

ENF Based Machine Learning Classification for Origin of Media Signals: Novel Features from Fourier Transform Profile

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Abstract— The Electric Network Frequency (ENF) of power grid is gaining a lot of interest in media forensics recently as it is considered a signature in audio or video recordings made in the vicinity of the grid. Multiple forensic applications, like estimating the location of recording and the time of recording has emerged exploiting this property. An ENF based machine learning classification system can be built utilizing the ENF signal extracted from the multimedia recordings, which can infer the physical location of recording. With the help of relevant features, the machine learning approach drastically reduces the time of identification compared to earlier methods such as using correlation. In this work, we report novel features used in a machine learning system, which act as identifying characteristics for detecting the location of origin of the multimedia recordings. In addition to features from the ENF variation itself, the utilization of the harmonic patterns extracted from the audio signals as novel features, enables a more accurate identification of the region of origin of the audio recordings. These characteristics were implemented in a multiclass support vector machine classification system to identify the grid of origin of the recorded power signals. With the inclusion of our proposed features, the classification accuracy of power recordings rose from previously reported 88.86% to 97.61% in our system.

Keywords— *Electric Network Frequency, machine learning, classification learning, support vector machines, multimedia forensics, estimation.*

I. INTRODUCTION

The electric network frequency (ENF), which is the supply frequency of the electrical power grid has a value of 50/60 Hz depending on the country where the grid is located. The instantaneous frequency varies from the nominal value owing to the fluctuations in the load demand across the grid and the quality of the load control mechanisms in place. These random fluctuations of the ENF are unique within a particular electrical network and can be considered as a ‘forensic signature’ for the grid [1]. At a particular instance of time, the pattern of these variations are almost same across

the same grid [2, 3]. These changing variations of the ENF with respect to time is termed as the ENF signal.

The application of ENF signal to detect tampered or altered audio recordings was proposed by Grigoras [4-6]. As the ENF signal gets embedded in the multimedia recordings created in the vicinity of electrical activity, this method of detection is currently getting popular in multimedia forensics applications [7-12]. The ENF signal leaves a forensic identifying mark of the power grid and consequently the location of the recording. The ENF signals can also be exploited in the identification of video signals [13]. The ENF signals get embedded in the audio recordings due to the mechanical or acoustic background hums, or the electromagnetic interferences generated by the power lines nearby. By connecting any audio recorder or soundcard to the power mains through a step-down transformer, clean ‘power recordings’ can be recorded [14, 15]. Employing a band-pass filter around the nominal (50/60Hz) frequency and subsequently applying a frequency estimating algorithm, the dominant frequency component around the nominal frequency can be estimated, thus generating the ENF signal.

The ENF signals from a particular grid although random, vary from those of other grids in their nature and manner of variations. Statistical features extracted from the ENF signals of different grids can thus be used to develop a machine learning system that can identify the grid of origin, and therefore the region of recordings [16, 17]. Machine learning classifiers [18, 19], as well as systems based on the convolutional neural networks (CNN) can also be used in media tampering detection [20, 21].

Before the advent of machine learning techniques, the sole focus was using the unique ENF pattern of the power grids as sole criteria to differentiate between the media recording signals originating from different power grids. As different grids generated unique ENF signals those signals were extracted from the clean power recordings and chronologically stored for future reference [5, 8].

TABLE I.
DESCRIPTION OF THE DATABASE

| Grid | No. of Power Recordings | No. of Audio Examples | Nominal Frequency (Hz) | Maximum Frequency (Hz) | Minimum Frequency (Hz) | Frequency Range (Hz) |
|------------------|-------------------------|-----------------------|------------------------|------------------------|------------------------|----------------------|
| Texas (A) | 54 | 6 | 60 | 60.06 | 59.98 | 0.08 |
| Lebanon (B) | 56 | 6 | 50 | 50.92 | 49.13 | 1.79 |
| Eastern U.S (C) | 66 | 6 | 60 | 60.07 | 59.98 | 0.09 |
| Turkey (D) | 63 | 6 | 50 | 50.07 | 49.94 | 0.13 |
| Ireland (E) | 66 | 6 | 50 | 50.11 | 49.94 | 0.17 |
| France (F) | 42 | 6 | 50 | 50.11 | 49.95 | 0.16 |
| Tenerife (G) | 62 | 6 | 50 | 50.17 | 49.80 | 0.37 |
| India (Agra) (H) | 61 | 6 | 50 | 50.34 | 49.73 | 0.61 |
| Western U.S (I) | 65 | 6 | 60 | 60.08 | 59.97 | 0.11 |
| Brazil (J) | 42 | - | 60 | 60.10 | 59.87 | 0.23 |
| Norway (K) | 72 | - | 50 | 50.24 | 49.86 | 0.38 |
| Australia (L) | 45 | - | 50 | 50.13 | 49.86 | 0.27 |

Whenever an audio file needed to be classified they were cross-referenced by correlating them with the database which is both time consuming and requires large storage capacities [5]. The machine learning approach greatly alleviates these problems. Moreover, in this work we found that a machine learning approach also lets us exploit other differentiating features from intrinsic characteristics (harmonics, Fourier transform profile etc.) of different grids, which when used in tandem with the features extracted from ENF signals, provide an enhancement in the ability of the machine learning system to classify the origin of recordings. We found that feature-sets can be developed for the support vector machine (SVM) classification system which does not arise from the extracted ENF signal, but from the temporal media signals itself. This paper proposes the utilization of the ‘Fourier Transform Profile’ or the pattern of the harmonics of the ENF in the media signals in the frequency domain as novel features.

A database [22] containing clean power recordings and noisy audio recordings from 12 different grids around the world, sampled at 1000Hz, was used in this work. Utilizing statistical features of the ENF signals, already discussed in [16], as well as proposed novel features mentioned in this paper, the location of recording of the media signals were discerned using machine learning techniques. Employing the extraction code and proposed features of [15], classification accuracy of power files rose from 88.86% to 97.61% in our system after the inclusion of our proposed features. A similar study on audio files could not be performed due to a scarcity of audio recordings in the database. In this paper, we will refer to the work in [15] as the ‘reference work’.

II. ENF EXTRACTION AND DATABASE DESCRIPTION

Audio recordings of 12 different grids from locations around the world were published by the authors of the reference work on an online database [22], which is a subset of the database used in their work. This dataset was made

available as part of the IEEE Signal Processing Cup 2016, and the complete dataset was not made public. The ENF extraction program employed by the authors was, however, available [23]. Hence, a comparative study using the extraction algorithm and code used in [16] was performed between their features and our proposed novel features in the dataset available. Even with the availability of our own extraction algorithm and program, we resorted to using the code from the reference work because it demonstrates the effects of the novel features on the classification efficiency by using a standard extraction algorithm and classification system in both cases. This effectively cancels out all other variables that might affect the accuracy apart from the features used. As the extraction code is exactly the same, the only difference between the two works are in the proposed features used in this work. To classify the data, MATLAB’s Error Correcting Output Code (ECOC) Multiclass Support Vector Machine (SVM) classification system was used utilizing both sets of features to understand their effects on classification accuracy.

Each of the grid contained power and audio data. The number of examples for power and audio recordings of each grid in the dataset, nominal frequencies of each grid and their range of variation is illustrated in Table I. As well as having significantly low number of audio recordings in comparison to the reference work, the audio files from Grids J to M were not available in the dataset. As this work focuses on power recordings only, initially each power file was divided into segments of ten minutes to generate a substantial number of training data of equal temporal length for future classifier predictions. Instantaneous ENF for frames of 5 seconds were estimated in a 10 min audio temporal segment. This resulted in a sample size of $S = 120$. For the extraction of the ENF signal, spectrum combining technique was employed for the estimation of each time frame’s dominant frequency component [23, 24]. Features acquired from the ENF signal was extracted using the same method used in the reference work utilizing the original code of the authors.

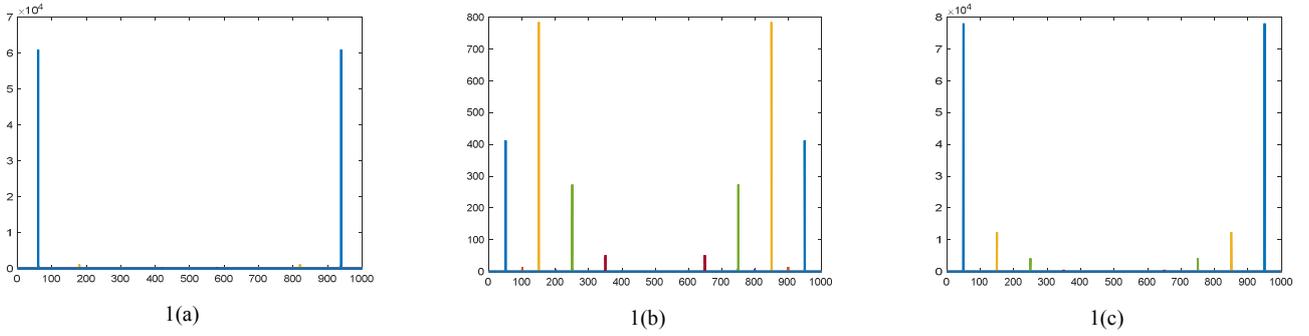


Fig. 1. Magnitude of the harmonic components of power recording from (a) Grid A, (b) Grid D, (c) Grid G.

III. FEATURE ANALYSIS

From the dissimilarities in the variations of the ENF signals, we can obtain meaningful statistical features for our classification system. We took a set of ENF signal segments of fixed sample size $S = 120$, we adopted all the 16 features included in the reference work and introduced 16 more features, all of which arise from the Fourier Transform profiles of the power recordings. An auto regressive (AR) statistical model was used similar to the one in [16]. To select the order of the AR model, the approximations to Schwarz's Bayesian Criterion and to the logarithm of Akaike's Final Prediction Error were computed [25, 26]. These computations revealed that a second order AR model is indeed the most optimized model for this dataset, thus corroborating the choice of AR model in the reference work.

TABLE II.
USED FEATURE SETS

| Feature Number | Feature sets | |
|----------------|--|---|
| 1 | Mean of the ENF segment | Feature used in the Reference Work [16] |
| 2 | Log (variance) of the ENF segment | |
| 3 | Log(range) of ENF segment | |
| 4 | Log(variance) of the approximation after F-level wavelet analysis (F=9) | |
| 5-13 | Log(variance) of nine levels of detail signals computed through F-level wavelet analysis from coarser to finer (F=9) | |
| 14-15 | AR(2) model parameters | |
| 16 | Log(variance) of the innovation signal after AR(2) modelling | Proposed Addition Features |
| 17-24 | Polynomial model parameter | |
| 25-32 | Normalized Amplitude of the Harmonic components | |

A. Fourier Transform Profile

Whenever a non-linear device or load is subjected to a source of sinusoidal voltage, the resulting current is not perfectly sinusoidal. Consequently, this gives rise to harmonics at the load terminals [27]. It was empirically evident from the dataset that the magnitude of the harmonic components of the power and audio recordings uniquely differs from one grid to another. The Fourier Transformed frequency domain data had significant variations in their magnitude at different harmonic frequencies in the recordings from one grid to another and showcased common patterns among same grid (Fig.1).

Even though there are specific guidelines to manage power quality criteria such as harmonics and inter-harmonics [28] and for particular equipment operating under the influence of harmonics [28, 29], individual nations makes their own regulations and adjustments to accommodate for their unique power consumption scenarios and national priorities, driven by unique qualities of their power system establishment and load management systems (e.g. the utilization of ripple control in some nations) [27]. The random difference of load and various harmonics control equipment at different grids and nations possibly give rise to the underlying statistical patterns in the harmonics of the clean power and audio recordings in a manner similar to that of the statistical patterns of the ENF. Recent research explores the possibility of recording devices affecting the quality of ENF and its harmonics embedded in the recording [30]. Further research is needed to fully identify the origins of the distinctions in the Fourier Transform profile and their similarity in the recordings within the same grid. To exploit this underlying property, the normalised magnitudes of the harmonic components of the ENF signal from the power data were extracted. These are directly obtained by applying the Discrete Fourier Transformation (DFT) on the time-domain 10 minute segment of power recordings $x(n)$, using the DFT of vector as following:

$$X(k) = \sum_{j=1}^n x(j) W_n^{(j-1)(k-1)} \quad (1)$$

Where $W_n = e^{(-2\pi i)/n}$ is one of n roots of unity, and k is the k^{th} frequency bin. The magnitudes of the eight ENF harmonic frequencies was then extracted from the frequency domain as an eight element vector data $H_m[n]$, where $m = 8$,

after bandpass filtering in the harmonic frequency ranges and searching for the maximum value.

A 7th degree polynomial model was fit over the normalized magnitudes of the harmonic components just extracted and the coefficients and the constant term of the fitted polynomial was used as distinguishing features termed as ‘Polynomial Model Parameters’ (features 17-24). The order of the polynomial was set on the basis of the number of data points that the polynomial fits on (8 element vector). Media recordings were sampled at 1000Hz. Therefore, any frequency component above 500Hz i.e. Nyquist frequency for this sampling rate will be aliased back to a frequency between 0 to 500Hz. This is evident from the Fig. 1 (b), where a total of 8 harmonics are visible in the 0 to 500Hz range. As we have grid frequencies of 50Hz and 60Hz only, we took the ENF harmonics of these two frequency components only in our estimation. The maximum possible harmonic component arising from a 50Hz or 60Hz are 8 harmonics (within the frequency components of 500Hz). Thus, 8 harmonic components result in 8 normalized magnitude points, which a 7-order polynomial fit perfectly traces. Moreover, each of the eight ‘Normalized magnitudes (amplitudes) of the harmonic components itself was also utilized as features (25-32). This is because, normalized amplitudes is a measure of the dominant frequency components and thus highlights the pattern of dominant components present among the Fourier Transform profile of the same grid. The complete feature set is listed in Table II. The features are added sequentially and their impact on classification efficiency are summarized in Table III.

TABLE III.
CHANGE IN EFFICIENCY OF CROSS VALIDATION FOR
FEATURE SETS INCLUSION.
FEATURES ARE ADDED CUMULATIVELY TO THE SYSTEM.

| Feature no. | Feature inclusions | Efficiency (Power File) |
|-------------|--|----------------------------|
| 1-16 | Original 16 Features | 88.86% |
| 17-24 | Polynomial model parameter | 93.77% |
| 25-32 | Normalized Amplitude of the Harmonic components | 97.61% |

B. Multiclass SVM Classification Learner

During the training phase of our Classification System we resorted to store the normalization parameters, and utilized them later for the normalization of the testing files. We employed a similar technique to the one utilized in the reference work. In this work, the ECOC multiclass model for the multiclass classification was implemented, using binary learners of support vector machine (SVM) on the MATLAB platform [31-34]. A recent work indeed suggests that SVM is a good choice of classifier for ENF classification [35]. The ECOC model reduces the multiclass problem of more than three classes to a set of binary classifiers. This requires a coding design, which determines the classes on which the

binary learners train on, and a uses a decoding scheme, which determines how the predictions or the results are aggregated. In the scenario of a three class system, for example, with a one-vs-one coding design, as well as a decoding scheme and the SVM learners, the ECOC model builds the classification model following the next steps [32-34, 36]. In Table IV, Learner 1 trains on the examples given from class 1 and class 2, and treats class 1 as the positive class and class 2 as the negative class. The rest of the learners are trained in a similar method.

Let M be the coding design matrix with elements $m_{\psi l}$, g be the loss of the decoding scheme, and s_l be the predicted classification score for the positive class of learner l . A new observation is assigned to the class ψ which minimizes the aggregation of the losses for the L binary learners as

$$\psi = \underset{\psi}{\operatorname{argmin}} \frac{\sum_{l=1}^L |m_{\psi l}| g(m_{\psi l} s_l)}{\sum_{l=1}^L |m_{\psi l}|} \quad (2)$$

So for a total of M classes, the system trains ${}^M C_2$ binary classifiers, where each binary classifier is trained on one of the ${}^M C_2$ possible pairs of classes and learns to differentiate between those two respective classes. Moreover, the ECOC implementation provides M probability or confidence values, for testing an example data, where the j^{th} probability value represents the confidence that the testing example belongs to the j^{th} class.

The multiclass classifier in our implementation used a Gaussian Radial Basis kernel function with the utilization of the automatic kernel scaling feature. MATLAB uses a heuristic method using subsampling to determine the scale value, when the kernel scale mode set to ‘Auto’. The MATLAB’s ECOC multiclass system used in this work and the LIBSVM used in the reference work, both employs a one vs one multiclass model, weighted SVM and performs similarly. [32, 33, 37]. Both sets of features, from the reference work and our implementation were used in this same classifier while training the system for comparison.

TABLE IV.
ONE VS ONE CODING DESIGN

| | Learner 1 | Learner 2 | Learner 3 |
|---------|-----------|-----------|-----------|
| Class 1 | 1 | 1 | 0 |
| Class 2 | -1 | 0 | 1 |
| Class 3 | 0 | -1 | -1 |

TABLE V.
CONFUSION MATRIX OF POWER RECORDINGS THROUGH CROSS-VALIDATION

| 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 | Grid M |
|------------------|-----------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| (A) Texas | 54 | 94.45 | - | 1.85 | - | - | - | - | - | 3.7 | - | - | - | - |
| (B) Lebanon | 56 | - | 100 | - | - | - | - | - | - | - | - | - | - | - |
| (C) Eastern U.S | 66 | 1.52 | - | 93.94 | - | - | - | - | - | 3.02 | 1.52 | - | - | - |
| (D) Turkey | 63 | - | - | - | 100 | - | - | - | - | - | - | - | - | - |
| (E) Ireland | 66 | - | - | - | 3.03 | 95.45 | 1.52 | - | - | - | - | - | - | - |
| (F) France | 42 | - | - | - | 4.76 | 2.38 | 90.48 | 2.38 | - | - | - | - | - | - |
| (G) Tenerife | 62 | - | - | - | 1.61 | - | - | 98.39 | - | - | - | - | - | - |
| (H) India (Agra) | 61 | - | - | - | - | - | - | - | 100 | - | - | - | - | - |
| (I) Western U.S | 65 | 1.54 | - | - | - | - | - | - | - | 98.46 | - | - | - | - |
| (J) Brazil | 42 | - | - | - | - | - | - | - | - | - | 100 | - | - | - |
| (K) Norway | 72 | - | - | - | - | - | - | - | - | - | - | 98.61 | 1.39 | - |
| (L) Australia | 45 | - | - | - | - | - | - | - | - | - | - | - | 100 | - |

IV. RESULTS

In this section, we present the results obtained from our analysis. Each of the proposed features affects the ability of the learning system to detect a region of origin of the multimedia file.

A. Comparative Analysis of Classification Accuracy using Cross-Validation

For calculation of efficiency of classification during cross-validation, MATLAB- Machine Learning and Statistics Toolbox functions were used. The cross-validation scheme selects a number of folds (or divisions) to partition the data into. Each fold is held out in turn for testing. MATLAB subsequently trains a model for each fold using all the data outside of that fold. We tested each model performance using the data inside the fold, then calculated the average test error over all folds. This method gives a good estimate of predictive accuracy of the final model trained with all the data present in the whole training dataset.

For the classification system trained on power recording we achieved an accuracy of 97.61% with a 20-fold Cross-Validation scheme selecting all the features (1-32) from Table II. Changes in efficiency with feature inclusion is shown in Table III.

Using the extraction code and proposed features of the reference work [16] in our dataset, we get cross-validation accuracy of 88.86% on power files. Classification accuracy of power files rose from 88.86% to 93.77% after the inclusion of features (17-24). Further addition of the Normalized Amplitude of Harmonic Components (25-32) features boost the efficiency to 97.61%. Due to the unavailability of enough audio recordings to solely train our classifier, we did not resort to the same comparative analysis of cross-validation on audio files. In Table III, the identification accuracy using only the original 16 features presented in [16] and with addition of our proposed features on top of the original features, is presented.

The detailed description of grid identification accuracy while using feature the complete feature set (1-32), has been illustrated in the confusion matrix in Table V.

V. CONCLUSION

In this work, we implemented a machine learning system to identify the Grids of origin of media files and explored some novel features that aids the ability of the machine learning system to identify the grids of origin. The ENF signals of different grids exhibit different statistical characteristics. We performed a comparative analysis with a previous work and increased the cross-validation identification accuracy of power recordings from 88.86% to 97.61%. We demonstrated that features extracted from the Fourier Transform Profile can act as a significant catalyst for boosting up the identification efficiency. In future, we will study the effect of the proposed features in audio recordings, which will require a large scale audio data collection from different countries. Since systems trained on power recordings are vital for audio classification, we believe our proposed features will enhance audio classification accuracy as well. Furthermore, we believe that exploring the effects of various classifiers such as random forests, neural networks, k-nearest neighbours etc. in our implementation and comparing their effectiveness in achieving higher classification efficiency, will provide us with newer insights.

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