the filter (Figure used from Advanced DSP on Seismic Data)

4.4 Machine Learning on Seismic Data (to augment DSP)

Apart from seismic exploration, seismic data analysis is an important part of the disaster management process and prediction. Machine Learning can help to tell us if a warning or a small seismic shock is really serious or just a false alarm for a disaster.

Machine Learning helps us learn from previous data; DSP based techniques will help us analyze the new signal from scratch. A combination of these techniques puts us in the best spot to make a decision or prediction.

We used the seismic bumps dataset from UCI Machine Learning Repository (https://archive.ics.uci.edu/ml/datasets/seismic-bumps). We then used three different clustering algorithms to know if the state is hazardous or non-hazardous based on the various input parameters. Amongst the three clustering algorithms (Logistic Regression, Random Forest, K- Nearest Neighbours) used- **Logistic Regression** even though quite simple gave the best result (**94% accuracy**). We could have performed deep learning with a bigger dataset and more computational resources. Unfortunately, seismic datasets aren't easily available for open-source research. More details about the input attributes and the processes involved, are available with the code and outputs (with markdown) attached at the end of the report in the appendix.

5 Disaster Management Application

5.1 Introduction

Seismic events are often the cause of damage to life and property throughout the world. Unlike other kinds of natural disasters like meteorological events (cyclones, droughts, hailstorms), hydrological events (floods) and forest fires, seismic events like earthquakes, rockfalls, landslides and avalanches are notoriously difficult to predict or forecast and also require a quick reaction and response time (in the order of seconds), to avoid or mitigate damage to the maximum extent possible. Only a few seconds of time might be essential, for example in industrial plants in which closing up of valves of pipes carrying toxic chemicals as soon as the first tremors (P Waves) are detected might save a lot of lives and prevent damage to equipment.

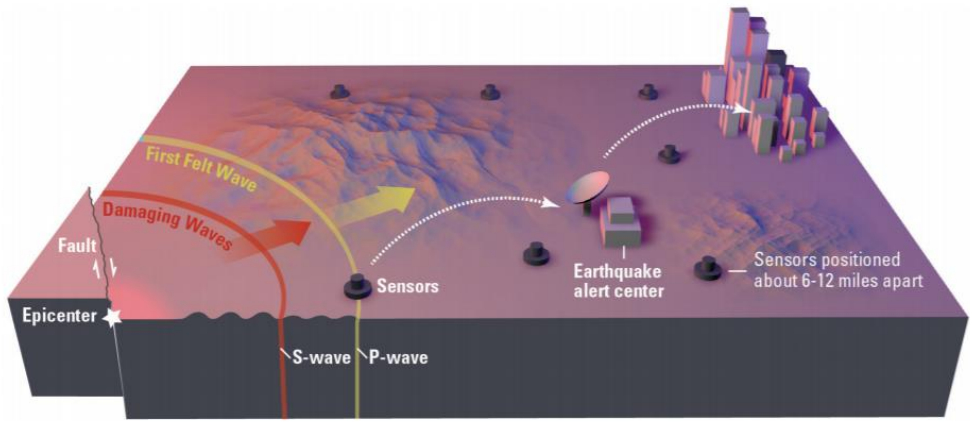

Figure 13 : Example of an earthquake alert system. The P Waves are detected first by the sensors installed in multiple places which transmit alerts to necessary locations thus ensuring preventive measures before the damaging S waves reach (Photo Credits - U.S. Geological Survey ShakeAlert Project)

Similarly, in the case of rockfalls and landslides along roads and railways in hilly areas, detection of such minor seismic events as soon as possible might help in warning the moving vehicles of imminent danger ahead. This might be crucial, for example in railway systems where even a medium sized boulder on the track might cause a train to derail, and the visibility ahead might be hindered due to short line of sight in hilly areas, and similarly in the case of roadways (with cars and trucks moving at speed), where traffic may have to be stopped as soon as a rockfall or landslide is detected nearby. The detection of such events quickly will also help in search and rescue operations, where again time is of the essence.

Figure 14 : A rockfall on a highway (photo credits - Pierre-Arnaud Chouvy)

Figure 15 : Example of a boulder which can derail a train (photo credits – CN Railway)

Such landslide and rockfall events in India are quite common, especially during the Monsoon season, in the Himalayan region in the north and northeast and also in the Western Ghats. These are often caused due to rising deforestation which leads to loss of tree cover and hence less obstruction to downhill movement of landmasses. These often cause disruption of roadways and railways, which might take hours or even days to repair at a stretch.

Therefore we have proposed a seismic alert system through the use of digital signal processing techniques to detect minor seismic events like rockfalls and landslides, utilising an embedded processor at various remote detection locations and wireless sensor networks for transmission of such detection data. This can be implemented, for example, along major highways in mountainous areas where communication links of cellular networks might not be available in all locations or might be unreliable otherwise. In such cases detection of such events in real time may be able to provide timely warning and alerts to people, which may help in mitigating the associated risks. In such systems detection through signal processing is essential, due to the nature of the seismic signals which have a high noise content (for example due to vehicular movements or other human activities or due to natural sources such as rivers).

5.2 Description of the System

The proposed seismic warning system broadly consists of three parts – the detection system, the alert transmission system and the alarm system. The detection system consists of the seismic sensors and associated processing equipment located in various remote locations, such as along roads in places frequently prone to rockslides acting as multiple sensor nodes. The alert transmission system consists of the communication link made through a wireless sensor network, with the sensors acting as wireless nodes and the alert being routed by hopping through multiple such nodes to the reaction system consisting of the alarm nodes and also the central node which notifies the necessary agencies, such as the signalling and train control division in case of railways or the local disaster management units and the traffic department in case of roadways. The alarm nodes, on the other hand may be distributed along the road itself, with warnings provided directly to the road users for example through warning horns indicating imminent danger ahead.

We describe each of these systems in brief detail in the next few sections, with emphasis on the detection system because this is where the main digital signal processing techniques come into play.

Figure 16 : Proposed System

5.2.1 Detection System – Sensors

The detection will be through sensors placed in suitable locations, such as in points frequently prone to rockslips. Sensors used for transducing the surface movements into electrical signals are called geophones (consisting of mechanical springs and magnetic coils) (already discussed in a previous section). Any deviation in the measured output voltage from the base line is regarded as seismic activity, which may be indicative of the velocity of the surface movement (m/s), or displacement (m) or even acceleration (m/s^2). Geophones are lightweight, robust sensors and do not require any electrical power for their own operation. Geophones usually have a usable frequency range of 7 Hz to 2000 Hz (depending upon the specific type). MEMS accelerometers have also been introduced into the market recently, but these are typically more suited for higher energy seismic wave detection such as in earthquakes instead of low energy ones such as in rockfalls and landslides.

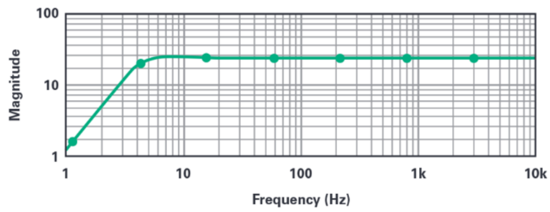

Figure 17 : Typical magnitude response characteristics of a geophone (picture credits – Analog Devices)

5.2.2 Embedded System – Detection of Seismic Event

The embedded processor system will be responsible for detection and identification of the seismic event from the sensor input. The embedded processor implements the digital signal processing algorithm that is used to identify a seismic event and distinguish it from noise.

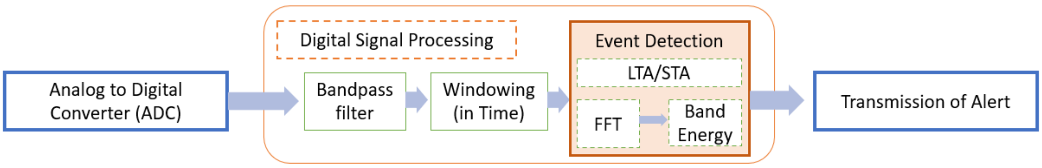

Figure 18 : The embedded processor system

The embedded system consists of an analog to digital (ADC) converter to first convert the analog geophone input into digital signals. The ADC will have to work at a sampling frequency above the Nyquist rate, in this case it can be twice the maximum usable frequency for the geophone (or the maximum frequency component which usually occurs in the particular kind of seismic event to be detected). This is followed by a band pass filter (approximately matching the usable frequency output range of the geophone), which acts to remove high frequency noise at the initial stages itself. This is followed by a windowing system which selects and stores the useful time series input from the past input data (as per the specific algorithm implemented). Next is the event detection part which consists of the specific DSP algorithm implemented (STA/LTA or Band energy calculation through FFT), which are described in a later section along with the corresponding windowing parameters. Whenever the event detection output exceeds some predetermined threshold, an alert is generated for a detected seismic event and transmitted to the wireless sensor network.

5.2.3 Data Transmission through Wireless Sensor Networks

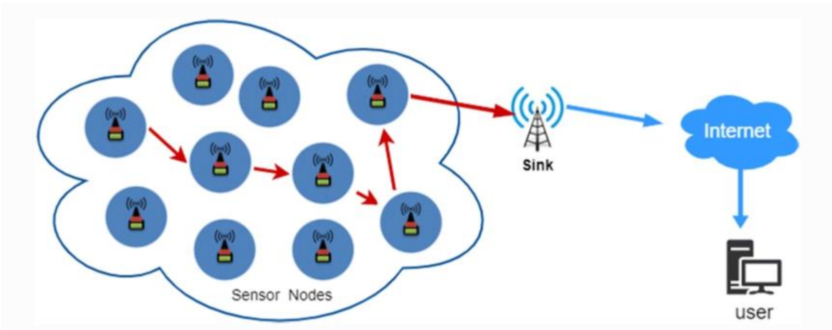

Figure 19 : Wireless Sensor Network Diagram (picture credits – Zaher et al., Wireless Personal Communications, 2020)

A Wireless Sensor Network is a group of spatially dispersed and dedicated sensors which are used for monitoring and recording the physical conditions of the environment (in this case the surface seismic activity) and organizing the gathered data at a central location. The various sensor node are able to relay signals between them (that is the signal can hop over different sensor nodes), and thus this reduces the infrastructural requirement in comparison to a system where each node only communicates with the central base node. The alert travels from the initial sensor node hopping through various other nodes, finally reaching the central node. Each sensor node has the detection system as discussed in the previous section, and a radio transceiver to transmit the alert to the next nearest node. It must also include an electronic interfacing system to ensure communication between the microcontroller and the wireless antenna and also a power source (such as battery or solar panels) to ensure power supply for the DSP chip and the communication antenna.

5.2.4 Reaction System

The reaction system basically consists of alerting users about the detected danger such as rockfalls or landslides. Thus the alert may be passed on to the monitoring / reaction agencies such as road maintenance and district disaster management units in case of events along roads or highways, which will help in quick reaction and accurate tracing of the event location for rescue and repair purposes. In case of railways, it might be the signalling and train control division, which might give instructions to the train on that section to either stop or proceed very cautiously. Moreover, the warning may be directly provided to road users near the event location, such that the affected section is immediately closed for road traffic to avoid any accidents. This could be through the use of audible warning horns provided at points along the roadside. The alert signal may directly be sensed/accessed by these alarm nodes instead of passing through the central nodes (to save time). Moreover, such alerts could be integrated through other channels, such as navigation systems (for example Google Maps), which can directly warn road users who are utilising GPS navigation.

Figure 20 : Alarm Systems which can be implemented across roadways (picture credits – Ben Franske)

5.3 Detection Algorithms

A variety of algorithms are used in detection of seismic signals. The most common ones are as below –

1. **Amplitude Threshold Triggering (ATT)** – ATT is a simple algorithm which detects a seismic event whenever the signal input value goes above a particular threshold. This threshold is predetermined and may be based upon the usual noise levels in the surroundings. This requires quite simple circuitry and is the quickest to detect any event (due to least computational time requirement and fastest triggering), however it is also the most susceptible to noise and may trigger false alarms too often.

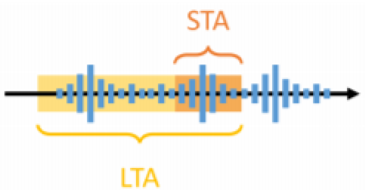

Figure 21 : STA/LTA Detector (picture credits - I-Lin Fang, ETH Zurich)

2. **STA/LTA Detector** – This is an algorithm which calculates the average of the present and past input signals over two time intervals, a short window and a long window, and takes the ratio of the two values (the windows are usually rectangular). On the occurrence of a seismic event, the rise in the short term average is much higher than the rise in the long term average, and hence the ratio exceeds some predetermined threshold and an event is detected. The advantage here is that the usual background noise is automatically accounted for using the long term average, and this system is not sensitive to variations is noise during different periods of the day / year. Moreover, this is not computationally expensive and is significantly accurate in detection of seismic events. Hence it provides a good tradeoff between detection time and error. This algorithm is widely used in systems for earthquake monitoring and detection.
3. **Z Detector** – Z detector calculates the mean and variance of the samples over some past time interval, and calculates how

many standard deviations the present sample is away from the mean, using the formula –

$$z_i = \frac{x_i - \mu}{\sigma}$$

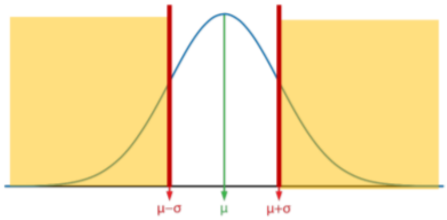

Figure 22 : Z Detector (picture credits - I-Lin Fang, ETH Zurich)

4. **Power Spectral Density** (Using STFT) – The power spectral density operates in the frequency domain. It first windows the samples to select some small past time interval (for short time fourier transform), and then calculates the corresponding power spectral density using Fast Fourier Transform (FFT). Following this the power content over a particular frequency band is calculated, and if this exceeds some predetermined threshold, the alert is generated.

For our system, we have implemented (through simulations), the LTA/STA algorithm and the Power Spectral Density algorithm, and hence we have described them in more detail below.

5.3.1 STA/LTA Triggering

There are two methods of STA/LTA triggering, both similar in approach. One is through the standard calculations of time averages over the short time (leading) window and the long time (trailing) window, and taking their ratios as shown below –

$$STA_i = \frac{1}{n_s} \sum_{j=i-n_s+1}^{i} x_i$$

$$LTA_i = \frac{1}{n_l} \sum_{j=i-n_l+1}^{i} x_i$$

$$Output = \frac{STA_i}{LTA_i}$$

Here the x_i correspond to the sample at time = I, and the n_s and n_l correspond to the length (number of samples) in the short time window and long time window respectively.

Thus the detection system will trigger whenever the output is greather than some threshold value, which can be determined according to experimental observations.

Another way possible here is through recursive calculation, whereupon the previous samples are replaced by the immediately preceding time average corresponding to the short or long time window. The calculation is as shown below –

$$STA_i = \frac{1}{n_s} \times x_i + \left(1 - \frac{1}{n_s}\right) STA_{i-1}$$

$$LTA_i = \frac{1}{n_l} \times x_i + \left(1 - \frac{1}{n_l}\right) LTA_{i-1}$$

$$Output = \frac{STA_i}{LTA_i}$$

5.3.2 Power Spectral Density Method (Using STFT)

The power spectral density method requires the calculation of the frequency domain components of the signal (the discrete fourier transform), which is implemented via the Fast Fourier Transform (FFT) algorithm. For this the sample inputs are first windowed upto some past time interval. Once the FFT is calculated, we determine the power contained in some predecided frequency band which is usually dominated by the seismic event frequency components, as opposed to noise and other events such as moving traffic. Once the power exceeds the set threshold, an alert is generated. The various steps are as described below –

1. Windowing – The time series samples within some past time interval, say 0.5 seconds is selected
2. FFT – The Fast Fourier Transform of the sample inputs within the previous window is calculated
3. Calculation of Power in the band – The Power Spectral Density as calculated from the FFT is used to calculate the

power over some specific frequency band (say 10 Hz to 70 Hz)

The above steps are repeated at each instance of time (each sample), taking the appropriate present and past inputs. Thus this technique is similar to a Short-time Fourier transform (STFT), with only the power in the relevant frequency bands taken into account at the final stage.

$$\mathbf{STFT}\{x[n]\}(m,\omega) \equiv X(m,\omega) = \sum_{n=-\infty}^{\infty} x[n]w[n-m]e^{-j\omega n}$$

$$\mathbf{spectrogram}\{x(t)\}(\tau,\omega) \equiv |X(\tau,\omega)|^2$$

This technique is clearly more computationally complex than the other techniques, and may take more time to detect the start of the seismic event (as window size required is large and perturbations in the time domain will take time to reflect in the frequency domain), however it has the advantage that this technique may be used to filter out the noise inputs. The typical frequency content of seismic events such as rockfall and landslides is typically lower (about 10 to 100 Hz) and do not usually contain high frequency components as compared to the vibrations induced by the wheels of a running train (greater than 300 Hz). Hence the presence of power in high frequency components may be used to avoid false alarm cases.

5.4 Simulation

We have simulated the LTA/STA Detector and the Power Spectral Density Method on a sample dataset using MATLAB.

The sample dataset was obtained from - Vancouver : University of British Columbia Library (dataset uploaded by Bohdan Nedilko), which consists of a time series data of geophone sensors kept underneath a rail in a mountainous region, and the seismic vibrations due to an artificially induced rockfall upon the tracks. The sampling frequency was 1000 Hz (time interval = 0.001 seconds) which is above the required Nyquist rate (spectral content of rockfall is usually concentrated between $10 - 100$ Hz, therefore Nyquist rate = 200 Hz).

The simulations were done in MATLAB, making use of the Signal Processing Toolbox wherever necessary, and the code is provided in the appendix.

5.4.1 LTA/STA simulation

The Short Term Window length was taken as 0.05 second ($n_s = 50$), and the long term window length was taken as 5 seconds ($n_l = 5000$). The plots obtained are shown below.

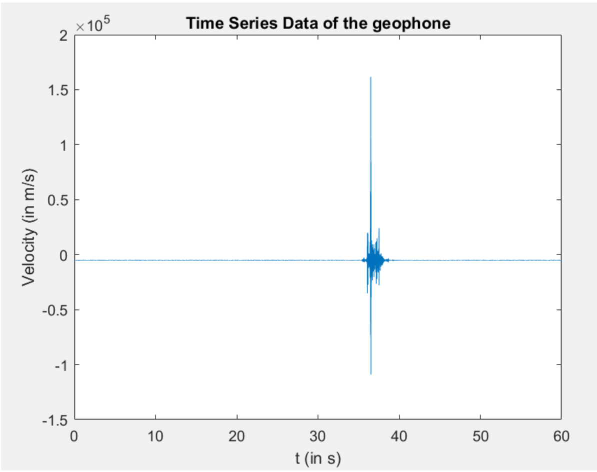

Figure 23 : Time Series Data of the Input Signal

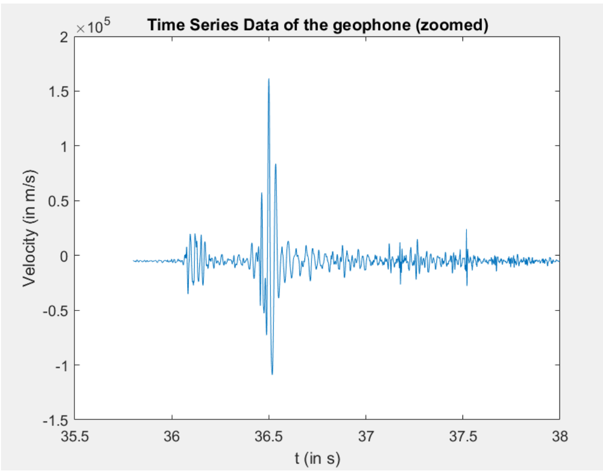

Figure 24 : Time Series Data of the input signal (Zoomed in)

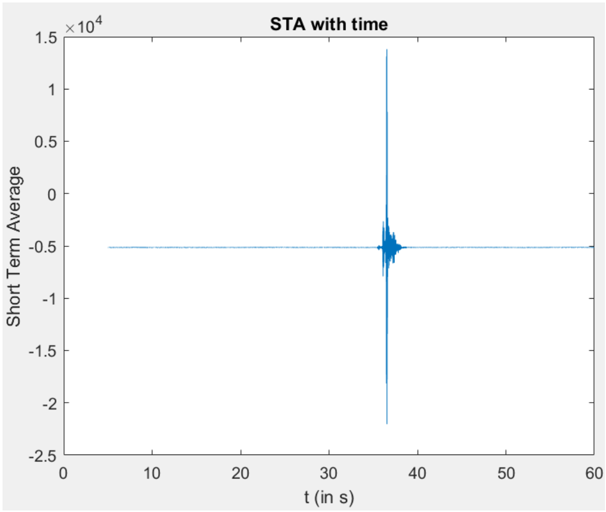

Figure 25 : Short Term Average with time

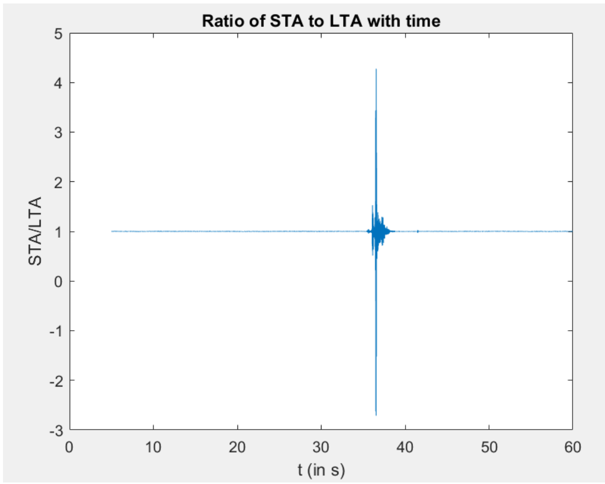

Figure 26 : Output with time

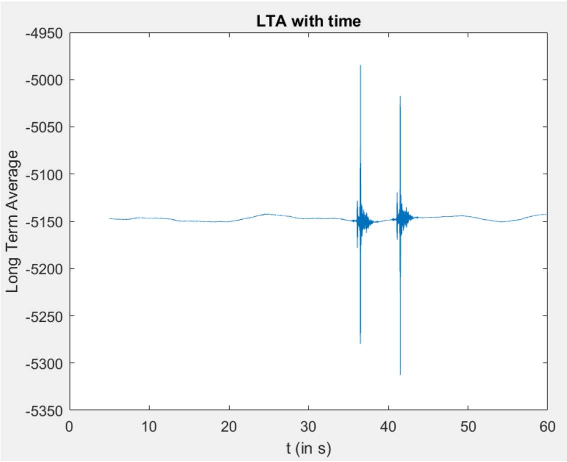

Figure 27 : Long Term Average with time

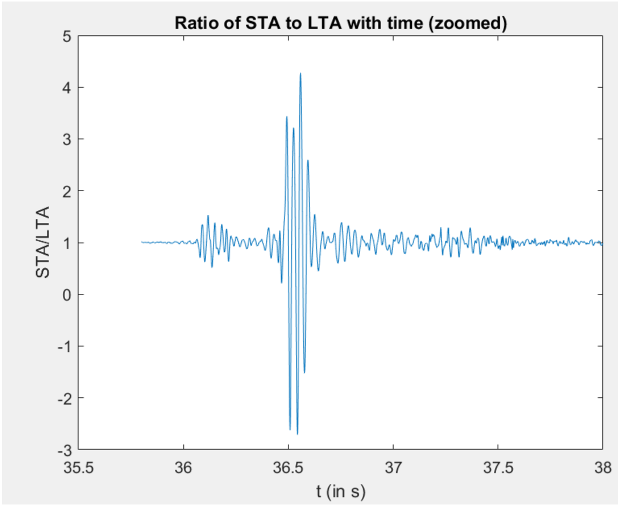

Figure 28 : Output with time (zoomed in)

The plots show that the STA/LTA Trigger works as expected. A suitable threshold could be used to detect the onset of the seismic event, such as STA/LTA = 2.5 in this case. The duration of the rockfall is roughly between 36 to 37.5 seconds.

5.4.2 PSD Triggering

Here we have taken a window length of 0.5 seconds for the time domain windowing (using a rectangular window). Following this, the short time fourier transform is calculated using FFT and then the power spectral density over the range 10 Hz to 70 Hz is integrated to obtain the requisite bandpower.

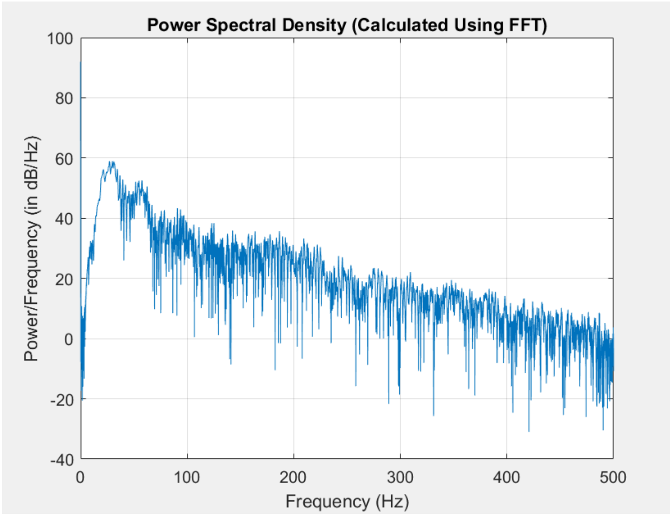

Figure 29 : Power Spectral Density over the entire time interval. The y axis is drawn in a logarithmic scale. It is apparent that the maximum frequency component is focused in the 10 to 100 Hz region.(in the range 40 to 60 dB)

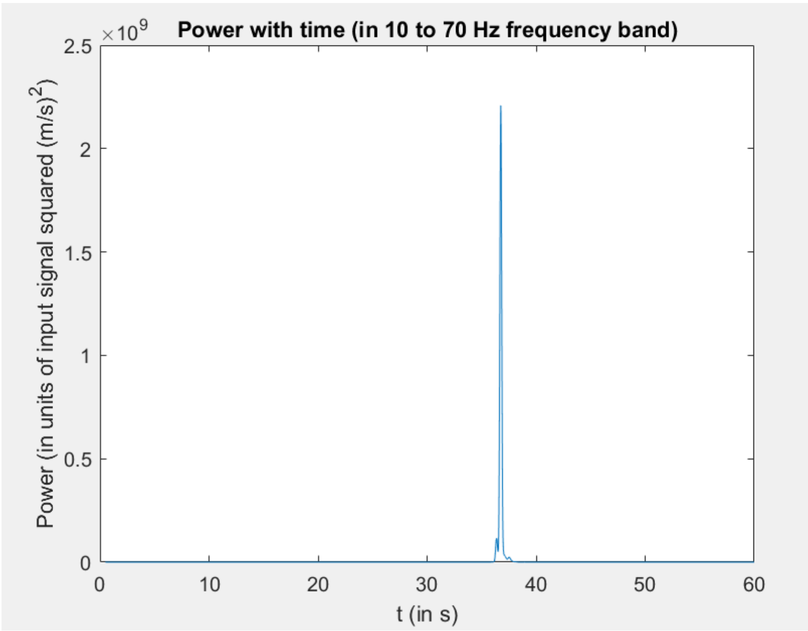

Figure 30 : Power in the relevant band vs Time

From the plot, it is visible that the signal power in the 10 to 70 Hz band increases quickly on occurrence of the rockfall at about 36.5 seconds. As is visible, this technique filters out the background noise quite effectively (the power is effectively flat zero on this scale at times outside the rockfall occurrence), and therefore this algorithm is more accurate than the LTA/STA Detector.

5.5 Implementation Details

In this section we briefly talk about the physical implementation modalities of the proposed system.

5.5.1 DSP Processor

To build our system, we can use a microcontroller which provides a good library of DSP functions. For example we can choose an ARM Cortex-M4 core-based STM32F469NIH6 micro controller unit, from STMicroelectronics, which includes a floating point unit (FPU) and a full set of DSP instructions (CMSIS DSP Software Library) which enables to perform the Fast Fourier Transfrom (FFT) quite easily. The price for this chip is roughly around ₹1,000 (only the chip) per unit.

Figure 31 : Example of the DSP chip (Picture credits – Emtrion)

5.5.2 Other Components

A suitable geophone could be used with usable frequency atleast from 10 Hz to 400 Hz, such as an SM-6 4.5 Hz geophone.

A analog to digital data converter (ADC) is also required which could be implemented through ADS1255 by Texas Instruments, which is a very low noise 24 bit Delta-Sigma precision ADC. This costs approximately ₹1,000 per unit as well.

Additional devices include the wireless communication module with antenna for the wireless sensor network, and the solar panels to power up the sensor node, with stored battery backup if required. The backend components including the central node and the warning and reaction system have to be implemented separately as well.

6 Conclusion

The use of digital signal processing techniques is wide and of great importance in a variety of fields. This includes Seismology, including the detection of seismic waves and also using them to map the subsurface features of the earth. Accordingly, we have studied the various techniques of DSP used in exploration seismology which are helpful in analysing the natural resources hidden inside the earth. These natural resources are of great importance for the energy security of the country, and can help in saving valuable foreign exchange for our country. Moreover, digital signal processing techniques can also be used to detect minor seismic events such as rockfalls and landslides, and as we have shown in our work, we can implement a real time seismic event detection system using DSP techniques which can be of great consequence in disaster management where quick reaction is necessary and hence save a lot of lives and also mitigate damage to property.

7 References

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controllers-microprocessors/stm32f469ni.html
11. ”CMSIS DSP Software Library”, In:
http://www.keil.com/pack/doc/CMSIS/DSP/html/index.html
12. B. K. Sharma, Amod Kumar and V. M. Murthy, ”Evaluation of Seismic Events Detection Algorithms”, In: Journal Geological Society Of India Vol.75, March 2010, pp.533-538

8 Appendix (MATLAB Codes used)

The MATLAB codes used for various simulations and plots are given in the next few pages

EE338 Group 24

This is the classification code for the Seismic Bumps dataset from [UCI Machine Learning Repository (https://archive.ics.uci.edu/ml/datasets/seismic-bumps)](https://archive.ics.uci.edu/ml/datasets/seismic-bumps). Here we will compare three methods of classification and retain the one which works best for this particular scenario. The dataset was first converted to csv file for easy input via pandas.

In [1]:

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, LabelEncoder, OneHotEncoder
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
```

We will explore KNN, Random Forest and Logistic Regression for our project.

Attribute Information:

Attribute information:

1. **seismic**: result of shift seismic hazard assessment in the mine working obtained by the seismic method (a - lack of hazard, b - low hazard, c - high hazard, d - danger state);
2. **seismoacoustic**: result of shift seismic hazard assessment in the mine working obtained by the seismoacoustic method;
3. **shift**: information about type of a shift (W - coal-getting, N -preparation shift);
4. **genergy**: seismic energy recorded within previous shift by the most active geophone (GMax) out of geophones monitoring the longwall;
5. **gpuls**: a number of pulses recorded within previous shift by GMax;
6. **gdenergy**: a deviation of energy recorded within previous shift by GMax from average energy recorded during eight previous shifts;
7. **gdpuls**: a deviation of a number of pulses recorded within previous shift by GMax from average number of pulses recorded during eight previous shifts;
8. **ghazard**: result of shift seismic hazard assessment in the mine working obtained by the seismoacoustic method based on registration coming form GMax only;
9. **nbumps**: the number of seismic bumps recorded within previous shift;
10. **nbumps2**: the number of seismic bumps (in energy range [10^2,10^3)) registered within previous shift;
11. **nbumps3**: the number of seismic bumps (in energy range [10^3,10^4)) registered within previous shift;
12. **nbumps4**: the number of seismic bumps (in energy range [10^4,10^5)) registered within previous shift;
13. **nbumps5**: the number of seismic bumps (in energy range [10^5,10^6)) registered within the last shift;
14. **nbumps6**: the number of seismic bumps (in energy range [10^6,10^7)) registered within previous shift;
15. **nbumps7**: the number of seismic bumps (in energy range [10^7,10^8)) registered within previous shift;
16. **nbumps89**: the number of seismic bumps (in energy range [10^8,10^10)) registered within previous shift;
17. **energy**: total energy of seismic bumps registered within previous shift;
18. **maxenergy**: the maximum energy of the seismic bumps registered within previous shift;
19. **class**: the decision attribute - '1' means that high energy seismic bump occurred in the next shift ('hazardous state'), '0' means that no high energy seismic bumps occurred in the next shift ('non-hazardous state').

In [2]:
```
model_accuracies = {'LogReg':0, 'RF':0, 'KNN':0}
df = pd.read_csv('https://drive.google.com/uc?export=download&id=1EWQI6RC1a_Qj
NgH3_MBB88cxCIhpQ641', header = None)
display(df)
```

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
0	a	a	N	15180	48	-72	-72	a	0	0	0	0	0	0	0	0	0	0	0
1	a	a	N	14720	33	-70	-79	a	1	0	1	0	0	0	0	0	2000	2000	0
2	a	a	N	8050	30	-81	-78	a	0	0	0	0	0	0	0	0	0	0	0
3	a	a	N	28820	171	-23	40	a	1	0	1	0	0	0	0	0	3000	3000	0
4	a	a	N	12640	57	-63	-52	a	0	0	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2579	b	a	W	81410	785	432	151	b	0	0	0	0	0	0	0	0	0	0	0
2580	b	a	W	42110	555	213	118	a	0	0	0	0	0	0	0	0	0	0	0
2581	b	a	W	26960	540	101	112	a	0	0	0	0	0	0	0	0	0	0	0
2582	a	a	W	16130	322	2	2	a	0	0	0	0	0	0	0	0	0	0	0
2583	a	a	W	12750	235	-10	-10	a	0	0	0	0	0	0	0	0	0	0	0

2584 rows × 19 columns

In [3]:
```
X = df.iloc[:, 0:18].values
y = df.iloc[:, 18].values

le_y = LabelEncoder()
y = le_y.fit_transform(y)
le_X = LabelEncoder()
X[:, 0] = le_X.fit_transform(X[:, 0])
X[:, 1] = le_X.fit_transform(X[:, 1])
X[:, 2] = le_X.fit_transform(X[:, 2])
X[:, 7] = le_X.fit_transform(X[:, 7])
```

In [4]:
```
sc_X = StandardScaler()
X = sc_X.fit_transform(X)
print(X)
```

```
[[-0.73230209 -0.77142023 -1.34374329 ...  0.         -0.24332671
  -0.22108685]
 [-0.73230209 -0.77142023 -1.34374329 ...  0.         -0.14551225
  -0.11774749]
 [-0.73230209 -0.77142023 -1.34374329 ...  0.         -0.24332671
  -0.22108685]
 ...
 [ 1.36555667 -0.77142023  0.74418976 ...  0.         -0.24332671
  -0.22108685]
 [-0.73230209 -0.77142023  0.74418976 ...  0.         -0.24332671
  -0.22108685]
 [-0.73230209 -0.77142023  0.74418976 ...  0.         -0.24332671
  -0.22108685]]
```

In [5]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, y, test_size = 0.2, ran
dom_state = 1)
display(X_train, X_train.shape)
display(X_test, X_test.shape)
```

```
array([[-0.73230209, -0.77142023, -1.34374329, ...,  0.        ,
        -0.24332671, -0.22108685],
       [-0.73230209, -0.77142023, -1.34374329, ...,  0.        ,
        -0.24332671, -0.22108685],
       [ 1.36555667, -0.77142023,  0.74418976, ...,  0.        ,
         1.08205916,  0.8123068 ],
       ...,
       [-0.73230209,  1.12339905, -1.34374329, ...,  0.        ,
        -0.24332671, -0.22108685],
       [-0.73230209,  1.12339905, -1.34374329, ...,  0.        ,
         0.05011666,  0.08893124],
       [-0.73230209, -0.77142023, -1.34374329, ...,  0.        ,
        -0.24332671, -0.22108685]])

(2067, 18)

array([[ 1.36555667,  1.12339905,  0.74418976, ...,  0.        ,
        -0.24332671, -0.22108685],
       [-0.73230209, -0.77142023, -1.34374329, ...,  0.        ,
        -0.22376382, -0.20041898],
       [-0.73230209, -0.77142023,  0.74418976, ...,  0.        ,
        -0.24332671, -0.22108685],
       ...,
       [-0.73230209, -0.77142023,  0.74418976, ...,  0.        ,
        -0.24332671, -0.22108685],
       [-0.73230209,  1.12339905,  0.74418976, ...,  0.        ,
        -0.16507514, -0.16941717],
       [ 1.36555667,  1.12339905,  0.74418976, ...,  0.        ,
        -0.24332671, -0.22108685]])

(517, 18)
```

Random Forest Classifier

In [6]:
```
rf = RandomForestClassifier(n_estimators = 10, criterion = 'entropy')
rf.fit(X_train, Y_train)
Y_pred = rf.predict(X_test)
print(confusion_matrix(Y_test, Y_pred))
model_accuracies['RF'] = accuracy_score(Y_test, Y_pred)
print(model_accuracies['RF'])
```

```
[[482   6]
 [ 28   1]]
0.9342359767891683
```

Logistic Regression

In [7]:
```
lr = LogisticRegression()
lr.fit(X_train, Y_train)
Y_pred = lr.predict(X_test)
print(confusion_matrix(Y_test, Y_pred))
model_accuracies['LR'] = accuracy_score(Y_test, Y_pred)
print(model_accuracies['LR'])
```

```
[[485   3]
 [ 28   1]]
0.9400386847195358
```

K Nearest Neighbours

In [8]:
```
knn = KNeighborsClassifier(n_neighbors = 5)
knn.fit(X_train, Y_train)
Y_pred = knn.predict(X_test)
print(confusion_matrix(Y_test, Y_pred))
model_accuracies['KNN'] = accuracy_score(Y_test, Y_pred)
print(model_accuracies['KNN'])
```

```
[[477  11]
 [ 29   0]]
0.9226305609284333
```

Logistic Regression, even though the most simplistic model out of the three, gives the maximum accuracy among these. One may choose any other classifier if his or her aim is different (for e.g. one may choose to have the least number of false negatives or false positives.)
Although all three models have high accuracy score >90%.

```
% A code for event detection using STA/LTA trigger
% Time Series data imported from the CSV file as a table
% time = table values for the time
% sensval = Output values of the geophone sensor (velocity in m/s)


t=table2array(time);
val=table2array(sensval);

figure
plot(t,val)
title("Time Series Data of the geophone");
xlabel("t (in s)");
ylabel("Velocity (in m/s)");

figure
plot(t(35801:38000,1),val(35801:38000,1));
title("Time Series Data of the geophone (zoomed)");
xlabel("t (in s)");
ylabel("Velocity (in m/s)");

sta=zeros(55000,1);
lta=zeros(55000,1);
ratio=zeros(55000,1);

for i=5001:60000
    for j=1:50
        sta(i-5000)=sta(i-5000)+val(i-j);
    end
    for j=1:5000
        lta(i-5000)=lta(i-5000)+val(i-j);
    end
    sta(i-5000)=sta(i-5000)/50;
    lta(i-5000)=lta(i-5000)/5000;
    ratio(i-5000) = sta(i-5000)/lta(i-5000);
end

new_t=t(5001:60000,1);

figure
plot(new_t,sta);
title("STA with time");
xlabel("t (in s)");
ylabel("Short Term Average");

figure
plot(new_t,lta);
title("LTA with time");
xlabel("t (in s)");
ylabel("Long Term Average");

figure
plot(new_t,ratio);
title("Ratio of STA to LTA with time");
xlabel("t (in s)");
ylabel("STA/LTA");

new_t2=t(35801:38000,1);
new_ratio=ratio(30801:33000,1);
```

```
figure
plot(new_t2,new_ratio);
title("Ratio of STA to LTA with time (zoomed)");
xlabel("t (in s)");
ylabel("STA/LTA");
```

```matlab
% A code for Spectral Domain Analysisi;
% Time Series data imported from the CSV file as a table
% time = table values for the time
% sensval = Output values of the geophone sensor (velocity in m/s)

t=table2array(time);
val=table2array(sensval);

freqsamp = 1000;

n=length(val);
xdft=fft(val);
xdft=xdft(1:n/2+1);
psdx=(1/(freqsamp*n))*abs(xdft).^2;
psdx(2:end-1)=2*psdx(2:end-1);
freq=0:freqsamp/length(val):freqsamp/2;

plot(freq,10*log10(psdx))
grid on
title('Power Spectral Density (Calculated Using FFT)')
xlabel('Frequency (Hz)')
ylabel('Power/Frequency (in dB/Hz)')

% Now windowing the time series data with a window length of 0.5 seconds

valwin=zeros(59500,500);

for i=501:60000
    for j=1:500
        valwin(i-500,j)=val(i-500+j);
    end
end

powrange = zeros(59500,1);

for i=1:59500
    powrange(i,1) = bandpower(valwin(i,:),freqsamp,[10,70]);
end

new_t=t(501:60000,1);

figure
plot(new_t,powrange);
title("Power with time (in 10 to 70 Hz frequency band)");
xlabel("t (in s)");
ylabel("Power (in units of input signal squared (m/s)^2)");
```