



Audio Watermarking with Patch-based Wiener Filtering

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ABSTRACT: Watermarking is a secure data transferring technique, which is used in protecting information like images, videos and audio. Audio watermarking is more impudent than image watermarking due to the dynamic control of hearing capacity over the visible field. To develop an audio watermarking scheme without changing acoustical quality is more difficult. Here proposes a spread spectrum audio watermarking scheme based on a geometric invariant feature. The watermark implanting is actually performed in the DFT domain. The various audio signal distortions like pitch-shifting, random cropping, time scale modification, etc are proposed to analyses in this paper. The proposed method uses average Fourier magnitude over log- coordinate, which can resist most of the audio signal distortions. The watermarked audio achieves high hearing quality in both objective and subjective quality evaluation. The proposed algorithm may work as a tool for securing knowledgeable properties of the musician and audio sharing companies because of its high performance quality and imperceptibility. Here use image as watermark, that is an image is embedded into audio. In this case image may be distorted by noises. Avoiding this problem here proposes a denoising method, that is patch-based wiener filtering.

KEYWORDS: Audio watermarking, geometric invariance, log coordinate mapping(LCM) feature, pitch shifting, time-scaling modification(TSM), Denoising bounds, image clustering, image denoising, linear minimum mean-squared-error (LMMSE) estimator, Wiener filter.

I.INTRODUCTION

The digital data can be processed, accessed, and it can be transmitted very quickly using network. There are numerous technical, legal, and organizational problems which arise when there is wide scale of use of digital documents. Digital information can be copied any number of times from one medium to another; they can be transmitted through networks, etc., all without compromising the quality of the dat. There is no way to distinguish between an original electronic documents and its copy. It is easy to change any part of unprotected electronic documents. One possibility here is to replace original signatures with cryptographic methods. Digital signature is data items formed by the signatory and created from the document that is to be signed. It relates the documents to the signatory in a secure and reliable way. Digital watermarking has been proposed as one way to accomplish this. Traditional data protection techniques such as encryption are not enough for audio copy right enforcement. They are usually not robust against modification of the data, or have only limited robustness and protect the embedded information against technical modifications that may occur during transmission and storage, like format conversion, compression, or digital-to-analog conversion. Watermarking, on the other hand, has the additional notion of resilience against attempts to remove the hidden data. A popular application of watermarking is to give proof of ownership of digital data by embedding copy right statements. It is obvious that for this application the embedded information should be robust against manipulations that may attempt to remove it. Other applications include data monitoring or tracking, in which the user is interested in monitoring data transmission in order to control royalty payments, or simply track the distribution to localise the data for marketing and sales purposes. Furthermore, digital watermarking may also be used for fingerprinting applications in order to distinguish distributed data sets Katzenb [2]. Audio watermarking should meet the following requirements: 1) Perceptual transparency. The watermark must be embedded without quality degradation, and the signal-to-noise (SNR) for watermarked audio verses original audio should be more than 20dB. That is the modifications caused by watermark embedding should be below the perceptible threshold, which means that some sort of perceptibility criterion should be used not only to design the watermark, but also quantify the distortion. As a consequence of the required imperceptibility, the individual samples that are used for watermark embedding are only



modified by a small amount. 2) Robustness. The watermark should survive common audio signal processing manipulations such as filtering, compression, and geometric distortion which include temporal scaling and pitch shifting. That is to ensure robustness despite the small allowed changes, the watermark information is usually redundantly distributed over many samples of the cover-data, thus providing a global robustness which means that watermark can usually be recovered from a small fraction of the watermarked data. Obviously watermark recovery is more robust if more of the watermarked data is available in the recovery process. 3) Security. The watermark should prevent unauthorized detection and removal, unless the quality of audio becomes very poor. In general, watermarking systems use one or more cryptographically secure keys to ensure security against manipulation and erasure of the watermark. As soon as a watermark can be read by someone, the same person may easily destroy it because not only the embedding strategy, but also the locations of the watermark are known in this case. 4) Bit rate. This is the amount of watermark data that may be reliably embedded within the host signal per unit time or space. A higher bit rate may be desirable in some application to embed copyright information. Reliability is measured using BER (bit error rate). 4) Complexity. It means the effort and time need to embed and retrieve a watermark. This parameter is essential if have real time applications. Another aspect addresses whether the original data in the retrieval process or not and need to distinguish between non blind and blind watermarking schemes. 5) Invertibility. It is the possibility to produce the original data during the watermark retrieval.

There have been a lot of techniques for audio watermarking. Haitsmaet *al.* [4] proposed an algorithm by slightly modifying the magnitude of the Fourier coefficients. It is robust to pitch invariant TSM, MP3, and echo addition. But it is not robust against pitch shifting. Kirovski *et al.* [5] applied spread spectrum watermarking. These techniques derived from the concept used in spread spectrum communication. The basic approach is that a narrow band signal is transmitted over the large bandwidth signal which makes them undetectable as the energy of the signal is overlapped. In similar way the watermark is spread over multiple frequency bins so that the energy in anyone bin is very small and certainly undetectable.

Most existing works focus on solving one given geometric distortion such as TSM, and random cropping. The proposed method in this paper aims to solve geometric distortions simultaneously, such as pitch-in-variant TSM, resample TSM, pitch shifting, random cropping, and jittering. We propose a geometric invariant feature, the average Fourier magnitude (AFM) over the log coordinate, which is invariant to these geometric distortions and DA/AD conversion, and is denoted by log coordinate mapping (LCM). In this paper the proposed watermark is embedded in LCM feature and is actually embedded in the Fourier coefficients without interpolation, thus eliminating completely the severe non-uniform interpolation distortion (Xiangui[1]). Here another problem is the noise attack on image. The challenge of any image denoising algorithm is to suppress noise while producing sharp images without loss of finer details. Here derivea high-performance practical denoising algorithm. In this paper proposea patch-based Wiener filter that exploits patch redundancyfor image denoising.

II.LOG COORDINATE MAPPING FEATURE AND GEOMETRIC INVARIANTS

Globalization and internet are the main reasons for the growth of research and sharing of information. However, they have become the greatest tool for malicious user to attack and pirate the digital media. The ease of content modification and a perfect reproduction in digital domain have promoted the protection of intellectual ownership and the prevention of the unauthorized tampering of multimedia data to become an important technological and research issue. Digital watermarking has been proposed as a new method to enforce the intellectual property rights, tracing of illegal copies of digital media and protect digital media from tampering. Several audio watermarking schemes have been presented over the years. The development of a geometric invariant audio watermarking scheme without degrading acoustical quality is challenging work. This paper proposes a geometric invariant feature, the average Fourier magnitude (AFM) over the log coordinate, which is invariant to geometric distortions and is denoted by log coordinate mapping (LCM) feature. The LCM feature is very robust to audio geometric distortions, such as time-scale modifications (TSM), tempo invariant pitch shifting, random cropping etc. In this section, present the log coordinate transform on the frequency index and examine the distortion of LCM features introduced by geometric distortion and DA/AD conversion.

Log Coordinate Transform on Frequency Index:

Geometric distortion can be described in the frequency domain as follows:



$$f' = \beta \cdot f(1)$$

Where β stands for the frequency scaling factor, f and f' are a frequency point of the original audio and the corresponding frequency point of a distorted audio, respectively. Frequency scaling by β can be converted into shifting by $\log \beta$ in the log coordinates. Taking the logarithm of (1), it can be rewritten as follows:

$$\log_b f' = \log_b \beta + \log_b f \quad (2)$$

Where b is the logarithm base. Thus geometric distortions can be easily manipulated in the log co-ordinate of frequency index. As amplitude scaling is unavoidable during attacks, here select a correlation based watermarking which can resist amplitude scaling. The host feature is the average Fourier magnitude (AFM) over the log co-ordinate frequency index. Given a signal, $s(n)=[S1.....Sn]$ I perform a DFT and get the Fourier magnitude $S(f)$. After selecting a portion of the normalized frequency indexes, here perform a log co-ordinate transform on frequency index as shown in

$$l = \text{floor} \left(\log_b \frac{f}{R} \right) + \frac{L}{2}$$

Where, $R = \sqrt{2} \cdot f_m$

$$b = 2^{1/L} \quad (3)$$

Where L is the number of log intervals and is specified by users. The selected frequency index f is mapped to discrete log co-ordinates $l(0 \leq l < L)$, so that the selected frequency coefficient $S(f)$ is mapped to a log co-ordinate mapping feature $a(l)$ which is defined as follows.

$$a(l) = \frac{1}{f_2 - f_1} \int_{f_1}^{f_2} s(f) df$$

Where,

$$f_1 = \min \{f(\text{floor}(\log_b f/R)) + L/2 = l\}$$

$$f_2 = \max \{f(\text{floor}(\log_b f/R)) + L/2 = l\} \quad (4)$$

III.WATERMARKING ALGORITHM

Watermark (W_i) is a direct sequence spread spectrum (DSSS) encoded with N_p bit bipolar PN sequence. The hidden data W consist of spread spectrum information watermark (W_i) and a tracking sequence T generated by a key. Apply DFT on the original audio signal $s(n)$ and obtain the Fourier magnitude $S(f)$ and the phase. Performing a discrete log coordinate transform to a portion of the normalized frequency indexes f_s , obtain the discrete log coordinate l .

Here several DFT magnitude coefficients are mapped to one LCM feature. Modify the Fourier magnitude $S(f)$ to embed the hidden bit $w(l)$ according to

$$\widehat{S}(f) = S(f)(1 + \alpha_e w(l)) \quad (5)$$

Where $S(f)$, are the Fourier magnitude coefficients before and after embedding, and α_e is the embedding strength. Finally, by performing an IDFT to the modified DFT coefficients, the watermarked audio signal $\check{S}(n)$ is obtained.

If is observed that not the whole range of average Fourier magnitude (AFM) over the log co-ordinates is suitable for embedding watermarks. The amplitudes near the highest frequency are small, and this part is sensitive to low-pass filtering. So we may set the watermark embedding region to the low and middle frequency components.

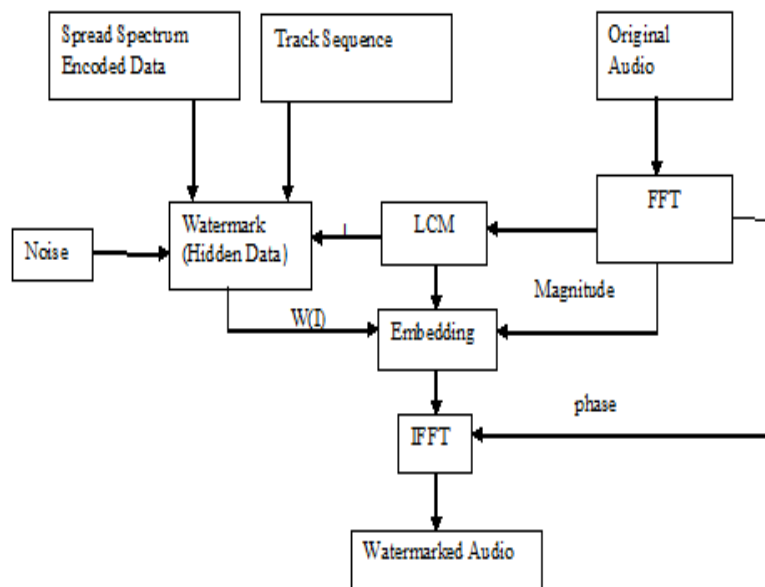


Fig .1. Watermark embedding block

WATERMARK EXTRACTION

Watermark is extracted from the average Fourier magnitude over the Log coordinate (LCM feature). The LCM feature may get translated after geometric distortion. The tracking sequence and the original PN-sequence may be known to the detector prior to extraction. First, apply the DFT on the watermarked audio signal $\check{S}(n)$ and obtain the magnitude coefficient $\check{S}(f)$.

Then perform a discrete log-coordinate transform to the frequency index f and average the entire magnitude $\check{S}(f)$ with the same discrete log- coordinate l . Then obtain the LCM feature $\hat{a}(l)$.

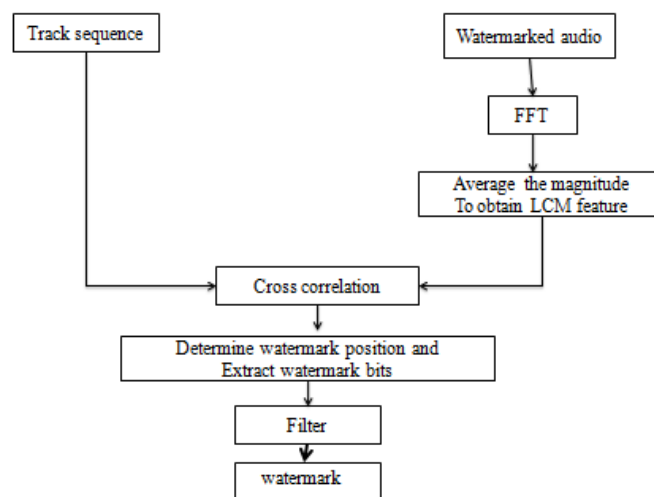


Fig.2. Watermark detection block



Computing the correlation between the tracking sequence T and LCM feature $\hat{a}(l)$, then determine the watermark embedding position. One way to track the location of watermark is to perform exhaustive shifting along the log axis and to calculate the cross correlation between the T and $\hat{a}(l)$ and then find the maximum correlation to locate the match position. However, the computation load for this exhaustive searching is heavy. A fast way to search the maximum correlation value is using correlation theorem. Append T with zeros to the same size of $\hat{a}(l)$ to obtain $g(l)$. Then the correlation between them is

$$c(k) = IDFT(\hat{A}(u) \cdot G^*(u)) \quad (6)$$

Where $G(u) = DFT[g(l)]$ and $\hat{A}(u) = DFT[\hat{a}(l)]$

Pick Np elements from $\hat{a}(l)$ to form a sequence $W(i)$, which corresponds to the embedded spread-spectrum sequence W_i from WT , and correlate with the original PN sequence. If the correlation value is larger than 0, the extracted bit is taken to be in favor of 1; otherwise, it is determined to be 0. The hidden watermark can thus be recovered.

EFFECTIVENESS OF LOG COORDINATE TRANSFORMATION ATTACKS

If we embed the watermark signal in to the Fourier magnitude of audio one to one and same scale, the original watermark will suffer the same distortion as the audio signal. When the synchronization attacks are applied to the watermarked audio, the Fourier magnitude of the audio will fluctuate and the frequency index will be scaled. The case of the watermark is the same. Obviously the original watermark and the survival watermark are not correlative.

The case is different when applying log coordinate transform in watermark embedding and extraction. Then apply log coordinate mapping to the watermark index and generate embedding position in DFT magnitude. Now one watermark bit will be embedded in multiple DFT magnitudes. After attacks there will be some fluctuations in magnitudes, and perform the average of the Fourier magnitudes. Before watermark extraction utilize log coordinate transform to retrieve the watermark index. Now the watermark bits can be extracted from the survival watermark signal correctly.

Under Random Cropping

Random cropping means that a portion of the audio is lost in the time domain, but in the frequency domain, it only introduces tiny fluctuations. To resist random cropping, the watermarking strategy must be global. As the length of audio clip varies after random cropping, the frequency index must be normalized after Fourier transform. Geometric distortion by random cropping can be described by the equation (1). A powerful tool to deal with the scaling factor is log coordinate transform. A logarithm could convert the scaling into shifting (2) in the logarithm axis.

Under Pitch Shifting

Pitch shifting is a very common form of processing used to change the base frequency without changing the tempo. Pitch shifting may be implemented as follows: resample an audio signal for shifting the pitch, then remove and insert some samples of resampled audio signal in the time domain in order to keep the tempo invariant. Removing and inserting some samples cause only a small fluctuation in the frequency domain. Theoretically there exists a statistically positive linear correlation between pitch shifted and original audio (1).

Under Pitch-Invariant TSM

Pitch invariant TSM can be considered to be removing and inserting some samples of audio signal while preserving the pitch. It causes only a small fluctuation to LCM feature in the frequency domain.

IV. PATCH- BASED FILTERING

In this paper, propose a patch based wiener filter we use a Patch based Wiener filter that exploit patch redundancy for image denoising. This framework uses both geometrically and photometrically similar patches to estimate the different filter parameters. These parameters can be accurately estimated directly from the input noisy image. The performance of this proposed method will be exceeding the current state of the art, both visually and quantitatively. The proposed denoising framework, requires us to infer various parameters from the observed noisy image. The procedure is algorithmically represented. We first identify geometrically similar patches within the noisy image. Once such patches are identified, we can use these patches to estimate the moments of the cluster, taking care to account for noise. Next, we identify the photometrically similar patches and calculate weights that control the amount of influence that any given patch exerts on denoising patches similar to it. These parameters are then used to denoise each cluster. Since we

use overlapping patches, multiple estimates are obtained for pixels lying in the overlapping regions. These multiple estimates are then optimally aggregated to obtain the final denoised image in detail.

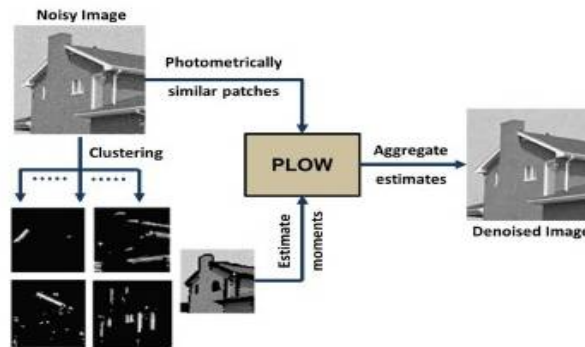


Fig.3. Outline of our proposed PLOW filtering method

In this method, noisy image is first segmented into regions of geometric structure, as shown in Fig. 4. The mean and the covariance of the patches within each cluster are then estimated. Next, for each patch, we identify photometrically similar patches and compute weights based on their similarity to the reference patch. These parameters are then used to perform denoising patchwise. To reduce artifacts, image patches are selected to have some degree of overlap (shared pixels) with their neighbors. A final aggregation step is then used to optimally fuse the multiple estimates for pixels lying on the patch overlaps to form the denoised image.

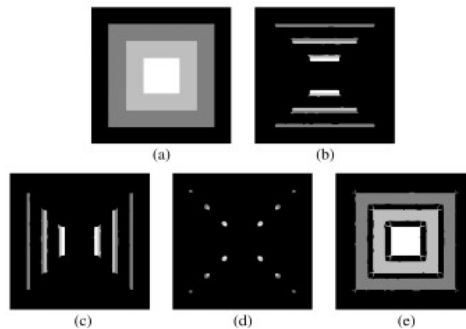


Fig.4. Clustering of a simple image based on geometric similarity.

A. PLOW FILTER : Motivation

In [11], we analyzed the performance bounds for the problem of image denoising. This was done from an estimation theory point of view, where we seek to estimate the pixel intensity z_i at each location from its noisy observation, i.e.,

$$Y_i = z_i + \hat{\eta}_i, \quad i=1, \dots, M \quad (7)$$

Here, $\hat{\eta}_i$ is assumed to be independent and identically distributed (i.i.d.), and is the total number of pixels in the image. In our paper, we specifically considered patch-based methods, where the observation model can be posed as

$$Y_i = z_i + \hat{\eta}_i \quad (8)$$

With $Y_i \in \mathbb{R}^n$ representing the vectorized $\sqrt{n} \times \sqrt{n}$ patch centered at i . Here showed that the MSE of denoising (estimating) any given patch in the image is bounded from below by

$$E[\|z_i - \hat{z}_i\|^2] \geq \text{Tr} [(J_i + C_z^{-1})^{-1}] \quad (9)$$

Where $\hat{z}_i \in \mathbb{R}^n$ is the estimate of z_i , $J_i \in \mathbb{R}^{n \times n}$ is the Fisher information matrix (FIM). The FIM, on the other hand, is influenced by the noise characteristics. When additive white Gaussian noise (WGN) is considered, the FIM takes the following form:

$$J_i = N_i I / \sigma^2 \quad (10)$$

Where I is the $n \times n$ identity matrix, σ is the noise standard deviation.

B. Derivation and analysis

Irrespective of the noise characteristics, the expression in (9) leads to the lowest MSE theoretically achievable by any patch-based denoising method. Here assume that such grouping is made available through some oracle clustering method. When the corrupting noise is the WGN, the LMMSE estimate of z_i from its noisy observation has the following each patch form

$$\hat{z}_i = z^- + C_z C_y^{-1} (y_i - z^-) \quad (11)$$

where z^- and C_z are the first and second moment of the pdf. The photometric similarity among patches, as required to exploit redundancy, is a stricter condition than the geometric similarity property used for clustering. We therefore require an additional step of identifying the y_i patches that are photometrically similar to any given patch y_i .

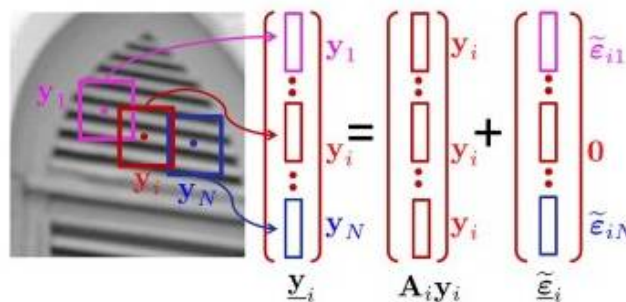


Fig. 5. Illustration of the data model formed by collecting all photometrically similar patches.

V. PLOW DENOISING ALGORITHM

Input: Noisy image: Y

Output: Denoised image: \hat{Z}

- 1: Set parameters: patch size $n = 11 \times 11$, number of clusters $K = 15$;
- 2: Estimate noise standard deviation $\hat{\sigma}$;
- 3: Set parameter: $h^2 = 1.75 \hat{\sigma}^2 n$;
- 4: Y^0 Prefilter image to obtain pilot estimate;
- 5: extract overlapping patches of size n from Y & Y^0 ;
- 6: compute LARK features for each y_i^0 ;
- 7: Ω_k geometric clustering with $-$ means;
- 8: foreachCluster Ω_k do
- 9: Estimate mean patch from $y_i^0 \in \Omega_k$;
- 10: Estimate cluster covariance from $y_i^0 \in \Omega_k$;
- 11: foreach Patch $y_i^0 \in \Omega_k$ do;
- 12: y_j^0 identify photometrically similar patches;
- 13: compute weights for all y_j^0 ;
- 14: estimate denoised patch using y_j ;
- 15: calculate estimate error covariance;
- 16: end



17: end

18 : aggregate multiple estimates from all $\{\hat{z}_i\}$ and $\{c_{ei}\}$

METHODS OF ANALYSIS

Quality of Watermarked Audio

The objective quality is measured by SNR and objective difference grade (ODG). The ODG value is mapped to the following description: 0 (insensitive), 1 (audible), 2 (slightly annoying), 3 (annoying), 4 (very annoying), and 5 (catastrophic). A subjective quality evaluation of the watermarking method was done by asking 10 persons to listen to the 4 audio clips. In the first phase of the test, participants were presented with the pairs of the original and the watermarked audio clips in the random order and asked to determine which one was the original clip and which one was not. A discrimination rate near to 50% means that the original and watermarked audio clips cannot be discriminated. In the second phase of the test, the persons are presented with the original and watermarked audio objects, and then give scores for each audio. The mean opinion score (MOS) determines the amount of distortion. The five point impairment scale is applied, 5.0 for imperceptible, 4.0 for perceptible but not annoying, 3.0 for slightly annoying, 2.0 for annoying, and 1.0 for very annoying.

Robustness Tests

To evaluate the robustness performance of the proposed algorithm, apply tests defined by the Secure Digital Music Initiative (SDMI) industry committee.

EXPERIMENTAL RESULTS

In the proposed method of audio watermarking not the whole range Fourier magnitudes AFM is suitable for embedding watermarks. The amplitude near the high frequency components are small and this part is sensitive to low pass filtering. So select the embedding region corresponding to the low and middle frequency components. In implementation, the actual watermark embedding is directly performed in the DFT domain based on the discrete log coordinate of the frequency index.

Consider audio clips, which are in .WAV format, mono, 16bits/samples, 20s, and 44.1-kHz sampling frequency. Choose the length of watermark $I=64$ bits, the length of tracking sequence $N_t=320$ and a total $L=960$ bits of hidden data are embedded. Adopt the length of DFT and equal to the length of the host audio clip, ie, $2044100=882000$. The length of the hidden data is $L=I_p+N_t$, which depends on the bits of the watermark L , the length of PN sequence N_p , and the length of the track sequence N_t . The value of L is selected by the user and could not be too large, because it represents the number of discrete intervals that the frequency indices are mapped to, and must ensure that each interval contains at least one frequency index.

The experiment is conducted to implement the proposed audio watermarking algorithm using MATLAB. Audio clips of fixed duration in the .WAV format is read to the MATLAB environment, that is to get the sampled values of the original audio clip at 44.1kHz sampling rate. Now corresponding DFT of the audio clip is computed by FFT algorithm, and obtain its magnitude. The hidden data of length $L = 960$ bits are obtained by combining the direct sequence spread spectrum (DSSS) encoded watermark bits with a track sequence. The preliminary simulation results are shown in the following figure.



• Fig. 6. Original and its converted binary image.

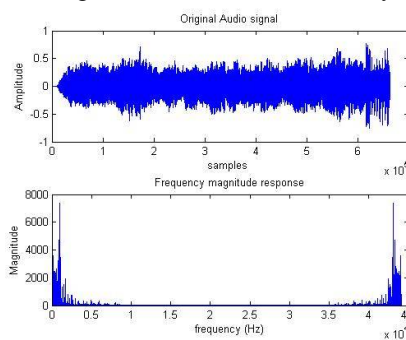


Fig.7. frequency magnitude spectrum of the audio signal.

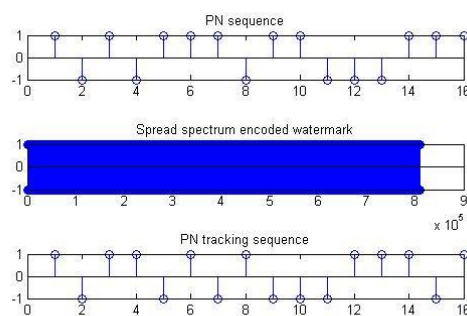


Fig.8. Bipolar PN sequence used for Spread spectrum encoding and track sequence used for efficient watermark extraction.

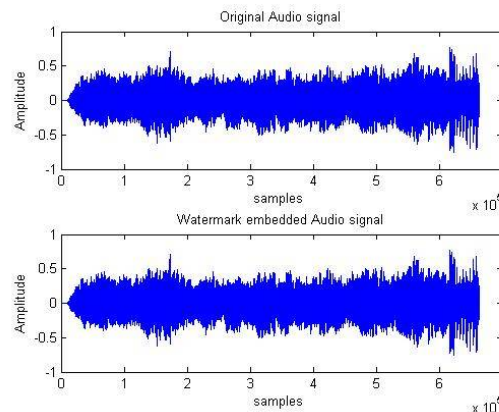


Fig. 9. Data to be embedded into audio signal.

VI.CONCLUSION

The proposed audio watermarking with patch based wiener filtering is an effective method for secure communication and data transfer scheme. Here developed an audio watermark embedding strategy. An image is used as watermark, so there is a possibility of attack noise to the image, there for an effective filter – patch based wiener filter is used for improving the efficiency of the system to avoid completely the severe distortions. Here also evaluating the denoising method through experiments on various images at different noise levels. Both the theoretical analysis and experimental results show that the proposed audio watermarking scheme is strong method against common signal processing operations, including low-pass filter, but also has conquered the challenging audio geometric distortion and achieves the best robustness against simultaneous geometric distortions such as TSM, pitch shifting, and random cropping. we have proposed a method of denoising motivated from our previous work in analyzing the performance bounds of patch-based denoising methods. We have developed a locally optimal Wiener-filter-based method and have extended it to take advantage of patch redundancy to improve the denoising performance. Our denoising approach does not require parameter tuning and is practical, with the added benefit of a clean statistical motivation and analytical formulation.

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