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PROJECT REPORT

NOVEL ELECTRIC NETWORK FREQUENCY CLASSIFICATION ALGORITHM AND AN ELECTRICAL POWER SIGNAL MEASUREMENT CIRCUIT

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ABSTRACT

We present two contributions in this work: i) a novel electric network frequency (ENF) classification algorithm, and ii) a circuit for measuring power signals from the power grid. We first propose a novel ENF signal estimation algorithm. This algorithm explicitly makes use of the harmonic information present in the signal and estimates the nominal frequency based on the most reliable harmonic. The ENF signal is estimated from the most reliable harmonic by employing a Gaussian weighting window to mitigate the effects of noise. We then extract features from the ENF signal estimate and train a Neural Network (NN) classifier using the provided training dataset. In addition to the previously proven features for ENF signals, we also use Auto Regressive Moving Average (ARMA) model parameters as features in this work. The proposed classification algorithm performs at 95.06% accuracy on the provided power signal and an accuracy of 85.5% for the audio signal. We also obtained an accuracy of 94% for the practice dataset provided for validation . The circuit to acquire the power signal from the grid is designed on the open source Arduino board. The accuracy of the proposed circuit is demonstrated by a comparison with the grid data obtained from the national network frequency monitoring agency in India.

Index Terms— Electric network frequency (ENF), power grids, classification, multimedia forensics.

1. INTRODUCTION

Electric network frequency (ENF) refers to the frequency of power supply in electric power grids. These frequencies are restricted to either 50 or 60 Hz worldwide. In practice, the ENF signal is not constant and the time variation can be attributed to variations in the production and the load, and to the control mechanism as well. This variation can be viewed as a random process whose mean corresponds to the nominal frequency. The statistical properties of the ENF signal typically present a unique signature of a power grid [1]. Digital media (audio and video) recordings also have ENF signals embedded in them due to interference from the power grid. This signal can be estimated to identify the location of recording [2]. The applications of ENF signal estimation are primarily in multimedia forensics since it allows for the identification of the location of the recording, time of recording and any tampering of the recording like editing the original signal etc. The localization (or labeling) of ENF signals to a particular grid has been formulated in the traditional data classification framework by Hajj-Ahmad et al. [3].

The process of ENF signal classification can be divided into three stages – ENF signal estimation, feature extraction and classification. ENF signal estimation methods using fast algorithms like the Fast Fourier Transform (FFT) are more popular [4] compared to other parametric methods [5]. The challenge in ENF signal estimation is the noise in the spectrogram of the signal. This problem is typically addressed by recognizing that harmonics of the nominal frequency are also present in the power or audio signal and combining the high signal to noise (SNR) region in the harmonic and suitable signal interpolation [4]. However, interpolating the spectrogram in the presence of noise introduces artifacts in the ENF signal which in turn leads to poor features and lower classification accuracy.

In this work we present an algorithm to address the ENF signal classification problem in the presence of noise. Our main contributions are a fast and robust ENF signal estimation algorithm and the identification of new features (ARMA model parameters) for ENF signals. Additionally, we propose a NN based classifier for classifying the ENF signal into one of ten possible classes (including none-of-the-above). This classifier is trained using the features proposed by Hajj-Ahmed et al. [2] and the proposed ARMA model features using the given training dataset. We also present an easy-to-implement circuit for power signal recording. We use an Arduino board and use python based programming to establish a serial interface between the board and a PC. The samples from the Analog-to-Digital Converter (ADC) is acquired and

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stored in PC at a rate of 1000 samples per second.

The rest of this report is organized as follows. Section 2 discusses relevant literature on ENF signal estimation and classification. We present the proposed ENF signal estimation algorithm in Section 3. The feature extraction and signal classification methodology is presented in Sections 4 and Section 5 respectively. The hardware circuit for power signal acquisition from the power grid and its performance evaluation is presented in Section 6. Results are presented and discussed in Section 7 followed by concluding remarks in Section 8.

2. BACKGROUND

In the following section, we introduce the ENF signal variation problem and review relevant literature on ENF signal estimation and grid localization. In an idealistic scenario for a particular power grid, the supply power (W_s) and the demand power (W_d) will be equal. As a result network frequency will be constant. However, in reality the power demand will vary. This variation is due to difference in load consumption of the customer with respect to time. This variation is temporary and and non-deterministic. Since, the generator is a mechanical device, it takes time to adapt to the changing power demands. The rate of change of network frequency is a function of difference in supply power and demand power which is given by

$$\frac{d\omega}{dt} = \frac{1}{2H}(W_s - W_d),$$

where H is the accumulated kinetic energy [6]. Also it should be noted that this change in frequency is bounded by $40mHz$ per second. However, the feedback path tries to adjust the power supply in response to the change in demand. Therefore, the statistical characteristics of the ENF signal primarily depend on the power demand and the feedback system.

ENF signal can be estimated from the power signal either directly recorded from the grid or from the digital audio recording. Several techniques can be used for signal estimation. These can be broadly classified into parametric and non-parametric methods. Among non-parametric methods, the zero-crossing method is the simplest. In this method, a one second frame from the signal is used to find the number of zero crossings which are computed over consecutive frames with some overlap. Although this method is easy, it is very much error prone at low signal-to-noise ratio (SNR). Spectrogram based approach is another non-parametric method wherein we define the power signal as sum of impulses. Since this approach gives us significantly higher accuracy as compared to zero crossing method it is widely used. [7].

In spectrogram method, a time-frequency analysis using Short-Time-Fourier-Transform (STFT) is employed with optimum window length and overlap. FFT is used to compute the power spectrum of each frame. Here, argument of the maximum energy in each frame is considered as instantaneous ENF of that frame. However, most of the signals are embedded with white noise. This raises a concern about wrong selection of maximum energy point due to white noise altering of the spectrum. As a solution to this problem, weighted energy technique known as spectral combining is proposed by Ahmad et al [4].

To address the problem of ENF signal estimation in the presence of noise, parametric methods are also used. The Multiple Signal Component (MUSIC) algorithm employs eigenvalue analysis of the auto-correlation matrix of the given signal. We consider some n sinusoids embedded in white noise and the n highest eigenvalues in the matrix spanning the signal. By knowing these n sinusoids, the pseudo spectral approach is used to find the instantaneous ENF. Another alternative to the MUSIC algorithm is Estimation of Parameter using Rotational Invariant Techniques (ESPIRIT) which uses signal sub-space rather than noise sub-space as in MUSIC algorithm [8][5].

ENF is analogous to frequency modulation with the carrier frequency as the nominal frequency. Here, the frequency deviation contains the network frequency fluctuations. The power signal is written as

$$s(t) = \sqrt{2}v(t)cos(2\pi f_c t + \theta(t)),$$

where $\theta(t) = 2\pi \int_0^t f_m(\tau)d\tau$, $f_m(t)$ is the instantaneous frequency. By demodulating the FM signal, the instantaneous frequency can be obtained as amplitude fluctuations at the base band. The spectrum of the signal will give the ENF information of the signal. Since the signal is in the base band and the ENF fluctuations are very small, this technique can bring down the high sampling requirement to extract ENF at nominal frequency. Thus, it can work with any ENF extraction technique mentioned above [9].

Even though the parametric methods give similar accuracy as that of spectral methods; they have a bigger computation and memory requirement. Thus we prefer to use spectral methods for ENF estimation. A new method of tracking ENF from the spectrogram is proposed and its accuracy is tested with state of the art spectral methods.

3. PROPOSED ENF ESTIMATION ALGORITHM

Let $x(t)$ be the continuous signal which contains the power signal. It can be represented as

$$x(t) = p(t) + \eta(t), \tag{1}$$

where $p(t)$ is the pure power signal and $\eta(t)$ is the noise. The noise can be from the recording system or the audio signals at low frequency. The signature of the power grid of a country can be found in ENF [1] which can be estimated easily in the discrete domain. The discrete form of the signal can be written as $x[n]$ with the sampling frequency f_s recorded over a duration of T sec. The Discrete Fourier Transform (DFT) of the signal

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-i2\pi nk/N}, \tag{2}$$

provides an impulse corresponding to the power signal, since it is a sinusoid, where N represents number of time samples and k is the frequency bin index. This makes spectral method an attractive tool for ENF estimation. The real time nature of FFT algorithms for DFT computation is also an advantage of this method. But tracking the ENF exactly in the presence of noise is challenging task. We propose a new ENF estimation method which is motivated from the state of art technique Spectral Combining [4]. It also tracks frequency deviation which is motivated by inertia of the generators [6].
To obtain the time signature of ENF deviation, we divide the signal into frames of size N_f with an overlap of N_O. The spectrogram of the signal $S(f,t)$ is computed over all the frames, which is the one sided magnitude of power spectrum. Number of frequency bins are set to N_{fft}. Then the frequency can be determined by the knowledge of sampling frequency f_s and the frequency resolution is f_s/N_{fft}

3.1. Selecting nominal frequency

From spectrogram we can essentially get the frequency changes over time from 0 to $f_s/2$ Hz. Now the question is which part of the spectrum tells about the ENF signal? With the knowledge of widely used network frequencies, which is either 50 or 60 Hz provides as more frequency localization. It is worth mentioning that in-spite of controlling mechanism, some grids have mean shifted ENF signature. So we have to use nominal frequency as the mean ENF value, which can be in the vicinity of 50 or 60. In some case ENF signature can only be seen in the harmonics of the fundamental nominal frequency. Also in some Digital Audio Recording (DAR) the fundamental nominal frequency are found to be suppressed by the filters. So the exact nominal frequency is found by looking at all the possible harmonics of 50 and 60.
Let $h = 1, 2, \ldots, N_h$ be the harmonics index. Let us consider a width band where we expect to see ENF. Let

$$F_{50} = [f_{50} - f_B,\ f_{50} + f_B], \tag{3}$$

and

$$F_{60} = [f_{60} - f_B,\ f_{60} + f_B], \tag{4}$$

be the width of interest in the base band. Although this parameter is crucial in spectral combining method, it is not in this method. f_B is considered to be twice greater than maximum known ENF fluctuation in a side band. For example US grid has a maximum frequency deviation of $0.02Hz$ so the width band can be considered as $0.04Hz$. Let the harmonic bands be

$$F = \{h \times F_{50},\ h \times F_{60}\}, \tag{5}$$

for all values of h. Next mean of spectrogram $S_{mean}(F)$ is computed over time for each frequency in F and normalized with the mean spectrogram. The frequency corresponds to the maximum value in $S_{mean}(F)$ and gives the nominal frequency in the harmonic band h. Given by,

$$f_c = \arg\max_f \{S_{mean}(F)\}/h. \tag{6}$$

Where h corresponds to the harmonic band where f_c is estimated. Now the ENF is known to fluctuate around f_c rather than 50 or 60 Hz which is used as nominal frequency. This can affect the behavior in database signal of grid B.

3.2. Right harmonics selection

ENF can be best extracted in one of the harmonic band about f_c where SNR is high. We adopt a similar strategy as that of spectral combining method. A signal band

$$F_s(h) = h \times [f_c - f_s,\ f_c + f_s], \tag{7}$$

half that of the width band is used for SNR computation. Where f_s is maximum frequency deviation in the band about f_c and $h = 1, 2, \ldots, H$. The corresponding width band is

$$F_n(h) = h \times [f_c - f_B,\ f_c + f_B]. \tag{8}$$

The entire band is divided into duration of length N_{dur}. Let the inner mean be

$$\mu(F_{in}(h), d) = mean\{S(F_s, h)\}_d. \tag{9}$$

Where d is the duration index and h is the harmonic index. Similarly the outer mean is computed over the difference frequency set $F_n \setminus F_s$

$$\mu(F_{out}(h), d) = mean\{S(F_n \setminus F_s, h)\}_d \tag{10}$$

This mean computation is carried out for all harmonics and for all durations. The weight for a particular harmonic and duration is given by

$$w(h,d) = \begin{cases} 0 & : \mu(F_{out}(h), d) > \mu(F_{in}(h), d) \\ \frac{\mu(F_{in}(h),d)}{\mu(F_{out}(h),d)} & : otherwise \end{cases} \tag{11}$$

Then the best harmonic strip is

$$h_{ENF} = \arg\max_h \left\{ \sum_d w(h,d) \right\} \tag{12}$$

The resultant signal strip $F_s(h_{ENF})$ is the best strip to extract ENF.

3.3. Gaussian weighted ENF tracking

An electric power generator rotates with heavy coils. The inertia associated with it limits it from switching to a new frequency instantaneously. Depending on the power demand the control system tries to switch the generator to a new frequency. But due to inertia, the maximum possible frequency change in one second is $40mHz$ [6]. With this knowledge the variation from one ENF value to another can be easily found by limiting our search in the proximity of the previous ENF value. This motivates us to use a Gaussian weighted spectrogram for frequency search.

Let $T_f = N_f/f_s$ be the time duration of one frame and $T_O = N_O/f_s$ is the overlap time. Then we can obtain ENF for a time period of

$$T_{ENF} = T_f - T_O. \tag{13}$$

Then the maximum frequency deviation from one instant of ENF to another is $T_{ENF} * 40mHz$. We observe that the smaller frequency changes occurs often and larger deviations are less. So the frequency deviation Δf from one instant to the next is likely to be observed with high probability in the neighborhood of previous ENF value $f_{ENF}(i-1)$. We weight the spectrogram in the selected strip with a Gaussian window having center at frequency $f_{ENF}(i-1)$. Let $f_{ENF}(i-1)$ correspond to the current frame and Gaussian window with center at the frequency $f_{ENF}(i-1)$ is used to weight i^{th} frame of spectrogram. Now $f_{max}(i)$ is obtained by finding frequency at which the weighted spectrum becomes maximum.

A quadratic interpolation is used to obtain the exact ENF frequency from the approximate frequency $f_{max}(i)$. Let $\delta f = f_s/N_{fft}$ be the frequency resolution then quadratic interpolation for three values α, β and γ is given by

$$\xi = \frac{1}{2}\frac{\alpha - \gamma}{\alpha - 2\beta + \gamma}. \tag{14}$$

Where $\beta = S(f_{max}(i+1))$, $\alpha = S(f_{max}(i+1) - \delta f)$ and $\gamma = S(f_{max}(i+1) + \delta f)$. Now the accurate estimate of ENF is located at $f_{max}(i) + \xi$. Once the ENF is obtained in a specific harmonic band h_{ENF}, the same can be obtained in the nominal frequency by dividing it with the harmonic index.

The advantage of this method is that it can greatly reduce the outliers. Also it removes the requirement of interpolating harmonic strips as in spectral combining. This can reduce noise getting added to ENF signal during interpolation. In addition to that, the approach is much faster than many of the spectral and parametric method since it requires only one time computation of spectrogram using FFT algorithm an tracking algorithm ENF estimation.

4. FEATURE EXTRACTION

ENF signal contains the signature of individual grid it comes from. Since ENF is not a deterministic signal and it highly depends on the power consumption of the country and the control mechanism used, it can be viewed as a random process. To classify the ENF based on the grid, it is important to capture the statistical parameter accurately in some features. The obvious approach to get features is to view ENF random variable. Hence, the moments play a key role in their characterization. Apart from the random nature a pseudo periodicity can be observed in some grid due to the feedback mechanism used. So computing moments in the multiresolution levels will also provide more information about the underlaying process. In addition to that in case of noisy ENF, as in the audio data, it is also possible to localize most of the noise in the higher decomposition levels. It is also studied that system identification approach such as Auto Regressive (AR) and Auto Regressive Moving Average (ARMA) models are effective in modeling ENF signal. With this understanding we broadly classify features into statistical and parametric features.

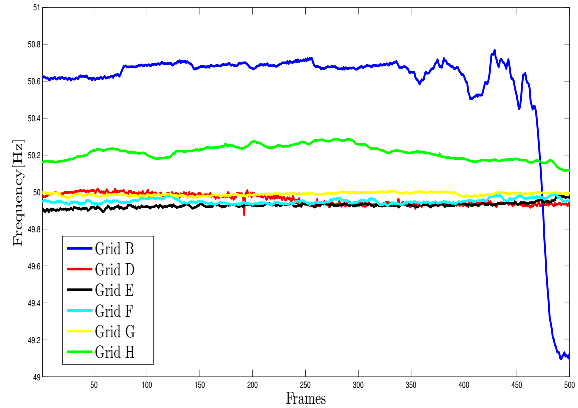


Fig. 1. ENF for 50 Hz Grids

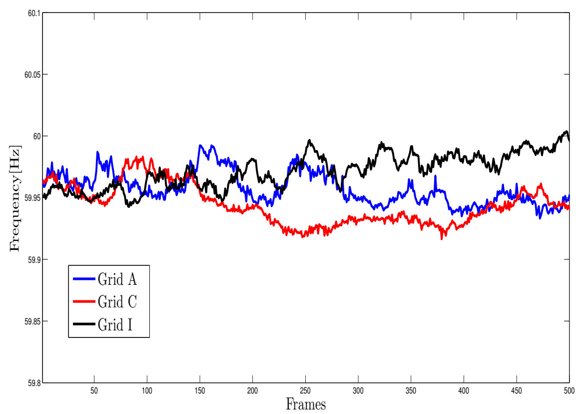


Fig. 2. ENF for 60 Hz Grids

4.1. Statistical features

This includes analyzing the signal in its original domain and in the wavelet domain. These features are found to be capturing the signature of ENF signal [3].

4.1.1. ENF domain

First set of features comes directly from the random nature of ENF in the original domain. Mean and variance are such significant features of an ENF signal. It can be noted that the mean of Grid H in figure 1 is always greater than 50. Nominal frequency shift is from 50/60 Hz is a common behavior in ENF signal for most of the grids. Variance as a parameter is also a significant feature because it is observed that Grid B is having high variations in ENF. Variance is the main parameter which characterizes the nature of network frequency deviation and can also tell how long it was away from the nominal frequency. In addition to that some of the grids show small dynamic range while others vary over a larger band of frequency, so the range of ENF frequencies will also add additional information.

4.2. Wavelet domain

In 60 Hz grids, ie A,C,I in figure 2, it can be noted that there exists a pseudo periodicity in the ENF. It is longer in C than in A and I, with I having a short pseudo periodicity. This can be viewed as how fast the feedback system can bring back the change in the network frequency. This kind of behavior can be well understood in wavelet domain where the different nature of periodicity will be captured in different wavelet levels. So the same statistical parameters can be used in multiple wavelet levels.

4.3. Parametric features

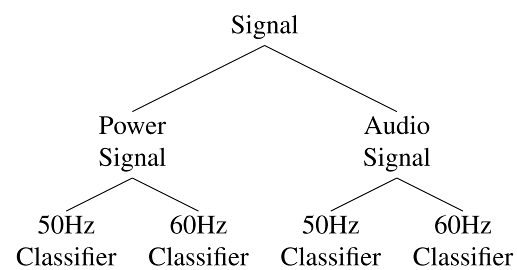
Auto Regressive models (AR) and Auto Regressive Moving Average (ARMA) are widely used for signal analysis and system identification, additionally AR models are also used for location identification [3]. We use an ARMA model known as Prony's method. We observe from our classification that Prony's method can model more accurately than simple AR models. The generator and the feedback control system can be viewed as a system and the key to identify the system is to study the error signal between the expected network frequency and the actual network frequency. This error signal represents ENF variations and Prony's method is used to identify the system based on this signal. Prony's method has been used for similar feature extraction in other area as well [10]. We are also using Steiglitz-McBride method which can also clearly distinguish few grids in the database provided. All the features used for classification are given in table 1

Table 1. Features used for classification

Type	Number	Features
Non parametric		
Original domain	1	Mean
	2	log(variance)
	3	log(range)
Multiresolution (L = 4)	4-7	log(variance) dwt details
	8	log(variance) dwt approximation
	9	Mean
Parametric		
ARMA (Prony's method)	10-13	Numerator
	14-17	Denominator
ARMA (Steiglitz-McBride)	18-21	Numerator
	22-25	Denominator

5. SIGNAL SPECIFIC CLASSIFICATION METHOD

A signal specific classification approach is used to classify the grids.This classification is done in three stages, as shown:



5.1. Distinguishing between Power and Audio

The first layer of classification involves categorising the signals into power and audio. Audio signals are found to have low SNR while, power signals have high SNR, this is the basis for the first layer's classification. The SNR is computed by finding the ratio of the energy in all harmonic strips to the total energy in the spectrogram. Signals whose SNR is above the threshold of 0.9 are classified as power signals while the others are classified as audio signals. The threshold is empirically determined.

5.2. Classification based on Nominal Frequency

The training dataset provided consists of 3 grids with $60Hz$ as the nominal frequency and 6 grids with a nominal frequency of $50Hz$. The computational efficiency and accuracy of the classifier is improved if the signals are segregated based on the nominal frequency, prior to the final classification.

Classifier	HLayer(1,2,3)	Training Function
Power 50	12,35,20	One Step Secant
Power 60	12,12,20	Scaled Conjugate Gradient
Audio 50	12,14,12	Levenberg-Marquardt
Audio 60	12,40,12	Resilient Backpropagation

Table 2. Number of Neurons for each hidden layer(HLayer) and Training Function for each classifier

5.3. Grid Prediction

The segregated signals are then classified into their probable grids by means of indidvidual classifiers for each category formed in the second layer.

There are a wide choose of classification algorithms out of which Support Vector Machine (SVM) is widely used. In location identification from ENF signal also utilize SVM to classify [3] with a Radial Basis Function (RBF) kernel. We observed that for small set of data linear kernel and radial kernel provide similar result.Since the current classification does not require huge amount of data to be classified we selected linear kernel for our basic studies.The accuracy of this classifier forms, the reference point for further studies, since the results are comparable with the state of art approach [3]. To overcome the low accuracy of the SVM classifier when used for audio signals we switched our classifier to Neural Networks.

We used a Neural Network with 3 hidden layers as it is recommended that for signal processing problems , more than 2 hidden layers should be used.Neural Networks can achieve optimal level of accuracy with right number of neurons and hidden layers.The parameters of the neural network are mentioned in Table 2. The Neural Network is designed with N features (1), (2), . . . , (N) and by providing labels $l(1), l(2), ..., l(M)$with N features and M grids.The input layer is fed with N features $\nu(1), \nu(2), ..., \nu(N)$ of a signal which output one of the M labels $l(1), l(2), ..., l(M)$.In our implementation we make use of MATLAB Neural Network Toolbox.We used a split percentage of 70:30 to train and validate the network. The None of the above case is addressed by observing the confidence number. After obtaining the confidence number a threshold is set to make the final decision . Results with the trained network over the practice and the test signal are provided in Section 7.

6. POWER SIGNAL: INDIAN GRID

Power from Indian grid is recorded from Indian Institute of Technology Hyderabad campus. The grid belongs to the southern part of India and is managed by Power Grid Corporation India (PGCIL) [11]. The recording is carried out by a simple Arduino UNO based circuit. The aim of the interfacing circuit is to step down the power line voltage and interface ADC to the PC. The circuit consists of a transformer which steps down the voltage. The transformer is having a $0-240V$ primary winding and $9V-0-9V$ secondary winding. We used center taping connection and one of the outer connection to get the $9V$ fluctuations about $0V$. Since Arduino input voltage range is in $5V$, we use a voltage dividing circuit which is designed such that $V_{rms} \times R_2/(R_1 + R_2)$ is $2V$. So the output of voltage divider will be $+2V\ -0\ -2V$ sinusoid. Now since Arduino can not handle negative voltage range, a mean shift is introduced by using a bias circuit of equal resistances R. One end of the bias circuit is connected to $V_{cc} = 5V$ and another to $GND = 0V$, of the Arduino board. The bias voltage is obtained at the dividing point of the resistance. By connecting this point to the center tap point of the transformer the resultant fluctuation will be $2.5V + 2V$ and $2.5V - 2V$ sinusoids. The voltage dividing point is connected to the analog input pin $A0$ and acquired through the ADC of the Arduino board with a sampling rate of $1000Hz$. Samples are then passed through a serial interface to PC. The serial data is received in ASCII format, then mean is subtracted to remove the effect of added bias voltage. To get the actual voltage levels, each ASCII value at each instant is divided with Arduino's quantization resolution which is $5/(2^{N_{bits}} - 1)$, where $N_{bits} = 10$ for the ADC. The schematic and the picture of the circuit is shown in figure 6. The transformer, bias circuit and Arduino board is also labeled in the circuit.

The recordings are carried out uniformly, over a duration of one week. A total of $10hr$ of recordings are made, which include both peak hours and off peak time. Details about the time of recording with proper labeling is provided in the READ ME file in the submission.

We also checked the accuracy of the recording with the data collected from Wide Area Synchronized Frequency Measurement System (WAFMS) [12]. WAFMS is an Indian government initiative to observe the network frequency fluctuation with sensors throughout the country. It is found that the ENF for the same duration of recording is exactly matching with the WAFMS signal as shown in figure 5. We also used the recorded signal to find out which database grid it belongs to and found that Indian grid belongs to Grid B in the provided database.

7. RESULTS AND DISCUSSION

In this section we present the results of the proposed ENF signal classification algorithm. This includes the performance of the proposed ENF signal estimation algorithm and the classification accuracy using the augmented set of features. In all our training and testing, samples of 10 sec duration were considered. To compute the spectrogram, a signal length of 5 sec with an overlap of 3 sec was considered. In order to obtain a frequency resolution of $30mHz$ so that any change

Sample Name	Sample number (1-50)
Practice	AHCFD,BGCND,AFBDC,INNAE,HBBAD,CGNFB,DFCHG,EIIHI,IHECF,FNGEI
Accuracy (%)	94

Table 3. Estimated grids for test signal.

Sample Name	Sample number (1-50)
Test	NDDAD,GNDAF,CNGBN,BFCEH,EHHHE,HEEAI,DNFHI,IECBD,ENIBE,FGNAG,
Sample Name	Sample number (51-100)
Test	IINIG,NAEEN,CAFDG,CENGI,EICEN,BEBHA,NIACG,AABIH,AADBA,GBFBB.

Table 4. Estimated grids for test signal.

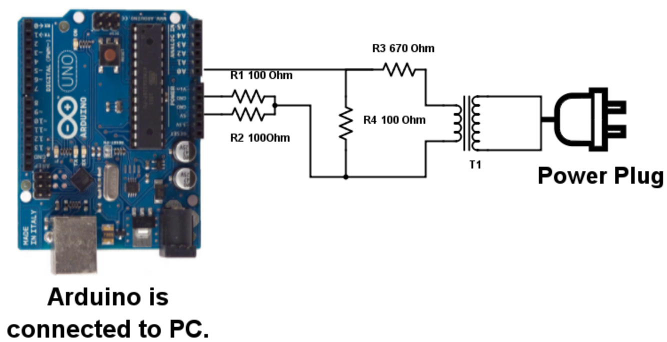


Fig. 3. Schematic of acquisition circuit

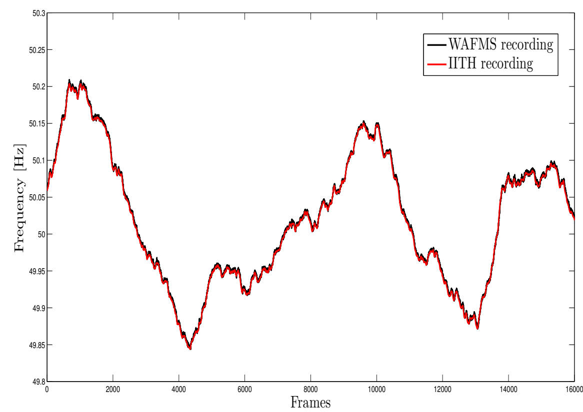


Fig. 5. ENF from WAFM and IITH recording

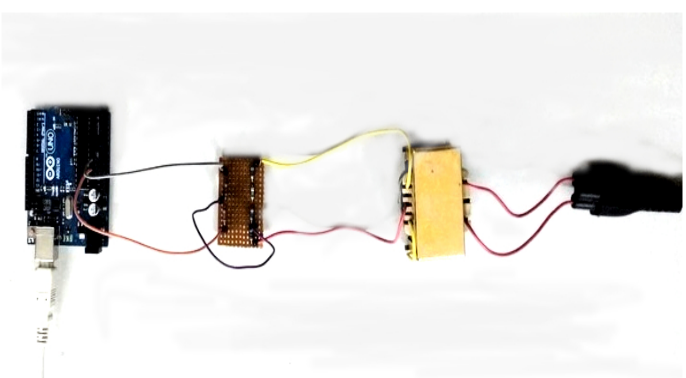


Fig. 4. Hardware for power signal acquisition

within the maximum generator frequency shift ($40mHz$) can be easily captured, we used 2^{15} FFT bins. We fixed the width band to be $1Hz$ with a signal width of $0.5Hz$. But this condition is violated in Grid B. In this case an initial ENF is extracted with the above width band and width signal. Then if the maximum deviation is greater than width signal then ENF is computed again for Grid B alone using width band as $3Hz$ and width signal as $1.5Hz$. We compare our ENF extraction method with Spectral Combining Method [4] by comparing with the MATLAB program provided by the authors. From figure 6 it is clear that outliers introduced by the out of band noise is more in the spectral combining method. With the new approach of tracking with Gaussian weighting more emphasis is given to variations with in the expected region. In this way ENF is made more accurate in our approach . Time taken to extract ENF using both the approach are given in the table. Computation is done on a laptop with Intel i5 x64-based processor, with a clock rate of $2.2GHz$ and memory of $8GB$.

As mentioned in the Section 4, we rely on previously proposed statistical features. In addition, two new sets of features obtained from ARMA models using the Prony's method

Table 5. Time taken for ENF extraction

Method	Time taken (Sec) for a 1 hour signal
Spectral Combining	59.88
Our approach	14.50

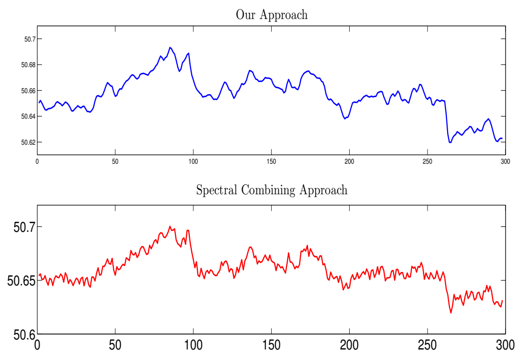


Fig. 6. ENF extracted using Our approach and spectral combining

and Steiglitz-McBride method are also used. Figures 7 and 8 show that grids can be clearly separated with the new set of features obtained from Prony's method and Steiglitz-McBride method. We use an ARMA model of order 4 in both these methods providing a total of 16 additional features. We use these features for our classification. Also, we found the best set of features for different classifiers in Section 5.

We selected Neural Network over SVM for classification mainly due to its classification accuracy. Classification accuracy in % for right classification is given in the table 6. This table clearly shows that Neural Network based classification is apt for location identification based on ENF criteria. Further detail classification accuracy of each grid in (%) is provided as a confusion matrix table 7 and 8. In all these classification experiments, an 80% to 20% training to test ratio is used from the training database provided for SP Cup 2016. It

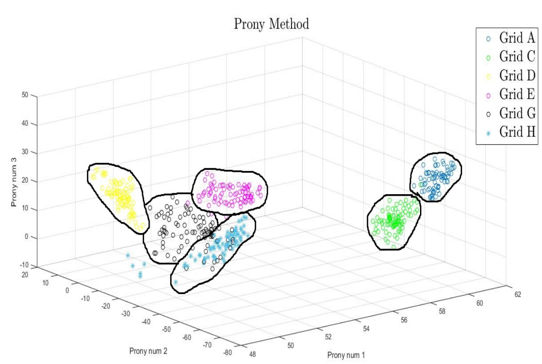


Fig. 7. Prony's method features for different grid

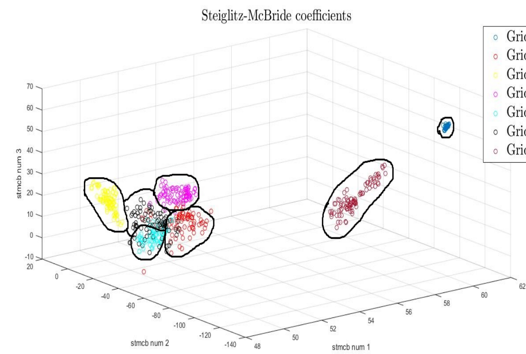


Fig. 8. Steiglitz-McBride method features for different grid

Table 6. Comparison between Neural Network and SVM classification (in % accuracy)

Classifier	$50Hz$ power	$60Hz$ power
SVM	84	90
Neural Network	94	95.9

is found that most of the power signals are 100% accurately classified except for a 90.9% accuracy for grid H.

We now go over and include audio signals into the classification scenario. To test classification audio signal, power signals and 50% of audio signals are used for training and the remaining 50% for testing. The (%) accuracy for both $50Hz$ and $60Hz$ grids are given in table 7.

Once the testing has been done with fraction of training and testing combination we tested performance of our classification method with the practice set. The results obtained for the practice set is given in table 7. The final testing is done on the unknown test signal and the results are provided in 7. The threshold for none of the above case is estimated to be 0.65 for power signal and 0.5 for audio signal.

We also recorded power signals from Indian grid and tested against the trained model. In all 10 min samples the signal is

Table 7. Confusion matrix (in %) for 50Hz power signal trained with 80% and tested with 20% of training database

B	100	0	0	0	0	0
D	0	100	0	0	0	0
E	0	0	100	0	0	0
F	0	0	0	100	0	0
G	0	0	0	0	100	0
H	0	0	0	0	9.1	90.9

Table 8. Confusion matrix (in %) for 60Hz power signal trained with 80% and tested with 20% of training database

A	100	0	0
C	0	100	0
I	0	10	90

Table 9. Accuracy of classification (Over 10 iteration)

Training Samples	Testing Samples	Accuracy (%)
Training dataset 50 Hz Power (80%)	Training dataset 50 Hz Power (20%)	93.6
Training dataset 50 Hz Power+ Audio (50%)	Training dataset 50 Hz Audio (50%)	84.9
Training dataset 60 Hz Power (80%)	Training dataset 60 Hz Power (20%)	98
Training dataset 60 Hz Power + Audio (50%)	Training dataset 60 Hz Audio (50%)	86.7

classified into Grid H with confidence level more than 90%. So we conclude that samples contained in Grid H is from Indian grid. Detailed explanation of using the MATLAB based GUI and the recorded signal from Indian grid is provided in the readme file.

8. CONCLUSIONS AND FUTURE WORK

We presented an algorithm for classifying the ENF signal into one of ten labels (including none-of-the-above). The proposed algorithm presented a fast novel technique for accurately extracting the ENF signal from power or audio signals. We also proposed new statistical features that include the ARMA model parameters of the ENF signal. A neural network classifier is trained using these features and the training dataset provided as part of the SPCUP data. The combination of the ENF extraction method and the new features (in addition to previously established features) resulted in a classifier that performs well over the provided practise and test databases. Specifically, our classifier performs at 94% accuracy on practice datasets.

We presented a simple but accurate circuit based on the open source Arduino framework that measures power signals from the electric grid. The accuracy of the proposed circuit was demonstrated by comparing it with the national network frequency monitoring agency in India.

As future work we plan to further improve the ENF signal features and the classifier – especially for audio signals. We also plan to make more power signal measurements in India and characterize the grid characteristics more comprehensively.

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