Modeling and Analysis of Electric Network Frequency Signal for Timestamp Verification

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***Abstract*—Electric Network Frequency (ENF) fluctuations based forensic analysis is recently proposed for time-of-recording estimation, timestamp verification, and clip insertion/deletion forgery detection in multimedia recordings. Due to the load control mechanism of the electric grid, ENF fluctuations exhibit pseudo-periodic behavior and generally require a long duration of recording for forensic analysis. In this paper, a statistical study of the ENF signal is conducted to model it using an autoregressive process. The proposed model is used to understand the effect of the ENF signal duration and signal-to-noise ratio on the detection performance of a timestamp verification system under a hypothesis detection framework. Based on the proposed model, a decorrelation based approach is studied to match the ENF signals for timestamp verification. The proposed approach requires a shorter duration of the ENF signal to achieve the same detection performance as without decorrelation. Experiments are conducted on audio data to demonstrate an improvement in the detection performance of the proposed approach.**

***Index Terms*—Electrical Network Frequency, Audio Authentication, Timestamp, Information Forensics.**

I. Introduction

In the modern era, a huge amount of digital information is available in the form of audio, image, video, and other sensor recordings. These recordings are generally stored on disks and other storage devices, and have metadata describing such important information as the time and the place of recording. However, digital tools can be used to modify the stored information. Developing forensic tools to authenticate multimedia recordings is an active area of research. In the recent years, Electric Network Frequency (ENF) signal based forensics techniques are increasingly being used to authenticate digital recordings [1] [2]. ENF is the supply frequency of electric power in distribution networks of a power grid. The nominal value of the ENF is 60 Hz in the United States and most parts of the Americas, and 50 Hz in Europe and Asia. An important characteristic of the ENF is that its value fluctuates around the nominal value because of varying loads on power grid [1]. These fluctuations are consistent across the geographical area covered in the same power grid [1] [3].

ENF signal is embedded in the digital audio recording made near the power sources because of the interference from electromagnetic fields generated by the power sources. Digital video recordings in an indoor fluorescent or incandescent lighting conditions can capture the ENF signal from near invisible flickering of the light sources [2]. This intrinsic embedding of the ENF signal in multimedia recordings has been used for such forensic applications as time-of-recording estimation and clip insertion/deletion forgery detection [1] [2]. Furthermore, our previous work [2] demonstrated the application of the ENF signal analysis to determine if the audio track in a given video was recorded with the visual data or superimposed later.

The methodology used in ENF signal analysis for time-of-recording estimation requires extraction of the ENF signal from a given audio or video by means of a temporal bandpass filtering followed by instantaneous frequency estimation as a function of time. These estimated frequencies are compared with a ENF signal database that contains historic ENF readings. The time corresponding to the maximum similarity between the ENF signal from multimedia and the ENF signal from the database is taken as the estimated time-of-recording of the given multimedia.

The current techniques in the literature for the ENF signal analysis typically require a long duration of multimedia recording to measure the similarity between the extracted ENF signal with the ENF database as ENF patterns may exhibit self-similarity over time. This pseudo periodic nature of ENF patterns is due to the cyclic nature of power demand and supply, and the control mechanism used to regulate power grids [4]. An increase in the load on a grid causes the supply frequency to drop temporarily; the control mechanism senses the frequency drop and additional power is drawn from adjoining areas to compensate for the increased demand. As a result, the load in adjoining areas also increases, and supply frequency drops. A similar mechanism is used to compensate for an excess supply that results in a surge in supply frequency. In the forensic applications of the ENF analysis, the effect of such pseudo periodic patterns is reduced if multimedia signal is of sufficiently long duration, typically 10-15 minutes [5]. Developing tools to authenticate relatively short recordings will help in enhancing the benefit and impact of the ENF based forensic techniques.

In this paper, we carry out a statistical study of the ENF signal and model it using an autoregressive process. This modeling helps us decompose the ENF signal into two components: a *predictive* process and an *innovation* process. We then use this proposed model to examine the performance under a simple binary hypothesis detection framework and to understand the effect of clip duration on ENF matching. The application scenario considered here is timestamp verification, where the authenticity of the attached timestamp in the metadata of a given recording needs to be verified. We propose the use of decorrelated *innovation* process for ENF matching, and experimentally validate the proposed approach using a

25-hours audio data. To the best of our knowledge, this is the first step in the literature towards addressing the statistical analysis and improved matching techniques of ENF signals. The proposed innovation process based matching may also be beneficial for a forensic examiner analyzing a possible forgery on ENF signals for different counter forensic scenarios [6].

The rest of this paper is organized as follows. In Section II, we describe an autoregressive model used to analyze the ENF signal. In Section III, we formulate the timestamp verification problem under a binary hypothesis testing framework and propose a decorrelation based approach to improve the detection performance of the system. In Section IV, we carry out experiments on audio data to study the performance of timestamp verification under the proposed model and using the decorrelation based approach for ENF matching. Section V concludes the paper.

II. Autoregressive (AR) Model for ENF

Autoregressive (AR) model is a common way of analyzing a correlated time series. An AR process is a regression of the current value of a time series based on the previous observed values. A time-series $u(n), u(n-1), \dots, u(n-M)$ represents realization of a real AR process of order M, denoted by AR(M), if it satisfies the following difference equation:

$$u(n) + a_1 u(n-1) + \dots + a_M u(n-M) = v(n), \qquad (1)$$

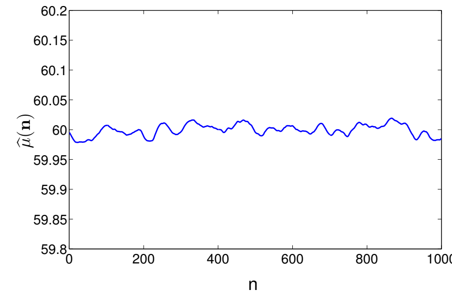
where $a_1, a_2, \dots, a_M$ are the constants representing a stable filter, and known as the AR coefficients, and $v(n)$ is a white noise process and uncorrelated with $u(n-1), u(n-2), \dots, u(n-M)$. The process $v(n)$ brings randomness to $u(n)$ and is known as an *innovation* process. In terms of linear filtering, an AR(M) can be generated by feeding $v(n)$ as an input to an all pole filter whose z-transform is given by $A(z) = \frac{1}{1-\sum_{m=1}^{M} a_m z^{-m}}$. Additionally, if $v(n)$ is a zero-mean Gaussian process of power σ_v^2, the output process $u(n)$ is also a zero-mean Gaussian wide sense stationary (WSS) process, and its power spectral density is a function of the filter parameters $a_1, a_2, \dots, a_M$, and σ_v^2. Given such a process $u(n)$, an estimate of the model coefficients and statistics of $v(n)$ can be obtained by solving a set of linear equations, known as the Yule-Walker equations. For detailed discussions on AR processes, readers are referred to [7].

A. *Statistics of ENF signal*

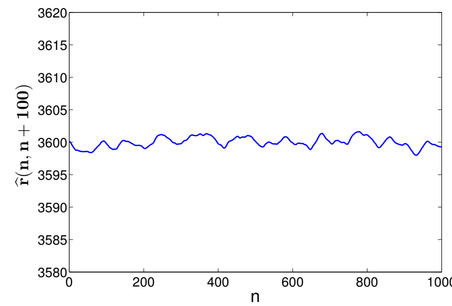
Let $f(n)$ denote ENF signal at any time n, and let $\underline{\mathbf{F}}(n) = [f(n), f(n+1), \dots, f(n+N-1)]^T$ represent a vector of N consecutive values of ENF at a given time instant n. The mean function $\hat{\mu}(n)$ and the auto-correlation function $\hat{r}(n, n+k)$ of ENF signal from a frame of N samples are estimated as follows:

$$\hat{\mu}(n) = \frac{1}{N}\sum_{l=0}^{N-1} f(n+l)$$

$$\hat{r}(n, n+k) = \frac{1}{N}\sum_{l=0}^{N-1} [f(n+l)][f(n+l+k)]$$



(a) Mean function $\hat{\mu}$(n)



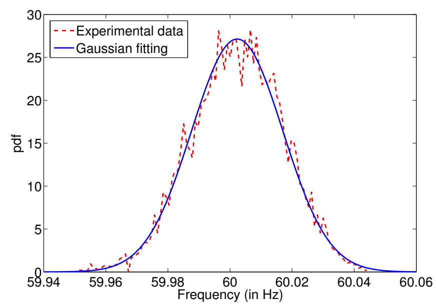
(b) Autocorrelation function $\hat{r}(n, n+100)$

Fig. 1. The mean and the autocorrelation function of a ENF signal recording.

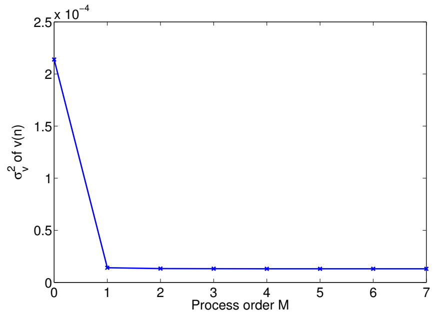
We record a ENF signal in the United States from the power-mains supply and estimate its instantaneous frequency, for example, using the weighted energy spectrogram method described in [2] [8]. We obtain an estimate of the instantaneous frequency every 16 seconds.

The plots of $\widehat{\mu}(n)$ and $\widehat{r}(n, n+100)$ for $N = 32$ (equivalently 512-seconds) and for different values of n are shown in Fig. 1. From these figures, we observe that value of the mean function $\widehat{\mu}(n)$ is very close to 60Hz. We also observe that the autocorrelation function is approximately independent of n for $k = 100$. Similar plots are obtained for different values of k. These results indicate that ENF signal exhibits some characteristics approximating a WSS process. More generally, if accounting for small variations in the autocorrelation function for different values of n, ENF signal can be approximated as a piecewise WSS in small segments. Furthermore, the probability density function (pdf) of $f(n)$ follows a Gaussian distribution as shown in Fig. 2(a) for a 25-hours long ENF signal recording from the power supply. Based on these observations, we model the ENF signal $f(n)$ as a Gaussian process that is piecewise WSS with mean value 60 Hz. To make it a zero-mean process, we subtract the nominal value of 60 Hz from the ENF signal. In our subsequent discussions, $f(n)$ is assumed to be a zero-mean process.

The resulting zero-mean $f(n)$ in a ENF segment $\underline{\mathbf{F}}(n)$ is then modeled as the output of a linear filter whose transfer function is given by $A(z)$, and a zero-mean white noise process $v(n)$ is fed as an input to it. The value of filter coefficients may be different for each segment of the ENF signal as $f(n)$ is assumed to be piecewise stationary. Since the model order



(a) pdf $f(n)$



(b) σ_v^2 for different M

Fig. 2. Histogram of $f(n)$ and power spectral density of $v(n)$ for a 25-hours long power-ENF recording.

of the ENF process is not known a priori, we estimate the order as the value of M that will minimize the estimated value of the power spectral density of the corresponding *innovation* process $v(n)$. The plot of the estimated σ_v^2 for different order M is shown in Fig. 2(b). From this figure, we observe that $M = 1$ achieves a low value of σ_v^2, and the variance stays approximately constant as we increase the order M. Based on these observations, we model the ENF signal $f(n)$ in a segment $\underline{\mathbf{F}}(n)$ as a simple first-order AR process as follows:

$$f(n) = a_1 f(n-1) + v(n) \tag{2}$$

Since $f(n)$ is a piecewise WSS, the value of a_1 may be different for each segment. The auto-correlation matrix of a N-point process $\underline{\mathbf{F}}(n)$ is calculated as $\mathbf{R} = E[\underline{\mathbf{F}}(n)\underline{\mathbf{F}}(n)^T]$, with $(i,j)^{th}$ entries of $\mathbf{R}$ denoted by $r(i-j)$. The value of $r(i-j)$ will be different for each segment as it is dependent on a_1 of each segment. Under this model, $\underline{\mathbf{F}}(n)$ follows a Gaussian distribution given by $\mathcal{N}(\underline{\mathbf{0}}, \mathbf{R})$. Based on this proposed model, next we define a timestamp verification problem and formulate it using a hypothesis testing framework.

III. Timestamp Verification as Hypothesis Testing

A hypothesis testing framework is widely used to model identification and classification problems in statistical detection. We use this framework to study the performance of timestamp verification using ENF signal. In timestamp verification, each query multimedia file Z is assumed to contain an embedded timestamp in the metadata denoted by n, representing the time-of-recording claimed in the file. We want to verify the authenticity of this timestamp, i.e, to determine if the recording actually took place at time n. We extract ENF signal from query Z using a bandpass filter followed by an instantaneous frequency estimation method, and denote it by $\underline{\mathbf{W}} = [w(0), w(1), \ldots, w(N-1)]^T$, where N is the length of the ENF signal $\underline{\mathbf{W}}$ extracted from the file.

A. Matching using ENF sequences

We start with a highly simplified model to help gain insights on the ENF matching problem while retaining analytical tractability. Let us denote an N-point reference ENF signal at time instant n as $\underline{\mathbf{F}}(n)$, which is stored in a database available to the detector. This database serves as a reference for the timestamp verification. Such ENF database can be built by a continuous recording of the voltage signal from the power mains supply, and extracting ENF signal using the instantaneous frequency estimation methods, as described in [2] [8]. Alternatively, the database can also be obtained directly from the power distribution companies as they generally keep a record of ENF signal [1].

As the sensitivity of different multimedia recording devices may be different and there may be interfering signals in the frequency band around the nominal ENF value, distortion may be introduced in ENF signal embedded in query Z. Based on such observations, $\underline{\mathbf{W}}$ can be assumed to be a distorted version of $\underline{\mathbf{F}}(\cdot)$ corresponding to the actual time-of-recording. We model this distortion using an additive white Gaussian noise vector $\underline{\mathbf{C}}(n) = [c(n), c(n+1), \ldots, c(n+N-1)]^T$ with distribution $\mathcal{N}(\underline{\mathbf{0}}, \sigma_c^2\mathbf{I})$, where $\mathbf{I}$ denotes a $N \times N$ identity matrix.

Under the settings described above, we model the ENF signal based timestamp verification as a binary hypothesis testing problem. We define two hypotheses, H_0 and H_1, as follows:

$$\begin{aligned} H_0 : \underline{\mathbf{W}} &= \underline{\mathbf{G}}(n) + \underline{\mathbf{C}}(n) \\ H_1 : \underline{\mathbf{W}} &= \underline{\mathbf{F}}(n) + \underline{\mathbf{C}}(n) \end{aligned}$$

Under the null hypothesis, the ENF signal $\underline{\mathbf{W}}$ is a sample from $\underline{\mathbf{G}}(n)$, which has the distribution of ENF database. We model the conditional distribution of $\underline{\mathbf{G}}(n)$ for a given a_1 as $\mathcal{N}(\underline{\mathbf{0}}, \mathbf{R})$, and $\underline{\mathbf{G}}(n)$ is assumed to be uncorrelated with $\underline{\mathbf{C}}(n)$. Since, a_1 also follows a distribution in a given long duration ENF signal, H_0 can be considered as a composite hypothesis parameterized on a_1. Under hypothesis H_1, ENF signal $\underline{\mathbf{W}}$ is the distorted version of the actual ENF signal $\underline{\mathbf{F}}(n)$ stored in the database corresponding to timestamp n.

A correlation based detector is used to measure the similarity between $\underline{\mathbf{W}}$ and $\underline{\mathbf{F}}(n)$ as follows:

$$\rho = \frac{1}{N} \frac{\underline{\mathbf{W}}^T\, \underline{\mathbf{F}}(n)}{\sqrt{\sigma_w^2}\sqrt{\sigma_f^2}} \tag{3}$$

where σ_w^2 and σ_f^2 are the variances of a component in $\underline{\mathbf{W}}$ and $\underline{\mathbf{F}}(n)$, respectively. Since the distribution of $\underline{\mathbf{W}}$ and $\underline{\mathbf{F}}(n)$ are Gaussian, ρ follows a Gaussian distribution. In practice, the value of ρ is obtained by using estimated values of σ_w^2 and σ_f^2 in the denominator of Eq. (3). The estimated values of σ_w^2 and σ_f^2 is computed as $\hat{\sigma}_w^2 = \frac{1}{N}\sum_{k=0}^{N-1} w(k)^2$ and $\hat{\sigma}_f^2 =$

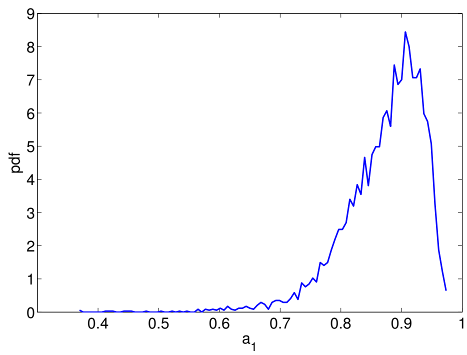


Fig. 3. pdf of a_1 from power data for $N = 32$.

$\frac{1}{N}\sum_{k=0}^{N-1} f(n+k)^2$, respectively. Because of the estimates are in themselves random variables as opposed to constants, the distribution of ρ may deviate from a Gaussian distribution. Such Transform techniques as a Fisher transformation [9] can be applied on the sample correlation coefficient ρ to make the resulting transformed distribution more Gaussian. In addition, this correlation based detector is not optimal under the assumed distributions for commonly used detection criteria, but is used here for a simplified analysis. A generalized likelihood ratio test [10] can be designed for optimal detection, but the subsequent analysis becomes too complex, and will ne considered in our future work.

Under the described framework, the detector decides the authenticity of intrinsically embedded timestamp in the given query Z by comparing the value of ρ with a pre-defined constant τ:

$$\delta_D(\rho) = \begin{cases} 1 & H_1 \text{ is declared if } \rho > \tau, \\ 0 & H_0 \text{ is declared if } \rho \leq \tau \end{cases} \tag{4}$$

The performance of the timestamp verification under our model can be evaluated using the false alarm probability, P_f, and the detection probability, P_d, defined as:

$$P_f = Pr(\delta_D = 1|H_0) \tag{5}$$
$$P_d = Pr(\delta_D = 1|H_1) \tag{6}$$

Where $Pr(\cdot)$ denotes the probability of the given event. The value of τ presents a trade-off between P_f and P_d. For a practical system, the value of τ should be chosen such that P_f is low and P_d is high.

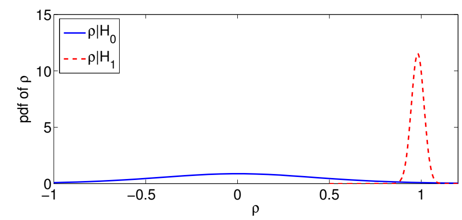
The expression for P_f and P_d can be obtained based on the following expressions for the detection statistics ρ:

$$\rho|H_0, a_1 \sim \mathcal{N}\left(0, \frac{1}{N} + A - B\right) \triangleq \mathcal{N}\left(\mu_{H0}, \sigma_{H0}^2\right) \tag{7}$$

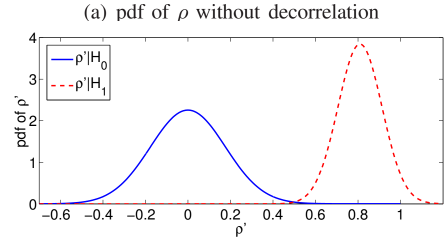
$$\rho|H_1 \sim \mathcal{N}\left(\frac{1}{\sqrt{1+\frac{1}{SNR}}}, \frac{1}{N}\left(\frac{1}{1+SNR}\right)\right) \triangleq \mathcal{N}\left(\mu_{H1}, \sigma_{H1}^2\right), \tag{8}$$

where $A = \frac{2SNR}{1+SNR}\frac{N-1}{N^2}\frac{a_1^2}{1-a_1^2}$ and $B = \frac{2SNR}{1+SNR}\frac{a_!^4(1-(a_1^2)^{N-1})}{N^2(1-a_1^2)^2}$. $SNR = \frac{r(0)}{\sigma_c^2}$ represents a measure of signal-to-noise ratio of ENF signal from multimedia. Detailed derivations of Eq. (7) and Eq. (8) are skipped in this paper due to space limit. The distribution of $\rho|H_0$ can then be estimated numerically after the distribution of a_1 is obtained from the power-ENF data. A plot of the distribution of a_1 for $N = 32$ from our power data collection is shown in Fig. 3. From this figure, we observe that the AR coefficient value of the process $f(n)$ has a high density around 0.9. Smaller deviations around that value indicates that process $f(n)$ approximately behaves as a WSS, and can be better modeled as a piecewise WSS process.

The plot of the pdf of ρ for N=32 and $SNR = 14.6$dB is shown in Fig. 4(a). The chosen values of SNR is based on the ENF signal extracted from our audio data and power data collection. The distribution of a_1 is computed directly from the power-ENF data. From Fig. 4(a), we observe that the distribution of ρ under H_0 and H_1 partially overlap and this will cause errors in detection.



(a) pdf of ρ without decorrelation



(b) pdf of ρ' from innovation processes

Fig. 4. pdf of ρ and ρ' under H_0 and H_1.

Under the detection statistics given by Eq. (7) and Eq. (8), the expressions for P_f and P_d can be obtained analytically by evaluating the following ezpressions:

$$P_f = Pr(\rho > \tau|H_0) \tag{9}$$
$$P_d = Pr(\rho > \tau|H_1) \tag{10}$$

B. *Matching using* Innovation *Process*

In Section III-A, we have formulated the problem of ENF signal based timestamp verification as a binary hypothesis testing problem. We have observed that the distribution of the detection hypothesis ρ under H_0 and H_1 shows a significant amount of overlap. A major contributor to this overlap is the correlation within an ENF signal over time, as evident from the autoregressive model of ENF signal described in Section II. Such correlation may lead to local peaks in the value of ρ at time shifts other than the true match and in turn a high false alarm probability. To improve the detection performance, we propose to use samples from the *innovation* process $\underline{\mathbf{V}}(n) = [v(n), v(n+1), \ldots, v(n+N-1)]^T$ for matching.

Using ENF signal model from Section II, the process $\underline{\mathbf{V}}(n)$ can be obtained after decorrelating the ENF signal $\underline{\mathbf{F}}(n)$ at time n by filtering it through a filter $H(z) = \frac{1}{A(z)} = 1 - a_1 z^{-1}$. The filter coefficient a_1 can be estimated using the Yule-Walker equations applied to the ENF data $\underline{\mathbf{F}}(n)$ at time n. Since $v(n)$ is an i.i.d. sequence for an AR process, such a methodology addresses the false alarm probability described above and thus provide an improvement in the detection performance.

By passing $\underline{\mathbf{W}}$ through the estimated filter $H(z)$, we obtain the corresponding query innovation process and denote it by $\underline{\mathbf{W}}_d = [w_d(0), w_d(1), \ldots, w_d(N-1)]^T$. Under this setting, for an embedded timestamp n in the given query Z, we use $\underline{\mathbf{W}}_d$ and $\underline{\mathbf{V}}(n)$ for hypothesis testing. The two hypotheses now become:

$$\begin{aligned} H_0 : \underline{\mathbf{W}}_d &= \underline{\mathbf{U}}(n) + \underline{\mathbf{D}}(n) \\ H_1 : \underline{\mathbf{W}}_d &= \underline{\mathbf{V}}(n) + \underline{\mathbf{D}}(n) \end{aligned}$$

where $\underline{\mathbf{D}}(n) = [d(n), d(n+1), \ldots, d(n+N-1)]^T$ is a vector of zero-mean colored Gaussian noise process, with its components given by $d(n) = c(n) - a_1 c(n-1)$, where a_1 is the AR coefficient for the corresponding segment. The power of the noise process $d(n)$ is denoted by σ_d^2. Under the null hypothesis, $\underline{\mathbf{W}}_d$ is a sample from $\underline{\mathbf{U}}(n)$. The distribution of the innovation sequences from ENF database, $\underline{\mathbf{U}}(n)$, can be modeled as $\mathcal{N}(\underline{\mathbf{0}}, \sigma_v^2 \mathbf{I})$ using a similar analysis to the modeling of $\underline{\mathbf{G}}(n)$ in Section III-A. To measure the similarity between $\underline{\mathbf{W}}_d$ and $\underline{\mathbf{V}}(n)$, we define a correlation based metric similar to Eq. (3) as follows:

$$\rho' = \frac{1}{N} \frac{\underline{\mathbf{W_d}}^T \, \underline{\mathbf{V}}(n)}{\sqrt{\sigma_{wd}^2}\sqrt{\sigma_v^2}} \tag{11}$$

where σ_{wd}^2 and σ_v^2 are the variances of components in $\underline{\mathbf{W}}_d$ and $\underline{\mathbf{V}}(n)$, respectively. In practice, the value of ρ' is obtained by using estimated values of σ_{wd}^2 and σ_v^2 in the denominator of Eq. (11). The estimated values of σ_{wd}^2 and σ_v^2 is computed as $\hat{\sigma}_{wd}^2 = \frac{1}{N}\sum_{k=0}^{N-1} w_d^2(k)$ and $\widehat{\sigma}_v^2 = \frac{1}{N}\sum_{k=0}^{N-1} v^2(n+k)$, respectively. The covariance matrix of the process $\underline{\mathbf{D}}(n)$ is not diagonal due to colored noise. However, under sufficiently high signal-to-noise ratio, the non-diagonal entries in the covariance matrix of $\underline{\mathbf{D}}(n)$ can be ignored to obtain a good approximation of the density of ρ', while keeping tractability of the solution. Under this assumption, the distribution of the detection statistics ρ' under H_0 and H_1 can be approximated as follows:

$$\rho' | H_0 \sim \mathcal{N}\left(0, \frac{1}{N}\right) \tag{12}$$

$$\rho' | H_1 \sim \mathcal{N}\left(\frac{1}{1 + \sqrt{\frac{1}{SNR'}}}, \frac{1}{N}\left(\frac{1}{1 + SNR'}\right)\right) \tag{13}$$

where SNR' is defined as $\frac{\sigma_v^2}{\sigma_d^2}$. Note that the value of SNR' is significantly lower than that of SNR, as filtering $\underline{\mathbf{W}}$ using the filter $1 - a_1 z^{-1}$ leads to an increase in the noise power σ_d^2 of the resulting signal $\underline{\mathbf{W}}_d$. As will be discussed in Section IV, even under this reduced signal-to-noise ratio, the detection performance of timestamp verification is improved by matching using *innovation* sequences. The plot of the pdf of ρ' under these hypotheses for the same parameters as used in Section III-A is shown in Fig. 4(b). Comparing this plot with Fig. 4(a), we observe that the overlap between the pdf of H_0 and H_1 is reduced, and as a result, the proposed matching using innovation process will have a better detection performance than matching ENF sequences directly.

The detector determines the authenticity of the embedded timestamp in a query file Z using the same decision rule in Eq. (4). The expressions for P_f and P_d can be calculated in a similar way.

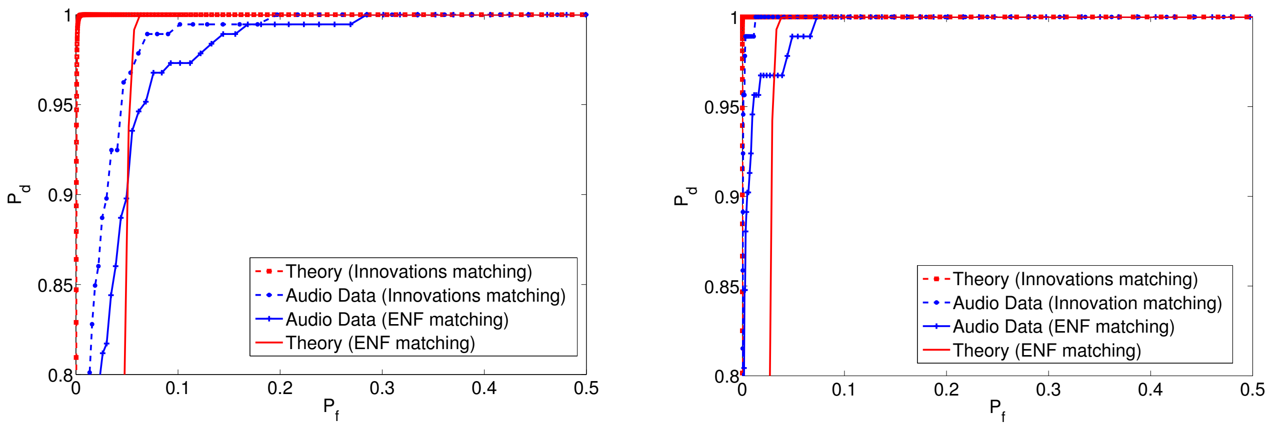
IV. Results and Discussions

A. Experimental Setup

In this section, we describe the experiments conducted on audio signal to measure the detection performance of timestamp verification under the proposed framework. We record a 25-hour long audio signal using a microphone at a sampling rate of 1KHz. We divide the recorded signal into segments of 256-seconds and 512-seconds. The beginning time index is stored in metadata as the time-of-recording for each segment. Instantaneous frequency is estimated at every 16-seconds of recording data using the weighted energy spectrogram method described in [2]. ENF database is recorded in parallel from the power supply, and the same weighted energy spectrogram mechanism is used to estimate the ENF signal from this recording. An estimate of the signal-to-noise ratio SNR for audio-ENF signal is obtained by assuming the power-ENF signal as clean signal, and subtracting the audio-enf signal from the power signal to get an estimate of the noise power. The value of SNR from this dataset is obtained to be 14.6dB. Each audio file is given to the detector with each possible timestamp $m \neq n$ for false matching, and $m = n$ for correct matching. This setting gives us 350 and 175 correct matching samples for segment lengths of 256-seconds and 512-seconds, respectively.

B. Results

For our audio experimental data, we use an AR(1) model to estimate the filter parameter a_1 of $A(z)$ for the power-ENF signal $\underline{\mathbf{F}}(n)$ at time n using the Yule-Walker equations. The plot of the estimated pdf of a_1 obtained from different segments of power-ENF signal for query length 512-second is shown in Fig. 3. To obtain $\underline{\mathbf{V}}(n)$ and $\underline{\mathbf{W}}_d$, we filter the power-ENF signal $\underline{\mathbf{F}}(n)$ and the query audio-ENF signal $\underline{\mathbf{W}}$ by passing them through $H(z) = 1 - a_1 z^{-1}$, where a_1 is the AR coefficient obtained from $\underline{\mathbf{F}}(n)$. Using the settings described in Section IV-A, we conduct a timestamp verification operation by a direct ENF sequence matching and decorrelated *innovation* sequence matching, respectively. The ROC curve for the detectors described in Section III-A and Section III-B, when 256-second and 512-second long query is used for timestamp verification are shown in Fig. 5(a) and Fig. 5(b), respectively. From these figure, we observe that the performance of the detector on audio data is comparable to the



(a) 256-second segments

(b) 512-second segments

Fig. 5. ROC characteristics of the correlation detector for ENF matching v.s. innovations matching at two query segment length (best viewed in colors).

performance by our analytical model. We also observe that using the innovation sequences for matching is significantly better than using the ENF sequences directly. For example, the probability of detection increases from 90% to 97% for a false alarm rate of 5% for 256-second segments, when innovation sequences are used for matching in our experiments. Similarly for 512-second segments, the probability of detection increases from 90% to 98% for a false alarm rate of 1% when *innovation* sequences are used for matching. We also observe a significant improvement in the detection performance when the query clip duration is increased from 256-seconds to 512-seconds for both the cases when direct ENF sequence and the *innovation* sequences are used for matching.

In addition, from Fig. 5(a) and Fig. 5(b), we observe a slight mismatch between the performance of the analytical model and the experimental results. Such mismatch may be due to a simplified first order AR model and a simpler binary hypothesis detection framework used in this paper. In general, correlation between query ENF sequence and ENF database is also high for time index near the actual time-of-recording. A composite hypothesis taking such correlated structures near the time index corresponding to time-of-recording into account would be a more desirable choice to model H_0. In our ongoing work, we are exploring such a framework on composite hypothesis to get a better prediction of the detection performance. The current binary hypothesis framework can be considered as a first-step exploration on the problem of ENF modeling for timestamp verification. Although the simplified analytical model presented in this paper has a gap with the realistic characteristics as observed from our experiments especially for the case when ENF sequences are directly used for matching, it shows that an AR process based decorrelation provides improvement in the detection performance, and this improvement is consistently observed when applied to audio data. The performance of the proposed model match more closely with the audio experimental data as segment length increases.

V. Conclusion

In this paper, we proposed a simple autoregressive analytical model for the electrical network frequency signal. The proposed model was used to study the problem of timestamp verification under a hypothesis detection framework. The trends in the receiver operating characteristics of the analytical model for different segment size used for matching were similar to that obtained from the experimental data. Based on the proposed model, a decorrelation based *innovation* process matching approach was adopted to improve the performance of the timestamp verification under the proposed framework. The experimental results with audio data demonstrated an improvement in the detection performance from 90% to 98% for a false alarm probability of 1% for 512-second long query segment when decorrelated *innovation* sequences are used for matching as compared with direct matching of ENF sequences.

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