Electric Network Frequency (ENF) Recognition

Abdelrahman Gaber*, Abdelrahman Zayed*, Basem Ahmed*, Eslam Elshiekh*, Hesham Aly*
Ibrahim Sherif*, Khaled Elgammal*, Omar Ahmadein*, Omar Elzaafarany* and Taha Gamal*
*Faculty of Engineering, Alexandria University, Egypt
Pursuit Of Processing Team
Leader's email: Abdelrahman.M.Zayed@ieee.org

***Abstract*—Power grids are available all over the world for their necessity in all our everyday activities. Each power grid has its own electrical network frequency pattern which is considered as a signature or a finger print of this power grid. Any audio/video recorded in a power grid, whether directly connected to the power mains or not, is affected by the ENF signature of this grid. Post processing could take place to extract the ENF pattern from recordings which can be used in localization of different media signals recorded among grids. This can be done through computing the cross correlation between extracted ENF and the original ENFs of the grids. Finding the time of recording becomes possible. There are much more applications for ENF extraction and recognition.**

In this project we have worked on data set of 9 (A to I) different grids provided by the contest. ENFs of these power grids are extracted for power and audio recordings then characteristic features of these ENFs are extracted and accurately selected. These features are used to feed two machine learning models: SVM and neural network. These machine learning models are used in correlating the practice data set, provided by the contest, and the grids from A to I. We also implemented a simple hardware circuit to record about 24 hours from our grid mains. Here we present our work methodology and propose our developed code for ENF extraction and recognition.

I. Introduction

ENF is considered as a fingerprint for each grid since each Power grid has its own generators and characteristic loads. Grid ENF pattern appear in any Audio/Video recording which can be used in localization of media signal among grids. In addition, time of recording of these media signals could be found through cross-correlation study.

We can make benefit of studying the cross correlation between the ENF extracted from a recorded audio/video and the corresponding power grids [1]. This has been used in literature in multiple applications including: Finding time-of-recording of media signal, Audio-visual binding, tampering detection, Localization of media signals within a power grid, Localization of media signal among grids, Historical alignment, and multimedia synchronization.

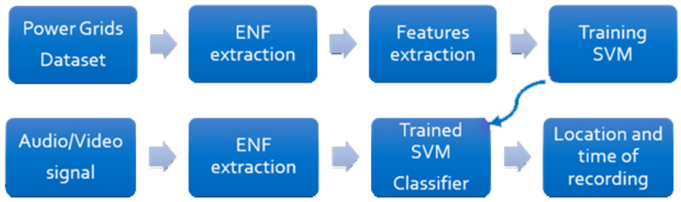

Fig. 1. Project Block Diagram

The remaining of the report is organized as follows. In Section II, we explain our method of extracting ENF signals, highlighting our resulting ENF signal and how we tackled the problem of rapid variations in ENF extracted from high noise audio. In Section III, we present our system's results on practice and testing data explaining our location classification system besides feature extraction and selection techniques. In Section IV, we present our recording circuit with analysis on our recorded data at different places, times of day, using direct power, and with audio recording. In Section V, we demonstrated an experiment on our recorded data to get the Time-of-recording of audio recordings. Section VI concludes the report with our possible future work.

II. Extraction of ENF signals

A. ENF Extraction Scheme

We apply ENF signal extraction on signal examples of 10 minutes, thus first step is to split the 1 hour recording from our data set into examples each consisting of 10 minutes. This is done for two reasons; first is to increase number of examples applied to our machine-learning model and to reduce the features dimensionality problem, second is to unify the length of our examples to be 10 minutes to save our examples in a matrix.

To extract ENF from 10-minutes examples first we need our algorithm to identify the nominal frequency is

Fig. 2. ENF extraction process

50 or 60 Hz. For that, our second step is to apply FFT on the example and filter around the possible 50 and then possible 60 Hz harmonics with ideal band pass filters of 1 Hz bandwidth. We then calculate energy for 50 Hz filtered signal and 60 Hz filtered signal and compare resultant energies, as the maximum is associated with the actual nominal. We did not include the 300Hz band into comparison, as it is common between 50 and 60 nominal. Actual nominal and the original example before FFT are inputs to third step.

Third step is that we split every example in time domain into non-overlapping windows of 5 seconds each. Each 5-seconds time window is applied on step four which extract the dominant frequency around the nominal frequency and its harmonics by combining weighted filtered spectra around each nominal.

Step four is to take FFT of the 5 seconds window and split the resultant spectrum into seven spectra each is filtered around a harmonic of the nominal value; i.e. filters have center frequencies of n multiplied by nominal frequency, for n is number of nominal of interest. Band pass of filters is 1.2 Hz multiplied by n to have wider window around higher harmonic bands. This is done because ENF information is spread with n factor at higher harmonics so window has to not cutoff ENF. We down sample every resultant filtered spectrum by n so that spectrum is moved into the nominal frequency band. Now we have got seven spectra filtered with 1.2 Hz around the nominal frequency; these spectra are input to step five.

Grids fingerprint appears do not exist only in the variation of the ENF around the nominal frequency (50-60 HZ), But also in its variation around the harmonics. Therefore, we can make use of the information exists at the harmonics in addition to that at the nominal. Therefore, we apply spectrum combining in steps five and six of our ENF extraction scheme.

Step five is to utilize a spectrum combining method to extract the significant ENF information inspired from ”Adi hajj ahmed” work [2]. We filter around each down sampled harmonic with two windows; first is the signal window. Its band corresponds to the maximum band that ENF signal can occur in; we chose the band to be 0.8 Hz because some grids have large variations as in grid B in our case. We calculate the power in this band, which approximates signal power. Second band is around with 1.2 Hz, which includes noise that can be approximated to be white Gaussian around signal. Power is calculated in this band and the signals power is subtracted from this power to result into adjacent noise power. We then divide signal power by noise power to have SNR what we utilize in step six.

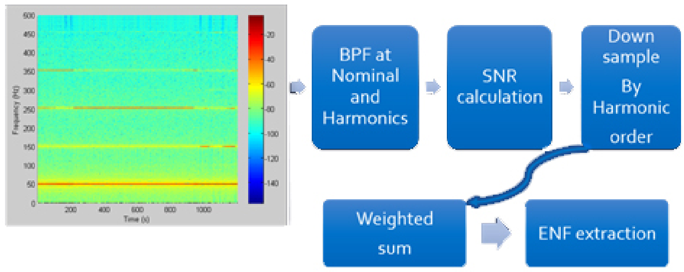

Fig. 3. Spectrum combining process in ENF extraction

Step six is to weight every spectrum (that results from filtering around harmonics) by its corresponding SNR value and add the resulting spectra into one combines spectrum; it is a spectrum around 50 Hz with significant ENF information from all the harmonics. We calculate the dominant frequency from this spectrum. Each resultant dominant frequency from step six is then extracted, then saved in a vector so that every element in the vector is a dominant ENF frequency corresponding to the time window, i.e. the vector is the ENF signal of the example. Figure 2 explains the process to extract the ENF, while figure 3 shows the process of applying spectrum combining method.

B. ENF Extraction Results

Resultant ENF examples of each grid are saved in a matrix to apply the features extraction. By concatenating

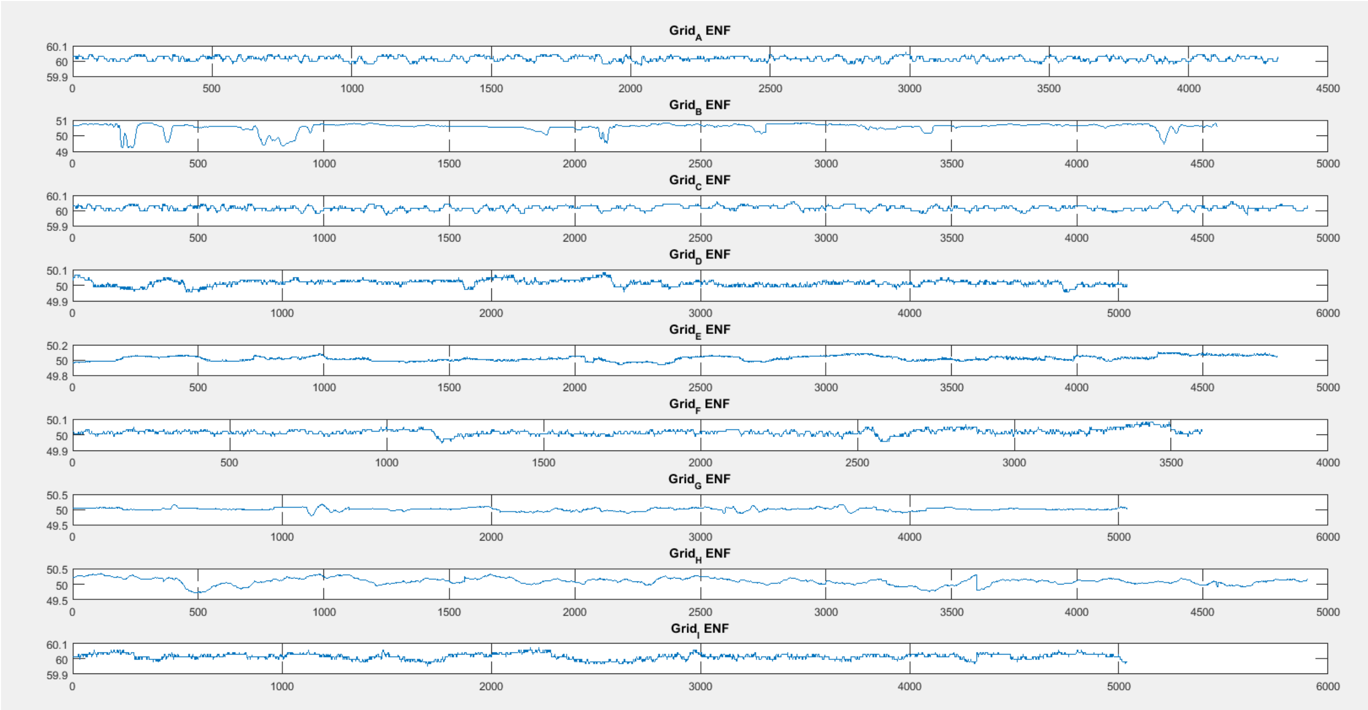

Fig. 4. ENF signals extracted from power recordings for "A" to "I" grids

the matrix rows we can visualize total ENF of each grid and visualize its characteristics; better understanding of the grid ENF is necessary in choosing better features that result in better separability in features space. Figure 4 represents ENF extracted from power recordings for "A" to "I" grids.

One serious issue in literature that we faced is that, ENF signal extracted from audio recordings with high noise have rapid changes. "Alan J. Cooper" proposes that increases the frame length fixes the rapid changes, which we verify [3]. These rapid changes occur because that in highly noise recordings ENF is not recognizable in some instant as noise has more power in the bands of interest. This could be fixed by adjusting the window length so that ENF is extracted from a longer time window. From here arises a tradeoff; a short window includes noisy variations and longer window captures less detail, so we have designed our window to be 5 seconds as a balanced option. Figure 5 represents ENF extracted from "A" grid audio recording at 1, 5 and 10 seconds windows respectively.

III. Location Classification/ Identification System

A. Practice and testing data results

1) Practice data results

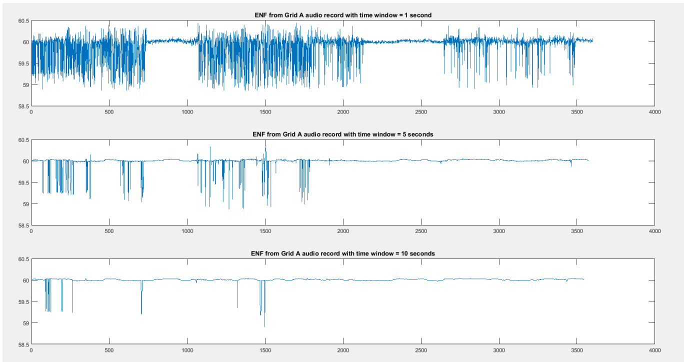

Fig. 5. ENF extracted from audio recording of "A" grid at different time windows

The best score we got from the feedback of the practice data was 82% by this classification: "AHCFF , BGIBD , AFBDC , IAAAE , FBBAD , CGFGB , DGCHG , EAIHI , HHDCF , FAGEI". The expectation and confidence ratio for Practice data are in Table I.

2) Test data results

our Prediction of testing dataset is: BFDCE , GFDAE , AAGBN , BFCEH , DHHBG , BBEAI , DBFHI , INCBE , EAIBE , DGAAG , IIAIE , HIEEC , CCFDG , CEIGI , EACEA , BDBHA , EIGCG , AABIH , CADBA , GBDBB

TABLE I
EXPECTATION AND CONFIDENCE RATIO FOR PRACTICE DATA

No.	Grid	Confidence	No.	Grid	Confidence
1	A	0.756	26	C	0.936
2	H	0.921	27	G	0.563
3	C	0.926	28	F	0.504
4	F	0.612	29	G	0.318
5	F	0.794	30	B	0.990
6	B	0.882	31	D	0.529
7	G	0.504	32	G	0.402
8	I	0.387	33	C	0.372
9	B	0.446	34	H	0.622
10	D	0.725	35	G	0.784
11	A	0.761	36	E	0.568
12	F	0.402	37	A	0.590
13	B	0.715	38	I	0.828
14	D	0.754	39	H	0.828
15	C	0.862	40	I	0.823
16	I	0.691	41	H	0.347
17	A	0.450	42	H	0.666
18	A	0.566	43	D	0.470
19	A	0.439	44	C	0.414
20	E	0.700	45	F	0.602
21	F	0.553	46	F	0.656
22	B	0.715	47	A	0.600
23	B	0.965	48	G	0.387
24	A	0.648	49	E	0.612
25	D	0.642	50	I	0.779

The expectation and confidence ratio for Test data are in Table II.

B. Feature Extraction

We tried many features but some of them were very useful like mean, variance and range. And some made a tiny improvement in the machine learning model. And other had no effect or decreased the learning process. Table III explains the details of each feature:

We compare between the signals by eyes then think of a features that can separate between those ENFs or search online for further features that can help us.

C. Feature selection

We tried to select useful features through two ways:

1) Manual way
   We test the machine learning with each feature to get the training accuracy then get the practice accuracy through the online feedback system, if the accuracy of each of them increased so it is a good feature, but if the accuracy of the training or the practice decreased so its not a useful feature then we remove it.
2) Through a Matlab function
   We made a function that can take all the features, and get the best of it through testing every group of features, and test the training machine and get the percentage of error for each group until it get the minimum error of all the groups, then get the corresponding group of features and it assumes those are the best features.

We saw that the system accuracy are as shown in Table IV.

TABLE IV
SYSTEM ACCURACY RESULTS ACCORDING TO THE FEATURES

	Training Accuracy	Practice Accuracy
All features	56%	58%
Manual way	78%	82%
Through the function	71%	72%

D. Location Classification and Identification System

In this system, we used the classification learner as a machine learning to make a proper-trained classifier that can detect every coming ENF and tell us its grid.

The best learners we found were the Linear SVM technique and bagged tree technique with cross validation of 5 or 10 features. The classifier takes the training data features and the response of each data features i.e. (1, 2,,9) and when setting the cross validation to 5 features it takes the rest of features and make the trained classifier of them and test by those 5 features then leave another 5 features and take the rest of features and make a better classifier until it finish all the features by this way. We saw that the system accuracy are as shown in Table V.

TABLE V
SYSTEM ACCURACY RESULTS ACCORDING TO THE CLASSIFIER

	Training Accuracy	Practice Accuracy
Linear SVM	69%	74%
Bagged Tree	78%	82%

Resultant Confusion matrix (figure 6) of our Bagged Tree system which is our choice indicates good separation between 50 and 60 hertz grids with little confusion within the 60 Hz grids A,C,I.

IV. CIRCUIT DESIGN AND DATA ANALYSIS FOR ENF ACQUISITION

A. Hardware Circuitry

The clean power signal was measured directly from the power mains using a simple circuit as shown in figure 1. Our circuit consists of a step-down 240/12 volt

TABLE II
EXPECTATION AND CONFIDENCE RATIO FOR TEST DATA

No.	Grid	Confidence	No.	Grid	Confidence	No.	Grid	Confidence	No.	Grid	Confidence
1	B	0.401	26	B	0.539	51	I	0.745	76	B	0.715
2	F	0.269	27	B	0.705	52	I	0.892	77	D	0.367
3	D	0.676	28	E	0.436	53	A	0.550	78	B	0.995
4	C	0.578	29	A	0.761	54	I	0.696	79	H	0.563
5	E	0.308	30	I	0.676	55	E	0.401	80	A	0.705
6	G	0.372	31	D	0.666	56	H	0.892	81	E	0.406
7	F	0.401	32	B	0.529	57	I	0.539	82	I	0.676
8	D	0.294	33	F	0.735	58	E	0.475	83	G	0.598
9	A	0.692	34	H	0.897	59	E	0.436	84	C	0.906
10	E	0.274	35	I	0.774	60	C	0.946	85	G	0.539
11	A	0.445	36	I	0.539	61	C	0.654	86	A	0.659
12	A	0.518	37	N	0.245	62	C	0.421	87	A	0.718
13	G	0.583	38	C	0.635	63	F	0.627	88	B	0.828
14	B	0.906	39	B	0.862	64	D	0.544	89	I	0.651
15	N	0.245	40	E	0.549	65	G	0.480	90	H	0.730
16	B	0.779	41	E	0.784	66	C	0.908	91	C	0.796
17	F	0.622	42	A	0.643	67	E	0.794	92	A	0.635
18	C	0.824	43	I	0.769	68	I	0.529	93	D	0.877
19	E	0.833	44	B	0.965	69	G	0.627	94	B	0.632
20	H	0.911	45	E	0.500	70	I	0.681	95	A	0.496
21	D	0.411	46	D	0.416	71	E	0.872	96	G	0.421
22	H	0.700	47	G	0.387	72	A	0.482	97	B	0.745
23	H	0.897	48	A	0.497	73	C	0.602	98	D	0.431
24	B	0.705	49	A	0.675	74	E	0.647	99	B	0.843
25	G	0.485	50	G	0.367	75	A	0.498	100	B	0.759

TABLE III
FEATURE DETAILS

Feature	**Explanation**	**Usefulness**
Mean	The average of each ENF	Very useful
Log(Variance)	How fare the values of ENF from the mean	Very useful
Log(Range)	The difference between maximum value and minimum value of the ENF	Very useful
Higher order moments	Statistical moments after mean and variance for the ENF signal	Some are useful
Discrete cosine transform	Compute DCT of the ENF	First coefficients are useful
Log (average power)	Compute the average power of ENF	Tiny useful
Wavelet(dB5) level 7	Wavelet transform to the level-7 for the type dB5	Useful
Wavelet(dmey) level 7	Wavelet transform to the level-7 for the type dmey	Tiny useful
max(fft(Wavelet(dB5)))	Compute maximum coefficient of the Fourier transform of ENF	Useful
Dct(Wavelet(dB5))	Compute DCT of Wavelet(dB5)	First coefficients are Tiny useful
AR model	The autoregressive model (2) for the ENF signal	Second coefficient is useful
Crossing the mean line	Compute number of crossing the mean line	Useful
Histogram	Probability of the repeated values of ENF	Useful

transformer, a voltage divider circuit, followed by an audio jack, which is also used to produce a fraction of input voltage suitable for USB sound card. USB sound card is used to protect laptop against any problem with recording circuit.

The main disadvantage of using USB sound card is its sensitivity and to overcome that we increased the output voltage our recording circuit. Clean power was recorded at a sampling rate of 8000 Hz and then was down sampled to 1000 Hz.

B. Comparison between our power and audio Recordings

The ENF in our grid has a nominal value of 50 Hz, but it usually fluctuates around its nominal value due to load variation. With the aid of the shown circuit, we record power for around 60 minutes and compare the power record to an audio record, recorded 5 minutes later in a quiet room to eliminate background noise as much as

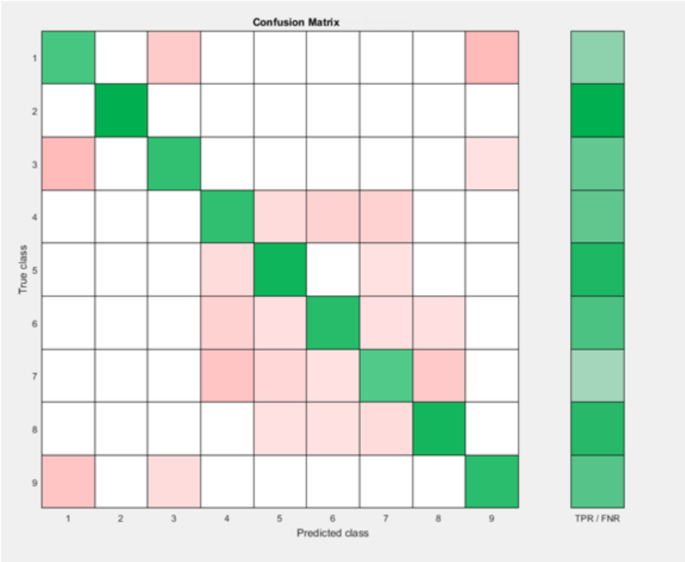

Fig. 6. The Resultant Confusion Matrix

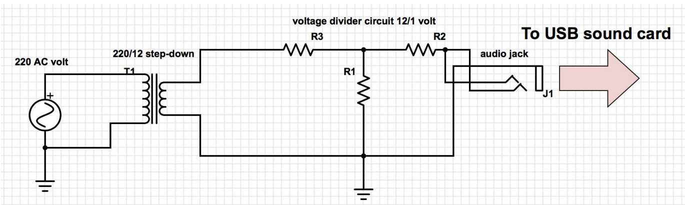

Fig. 7. circuit schematic

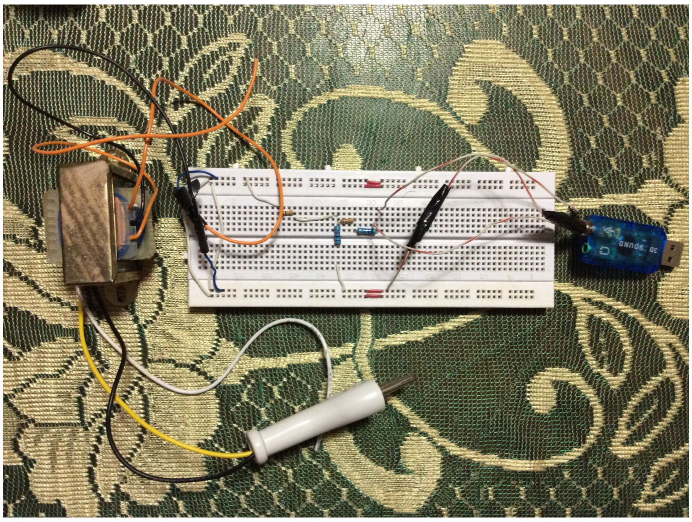

Fig. 8. Actual circuit design

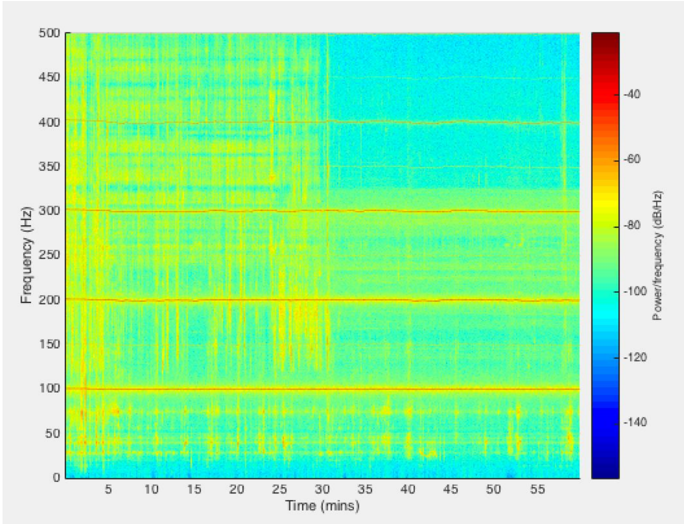

Fig. 9. power signal spectrogram recorded at 11:20 PM

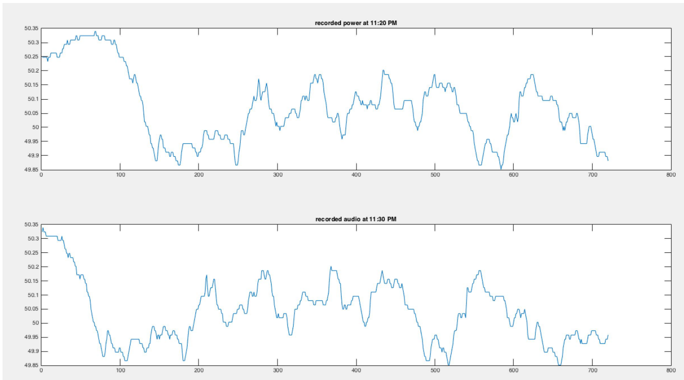

Fig. 10. ENF extracted from power and audio

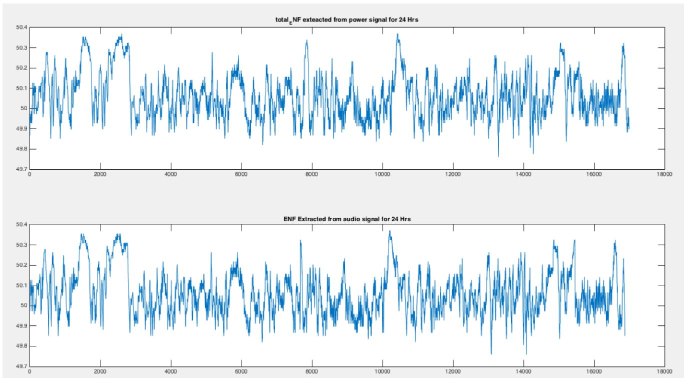

Fig. 11. 24-hours of power and audio recording

possible, to ensure that the circuit is working correctly. The record took place in Sidi-Besher, Alexandria, Egypt on Wednesday December 30th at 11:20 PM. using MATLAB we drew the spectrogram of both power and audio as well as ENF extracted power as shown in the Figures (9 - 10 - 11)

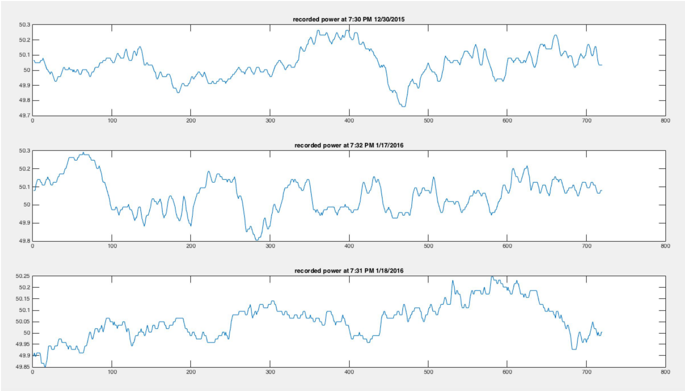

Fig. 12. power records recorded at different days

C. Similarity analysis of our grid to training data grids

We applied our grid example to the classifier model, and took mean of the similarities acquired for each example to arrive to the overall similarity of our grid, as shown in Table:VI. Here we find that our grid has zero similarity with grids A,C,I which is logical because our grid is a 50 Hz grid and has high similarity with grid B which has closest variations to our grid.

TABLE VI
SIMILARITY ANALYSIS OF OUR GRID TO TRAINING DATA GRIDS

Grid	Grid similarity ratio
A	0
B	0.86902
C	0
D	0.014943
E	0.034826
F	0.014856
G	0.049699
H	0.016659
I	0

D. Results at different Times and places

Another experiment was done by comparing three records recorded in the same time but at different days to check if ENF vary with time or not. The result was as shown in Figure 12

From the shown figure it is clear that ENF changes with time. also we record power for to different areas in Alexandria, Smouha and Sidi-Besher, to check if these two areas belong to same grid or not by comparing the extracted ENF. The records in Figures(13-14) were recorder on December 30th at 10:30 PM, and they show that each area belongs to different power grid.

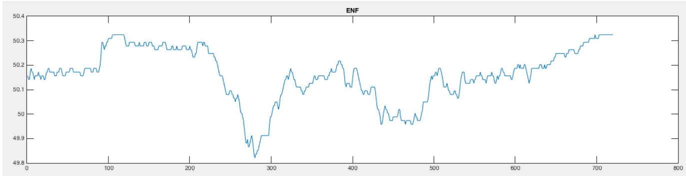

Fig. 13. ENF extracted from Smouha grid

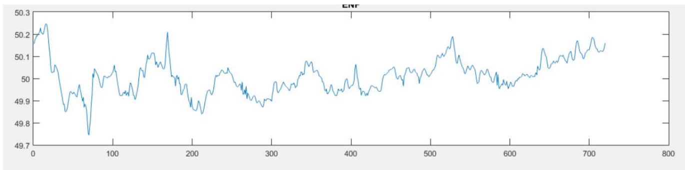

Fig. 14. ENF extracted from Sidi-Besher grid

E. Results at different recordings conditions

Studies confirmed that the presence of background noise, generated by mains power electronic devices, near the recording device is a carrier of ENF artifacts.
To Examine Effect of different recording conditions as additional analysis, we utilized: recorder mic with a grounded monopole antenna; received radio FM signal at 88 MHz; and received FM signal at 108 MHz. the recording method is shown in figure 15
The device used in the recording: HP Pavilion DV6 laptop.
Recording Location: Smouha, Alexandria, Egypt.

Recorded Data:
Recod_A1: recorded on Wednesday (30/12/2015) at 10:30 PM. We recorded the noise received when connecting the recorder mic with a monopole antenna (here the antenna acts as a ground no need for any down conversion).
Record_A2: recorded on Saturday (9/1/2016) at 12:49 PM. We have recorded the received FM signal at 88 MHz which is a void band.
Record_A3: recorded on Friday (15/1/2016) at 11:48 AM. We recorded the noise received when connecting the recorder mic with a grounded monopole antenna.
Record_A4: recorded on Friday (15/1/2016) at 7:27 PM. We have recorded the received FM signal at 108 MHz which is a void band.

The Spectrogram and the ENF of each recording are shown in figures: 16-17

Fig. 15. Methods of data recording

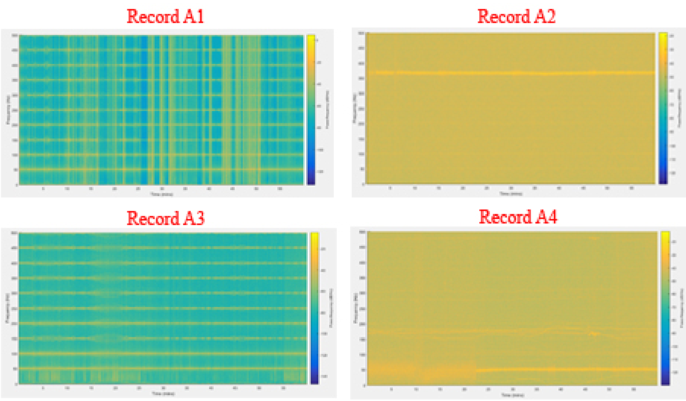

Fig. 16. Spectrogram of different recordings

V. Time of Recording Application on Our Recorded Data

1) Experiment explanation: Firstly, we recorded power signal using our power recording circuit for consecutive twenty four hours and extracted ENF from it to be used as a reference for our grid variation.
Step two: we recorded voice data using htc one phone to record audio data that carries ENF, it was performed

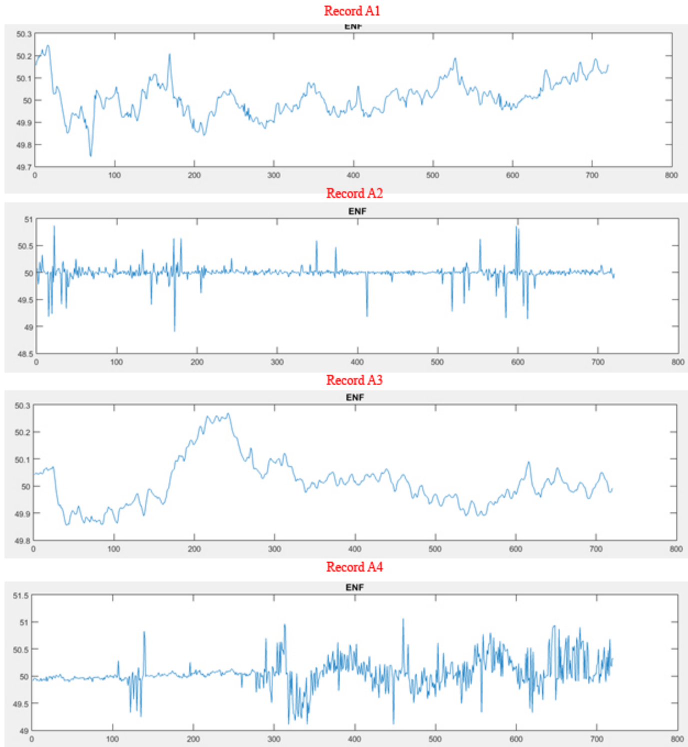

Fig. 17. ENF extracted from different records

near an operating transformer to catch electromagnetic effect of the ENF. Audio recording was done for the same 24 hours that power recordings were performed at.
Step three: we divided the audio recording into a matrix, each row of the matrix represented a ten minutes of audio recording that we want our system to identify its time of recording.
Step four: we extracted ENF signal from each example organizing them in a matrix; each row of the matrix represents ENF signal for ten minutes; time of recording of each of these example was already known before to compare the system accuracy against; this was done by organizing the matrix so that every row has a time of recording offset by ten minutes from the row above, initial time was known and thus placing of a row can be converted into a time of recording.
Step five: we a created a scheme that identifies time of recording; it gets the cross correlation factor between the example with shifted window applied on the reference twenty four how recordings; greater values of cross correlation factor indicates similarity between example and a given window. We find the shift at which cross correlation factor occurs, it indicates the estimated time shift between the example and the start of the reference

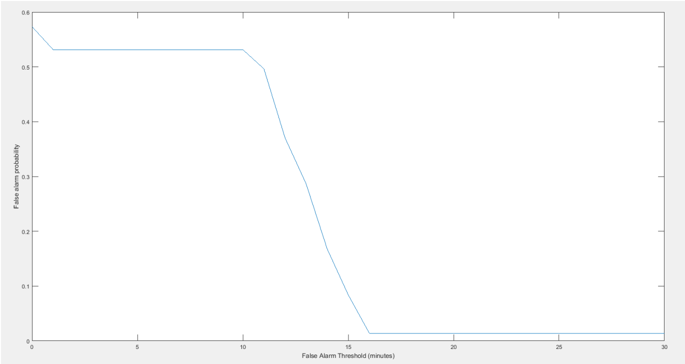

Fig. 18. our system gave a false alarm probability of 1.4% for error threshold greater than sixteen minutes

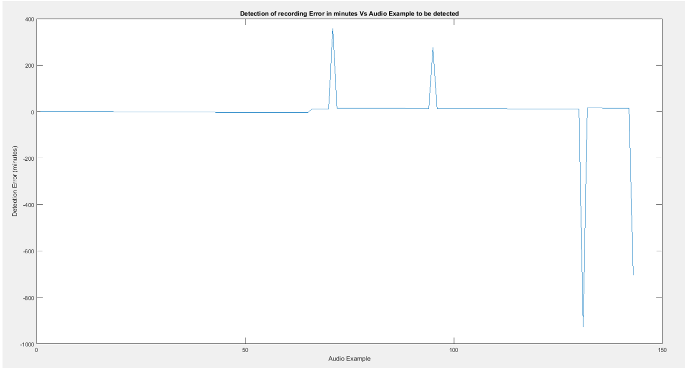

Fig. 19. error taken from our system

power data.
Step six: we used every ENF row as an example applied to the scheme in step five, we compared the estimated shift with the actual shift that we already know; this difference between estimated and actual shifts is our systems error in identifying that example.
Step seven: we saved the error values of the examples and put a threshold for the error so that any error greater than that threshold is considered a false alarm; we applied the threshold condition on the error values to get a false alarm probability of the system. Step eight: we repeated step seven for different thresholds and plotted the false alarm probability over the false alarm threshold to visualize in which error margin can our system give acceptable time of recording identification.

2) Results: Figure 18 indicates that our system gave a false alarm probability of 1.4% for error threshold greater than sixteen minutes, which means our system can identify sound recording with acceptable accuracy within sixteen minutes margin.

The error curve is shown in figure 19 which visualizes error taken from our system; the four peaks represent false alarms.

VI. Conclusion and Future Work

In this report we have described our ENF extraction method with results of given grid recordings and justification of our choosing of time resolution. We explained our location classification system, highlighting results, chosen features and chosen classifier system. We have presented our hardware recording circuit with an analysis of recordings at different times, places and recording conditions. And we have presented an experiment on recorded data to figure out time of recording of audio files using the data base of power signal that we have recorded.

Possible future work includes: examining ENF patterns for more cities in our country (Egypt), implementing our MATLAB code on DSP kit for real time localization of live streaming audio/video recordings and proposing our contribution in ENF recognition and our computed features in a research paper.

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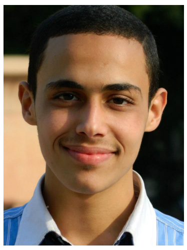
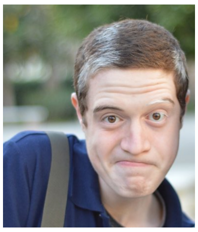
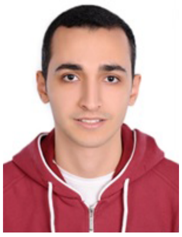


Abdel-Rahman Gaber is a 4th year student, candidate for B.Sc. in Electronics & Communications, Faculty of Engineering, Alexandria University, Egypt. He had a two months internship in Si-Ware Systems Co. Cairo, Egypt; in the Digital Design department in Summer 2014. His interest fields are Digital Design, Embedded Systems, Digital Signal Processing, and Computer Architecture.



Abdelrahman Zayed will earn the B.E. degree in communications and electronics engineering from the Faculty of Engineering, Alexandria University, Egypt in 2016. Abdelrahman is ranked 1st on his class, He had a two months internship in Si-Ware Systems (SWS) in the system design department in Summer 2015. His interest fields are embedded systems, digital signal processing, digital communication systems and optical communication systems.



Basem Galal will earn his B.Sc. from the Department of Electrical Engineering from the Faculty of Engineering, Alexandria University, Egypt in 2016. Basem has been working as an undergraduate research assistant in the Department of Computer Science and Engineering, Egypt-Japan University of Science and Technology since October 2014. His basic background is in machine learning and His research interests is machine learning (theory and application) especially deep learning.

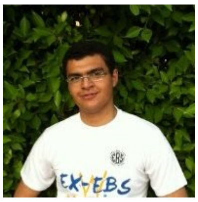
Eslam El. Sheikh is currently undergraduate student at 4th year of Electronic and Communication department, Alex university, Egypt. He worked on projects like Sumo Robot and Auto Pilot Airplane. In 2015 Eslam worked on Wireless Body Area Networks as an internship in Egypt-Japan University of Science and Technology. Eslam is interested in wireless communication field, embedded systems, digital signal processing and mobile Robots.

Hesham Ali is a 4th year student at department of communications and electronics, Alexandria university, Egypt. He is currently working on a PLL design for multi-standards transceiver. In 2015 he worked on some project like auto pilot airplane and OTA design. He is interested in analog circuit design, PLL design, DSP, and RADAR systems.

Ibrahim Sherif is currently at 4th year, Department of Electronics and Communications, Alexandria, Egypt. His target research fields are Digital Signal Processing, Machine learning and analog/RF Integrated Circuits design. He was in an internship on software Defined Radio (SDR) at Spectratronix in September 2015 and he got a training on coffee-can radars in E-JUST in 2014. He worked on many related project including face recognition using eigenfaces, OTA Design and PLL design for multi-standards transceiver.

Khaled Elgammal is a 4th year student, department of communications and electronics engineering, Alexandria university. His background is in problem solving algorithms. He is interested in embedded systems, signal processing, machine learning and radar systems.

Omar Ahmadein will receive his B.Sc. from the Department of Electrical Engineering, Faculty of Engineering, Alexandria University, Egypt in 2016. He worked as an undergraduate researcher at CSNP in VT-MENA in RFID tags. He also works as an undergraduate researcher in E-JUST in BioMems. He was an undergraduate trainee in E-Just in Digital Design. His research interests are in Biomedical Engineering, Digital Signal Processing, RADAR, Microwave Engineering, and Electromagnetics.



Omar Elzaafarany is currently at 4th year, Department of Electronics and Communications. He is ranked third on his department. He is ranked second on the 10th International Microelectronics Olympiads held in 2015 in AUC. He is interested in Digital Signal Processing (DSP), Wave Propagation and Microwaves. His target research fields are remote sensing, image processing, radiology and bio imaging. In September 2015, He got a training on software Defined Radio (SDR) at Spectratronix.

Taha Gamal is currently an undergraduate student (4th year) at Communication and Electronic Department, Alexandria university, Egypt. His interesting topics are Programming, Digital Signal Processing, Embedded System, and Digital Circuit Design. He has worked on Model Predictive Control project, Quad ATM User-to-Network Interface and Forwarding digital verification project. His current research includes Internet-Of-Things Technology.