2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC)
21 - 23 Dec 2017, Dhaka, Bangladesh

Power File Extraction Process from Bangladesh Grid and Exploring ENF Based Classification Accuracy using Machine Learning

Samin Yeasar Arnob[1*], Riyasat Ohib[1], MD. Muhtady Muhaisin[1], and Tanzil Bin Hassan[1]
[1]Department of Electrical and Electronic Engineering
Islamic University of Technology (IUT)
Board Bazar, Gazipur-1704, Bangladesh
[*]saminyeasar@iut-dhaka.edu

***Abstract*— The Electric Network Frequency (ENF) is the supply frequency of power distribution networks, which can be captured by multimedia signals recorded near electrical activities. It normally fluctuates slightly over time from its nominal value of 50 Hz/60 Hz. The ENF remain consistent across the entire power grid. This has led to the emergence of multiple forensic application like estimating the recording location and validating the time of recording. Recently an ENF based Machine Learning system was proposed which infers that the region of recording can be identified using ENF signal extracted from the recorded multimedia signal, with the help of relevant features.**

As supervised learning process requires ground truth to train classifier for identifying future unknown data, in this work- we report Power Recording data extraction process from the National Grid of Bangladesh. Furthermore, we used ENF data – derived from Power Recordings, to compare grids around the world and found out classification accuracy of Bangladesh National Grid. ENF derivation process from Power Recording data and set of features, which serve as identifying characteristics for detecting the region of origin of the multimedia recording- are followed from published work. We used those characteristics in a multiclass Machine Learning implementation based on MATLAB which is able to identify the grid of the recorded signal.

Keywords—Electric Network Frequency; Grid; Forensics; Estimation; SVM; Fine Gaussian; Machine Learning.

I. Introduction

The supply frequency of the power distribution network i.e. ENF has a nominal value of 50/60 Hz. The instantaneous frequency fluctuates about the nominal value due to the load control mechanisms and the changes in the load demands within the power grid. The fluctuations of the ENF although random, are unique within a particular electrical network [1]. The tendency of these variations, at a particular time, are almost same throughout the same grid. These variations of the ENF over time is defined as the ENF signal.

The use of ENF signal to identify modified audio recordings was proposed by Grigoras [2-5] presently being used in multimedia forensics applications, as the signal gets embedded in the multimedia recordings made in the vicinity of electrical activity. The ENF signals can also be used to identify and classify video signals as well [6]. The audio recordings can pick up the signals due to the mechanical or acoustic hums or electromagnetic interferences from the power lines. The clean Power Recordings can be extracted using an audio recorder connected directly to the power mains via a step-down transformer [7]. Applying a Band-Pass Filter around the nominal frequency and employing a frequency estimation algorithm, the dominant frequency surrounding the nominal frequency can be estimated frame-by-frame, thus forming the ENF signal.

In our work, we have extracted power recordings with the help of sensing circuit from National Power Grid of Bangladesh and used it alongside the other grid data available [8], which helps us get a picture of how much efficient the extraction mechanism is for classifying the grid of origin in Bangladesh. Using statistical features derived from the ENF signals, already discussed in [9], the region of recording of the media signals were differentiated based on a Machine Learning approach.

II. ENF Extraction and Database Description

The In this section we describe the database of Power Recordings. Subsequently, we discuss the procedure and methodology adopted, to extract Power Recording data from Bangladesh National Grid. We end this section by analyzing the similarities and dissimilarities between the extracted ENF signals, and using set of features [9] we found out classification accuracy of Bangladesh National Grid.

A. Database Description and Feature Extraction

Media recordings of 11 different grid from all over the world were available on an online database [8] published by the authors of [9] which is subset of the data used in their work and the whole dataset was not published by the authors. However the ENF extraction code [10] used by the authors of [9] was available, therefore using their extraction algorithm and code we performed feature extraction process from our ENF data. The number of available examples for Power Recordings of each grid, nominal frequencies corresponding to each grid and their range of variation are provided in Table-I. The Database contained variable numbers of Power Recordings across all grids.

This should be noted that, as number of training data is varying in a large scale, and different grid combinations have been used for classification in our work, grid-wise efficiency and over-all efficiency will vary from [9].

978-1-5386-2175-2/17/$31.00 ©2017 IEEE

B. Hardware Implementation

A circuit has been built to collect the Power Recordings from the Bangladeshi power grid for analyzing the ENF variation present. The setup was built with least cost possible while not compromising the efficiency and accuracy. After completing the circuit, ten hours of reference Power Recording were collected at different times of the day in different days of a week. With the help of a voltage divider, 6V was converted into 200mv (p-p). We avoided the use of passive circuit elements while building the setup, so that unnecessary frequency fluctuation can be avoided. This setup (schematic in Fig. 2) was connected with the sound card of a Computer. Thus the originally transmitted electrical signal was recorded using an audio recorder software.

C. Methodology

To obtain the power data of the grid, 220 V was stepped down to 6 V with a transformer. Then, to bring the voltage level down to the low acceptable range of the sound card of the computer, we have resorted to a simple voltage divider circuit. The 6V transformer output was converted into 200 mV (p-p), and connected to the soundcard of a computer. Bearing in mind the change of load conditions at different times of the day, we have collected Power Recordings during mornings, afternoon, midnight and early mornings of different days of the week. The components those are being use are:

- One 220V-6V step-down transformer
- Resistors of value 100kΩ & 10kΩ
- One 3.5mm headphone jack
- Jumpers
- Sound Card of a laptop

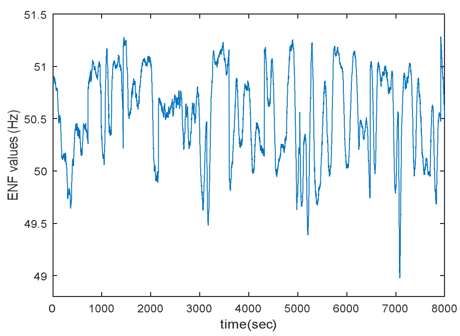

Fig. 1. ENF variation of collected signal through our sensing hardware.

We collected ten hours of Power Recordings from the Electric mains from Gazipur District of Bangladesh. ENF has then extracted from Power Recordings using [10]. Main recording of each power file was at first divided into segments of ten minutes to create substantial number of datasets so that we can train our program properly for future prediction. Each of the segments were divided into non-overlapping frames of 5 seconds duration & then Spectrum Combining method [11] was used for estimating the dominant frequency component of each time frame.

D. Analysis of Recorded ENF signal

After extracting the ENF signals from the Power Recordings using [10], we noticed some similarities and dissimilarities of the signal from the ENF signals of the Power Recordings of grids provided to us. We immediately noticed the high dynamic range of the ENF signal collected from Bangladesh in Fig 1. The ENF signal fluctuated from around 48.99Hz to over 51.26Hz and for most of its duration Bangladeshi grid displays consistently high variations. This is because of the poor control mechanism and high load variation [1] in the National Grid of Bangladesh.

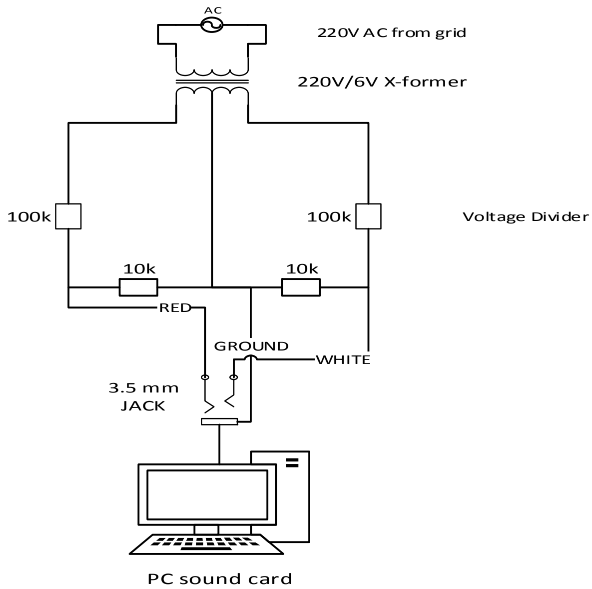

Fig. 2. Schematic Diagram of Circuit

III. TRAINED CLASSIFICATION SYSTEM

While training the Classification System the normalization parameters were stored, and later used to normalize the Testing Data. We have resorted to a similar technique as the one reported in [9]. In this work, a multiclass classifier based on the Error-correcting output codes (ECOC) multiclass model using support vector machine (SVM) binary learners on the MATLAB platform [12-15]. This employs a one vs one model. A Gaussian Radial Basis kernel function with automatic kernel scaling was used. When the Kernel scale mode is set to 'Auto', MATLAB uses a heuristic procedure to select the scale value; the heuristic procedure uses subsampling [16]. Both the LIBSVM, used in the previous work and MATLAB's ECOC multiclass system uses a one vs one multiclass model, weighted SVM, and works in a similar way [12, 13, 17].

IV. RESULT

For the classification system trained only on Power Recording we achieved an overall accuracy of 89% with a 20-fold Cross-Validation scheme selecting all the features. Grid Bangladesh (L) has identification accuracy of 98.3%.

To closely understand the results of the confusion matrix is presented in Table II. Here, the efficiency of in predicting various grids are presented.

TABLE I. **Description of the Database**

Grid	No. of Power Examples	Nominal Frequency (Hz)	Maximum Frequency (Hz)	Minimum Frequency (Hz)	Frequency Range (Hz)
(A) Texas	54	60	60.03	59.97	0.06
(B) Eastern U.S	66	60	60.04	59.96	0.08
(C) Turkey	63	50	50.06	49.94	0.12
(D) Ireland	66	50	50.08	49.93	0.15
(E) France	42	50	50.08	49.94	0.14
(F) Tenerife	62	50	50.14	49.80	0.34
(G) India (Agra)	61	50	50.32	49.72	0.60
(H) Western U.S	65	60	60.05	59.95	0.10
(I) Brazil	42	60	60.07	59.87	0.20
(J) Norway	72	50	50.11	49.87	0.24
(K) Australia	45	50	50.10	49.87	0.23
(L) Bangladesh	60	50	51.26	48.99	2.27

TABLE II .**Confusion Matrix**

Testing Classes	No. of Examples	Grid A	Grid B	Grid C	Grid D	Grid E	Grid F	Grid G	Grid H	Grid I	Grid J	Grid K	Grid L
(A) Texas	54	83.3%	7.4%	-	-	-	-	-	9.3%	-	-	-	-
(B) Eastern U.S	66	7.6%	89.4%	-	-	-	-	-	3%	-	-	-	-
(C) Turkey	63	-	-	80.9%	4.8%	7.9%	3.2%	1.6%	-	-	1.6%	-	-
(D) Ireland	66	-	-	9.1%	84.8%	-	6.1%	-	-	-	-	-	-
(E) France	42	-	-	28.6%	2.4%	64.3%	4.7%	-	-	-	-	-	-
(F) Tenerife	62	-	-	6.5%	1.6%	-	85.5%	4.8%	-	-	-	-	1.6%
(G) India (Agra)	61	-	-	1.6%	-	-	6.6%	91.8%	-	-	-	-	-
(H) Western U.S	65	4.6%	1.6%	-	-	-	-	-	93.8%	-	-	-	-
(I) Brazil	42	-	-	-	-	-	-	-	-	100%	-	-	-
(J) Norway	72	-	-	2.8%	-	-	-	1.4%	-	-	95.8%	-	-
(K) Australia	45	-	-	-	-	-	-	2.2%	-	-	-	95.6%	2.2%
(L) Bangladesh	60	-	-	-	-	-	-	1.7%	-	-	-	-	98.3%

While using the same features and same ENF extraction process from previous work [9], over-all and grid-wise identification accuracy in our work is lower. The reason is, we don't have the exact datasets used in [9]. Rather we used only a subset of data used in [9] - which is available online [8]. No of data for each grid are much less in our work. As more training data generally leads to better approximations and accuracy of the Machine Learning system [18], the lack of data in compared to the work in [9] explains the somewhat reduced accuracies of this program. Additionally, another important factor is that, combination of grids - used in classifier, are different as well.

From Table-II we find drastic variation of accuracy while classifying different grids. For example, classification accuracy of Brazil grid (J) is 100% but for France grid (E) we get much lower classification accuracy of 64.3%. This variation occurs due to the presence of other grids with very similar characteristics. In this case, Turkey grid (C) has been falsely identified as France grid (E) 28.6% times. This problem can be reduced if we can train the classifier with large amount of training data.

From ENF data it's evident that ENF collected from Bangladesh grid (L) fluctuates in wider range than any other grids mentioned. We know this is due to the instantaneous frequency fluctuates about the nominal value due to the load control mechanisms and the changes in the load demands within the power grid. [1] Due to poor load control mechanism, produced ENF fluctuates a lot in Bangladesh grid (L) and this characteristics helps to detect Bangladesh grid (L) with a classification accuracy of 98.3% can be evident from Table II.

Bangladesh grid (L) has been falsely identified as India grid (G) with a very small percentage (1.7%). We believe, new novel features and more training data would resolve this issue.

As most of datasets available online [8] are collected form developed countries, Bangladesh grid (L) was possible to easily detect for having wide ENF fluctuation. We need data from different developing countries for better analysis.

V. CONCLUSION

In this work, we have described the method of extracting the Power Recording from Bangladesh National Grid. We analyzed the ENF comparing Power Recording from 11 other grids around the world using Machine Learning. From confusion matrix we have found Bangladesh grid (L) to be classified with 98.3% efficiency which is a great news as ENF data can be used for multiple forensic application like estimating the recording location. As we have mostly compared with data from grids with advanced load control mechanism, wide fluctuation range of Bangladesh National grid was easily identified. Moreover, this work also demonstrates the applicability of MATLABs ECOC Multiclass Classification System in classifying the region of origin of multimedia recordings through the analysis of ENF signals embedded in them. In future, performance comparison of with the grid data available from the developing countries like Bangladesh will be performed. Also, we are working on finding other novel features to make the classification process more robust in the future.

VI. REFERENCES

[1] Bollen, M.H. and I. Gu, Signal processing of power quality disturbances. Vol. 30. 2006: John Wiley & Sons.

[2] Grigoras, C., Digital audio recording analysis–the electric network frequency criterion. International Journal of Speech Language and the Law, 2005. 12(1): p. 63-76.

[3] Grigoras, C., Applications of ENF criterion in forensic audio, video, computer and telecommunication analysis. Forensic Science International, 2007. 167(2): p. 136-145.

[4] Grigoras, C. Applications of ENF Analysis Method in Forensic Authentication of Digital Audio and Video Recordings. in Audio Engineering Society Convention 123. 2007: Audio Engineering Society.

[5] Grigoras, C., Applications of ENF analysis in forensic authentication of digital audio and video recordings. Journal of the Audio Engineering Society, 2009. 57(9): p. 643-661.

[6] Garg, R., A.L. Varna, and M. Wu. Seeing ENF: natural time stamp for digital video via optical sensing and signal processing. in Proceedings of the 19th ACM international conference on Multimedia. 2011: ACM.

[7] Maher, R.C., Audio forensic examination. Signal Processing Magazine, IEEE, 2009. 26(2): p. 84-94.

[8] Adi Hajj-Ahmad, M.W. IEEE Signal Processing Cup 2016, DATASETS 2016; Available from: http://spcup16.ece.umd.edu/datasets.php.

[9] Hajj-Ahmad, A., R. Garg, and M. Wu, ENF-Based Region-of-Recording Identification for Media Signals. Information Forensics and Security, IEEE Transactions on, 2015. 10(6): p. 1125-1136.

[10] Adi Hajj-Ahmad, R., MinWu,. Spectrum Combining for ENF Signal Estimation - Dataset & Codes,. 2013 [cited 2017 March 03]; Available from: http://cwwongpatch2.no-ip.org/mast_new/research.php?t=enf.

[11] Hajj-Ahmad, A., R. Garg, and M. Wu, Spectrum combining for ENF signal estimation. Signal Processing Letters, IEEE, 2013. 20(9): p. 885-888.

[12] Allwein, E.L., R.E. Schapire, and Y. Singer, Reducing multiclass to binary: A unifying approach for margin classifiers. Journal of Machine Learning research, 2000. 1(Dec): p. 113-141.

[13] Escalera, S., O. Pujol, and P. Radeva, Separability of ternary codes for sparse designs of error-correcting output codes. Pattern Recognition Letters, 2009. 30(3): p. 285-297.

[14] Escalera, S., O. Pujol, and P. Radeva, On the decoding process in ternary error-correcting output codes. IEEE transactions on pattern analysis and machine intelligence, 2010. 32(1): p. 120-134.

[15] Fürnkranz, J., Round robin classification. The Journal of Machine Learning Research, 2002. 2: p. 721-747.

[16] MathWorks, M. Choose Classifier Options. 2016 [cited 2017 31 March]; Available from: https://www.mathworks.com/help/stats/choose-a-classifier.html#bunt0n0-1.

[17] Chang, C.-C. and C.-J. Lin, LIBSVM: a library for support vector machines. ACM Transactions on Intelligent Systems and Technology (TIST), 2011. 2(3): p. 27.

[18] Banko, M. and E. Brill. Scaling to very very large corpora for natural language disambiguation. in Proceedings of the 39th annual meeting on association for computational linguistics. 2001: Association for Computational Linguistics.