Exploring Power Signals for Location Forensics of Media Recordings

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Abstract— **Electric Network Frequency is the frequency of power distribution networks in power grids that fluctuates about a nominal value with respect to the changing loads. Its ubiquitous nature has made notable contributions to forensic analysis that has substantiated its use as a significant tool in this area. In this paper we have proposed a technique to identify the power grid in which the ENF-containing signal was recorded, without the assistance of concurrent power references. The recognition of the appropriate power grid is facilitated by certain statistical attributes extracted from the varying ENF signals that serve as an instrument of comparison. These features are distinctive to the grid-of-recording and are given as inputs to the training phase of a machine learning system. The learnt characteristics are then applied by this system to match the ENF signals to their respective power grids with utmost efficiency.**

Keywords— ENF,STFT,Quadratic Interpolation,SVM

I. INTRODUCTION

Electric network frequency is a newly developed emerging technology of today. This inherent feature of audio and video recordings is a foolproof method for forensic analysts to determine their authenticity and to retrieve the time and location of the original signal recording.

Since the introduction of the topic by Catalin Grigoras, Director National Centre for Media Forensics (NCMF) and assistant Professor at University of Colorado,Denver, it has been widely researched. Determination of the authenticity of recordings is facilitated by the unique time signatures each possess for a particular grid-of-recording when power signals are used as references[8]-[11]. The utility also extends to the detection of tampering in a multimedia signal by checking for discontinuities in the ENF signal extracted from the media file. The usual basis for inspection is by comparing the extracted ENF and the reference ENF from a concurrent power source. However in situations without any reference to these sources, the use of statistical properties of different power grids enable them to be reflected in the altering ENF signals. This establishes the actuality of different variations in ENF signals of the same nominal value.From Fig.1 it can be seen that different grids with same nominal value can exhibit distinguishable variations due to their unique statistical characteristics.

The estimation of the grid-of-origin of a media signal is executed by analyzing the immanent characteristics fed to a machine learning system.

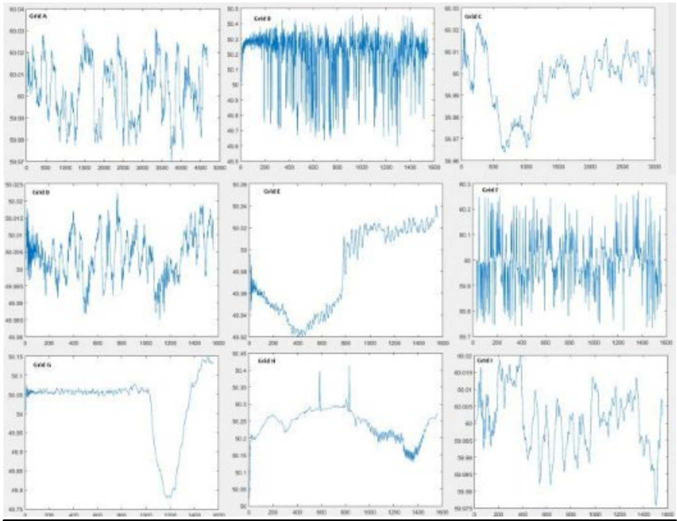

Fig. 1 ENF components extracted from power signals of different grids

But this assessment possesses limitations when it comes to sounds recorded from deserted areas due to its dependence on electricity. However, when an audio file is recorded under the influence of a network supply their presence can be noted as the “hum” that accompanies the distribution of electricity. The electromagnetic fields along with the mains current in the audio equipment influence the intrusion of electrical noise into the audio systems. This noise is associated with an alternating current with its fundamental frequency being 50 or 60Hz. Although the variations maybe random there can be found a regularity to its fluctuations about the nominal value, which is 60Hz in North America and 50Hz in most other places. Electricity production is contingent on the power demand. Difference in the supply and demand of power introduces variations in the AC frequency due to change in the speed of generator rotation; higher demand causes a decrease in generator speed and hence the frequency; and lower demand results in increased generator speed and frequency. This explains the pseudo-periodic behavior of which is responsible for the control mechanism of its regulation [12]. The network operators officiate between shedding of load or generation when presented with a change in frequency due to dissimilarity between average rate of demand and supply. The former used to compensate under frequency and latter for over frequency conditions [5].

These fluctuations introduced are random,non-predictable and most importantly constant across a transmission line grid.

The recorded ENF may also have harmonics which are used for analysis with some of them having higher power than the fundamental frequency.

Most of the power in a network is a result of the turbine-driven alternating current generators. The speed of rotation of the turbines plays a decisive role in determining the theoretical value of the ENF. The generating systems operate in synchronicity to deal with the changes regarding supply and demand of power. The synchronicity of the generators produce a uniformity of ENF across any geographic part of the grid and, over a period of time, the dynamic behavior of the supply and demand provides a unique ENF deviation pattern [6]. Ideally the constancy of the EMF value is possible when the sum of all loads and losses equals the total generation of the networks. It has been found that there are various instances favoring the recording of ENF with the audio signal. Poor power supply regulation, earth between recording instruments, inductive coupling of ENF currents due to electromagnetic fields are some among them. An interconnected system is the site of similar ENF variations and the extent of this dissimilitude shares an inverse relation to the implicit frequency deviation [12]. From this it is unequivocal that larger power grids have smaller frequency alterations. The method of ENF extraction we have used is a frequency domain approach. Although Fast Fourier Transform (FFT) leads to faster processing of the signal, the precision is compromised by the time bandwidth product. This is explained by the Fourier transform theory as the "uncertainty principle" which states that you cannot obtain arbitrarily high resolution in both the time and frequency domains simultaneously, making low frequency signals that vary with time very difficult to estimate (Czyzewski et al. 2007). The small signal energy of ENF makes it susceptible to noise interference which led to the usage of Short Term Fourier Transform. Short Term Fourier Transform (STFT) combined with quadratic interpolation method has been incorporated in an automated function-main to extract ENF from all types of recorded files. The filter design used for the extraction process is a Chebyshev-Type II for frequencies 50Hz, 60Hz and its first harmonics. The extraction and matching of the derived data are done using Mathworks MATLAB. The dominant frequencies chosen are plotted against time axis which shows the inherent ENF. The rest of the paper is organized as follows. Section II deals with the ENF extraction process and feature selection. Section III sees the training of the machine learning system with the derived features as input matrix with the labels to get a model of the system. Section IV has the testing phase of the model with the feature vector to get predicted labels. Section V gives the experimental setup followed by the results and conclusions in section VI.

II. ENF EXTRACTION

A. An Overview on ENF and Extraction Techniques

ENF gets captured in audio signals as a by-product of the recording process. ENF components might find their way into audio recordings due to poor power supply regulation, earth loops between recording equipments or inductive coupling of ENF currents with recorder circuitry due to electromagnetic field emanating from recorder power supply components, like transformers etc., or from other nearby mains run equipments. The authentication process begins with the extraction and analysis of ENF from audio and power recordings. The ENF extraction requires the implementation of down sampling followed by the analysis of power components. The latter part can be done in a number of ways such as the Short Time Fourier Transform (STFT) Method, Zero Crossing Method, Auto-Regressive Parametric Method etc., in accordance with the specific requirements. . As per the previous works of Catalin Grigoras ,the STFT or Fast Fourier Transform (FFT) methods can be used to evaluate long term fluctuations in ENF while the Zero Crossing and AR Methods are intended for evaluation of short term fluctuations of ENF components.

There are basically three main methods used in ENF extraction: „time/frequency domain analysis" based on spectrogram, „frequency domain analysis" based on calculation of maximum magnitude of power spectra from a series of consecutive time segments, "time domain analysis" based on zero crossing measurements of a band pass filtered signal. The method used here is STFT method which is a frequency domain analysis of ENF.

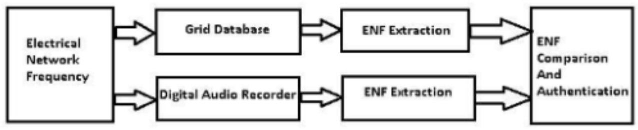

Fig. 2 Steps in ENF analysis

The recorded ENF might contain harmonics as well, which might have a power higher than the fundamental frequency. So harmonics are to be considered in analysis of ENF; even though harmonics above 3[rd] harmonic might not be useful due to their contamination by lower frequency audio signals. In order to get the dominant harmonic we have to analyze the spectrogram of the signal. Power signals contain only pure ENF components and its harmonics, whereas recorded audio signals contain ENF and its harmonics superimposed with audio information and noise. We can differentiate Power and Audio signals by observing the spectrograms of Fig,2(a),(b).

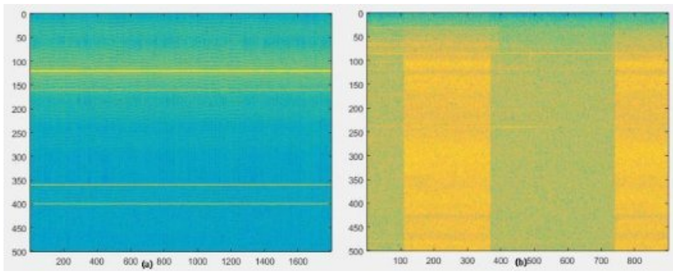

Fig. 3 (a)Spectrogram of a Power Signal; (b) Spectrogram of an Audio Signal

The problem of superimposed noise calls for the use of filters. In order to find the filter parameters, we take the spectrograms of the given signals, analyze them to find the frequency at which maximum average magnitude variations occur and to design the filters using fda tool in matlab.

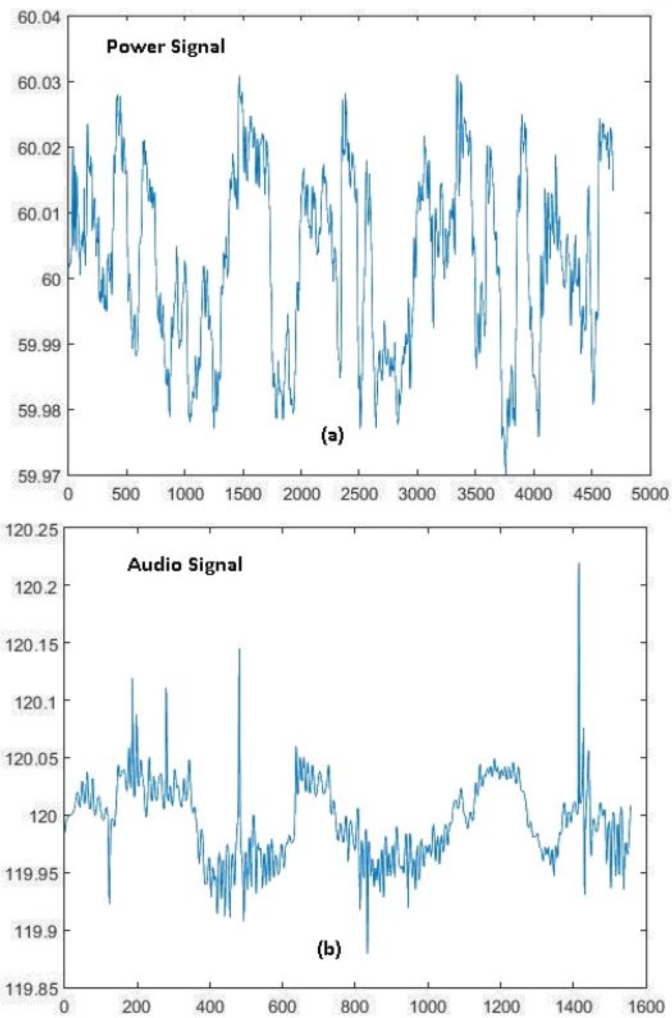

Fig. 4 ENF signals of (a) Power signal (b) Audio signal

Type II Chebyshev Filters of order in the range- 100 to 300 were found to be the most effective in noise filtering (fig.3). Power signals were then subjected to STFT and ENF was obtained. Though no filter is necessary for power signals due to the fact that it contains no unwanted signals a filter is recommended to remove the weaker harmonics.

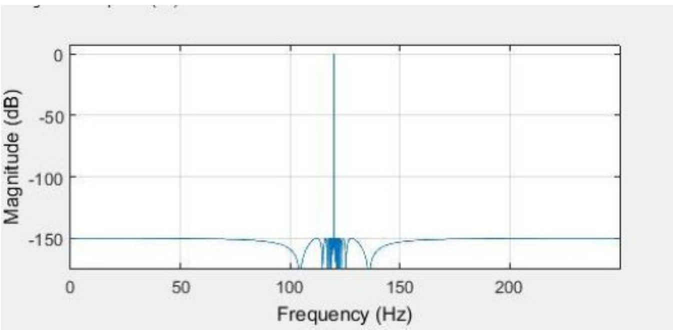

Fig. 5 Frequency response of Chebyshev filter

On filtering the audio samples with their corresponding filters, we could remove the unwanted signals and this process did not interfere with the ENF variations. Once the filtering was done, STFT of the filtered signal was taken, transforming the time domain signal to frequency domain and thus making the analysis simpler. The ENF components of electric grids are centered either at 50Hz or 60Hz and their first harmonics fall around 100Hz and 120Hz.In accordance with the Nyquist rate, the sampling frequency of the signal must be twice that of the maximum frequency content. But the power and audio signals available for the experiment were sampled at 1 kHz which contained more information than what was needed. Thus, to increase the processing speed we downsampled it to about 333Hz.

B. Short Time Fourier Transform

STFT is defined as the magnitude Fourier transform (FT) taken on a portion of a signal, by applying a sliding window, so as to cover the whole signal. In short, the signal is fragmented to a number of segments and Fourier Transform of each segment is taken. Each FT provides the spectral information of a separate overlapping time blocks of the signal, providing simultaneous time and frequency information.

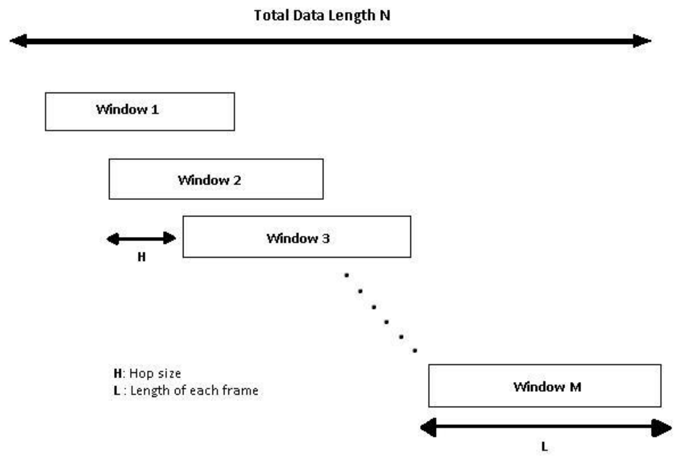

Fig. 6 Segmentation and overlap scheme used in STFT

The STFT is then obtained by splitting the input signal x consisting of n=0,1,2....N-1 data samples into M frames.

$$x_m(n) = x(n - mH)$$

The mth frame xm(n) with L as the hop size (samples advanced between each sampling frame) is multiplied with a weighing window. The window can be rectangular, elliptical, hanning, hamming etc. according to the requirement.Here we have made use of hamming window with window length of 1024. (Fig.4)

$$xw(n) = x_m(n) \cdot w(n)$$

xw(n) is extended by zero padding by a factor b to get xw`(n).Each frame is then converted to the frequency domain by using a length P FFT which produces STFT at frame m,

$$Xm(n) = \sum_{n=0}^{P-1} xw'(n) e^{-\frac{j2\pi k f s}{P}}$$

$$L = H \times D$$

where fs is the sampling frequency in Hz , k is the k^{th} frequency bin. The hop size H is set to match the ENF sampling time interval of the archiving database and the FFT transform size P is variable and dependent on a user defined sample interval multiplication factor D, to be described:

$$P = H \times f_s \times b \times D$$

The number of windows required is contingent to the length of the signal.

$$M = \frac{N - L + H}{H}$$

The STFT and FFT methods are essentially the same except for the difference in the way in which the outputs are represented: STFT produces a spectrogram while FFT gives the spectral magnitude. In practice, both of them are based on discrete Fourier transform and are computed using FFTs.

The problems encountered while working with these methods are:

(I) The precision of measurements made on the ENF signals.This is not only because of the practical limitations but also based on „Heisenberg"s Uncertainty Principle". The principle states that you cannot obtain high resolution in both time and frequency frame simultaneously.

$$\Delta t \cdot \Delta f = \frac{1}{4\pi}$$

Δt - Depicts the accuracy with which the spikes in time can be easily differentiated in the frequency domain. Δf - Depicts the accuracy with which two spectral components can be easily differentiated in the time domain. Due to this uncertainty we observe that Narrow Windows provide excellent time localization while Wide Windows provide excellent frequency localization.Hence, an appropriate window length has to be selected for optimum values of both frequency and time localization. (II) The recorded ENF signal energy is usually small,producing frequency estimates that are susceptible to error due to noise. Fourier transform uncertainty principle, including those based on parametric frequency estimators (Czyzewski et al. 2007), zero padding/interpolation schemes (Abe and Smith 2004) and signal derivatives (Desainte-Catherine and Marchand 2000) are proposed to eliminate this error.

Each STFT filter is analyzed to find the local maximum or peak in the magnitude spectrum corresponding to the ENF. The ENF peak value of any frame is unlikely to coincide with the exact frequency position of an FFT transform due to imprecise frequency estimates. One technique that can be deployed is that of zero padding where zeros are appended to the time domain data before taking FFT.An advantage of zero padding in time domain is that it increases FFT size, giving a narrower bandwidth and producing more densely sampled spectrum providing accurate interpolation in frequency domain and hence accurate ENF. However, to gain reasonable accuracy, the zero padding factor must be very large which requires high computational power.

C.Quadratic Interpolation Method

Once STFT of the given signal is obtained , in order to extract the enf ,from each time block of stft we will have to find the dominant frequency. Several methods are used to find this dominant frequency are (1) Maximum Magnitude (2) Weighted average (3) Quadratic Interpolation.

In maximum magnitude method we select the frequency sample with maximum magnitude as the apt representation of the whole block. But this representation was found to be inaccurate as it neither considered the characteristic property of the maximum frequency, neglecting the effect of magnitudes of neighbouring frequencies nor the fact that the maximum could occur at a point lost during sampling.

In a weighted frequency method, we consider the effect of magnitudes of neighbouring frequencies during the calculation of dominant frequency. Here the sum of product of each frequency and its magnitude is divided by sum of individual magnitudes. The equation need not be applied throughout the graph, but only across a small bandwidth of 2*delta f giving rise to the following equation:

$$fav = \frac{\sum_{n=f-\Delta f}^{f+\Delta f} fn.Mn}{\sum Mn}$$

fav: average weighted frequency

Δf :change in frequency

fn:frequency sample Mn:Magnitude of frequency sample

In order to overcome the computational limitations due to higher order zero padding factors , a quadratic interpolation of ENF sinusoidal spectral peak has been used in conjunction with a mild zero padding factor as described by Abe and Smith(2004). This method is computationally efficient as it uses relatively low FFT size and gives high resolution ENF estimate.

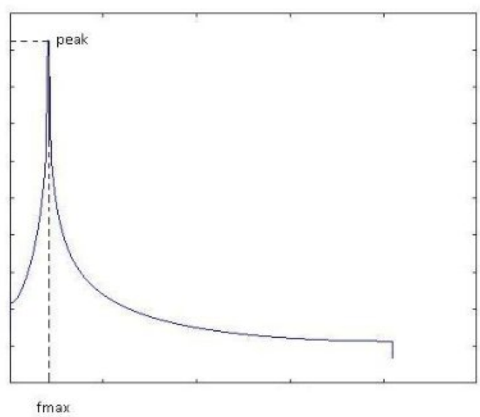

Fig. 7 Maximum magnitude method

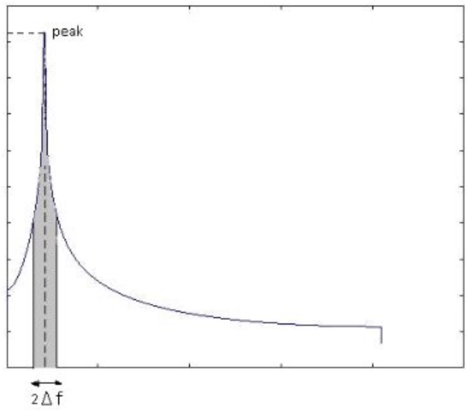

Fig. 8 Weighted average method

The QIFFT can be determined by following the steps given below:

a) Select the FFT f2 bin having maximum magnitude over the spectral bandwidth of interest.

b) Select the adjacent FFT bins f2−1(f1) and f2+1 (f3) on either side of the peak

c) Fit a second order (quadratic) model to the 3 data points using the following formula

$$A = \frac{(m3 - m2)}{(f3 - f1)(f3 - f2)} - \frac{(m1 - m2)}{(f3 - f1)(f1 - f2)}$$

$$B = (m1 - m2) + \frac{a(f2^2 - f1^2)}{(f1 - f2)}$$

$$C = m1 - A(f1^2 - Bf1)$$

Giving rise to a quadratic equation of the form:

$$Af^2 + Bf + C = D$$

d) The peak point of the QIFFT is the estimated peak point of the quadratic model which can be obtained by taking the first derivative of the equation $Af^2+Bf+C=D$ (Fig.7). Second Derivative of this equation need not be taken as we already know that the central point in the curve is approximately of maximum magnitude . So the second derivative will always be negative (ie. Maximum point).

$$2Af + B = 0$$

$$f = -\frac{B}{2A}$$

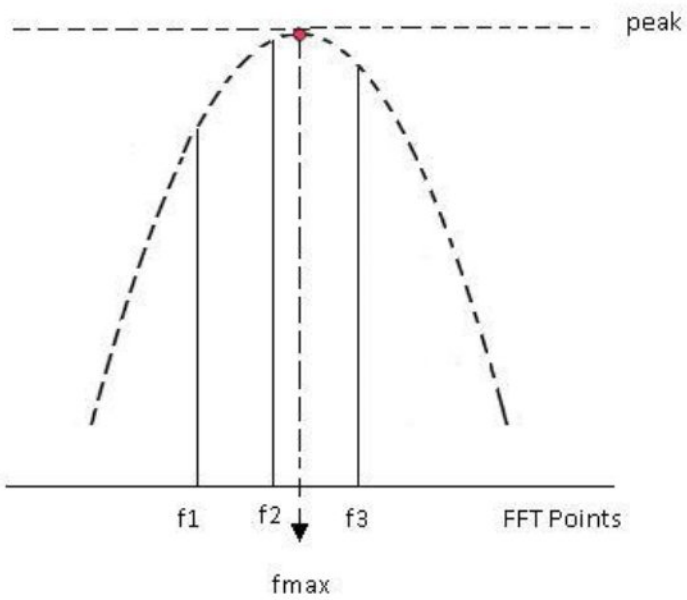

Fig. 9 Quadratic interpolation method

This process is repeated for each time frame ,and thus we obtain the dominant frequencies of respective frames.These frequencies are stored in a one dimension array and plotted against time index obtained during Short Time Fourier Transform.

Using this procedure , we extract the ENFs of Audio and Power signals of given 9 grids and cluster them into different matrices.Various parameters are extracted from this data and separately for each grid, that form the characteristics of the respective grids based on which future classifications of signals can be done. These parameters are then stored into the matrix sequentially and used in SVM training.

III. Feature Classification

The set of unique features that serve as the criteria of discrimination between the fluctuating ENFs are briefed below.

A. Skewness

Skewness is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it appears the same to the left and right of the center point. Skewness tells us about the direction of variation of the data set.(Fig.8)

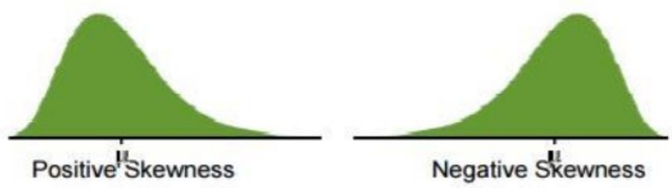

Fig. 10 Skewness

The skewness characterizes the degree of asymmetry of a distribution around its mean. While the mean, standard deviation, and average deviation are dimensional quantities for they have the same units as the measured quantities xj , the skewness is conventionally defined with the intention of making it non- dimensional. It is a pure number that characterizes only the shape of the distribution.

B. Kurtosis

This is a highly used quantity in the field of probability and statistics that reveals whether the data are peaked or flat, relative to the normal distribution. The kurtosis of a random variable X is denoted by kurt(X). It is defined by the formula given below:

$$kurt(X) = \frac{E[(X-\mu)^4]}{\sigma^4}$$

The kurtosis is also a non-dimensional quantity that measures the relative peakedness or flatness of a distribution relative to a normal distribution. A distribution with positive kurtosis is termed leptokurtic; the outline of the Matterhorn is an example. A distribution with negative kurtosis is termed platykurtic; the outline of a loaf of bread is an example. The distribution which does not fall under the previously stated categories comes under mesokurtic.

C. Anova1

ANOVA 1 measures two sources of variation in the data and compares their relative sizes based on these variations. The different areas of variation include:

- variation BETWEEN groups- for each data value the difference between its group mean and the overall mean is analyzed.

- variation WITHIN groups-for each data value the difference between the value under consideration and the mean of its group are scrutinized

D. Wavelet threshold coefficients

Wavelet techniques have become an attractive and efficient tool in function estimation. The discrete wavelet transform of a noisy data is an estimator of the wavelet coefficients. Several studies have demonstrated the effectiveness of the wavelet, decomposition as a tool for reducing large amounts of data down to compact, *wavelet synopses* that can be used to obtain fast, accurate approximate answers to user queries. Conventional wavelet synopses are based on minimizing the overall root-mean-squared (i.e., L_2-norm) error in the data approximation.

E. Percentile

Y = prctile(X,p) returns percentiles of the values in a data vector or matrix X for the percentages p in the interval [0,100].

F. Wavelet Noise Thresholding

The wavelet coefficients calculated by a wavelet transform represent the change in time series at a particular resolution. By looking at the time series in various resolutions it should be possible to filter out the noise.

1. Hard thresholding. Hard thresholding sets any coefficient less than or equal to the threshold to zero. Given below is the code for this thresholding.

```
if (coef[i] <= thresh)
coef[i] = 0.0;
```

2. Soft thresholding. Hard thresholding sets any coefficient less than or equal to the threshold to zero. The threshold is subtracted from any coefficient that is greater than the threshold. This moves the time series toward zero.The code for this threshold has been given below.

```
if (coef[i] <= thresh)
coef[i] = 0.0;
else
coef[i] = coef[i] - thresh;
```

While computing the above features for maximum efficieny,we have also coupled a few of these features to yield notable contributions. One such coupling is finding the percentile and mean of the wavelet threshold coefficients

- wthcoef('d',C,L,N) which returns coefficients obtained from [C,L] by setting all the coefficients of detail levels defined in N to zero.
- wthcoef('d',C,L,N,P) returns coefficients obtained from the wavelet decomposition structure [C,L] by rate compression defined in vectors N and P. N contains the detail levels to be compressed and P has the corresponding percentages of lower coefficients to be set to zero. N and P must be of the same length. Vector N must be such that 1 ≤ N(i) ≤length(L)-2.

IV. TRAINING PHASE

This phase is an integral part of the grid identification process. Training would facilitate a suitable model of our learning system that would be the input along with the characteristics of the grid in the testing phase. Training of a system involves the usage of machine learning where the integration of pattern recognition and computer learning is done with a statistical approach. This operation can be summarized as learning the structure from only a given data set. The main focus of training phase is to produce a model of the system by having the machine learn through artificial intelligence. The set of algorithms that defines machine learning is given by Support Vector Machines and the learning undertaken is a supervised one (Fig.9). Here we used this learning machine to learn the characteristic features of the power grid and to be able to classify different signals to the right power grid. . The ease of application of complex mathematical calculations to big data is reflected by the advancement in technological calculations. Mathematically the mapping of statistical attributes is done to the corresponding grid-of-recording (denoted by its label).

$X \rightarrow Y$, where $x \in X$ is the characteristic and $y \in Y$ is a class label.

We have been given with 9 power grids- A,B,C,D,E,F,G,H,I denoted by the class labels from 1 to 9 respectively. The algorithm follows a 9-class classification with $x \in$ set of selected features and $y \in \{0,1,2,3,4,5,6,7,8,9\}$.

The input sets are given under „X" and the output sets are given under „Y" and the training set comprises of the vectors { (x1, y1), (x2, y2)……… (xn,yn)}.

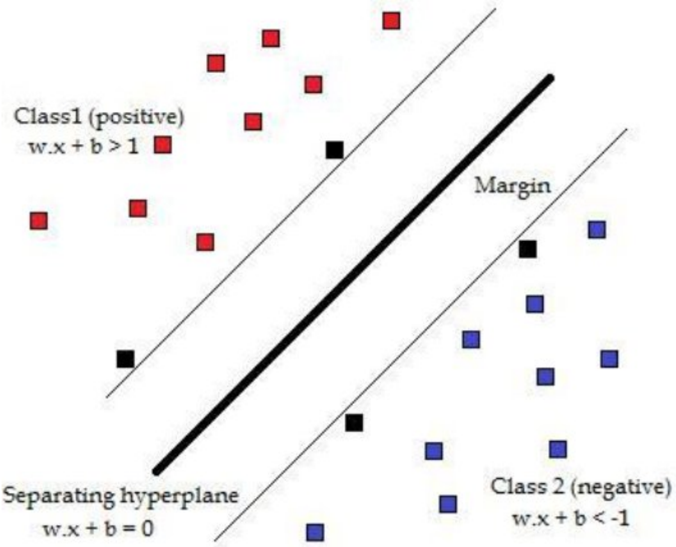

Fig. 11 Ideal vector support machine

The working follows along the lines that for a previously seen $x \in X$; $y \in Y$ are predicted with maximum accuracy. The output of the training algorithm gives a model of the system that contains a set of distinctive parameters that are unique to a power grid. The inputs comprise of testing instance matrix which is essentially the characteristics of the output matrix along with the training label vector to yield a model of the system (Fig.10). The learning progresses with the use of a classifier defined by y=f(x, a), where „a" denote the parameters of the function. The machine is organized to learn iteratively without being explicitly programmed for the target output and is led to find the unspecified values through an automated learning process. The importance of self learning is enhanced by the ability of the models to adapt independently producing reliable results from what they have learnt in previous computations.

The apt model is chosen from the set of hyperplanes in that validates the following equation :

$$f(x, \{w, b\}) = \text{sign}(w \cdot x + b).$$

Furthermore, generalization of the functions to be used for the training data set cannot be guaranteed as only training data is available and the learning is unsupervised.

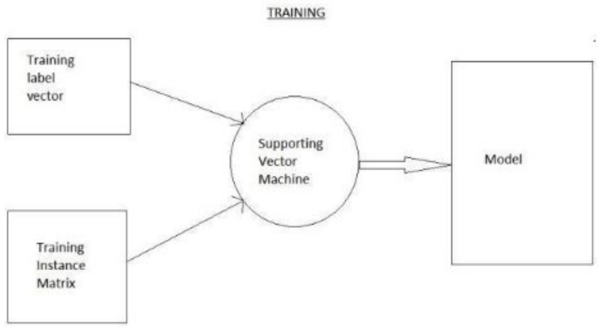

Fig. 12 Training phase

Application of Supporting Vector Machine (SVM) was advanced with the help of LibSVM (Version 3.21) which is an open source machine learning library, written in C++ and developed at the National Taiwan University. Sequential Minimal Optimization algorithm solves the quadratic programming problem that arises during the training of SVM. Classifying the unique features of the ENF was simplified with the LibSVM tool that implemented this algorithm for Kernalised SVM. The LibSVM tool was imported into Mathworks MATLAB by the execution of the code "**mex_setup**". Once compatible with the computing language, the machine was trained by using the code:

Model=svmtrain(label,input);

The above code trained the machine with the label and input that refer to the power grid and its features respectively to give an output that models the system. The model consists of the unique parameters which is structure containing information about the SVM classifier.

Input contains the matrix of training data, where each row corresponds to an observation or replicate, and each column corresponds to a feature or variable.

Label is a categorical matrix with each row representing a class label. Each element of the Label specifies the grid of the corresponding row of training. The number of elements in the row of training is specified by each element of this matrix.

Return Model Structure:

The 'svmtrain' function returns a model which can be used for future prediction. It is an organized structure with the following observed attributes- {Parameters, nr_class, totalSV, rho, Label, sv_indices, ProbA, ProbB, Nsv, sv_coef, SVs}

V. Testing Phase

The next phase after the training of the machine is to test its functionality by the prediction of the expected labels with the given set of input features. The inputs consist of a testing label matrix, testing instance matrix and a model that yields a predicted label for output (Fig.11). The mechanism employed is the working of the machine under independent conditions to predict the output after being trained with an instruction algorithm. The self learning technique strengthens its capability of projecting the plausible power grids. The model of the system along with the input statistical attributes is tested by the machine to predict the appropriate grid-of-recording. The Matlab executable code provided by LibSVM tools for predicting the label:

[Predict_label]=svmpredict(testing_label_matrix,testing_instance_matrix, model);

svmpredict is designed to find the label vector and return the values into the predicted label matrix.

Testing label vector is an m x1 vector of prediction labels that refer to the grid-of-recording where values are assigned for each grid synchronously from 1 to 9.

Testing instance matrix is an m x n matrix of m testing instances with n statistical features of the power grid.

Model is the output obtained from svmtrain that gives the behavioural pattern of the system.

The purpose of this function is to predict a class of the new input data according to a pre-trained model.

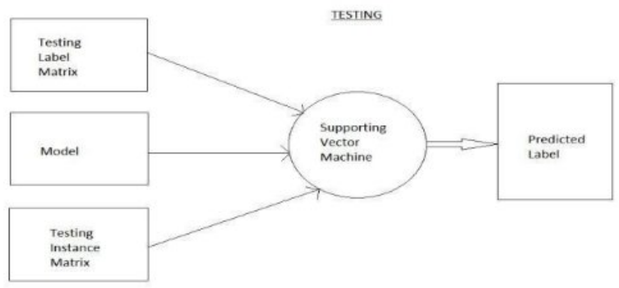

Fig. 13 Testing phase

VI. EXPERIMENTAL SETUP

The circuit used in recording ENF signals has two main components - a center tapped step down transformer and a voltage divider circuit. The output of the transformer is passed through a voltage divider circuit and recorded using Audacity software via a dual channel audio jack.

Principle and Working:

A. Step down Transformer

A step down transformer reduces the alternating voltage supplied by the power grid (230V, 50Hz in India) to an easily recordable value of 6V, 50Hz.This static device helps transform the electric power without affecting the frequency of the signal. The alternating currents in the power grid along with the alternating electromagnetic fields induce an alternating current in the primary coil of the transformer. As per the property of their high mutual induction, an electromotive force is induced into the secondary coil through their magnetically linked path of reluctance. This in turn produces a current in the secondary loop that facilitates a transfer of energy between the two loops. The conversion of energy obeys Faraday‟s Law of Electromagnetic Induction. The direction of the induced emf is validated by Lenz‟s law.

For the primary coil:

$$e= -N\partial\phi/\partial t$$

For the secondary coil:

$$e= -M\partial I/\partial t$$

where M= Mutual inductance of the coils $\partial I/\partial t$=rate of change of current $\partial\phi/\partial t$= rate of change in magnetic flux linkage e= induced electromotive force

The output of the step down transformer is an RMS value and its peak value is given by the product of square root of 2 with the RMS value that is approximately 8.5V (at the terminals 7 and 9 of the Fig.12).

B. Voltage Divider

The voltage divider circuit drops the value of this voltage over the four resistors as shown below.

The voltage dropped per resistor is:

$$6\sqrt{2}/4=2.12\ V$$

The voltage that reaches the laptop through a single channel of the audio jack is 2.12V which facilitates the recording of the audio signal. The ENF that has been extracted from the power signal recording can be seen to exhibit a high degree of correlation with the ENF extracted from the power main components at that specific time.

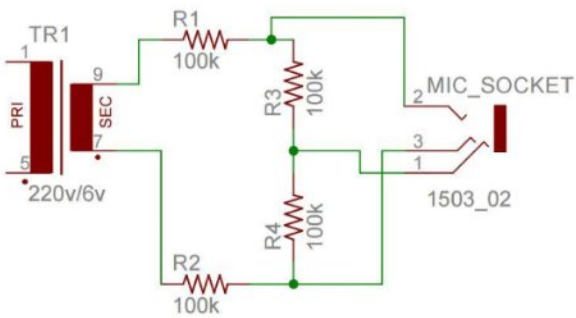

Fig. 14 Circuit diagram for ENF recording

The audio jack used has a dual channel interface that facilitates recording of the same voltage in both the channels. Audacity is the software used to record the audio signal without noise cancellation at a sampled rate of 1000. Using this software we were able to record audio worth 10 hours long. During the initial stages of recording, the audio recording in ".wav" format was read into the MATLAB program and its spectrogram was plotted following the sampling of the signal for a shorter time frame. The spectrum showed clear demarcations between the frequencies as only the fundamental frequency (50 Hz) and its harmonics stood out (shown in Fig.13). With the prior knowledge of the expected frequency of any power grid in India which has its nominal value around 50 Hz, we resolved that our power recording was accurate. With this confirmation we proceeded further with the recording of the audio signal using Audacity software.

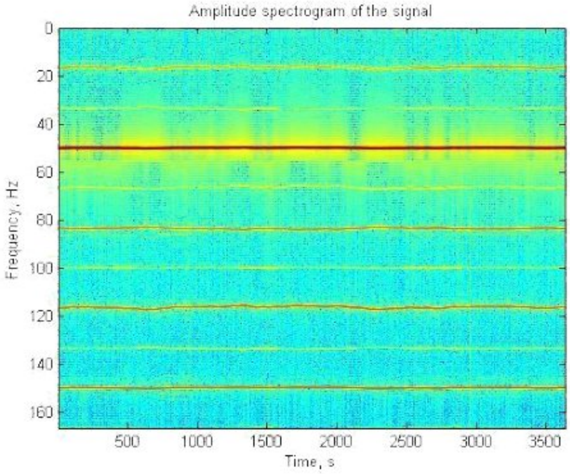

Fig. 15 Spectrogram of recorded ENF signal

VII RESULTS AND CONCLUSIONS

The objective of this paper was to familiarize with the tools for the analysis of ENF signals, to check whether the signal is authentic and to formulate a method to find the ENF from arbitrary audio signals by extracting its features; that have been compared with the stored parameters of the nine grids which helped in their classification to the respective power grids. We have devised a basic circuit to record the ENF from power signals. We also developed a GUI in MATLAB for ENF extraction and matching. This system plays an important role in forensics and could yield to more rewarding results with optimized usage. The self learning governance fueled by the training and testing of the machine is the main highlight in our paper. Major attention was given to the development of the machine learning system that did the classification for the testing phase after the training phase was computed. The results of the testing phase have been formulated below.

A. Practice Data Results:

Classification accuracy: 40%
The end results after matching the practice data set of 50 elements to their respective power grids :
CHCDB,BBCFD,CDBDC,CCBCE,BBBBB,BBDDB,DBBBG,EBBHI,BHECD,BBEBI

B. Test Data Results:

The end results after matching the test data set of 100 elements to their respective power grids:
FBDBB,DDBCD,BBGBE,BDCDH,BHHBB,BBBCI,DFDHF,CBCBE,GCIBG,EEBCE,BCCBB,HCGBC,BBBDE,CDCBC,DCCBB,BBBBB,BIBBG,BCBCH,BBDBC,EBDBB

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