A Digital Audio Watermarking Algorithm Resist to Low Bits Rates Compression

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***Abstract*-Digital watermarking is a technique used to embed an extra piece of information into multimedia signals. Digital watermarking can be realized by many different methods, but the common existing techniques for watermarking are confronted with the problems of perceptible quality degradation and the inherent conflict between imperceptibility and robustness, which is introduced by the watermark embedding. In this paper, a novel audio zero-watermarking scheme based on lifting-based wavelet transformation (LWT) and non-negative matrix factorization (NMF) for content authentication is proposed. First the audio is divided into frames by fixed length and then frequent components are obtained by three-level LWT in every frame. Secondly the audio frame is approximately represented as a product of a base matrix and a coefficient matrix by NMF. Finally the feature vector is obtained by quantifying the coefficient matrix, and then the copyright information is obtained by calculating the watermark and feature vector. The performance of proposed algorithm is analyzed by common signal processing, and experiment results show that the proposed scheme is robust and secure.**

Keywords-Audio Watermarking; Non-negative Matrix Factorization; Lifting-based Wavelet; Normalized Hamming Distance; Signal to Noise Ratio

I. INTRODUCTION

In recent years, the distribution of digital media has grown rapidly. Versatile and simple-to-use software and decreasing prices of digital devices have made it possible for consumers from all around the world to create and exchange multimedia data. Broadband Internet connections and near error-free transmission of data facilitate people to distribute large multimedia files and make identical digital copies of them. A perfect reproduction in digital domain has promoted the protection of intellectual ownership and the prevention of unauthorized tampering of multimedia data become an important technique and research issue. As a result, a technique called digital watermarking is introduced to protect the ownership of these contents.

Digital watermarking has been proposed as a new, alternative method to enforce intellectual property rights and protect digital media from tampering. Digital watermarking is defined as imperceptible, robust, and secure communication of data related to the host signal, which includes embedding into and extraction from the host signal. Successful watermarking algorithms must comprise of a number of features to provide the level of security that is required [1]. These features include:

Imperceptibility. Embedding this extra data must not degrade human perception about the object. Namely, the watermark should be 'invisible' in a watermarked image/video or 'inaudible' in watermarked digital music. Evaluation of imperceptibility is usually based on an objective measure of quality called signal-to-noise ratio (SNR) or a subjective test with specified procedures.

Security. The watermarking procedure should rely on secret keys, not the algorithms secrecy, to ensure security, so that pirates cannot detect or remove watermarks by statistical analysis from a set of images. The algorithm should be published [2] and an unauthorized user, who may even know the exact watermarking algorithm, cannot detect the presence of hidden data, unless he/she has access to the secret keys that control this data-embedding procedure.

Robustness. The embedded watermarks should not be removed or eliminated by unauthorized distributors using common processing techniques including lossy compression, linear or nonlinear filtering, cropping, and others.

Adjustability. The algorithm should be tunable to various degrees of robustness, quality, or embedding capacities [2] to be suitable for diverse applications.

Real-time processing. Watermarks should be rapidly embedded into the host signals without much delay, so that integrated streaming/watermarking functionality in the delivery of audio over a network can be enabled. Also, a web crawler should support fast watermark extraction/detection to authenticate multimedia presentations delivered over networks.

The main challenge in digital audio watermarking and steganography is that if the perceptual transparency parameter is fixed, the design of a watermark system cannot obtain high robustness and a high watermark data rate at the same time. Most audio watermarking schemes rely on the imperfections of the human auditory system (HAS). In the time domain, it has been demonstrated that the HAS is insensitive to small level changes [3] and insertion of low-amplitude echoes [4]. Data hiding in the frequency domain takes advantage of the insensitivity of the HAS to small spectral magnitude changes [4-6]. Quantization index modulation is another type of data hiding algorithms that increases the security of the augmented data at the cost of decreased tolerance to attack noise stronger than the watermark modulation. The Discrete Wavelet Transform has recently provided a new dimension to audio watermarking and a lot of new watermarking algorithms are based on this concept [7].

In this paper, a novel audio watermarking scheme employing LWT and NMF for content authentication is proposed. The remaining of this paper is organized as follows. The concept of Non-negative Matrix Factorization is briefly introduced in Section Ⅱ. In Section Ⅲ and Section Ⅳ, the details of the proposed scheme and performance evaluation are presented. A conclusion is drawn in Section Ⅴ.

II. NON-NEGATIVE MATRIX FACTORIZATION

Given a set of multivariate n-dimensional data vectors, the vectors are placed in the columns of an n×m matrix V where m is the number of examples in the data set. This matrix is then approximately factorized into an n×r matrix W and an r×m matrix H. Usually r is chosen to be smaller than n or m, so that W and H are smaller than the original matrix V. This results in a compressed version of the original data matrix. The common description of NMF is as follows:

$$V \approx WH \tag{1}$$

The Equation (1) can be rewritten column by column as $v \approx Wh$, where v and h are the corresponding columns of V and H. In other words, each data vector v is approximated by a linear combination of the columns of W, weighted by the components of h. Therefore W can be regarded as containing a basis that is optimized for the linear approximation of the data in V. Since relatively few basis vectors are used to represent many data vectors, good approximation can only be achieved if the basis vectors discover structure that is latent in the data.

To find an approximate factorization $V \approx WH$, we first need to define cost functions that quantify the quality of the approximation. Such a cost function can be constructed using some measure of distance between two non-negative matrices A and B. In the NMF literature, two popular cost functions have been studied. The first is the classical Euclidean distance or Frobenius norm, given by

$$\|A - B\|^2 = \sum_{ij} (A_{ij} - B_{ij})^2 \tag{2}$$

Another useful measure is

$$D(A \,\|\, B) = \sum_{ij} (A_{ij} \log \frac{A_{ij}}{B_{ij}} - A_{ij} + B_{ij}) \tag{3}$$

The above measure is known as the generalized Kullback-Leibler (KL) divergence. It reduces to the standard KL divergence, or relative entropy, when $\sum_{ij} B_{ij} = 1$ so that the matrices can be regarded as normalized probability distributions.

The lack of convexity of the aforementioned costs in both factors W and H means that it is unrealistic to expect a computationally efficient algorithm in the sense of finding a global minimum. Using an approach that is similar to the one used in Expectation–Maximization (EM) algorithms, Lee and Seung[6] introduced NMF algorithms commonly used to obtain such factorizations. While each objective function could be minimized using several different iterative procedures, the update strategies that are given next are for their ease of implementation and also because they monotonically decrease their respective objective functions.

Theorem 1 The Euclidean distance $\|V - WH\|$ is not increasing under the update rules,

$$H_{a\mu} \leftarrow H_{a\mu} \frac{(W^T V)_{a\mu}}{(W^T WH)_{a\mu}} \tag{4}$$

$$W_{ia} \leftarrow W_{ia} \frac{(VH^T)_{ia}}{(WHH^T)_{ia}} \tag{5}$$

The Euclidean distance is invariant under these updates if and only if W and H are at a stationary point of the distance.

Theorem 2 The divergence $D(V \,\|\, WH)$ is not increasing under the update rules

$$H_{a\mu} \leftarrow H_{a\mu} \frac{\sum_i W_{ia} V_{i\mu} / (WH)_{i\mu}}{\sum_k W_{ka}} \tag{6}$$

$$W_{ia} \leftarrow W_{ia} \frac{\sum_\mu V_{i\mu} / (WH)_{i\mu}}{\sum_V H_{aV}} \tag{7}$$

The divergence is invariant under these updates if and only if W and H are at a stationary point of the divergence.

Proofs of these theorems can be found in[6]. For now, it may be noted that the updates are multiplicative. It is also straightforward to see that the multiplicative factor is unity when $V = WH$ so that perfect reconstruction is a necessarily fixed point of these update rules. Meanwhile the non-negativity constraints on both W and H do not come without an increase in approximation error.

III. AUDIO WATERMARKING ALGORITHM

In general, an audio watermarking can be constructed by preprocessing, extracting, and post processing appropriate audio features. In order to improve the property of feature extracting, the preprocessing of audio is always used. The common audio preprocessing includes applying a low-pass filter, rescaling, or adjusting the components of audio, and so on. To achieve robustness, security, and compactness, the feature extraction is the most important stage of constructing an audio watermarking. A robust audio feature extraction scheme should withstand various audio processing that does not alter the semantic content. Various audio watermarking schemes mainly differ in the way randomized features and extracted. For post-processing, the aim is to compress the length of watermarking sequence and without lessening the magnitude feature. In this paper, in order to improve the validity and veracity of audio retrieval, a novel robust audio watermarking algorithm is proposed. The framework of proposed watermarking algorithm is shown in Fig.1, which includes the following steps:

The input audio signal is split into frames, which are in turn windowed by Hamming window to reduce the discontinuity effects. The number of frames is determined by the total length of the audio record and the frame size.

The every frame is decomposed to level-based lifting wavelet coefficients. Select the low-frequent sub bands of decomposed coefficients and then get the coefficients W by

$$W(i) = \sum_{j=1}^{256} Ca3(j) \tag{8}$$

Reshape the coefficients W to non-negative matrix V, then applying the NMF to matrix V and obtain the corresponding coefficient matrix H. In order to compress the feature-bearing coefficient matrix, its entries are coarsely quantized to produce a binary matrix h(i) according to the following rule (9), where $S(i) = \sum_{j=1}^{256} H_{ji} \quad 1 \le i \le k$, $\bar{s}$ is a mean of every column coefficients S(i).

$$h(i)=\begin{cases}1 & S(i)>\bar{s}\\ 0 & otherwise\end{cases} \quad 1\le i\le k \tag{9}$$

Generate the watermark with using the secret-key, and then the copyright information is obtained by calculating the watermark and feature vector.

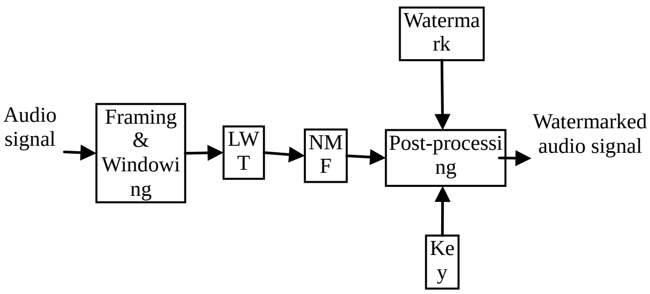

Fig. 1 Block diagram of the robust audio zero-watermarking

IV. EXPERIMENTAL RESULTS

A. Robustness Analysis

The most important requirements for a robust watermarking are its robustness and discrimination power. In order to test the robustness a watermarking block was extracted from four audio excerpts (16Bit Stereo 44.1kHz): “O Fortuna” by Carl Orff, “Success has made a failure of our home” by Sinead o’Connor, “Say what you want” by Texas and “A whole lot of Rosie” by ACDC. All the excerpts were then subjected to the following processing:

Performance metrics and experiment setup: to measure the performance of audio zero-watermarking, the normalized Hamming distance (NHD) between the binary sequences is employed. The defined of normalized Hamming distance is:

$$d(h_1,h_2)=\frac{1}{L}\sum_{k=1}^{L}|h_1(k)-h_2(k)| \tag{10}$$

where $h_1(k)$, $h_2(k)$ are different audio zero-watermarking sequence values; L is the length of audio zero-watermarking. The normalized Hamming distance d has the property that for dissimilar sequence, the expected of d is closed to 0.5, else the expected is closed to 0.

Signal to noise ratio (SNR) is a statistical difference metric which is used to measure the similitude between the undistorted original audio signal and the distorted watermarked audio signal. The SNR computation is done according to (13), where S corresponds to the power of an audio signal, and N corresponds to the power of noise signal, so the term of SNR can be defined as:

$$SNR(dB)=10\log_{10}\frac{S}{N} \tag{11}$$

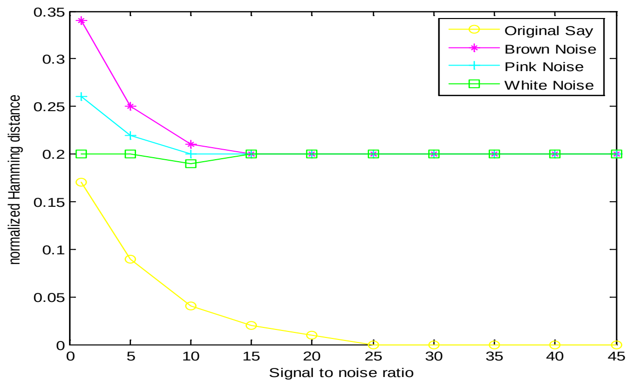

Fig. 2 Normalized Hamming distance of ‘Say’ under various low bit rates

TABLE I. NHD AND NC OF PROPOSED ALGORITHM UNDER BROWN NOISE ATTACKS

SNR (dB)		1	5	10	15	20	25	30	35	40	45
Say	*NC*	0.72	0.85	0.94	0.97	0.98	0.99	0.99	0.99	0.99	1
	NHD	0.28	0.15	0.05	0.02	0.01	0.00	0.00	0.00	0.00	0.00
Say 48	*NC*	0.66	0.74	0.79	0.79	0.79	0.79	0.80	0.79	0.79	0.79
	NHD	0.34	0.25	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Say 56	*NC*	0.66	0.74	0.79	0.79	0.79	0.80	0.79	0.79	0.79	0.79
	NHD	0.34	0.25	0.21	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Say 64	*NC*	0.66	0.74	0.79	0.79	0.79	0.80	0.79	0.79	0.79	0.79
	NHD	0.34	0.25	0.21	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Say 96	*NC*	0.66	0.74	0.79	0.79	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.34	0.25	0.21	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Say 128	*NC*	0.66	0.74	0.79	0.79	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.34	0.25	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20

TABLE II. NHD AND NC OF PROPOSED ALGORITHM UNDER PINK NOISE ATTACKS

SNR(dB)		1	5	10	15	20	25	30	35	40	45
Say	*NC*	0.82	0.91	0.96	0.97	0.98	0.99	0.99	0.99	0.99	1
	NHD	0.17	0.09	0.04	0.02	0.01	0.00	0.00	0.00	0.00	0
Say48	*NC*	0.73	0.77	0.79	0.79	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.26	0.22	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Say56	*NC*	0.73	0.76	0.78	0.80	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.27	0.23	0.21	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Say64	*NC*	0.73	0.76	0.79	0.79	0.79	0.79	0.79	0.79	0.79	0.79

	NHD	0.26	0.23	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Say96	*NC*	0.73	0.76	0.79	0.79	0.79	0.79	0.80	0.79	0.79	0.79
	NHD	0.26	0.23	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Say128	*NC*	0.73	0.77	0.79	0.79	0.79	0.80	0.79	0.79	0.79	0.79
	NHD	0.26	0.22	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20

TABLE III. NHD AND NC OF PROPOSED ALGORITHM UNDER WHITE NOISE ATTACKS

SNR(dB)		1	5	10	15	20	25	30	35	40	45
Say	*NC*	0.95	0.97	0.98	0.99	0.99	0.99	0.99	1	1	1
	NHD	0.04	0.03	0.01	0.01	0.00	0.00	0.00	0	0	0
Say 48	*NC*	0.80	0.80	0.80	0.79	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.19	0.19	0.19	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Say 56	*NC*	0.80	0.80	0.80	0.80	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.19	0.19	0.19	0.19	0.19	0.20	0.20	0.20	0.20	0.20
Say 64	*NC*	0.80	0.80	0.80	0.80	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.20	0.20	0.19	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Say 96	*NC*	0.80	0.80	0.80	0.80	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.19	0.19	0.19	0.19	0.20	0.20	0.20	0.20	0.20	0.20
Say 128	*NC*	0.80	0.80	0.80	0.80	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.19	0.19	0.20	0.19	0.20	0.20	0.20	0.20	0.20	0.20

TABLE IV. NHD AND NC OF PROPOSED ALGORITHM UNDER BROWN NOISE ATTACKS

SNR(dB)		1	5	10	15	20	25	30	35	40	45
O	*NC*	0.78	0.86	0.95	0.99	0.99	0.99	0.99	0.99	0.99	1
	NHD	0.22	0.14	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0
O 48	*NC*	0.78	0.86	0.94	0.98	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.22	0.13	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.00
O 56	*NC*	0.80	0.80	0.80	0.80	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.20	0.20	0.19	0.20	0.20	0.20	0.20	0.20	0.20	0.20
O 64	*NC*	0.80	0.80	0.80	0.80	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.19	0.19	0.19	0.19	0.20	0.20	0.20	0.20	0.20	0.20
O 96	*NC*	0.78	0.86	0.94	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.22	0.14	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.00
O 128	*NC*	0.78	0.86	0.94	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.22	0.14	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.00

TABLE V. NHD AND NC OF PROPOSED ALGORITHM UNDER PINK NOISE ATTACKS

SNR(dB)		1	5	10	15	20	25	30	35	40	45
O	*NC*	0.80	0.80	0.80	0.80	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.20	0.20	0.19	0.20	0.20	0.20	0.20	0.20	0.20	0.20
O 48	*NC*	0.80	0.80	0.80	0.80	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.19	0.19	0.19	0.19	0.20	0.20	0.20	0.20	0.20	0.20
O 56	*NC*	0.88	0.95	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.10	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
O 64	*NC*	0.88	0.95	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.10	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
O 96	*NC*	0.88	0.95	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.10	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
O 128	*NC*	0.80	0.80	0.80	0.80	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.20	0.20	0.19	0.20	0.20	0.20	0.20	0.20	0.20	0.20

TABLE VI. NHD AND NC OF PROPOSED ALGORITHM UNDER WHITE NOISE ATTACKS

SNR(dB)		1	5	10	15	20	25	30	35	40	45
O	*NC*	0.80	0.80	0.80	0.80	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.19	0.19	0.19	0.19	0.20	0.20	0.20	0.20	0.20	0.20
O 48	*NC*	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
O 56	*NC*	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
O 64	*NC*	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
O 96	*NC*	0.80	0.80	0.80	0.80	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.20	0.20	0.19	0.20	0.20	0.20	0.20	0.20	0.20	0.20
O 128	*NC*	0.80	0.80	0.80	0.80	0.79	0.79	0.79	0.79	0.79	0.79
	NHD	0.19	0.19	0.19	0.19	0.20	0.20	0.20	0.20	0.20	0.20

TABLE VII. NHD AND NC OF PROPOSED ALGORITHM UNDER BROWN NOISE ATTACKS

SNR(dB)		1	5	10	15	20	25	30	35	40	45
Success	*NC*	0.76	0.86	0.95	0.98	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.23	0.13	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Success 48	*NC*	0.76	0.86	0.95	0.97	0.97	0.97	0.97	0.97	0.97	0.97
	NHD	0.23	0.13	0.04	0.02	0.02	0.01	0.02	0.02	0.02	0.02
Success 56	*NC*	0.76	0.86	0.95	0.98	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.23	0.13	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Success 64	*NC*	0.76	0.86	0.95	0.98	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.23	0.13	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Success 96	*NC*	0.76	0.86	0.95	0.98	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.23	0.13	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Success 128	*NC*	0.76	0.86	0.95	0.98	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.23	0.13	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00

TABLE VIII. NHD AND NC OF PROPOSED ALGORITHM UNDER PINK NOISE ATTACKS

SNR(dB)		1	5	10	15	20	25	30	35	40	45
Success	*NC*	0.85	0.93	0.97	0.98	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.12	0.06	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Success 48	*NC*	0.85	0.92	0.96	0.97	0.97	0.97	0.97	0.97	0.97	0.97
	NHD	0.13	0.06	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Success 56	*NC*	0.85	0.92	0.97	0.98	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.13	0.06	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Success 64	*NC*	0.85	0.93	0.97	0.98	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.13	0.06	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Success 96	*NC*	0.85	0.93	0.97	0.98	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.13	0.06	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Success 128	*NC*	0.85	0.93	0.97	0.98	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.13	0.06	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00

TABLE IX. NHD AND NC OF PROPOSED ALGORITHM UNDER WHITE NOISE ATTACKS

SNR(dB)		1	5	10	15	20	25	30	35	40	45
Success	*NC*	0.94	0.96	0.98	0.99	0.99	0.99	0.99	0.99	0.99	1
	NHD	0.05	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0
Success 48	*NC*	0.94	0.95	0.97	0.98	0.98	0.97	0.97	0.97	0.97	0.97
	NHD	0.05	0.03	0.02	0.01	0.01	0.01	0.02	0.02	0.02	0.02
Success 56	*NC*	0.94	0.96	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.05	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Success 64	*NC*	0.94	0.96	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.05	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Success 96	*NC*	0.94	0.96	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.05	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Success 128	*NC*	0.94	0.96	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.05	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00

TABLE X. NHD AND NC OF PROPOSED ALGORITHM UNDER BROWN NOISE ATTACKS

SNR(dB)		1	5	10	15	20	25	30	35	40	45
Whole	*NC*	0.75	0.85	0.93	0.98	0.99	0.99	0.99	0.99	0.99	0.99
	NHD	0.25	0.14	0.06	0.01	0.01	0.00	0.00	0.00	0.00	0.00
Whole 48	*NC*	0.72	0.80	0.84	0.86	0.86	0.86	0.86	0.86	0.86	0.86
	NHD	0.27	0.20	0.15	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Whole 56	*NC*	0.72	0.80	0.84	0.85	0.86	0.86	0.86	0.86	0.86	0.86
	NHD	0.27	0.20	0.15	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Whole 64	*NC*	0.72	0.80	0.84	0.85	0.85	0.86	0.86	0.86	0.86	0.86
	NHD	0.27	0.20	0.15	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Whole 96	*NC*	0.72	0.80	0.84	0.85	0.86	0.86	0.86	0.86	0.86	0.86
	NHD	0.27	0.20	0.15	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Whole 128	*NC*	0.72	0.80	0.84	0.85	0.86	0.86	0.86	0.86	0.86	0.86
	NHD	0.27	0.20	0.15	0.13	0.13	0.13	0.13	0.13	0.13	0.13

TABLE XI. NHD AND NC OF PROPOSED ALGORITHM UNDER PINK NOISE ATTACKS

SNR(dB)		1	5	10	15	20	25	30	35	40	45
Whole	*NC*	0.84	0.91	0.95	0.97	0.98	0.99	0.99	0.99	0.99	1
	NHD	0.15	0.08	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0
Whole 48	*NC*	0.79	0.84	0.85	0.85	0.86	0.86	0.86	0.86	0.86	0.86
	NHD	0.20	0.15	0.14	0.14	0.13	0.13	0.13	0.13	0.13	0.13
Whole 56	*NC*	0.79	0.84	0.85	0.86	0.86	0.86	0.86	0.86	0.86	0.86
	NHD	0.20	0.15	0.14	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Whole 64	*NC*	0.79	0.83	0.85	0.86	0.86	0.86	0.86	0.86	0.86	0.86
	NHD	0.20	0.16	0.14	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Whole 96	*NC*	0.79	0.83	0.85	0.86	0.86	0.86	0.86	0.86	0.86	0.86
	NHD	0.20	0.16	0.14	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Whole 128	*NC*	0.79	0.84	0.85	0.86	0.86	0.86	0.86	0.86	0.86	0.86
	NHD	0.20	0.15	0.14	0.13	0.13	0.13	0.13	0.13	0.13	0.13

TABLE XII. NHD AND NC OF PROPOSED ALGORITHM UNDER WHITE NOISE ATTACKS

SNR(dB)		1	5	10	15	20	25	30	35	40	45
Whole	*NC*	0.95	0.96	0.98	0.98	0.99	0.99	0.99	1	1	1
	NHD	0.04	0.03	0.01	0.01	0.00	0.00	0.00	0	0	0
Whole 48	*NC*	0.85	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86
	NHD	0.14	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Whole 56	*NC*	0.85	0.85	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86
	NHD	0.14	0.14	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Whole 64	*NC*	0.85	0.85	0.85	0.86	0.86	0.86	0.86	0.86	0.86	0.86
	NHD	0.14	0.14	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Whole 96	*NC*	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86
	NHD	0.14	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Whole 128	*NC*	0.85	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86
	NHD	0.14	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13

Table Ⅰ-Ⅻ and Fig. 2-4 show the performance metrics of the proposed algorithm. The normalized Hamming distances of origin audios and low bits rates compression audios are nearly invariable. Meanwhile, the NC of extracted watermark image and original watermark image is shown. From the results of experiments it can be drawn that the copyright information is clear and perceptible.

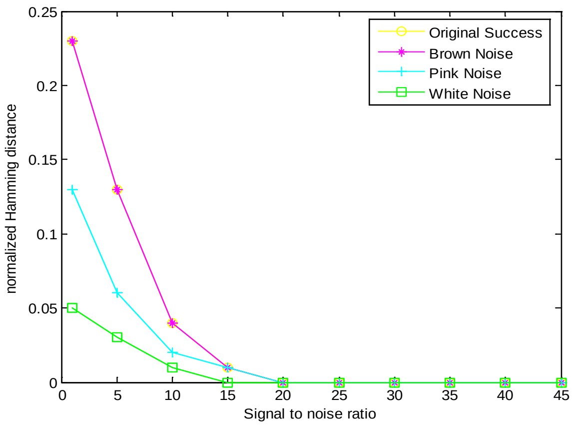

Fig. 3 Normalized Hamming distance of 'Success' under various low bits rates

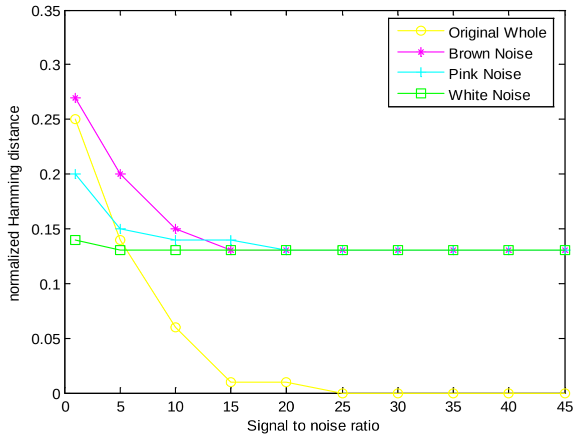

Fig. 4 Normalized Hamming distance of 'Whole' under various low bits rates

B. *Security Analysis*

In addition to robustness and discrimination power, another important performance aspect of audio watermarking is security. The copyright information should not be easily forged or estimated without the knowledge of the secret key. In this paper, the security of proposed algorithm totally depends on the user key. That means with the user key differences, the copyright information sequence is extracted from the same audio is different.

About 400 secret keys are generated from the interval [0, 1], and the 200th value is set equal to the original secret key. The results are shown in Fig. 5. It can be observed that the proposed algorithm provides a high level of security to audio watermarking for a given application.

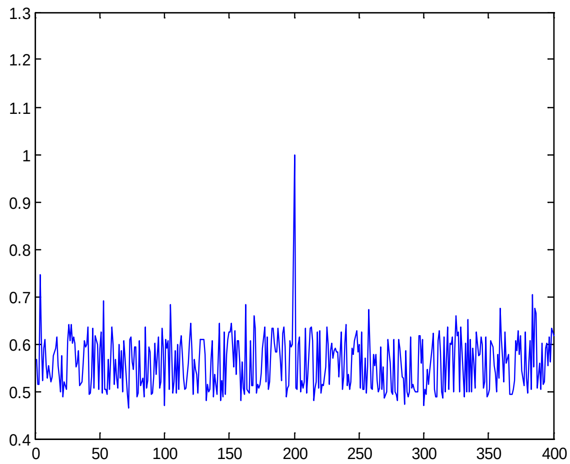

Fig. 5 Right bit rates under various user keys

Although the proposed algorithm is robustness and security, the method is not sensitive enough to detect the small-area tampering. This is because the feature vector extracted from the audio is a global-based feature, which is unable to capture small changes in the audio.

V. CONCLUSION

The illegal distribution of digital audio products and music files in particular has been a major problem for the industry for more than a decade. In this paper, we proposed an imperceptible (inaudible) and robust audio watermarking technique based on cascading two powerful mathematical transforms; the lifting-based wavelet transformation (LWT) and non-negative matrix factorization (NMF). The watermark bits were neither embedded directly on the wavelet coefficients, nor on the elements of singular values of the DWT sub-bands of the audio frames. By virtue of cascading the two transforms, inaudibility and different levels of robustness were achieved, as we have demonstrated using pop music and speech audio signals. The simulation results obtained to verify the effectiveness of audio watermarking as a reliable solution to the copyright protection problem which the music industry is facing.

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