

AN EVALUATIVE ENF-BASED FRAMEWORK FOR FORENSIC AUTHENTICATION OF DIGITAL AUDIO RECORDINGS

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Abstract. The frequency of the power distribution network signal is randomly fluctuating over time around its nominal value. Under the Electric Network Frequency (ENF) Criterion, these fluctuations are a reliable timestamp for use in verifying or finding the time interval during which an audio recording was made. As a three-step authentication framework, the ENF Criterion includes the build of a reference database, the detection and recovery of the trace from analyzed audio as well as the matching of the trace against a reference. The methods described in literature for trace extraction and matching work well in uniform noise conditions, but perform poorly with variable ENF trace quality. Such difficulty often appears with forensic speech recordings, in which the superposition of the trace with variable signal components is hard to avoid. The paper contributes to stages two and three of ENF Criterion, through adapted extraction and matching methods which work in both variable and stationary signal quality conditions, while reporting the match in an evaluative fashion.

Key words: electric network frequency, digital audio authentication, relevance matching.

1. INTRODUCTION

In the XXI-th century, the power distribution networks are ubiquitous, and a growing proportion of personal and household appliances need electric energy to work. From either rechargeable batteries or electric network adapters, the energy they use rely on a local area power network which in turn may be connected to a national coverage power distribution network, usually called *grid*. When used in isolation, the frequency of the local electric networks may not be synchronous to the national grid. Variations of the network frequency arise mainly because of the variable balance between the total generated power and the total power consumption. In order to maximize the reliability and availability of the power supply, the European Network of Transmission System Operators for Electricity (ENTSO-E) was built by network operators from 34 countries to run a common energy market.

The planning of energy market uses time divisions such as one hour or a quarter of an hour. For each time division, the power production is set up according to the power requests, and the network frequency is maintained the closest possible to the nominal network frequency, f_G . With constant load, the rotating parts of active generators accumulate a constant total kinetic energy that corresponds to a constant electric angular rotation speed and to the generation of a fixed frequency grid signal. In real networks, the load is variable for obvious reasons, and the temporary imbalance is reacted upon by the network control mechanisms, which are designed to maintain the grid standard parameters. According to [1], the difference between the available and requested power at time t determines the variation of the grid signal angular frequency, $\omega_G = 2\pi f_G$,

$$\frac{d\omega}{dt} = \frac{\omega_G}{2W_t} (P_g^t - P_c^t), \quad (1)$$

where ω is the angular frequency, ω_G its nominal value, W_t is the cumulative kinetic energy of generators active at time t , while P_g^t and P_c^t are the generated and consumed power, respectively. The generated

power is controlled in order to target the consumed power, leading to variations of the frequency as short jumps followed by exponential decays to the balance level. Since frequency errors of 150 mHz or more are critical to the system, the relevant bandwidth of ENF covers at least the interval from 49.7 Hz to 50.3 Hz.

Given the unpredictable way the small consumers connect to the grid and disconnect from it, as well as the variable load of major consumers, the network control is permanently required to generate power as balanced to the load as possible. While covering more than the surface of continental Europe, the synchronous common energy market implies that member networks share parameters such as the signal frequency and phase. This should be true all the time, but fast local network events make the local generators remain a little bit behind the changes, while still acting to achieve balance again. This allows reference databases recorded locally to capture signatures of the location if a fast pace collector is used.

Early research in the field, conducted by Grigoraş [2] has shown that the Electric Network Frequency (ENF) variations are highly random and slow variations in different areas of the network are correlated. Thus the stage was set for using the ENF variations as a timestamp, and use it in a powerful digital recording authentication tool, namely the ENF Criterion, provided a reliable ENF trace was detected in a questionable carrier file. The ENF traces that exist in the recorded material are detected and extracted for analysis. After the questioned ENF trace was found as possibly coming from the grid, through either acoustic or electromagnetic interference, it is recovered as a series of frequency samples. In turn, the sequence is compared to a ground truth reference, which may be obtained by logging the frequency variations over time, and storing the logs in a searchable structure such as an ENF reference database. Based on the similarity in shape between the trace sequence and a candidate reference sequence which covers the same duration, a match may be declared. In evaluative frameworks all possible interpretations of such similarity must be considered, not only that observed high similarity imply the reference occurred in the very timeframe during which the recording was made.

The rest of the paper is outlined as follows. In Chapter 2, the main papers and results in the field are briefly reviewed. Chapter 3 describes the baseline framework, the evaluation principle, and the proposed evaluative framework. Chapter 4 assesses the performance of proposed framework, while Chapter 5 accommodates the discussions and the conclusions of the research.

2. LITERATURE REVIEW

The ENF Criterion consists of three stages, namely the collection of the reference database, the detection and recovery of ENF sequences from trace carrier audio, and the matching of the trace against the reference. All three were tackled in a number of ways since the introduction of the criterion. The first stage is a long term task, as an ENF reference database is useful if it covers the last several years. Solutions must also be designed for efficient search of ENF sequences similar to a given pattern, such as the one in [3]. The second stage, by far the most complex and intriguing, is the detection and recovery of ENF traces, especially in low Signal-to-Noise Ratio (SNR) conditions. The third stage deals with verifying if the trace sequence matches the database at the alleged time of recording, or finding the unknown time the audio was recorded, and assessing the evidence. It should be pointed out that detection of the trace and the carrier file analysis for edit points are very important, and should be performed before the assessment of trace matching.

Besides the framework in [2], which we review in Chapter 3, another *de facto* standard ENF-based authentication framework was described in [4]. The reference database was built by locking a phase loop on the 100-th harmonic of the grid frequency, and taking the locked frequency, divided by 100. The ENF trace audio carrier signal was down sampled to 300 Hz, then band-pass filtered to the bandwidth of interest (49.5 Hz – 50.5 Hz). By finding the peak magnitude of the Fast Fourier Transform (FFT), followed by quadratic interpolation (QIFFT), a 1.5-second step sequence was obtained. Using analysis windows which overlapped 93%, and zero padding to 400%, a frequency resolution of 0.7 mHz was obtained. In the stage of ENF trace recovery, the robustness against noise was improved by a Threshold Dependent Median Filtering (TDMF), while the goodness of sequence matching was evaluated through the Minimum Square Error (MSE). The matching results were categorical, even for 2-minute long sequences. The quality limits of the input were not discussed, although the exclusive use of the third ENF harmonic was counter-recommended based on its assumed contamination by lower frequency speech components.

In [5], the matching stage was analyzed using clean signals for dating recordings shorter than 10 minutes. The Cross-correlation Coefficient (CC), was recommended as a shape similarity measure in such cases given that it was shown to outperform the MSE, motivated by its immunity against recorder frequency offset. The MSE distributions, computed between randomly chosen different sequences from reference were shown not to reach 0, but stay far enough for a safe non-match decision threshold.

The ENF trace was estimated in [6] using a Maximum Likelihood (ML) estimator, based on the periodogram of the signal, and a multi-tone signal model. A threshold was established, parameterized on Total Harmonic Distortion (THD), to decide whether the single-tone signal model would perform better than the multi-tone model. The precision of the estimator increases cubically with harmonic order. Reported performance was obtained on traces with medium to high SNR, sampled at 44.1 kHz, using 25 harmonics, and a FFT size of 2^{21} for each 2-second window. An evaluative framework was described for trace detection.

Instantaneous grid frequency was extracted in [11] and analyzed for edit detection over non-speech regions of speech recordings. A set of five assumptions were made, which made reported results possible.

The trace in [10] was preprocessed using signal sign, clipping and Chebyshev polynomials of the first kind, in order to reduce analysis window duration by estimating a higher order harmonic instead of the fundamental. The duration was reduced from the 25 s, necessary for a frequency resolution of 0.04 Hz, to an accepted value of 7.5 s, corresponding to the use of the third harmonic with the same frequency resolution. The input signal was generated using a chirp method, then the known frequency trajectory was compared to the one obtained by estimating the frequency each 0.25 s using a 25 s window analysis. The matching examples offered have shown preprocessing as having a good influence on matching. An ENF-based blind splicing detector was proposed, based on thresholding variations of the first derivative of the frequency. All 7680 splicing points were detected using the 5-th and 7-th harmonics.

An optimization of the system in [4] was described in [7], where the 7-th harmonic of ENF was identified as an optimum for both reference and trace ENF extraction. The analysis window was arguably set at 7.5 seconds, while claiming that increasing the database time resolution below a 15 seconds step is futile.

In [8] a 16-second-step sequence was modeled as an Auto Regressive (AR) process, which was then split by Linear Prediction (LP) in a predictive process and an innovation-based other. The sample correlation coefficient distributions for innovation-based process show good separation as compared to raw ones. The detection decision was based on a hypothesis testing framework, with the null hypothesis parameterized on the first LP coefficient, and a hard pre-defined threshold. Quality of input trace was not considered.

Currently, one important trend in audio forensics is the introduction of evaluative reporting paradigm, increasingly promoted by forensic bodies such as European Network of Forensic Science Institutes (ENFSI) [9], because such frameworks produce identification results accompanied by strength of the evidence.

3. BASELINE AND PROPOSED ENF-BASED AUTHENTICATION FRAMEWORKS

3.1. BASELINE ENF-BASED AUTHENTICATION FRAMEWORK

ENF literature and real-life carrier file databases are still scarce, so that direct comparisons are hardly possible between ENF-based frameworks. In order to compare the performance of our framework to the state-of-the-art, we implemented the three stages of the baseline authentication framework by following the guidelines described in literature. In doing so, we considered the framework described in [2]. Thus, from recordings made at 8 kHz sample rate, the extraction process, for both reference database building and trace recovery, starts with an anti-aliased decimation to 120 Hz followed by a band-pass filtering between 49.5 Hz and 50.5 Hz. The output of band-pass filter is fed to a 4096-point Hann-windowed FFT, 400% zero-padding, 88% overlapping, whose magnitude peak is obtained by quadratic interpolation (QIFFT).

In matching the recovered trace against the reference database, the CC and MSE are used as shape similarity indicators. For a given pair of trace and reference sequences sharing the same length and step size, either the reference is labeled as *match*, if the shape similarity of the trace to the reference reaches at least an empirical threshold, or the given reference sequence is classified as *non-match*. The evidence strength may have only one of the two extreme values, no matter which context the trace was obtained from. The value of empirical threshold, although not published in [2], was set according to [5], by finding minimum root mean squared (rms) differences between two randomly chosen non-matching ENF sequence of given length.

The best practice manual (BPM) of ENFSI on ENF-based authentication [9] outlines the three-stage structure of ENF Criterion and sets recommended parameter values for practical usage with ENF-based frameworks. We included all its provisions in our implementation of baseline framework. However, the BPM warns practitioners about precautions to be taken in order to successfully use the non-evaluative criterion, while in section 6.3 of the document a Bayesian approach was even called for.

There is no data to uphold categorical conclusions on ENF sequence matching. When a recovered ENF trace is compared to a reference sequence, a shape similarity measure is computed. Even if the computed similarity is very high, the occurrence of the same grid sequence at other time is still possible. Likewise, if the similarity is very low, this may have various causes besides the sequences non-match. During the forensic examination of questioned audio, one cannot deal with such uncertainty without assessing the strength of evidence. To date, the Bayesian reasoning under uncertainty is the most balanced and scientifically valid framework to use in forensic authentication of evidence. It presumes that uncertainty on a key issue in the case has been numerically expressed as probabilities under two mutually exclusive hypotheses, which are formulated so as to help in solving the issue at hand. In matching ENF sequences, we use the following hypotheses:

H_0 : “the trace sequence occurred at the same time as reference sequence;” and

H_1 : “the trace sequence *did not* occur at the same time as the reference sequence.”

The null hypothesis, H_0 , is tested using the theorem of Bayes, which states that the posterior *odds* of hypotheses in the light of new evidence, will be obtained by multiplying the *odds* based on prior knowledge with the Likelihood Ratio (LR) of newly seen evidence. While *odds* are the ratio of probability in favor of an event to probability against it, the theorem expression we use is,

$$\frac{P(H_0|E)}{P(H_1|E)} = \text{LR} \times \frac{P(H_0)}{P(H_1)}, \quad (2)$$

where $P(\cdot)$ denotes probability, while H_0 and H_1 are the competing hypotheses from casework. For simplicity, the prior knowledge was assumed as the most general knowledge base, and thus it was omitted.

The choice of “likelihood” as the name of the parameter is explained as follows. If A is invariant, the notation $P(X|A)$ denotes a *conditional probability of X, given that A has occurred*. For a known X , instead, the same notation denotes the *likelihood that X has occurred, given the variable conditional event, A*.

Values of LR greater than 1 support hypothesis H_0 , while values lower than 1 support the hypothesis H_1 . While values of LR supporting one hypothesis and values supporting the other span very different domains, the lending of fractional support to a hypothesis may appear counterintuitive. Based on LR being computed from positive numbers, this is usually clarified by passing the likelihoods through a logarithm of a usual base, so that the newly obtained measure is called “the Log-Likelihood Ratio (LLR).” In interpreting the values of LLR, the absolute value shows the degree of support, while the sign indicates the hypothesis receiving it. In this setup, the match of sequences is shown by the positive sign of LLR.

3.2. PROPOSED ENF-BASED FRAMEWORK

The framework we propose is an evaluative implementation of ENF Criterion, with our contributions at second and third stages. Upon archiving the grid audio recorded files, they were also collected as a reference ENF database. For the purposes of current research, the ENF reference was extracted by downsampling the signal to 1000 Hz, then band-pass filtering it between 49.7 Hz to 50.3 Hz. Next, the signal was analyzed following two separate directions.

The first direction aims towards checking the continuity of ENF trace. The amplitude and phase variations of ENF trace signal are examined as revealed from the corresponding analytic signal. Since in the complex plane $s(n) = a(n)e^{j\phi(n)}$, the trace is completely described by the trace component envelope $a(n)$ and the trace component phase $\phi(n)$. By denoting it $s(n) = s_{re}(n) + js_{im}(n)$, where $s_{re}(n)$ is the initial real-valued signal, $j = \sqrt{-1}$, and $s_{im}(n) = \text{HHT}(s_{re}(n))$ is the Hilbert-Huang Transform (HHT) of the signal, amplitude and phase variations are computed using the following equations,

$$a(n) = |s(n)| = \sqrt{s_{re}^2(n) + s_{im}^2(n)}, \text{ and} \quad (3)$$

$$\varphi(n) = \angle s(n) = \arctg\left(\frac{s_{im}(n)}{s_{re}(n)}\right), \quad (4)$$

and checked for discontinuities. Phase jumps are first spotted by analyzing the first order difference of the unwrapped version of “instantaneous phase” in (4), then treated according to [10].

The second direction of analysis is ENF trace recovery, for which the trace samples are extracted using a software emulator of the collector module described in [3], with a sample rate of 100 per second.

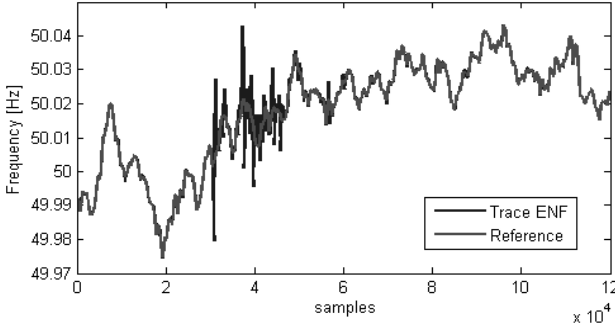


Fig. 1 – Recovered trace matching reference, usually misclassified by baseline frameworks.

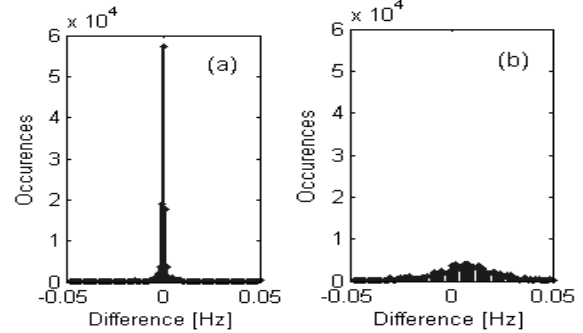


Fig. 2 – Histograms of RS for (a) a matching sequence pair, (b) a non-matching or inconclusive sequence pair.

If trace (ENF) carrier audio is found free of editions, the recovered trace is compared to all reference sequences of the same length, in order to find the reference sequence most similar in shape, and therefore the time its recording has started at. Based on the available clues from the casework, the search domain is determined and pruned using the techniques described in [3]. Each potential matching reference sequence is checked afterwards, using the new shape similarity measure we propose, namely the Relevant Similarity (RS). The RS is the number of ENF trace samples which are closer to reference samples than a fixed threshold. By using this measure on a short-term basis, the proposed framework will be shown as able to detect audio montage in the carrier audio such as deletions, insertions, and so on, and even determine the amount of data involved.

Although for most regions of trace carrier audio the assumption of noise uniformity is correct, strong local interferences can lead the baseline system into denying the match for some truly matching sequence pairs, like those in Fig. 1. If the comparison is done on short-term windows, one shape similarity measure must be computed for each window, and the results must be aggregated afterwards. One fast synthetic way to appraise the result set of a window-wise sequence comparison is to build their histogram. For precise statistics, the probability density distribution functions (pdfs) are better. The shape similarity to reference of the whole recovered trace can be assessed from the histogram of the RS result set. In Fig. 2, example histograms of Short Term Relevant Similarity (STRS) are shown for both matching and non-matching or inconclusive sequence pairs, with a window of one second and a threshold of 0.002 Hz.

4. EXPERIMENTAL EVALUATIONS

For testing the proposed framework we used a database amounting to 4464 grid signal files, each 10-minute long, which we recorded consecutively during 31 days in a fixed setup. Using baseline and proposed frameworks, the reference ENF sequences were extracted and stored. The baseline and proposed frameworks were then compared for steady power of noise. The signal-to-noise ratio (SNR) was ensured between the trace component and the in-band power of the background from which it is recovered.

First, the baseline framework was applied to a trace file database, built by mixing the constant power reference signal files with controlled power noise. The probability distribution functions (pdfs) of CC shape similarity scores were built for both hypotheses, as shown in Fig. 3, considering four selected values of SNR. In the diagrams for lower SNR, the pdf for hypothesis H_0 gets thinner while the other moves to lower ranges.

CC pdfs for non-matching sequences are offset from zero, mainly because of the self-similarity of ENF sequences, which is an important source of false positive match errors. The CC pdf diagrams for high SNR show that one can safely conclude analysis with probability opinions bordering certainty over the shape matching of ENF sequences. Meanwhile, for low SNR there is a strong need to consider both the odds that a given shape similarity degree corresponds to a matching pair and the odds that the same degree corresponds to a non-matching pair. Although the baseline delivers categorical conclusions and does not consider computing the strength of the sequence match evidence, we propose the following equation,

$$LR = \frac{\text{pdf}(CC|H_0, D)}{\text{pdf}(CC|H_1, D)}, \quad (5)$$

where D denotes the contextual data, such as the SNR value, and the length of the trace. For SNR values which make CC distributions overlap significantly, conclusions of categorical nature must be replaced with probabilistic ones. The decision whether the sequences match or not given the computed CC, is in favor of the hypothesis whose pdf, at the estimated SNR, gives the highest probability density for the given CC. Therefore the corresponding decision threshold is located at the pdfs common interception point. It clearly comes out from Fig. 3 that such threshold is variable with the SNR. Because of this variation, the performance of CC based systems depends on the a priori knowledge or computation of SNR threshold.

Second, we explored the performance of RS in matching ENF sequences by applying the proposed framework in a non-evaluative setup, on the same trace file database. The shape similarity was measured by using RS on a long term basis, with an intrinsic distance of 0.002 Hz. As shown in Fig. 4, the non-match pdfs built for RS are zero-centered, while the distribution separation decreased. This is a downside of directly replacing CC for RS, which can be observed by comparing the pdf diagrams of CC (Fig. 3) and RS, for the same SNR. This downside can be explained as an effect of the large time span of compared ENF sequences, which is favorable to unwanted compensation of sample-wise positive and negative sequence differences.

The RS shape similarity measure is able to perform long term sequence comparisons in evaluative frameworks, for high SNR of the trace. Its disadvantage for low SNR can be removed by applying the RS-based shape comparison on a short-term basis, which we evaluated in the third experiment.

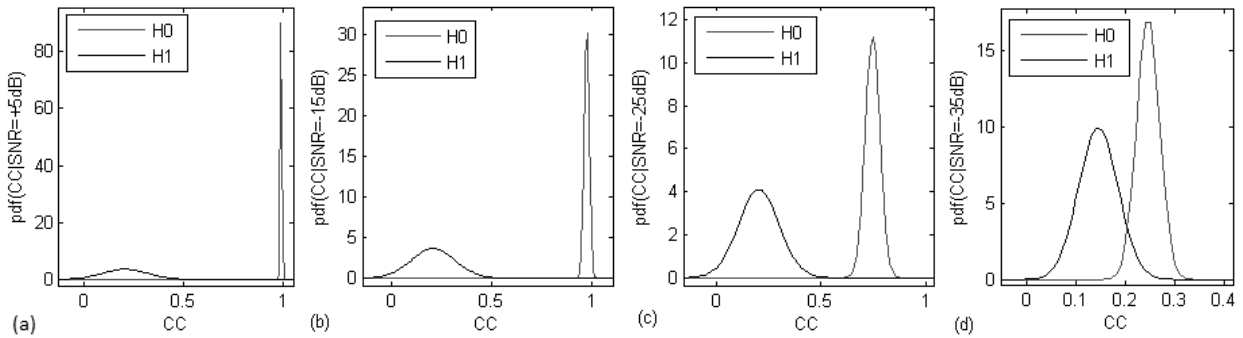


Fig. 3 – The pdfs of CC for matched and non-matched sequences for several SNRs: a) 5 dB; b) –15 dB; c) –25 dB; d) –35 dB.

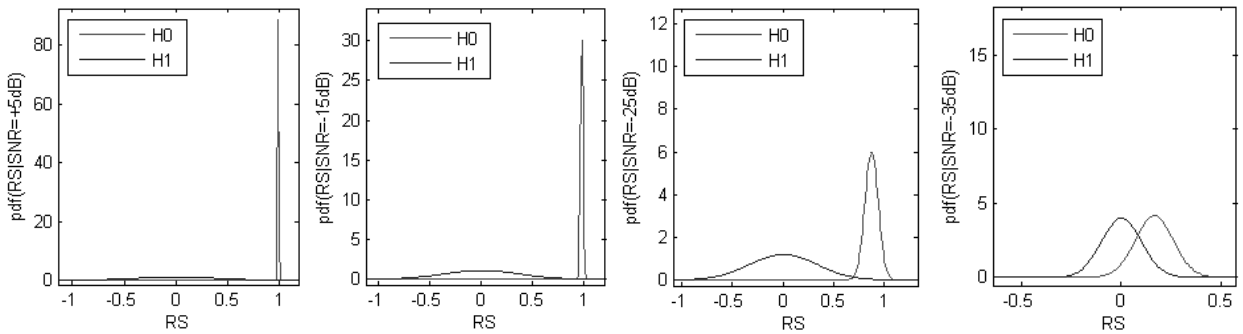


Fig. 4 – The pdfs of global RS for proposed framework, at steady SNRs of: a) 5 dB; b) –15 dB; c) –25 dB; d) –35 dB.

For the third experiment, the proposed framework was applied to the trace database. The matching was performed using the Short Term Relevant Similarity (STRS), and the pdfs of STRS are presented in Fig. 5 for several SNR values. The RS for a short-term window was considered a match if at least 50% of sequence samples were closer to their counterpart than 0.002 Hz. Two sequences match STRS-wise if the RS-matched short-term windows cover at least 2 minutes. The consequence of the proposed matching, visible in Fig. 5, is that for SNR values of at least -25 dB, the pdfs for the two forensic hypotheses appear not to change. By using the proposed framework on controlled mixtures, with rock music as the background of ENF traces, we found that the proposed framework is a working solution for the case of input trace sequences with variable quality. The short-term windows with SNR higher than -25 dB share a new property: the same SNR independent contribution to the computation of the strength of sequence-wise match evidence.

It is highly difficult to compare the performance of such frameworks on practical ENF carrier recordings because of so many unpredictable factors of influence to consider. By testing the proposed framework on controlled mixture databases, its performance was established.

The computed STRS series may also be used in revealing traces of audio file editing. If the short-term comparison windows are numbered, we seek along the reference for each window in the trace sequence. For unedited sequences, the ordering numbers of matching windows must be consecutive. If window numbers form two or more separate sequences, a fast analysis may result in finding traces of deletions, insertions, duplications or swappings, while the amount of material involved is trivial to compute. In high noise case, a much larger range of possibilities exists, because of the uncertainty around non-matching windows that occur in between matching sequences. The reliability of such findings can be consolidated afterwards by computing complementary shape similarity indicators, such as the MSE.

5. CONCLUSIONS

An evaluative ENF-based framework was presented in the current paper for authentication of digital audio recordings with variable trace quality. To our knowledge, this is the first approach of this kind.

A new similarity measure was introduced, namely the Relevant Similarity (RS). It allows the match computation to focus only on relevant samples, either globally or short-term wise (STRS). Unlike other methods presented in the literature, the local quality of ENF trace is considered in this approach.

The logarithmic strength of the sequence match evidence can be computed as the sum of the individual LLRs on short-term comparisons over the entire trace.

Although the minimum quality threshold for trace carrier recording analysis is essentially the same as for the baseline, proposed framework is immune to large numbers of affected samples in the trace sequence. Sequences of matching short-time windows in the trace that cover more than 2 minutes are enough to conclude that ENF sequences match. While much of the performance of baseline framework results from the averaging property of the Fourier transform, the proposed framework, due to placing erroneous or missing samples out of the matching, shows better applicability and results than baseline framework and methods described in [2, 4, 5, 7, 8]. Any short-term window of ENF trace may participate in matching by proposed method, while with the method in [6] the estimation of trace ENF was only useful on long silent parts of input recordings.

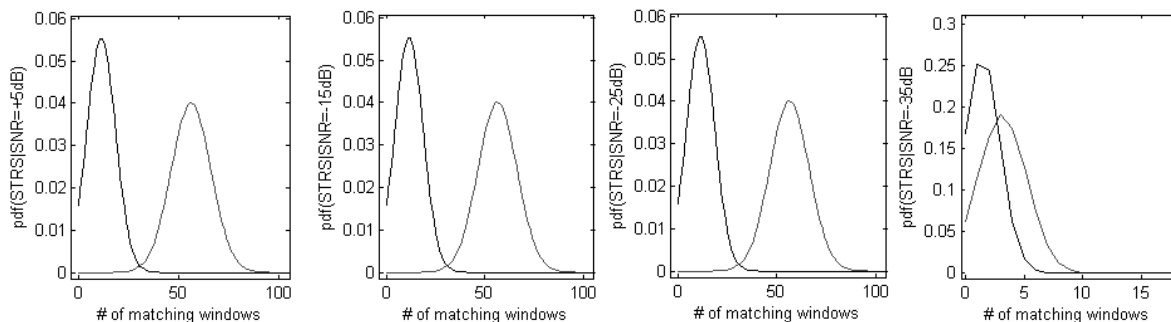


Fig. 5 – The pdfs of STRS for both hypotheses under several SNRs: a) 5 dB; b) -15 dB; c) -25 dB; d) -35 dB.

It often happens that matching sequences reported outside an evaluative framework, unaware of their limited strength as evidence, are mistaken as *facts*. However, even the baseline framework fails to recognize that because the signal quality criteria are considered globally, the risk of error at the sequence matching stage is increased. The uncertainty over the match, usually suppressed in the literature by considering convenient environments, is mandatory to estimate in forensic applications because, in practice, errors may be inflicted by any untamed circumstance such as the level or nature of ENF carrier signal contents, self-similarity of ENF reference, missing ENF samples because of trace dropouts, or because of erroneous computation of some values.

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