Multimed Tools Appl
DOI 10.1007/s11042-010-0515-1

An audio watermarking scheme using singular value decomposition and dither-modulation quantization

Vivekananda Bhat K · Indranil Sengupta · Abhijit Das

Abstract Quantization index modulation is one of the best methods for performing blind watermarking, due to its simplicity and good rate-distortion-robustness trade-offs. In this paper, a new audio watermarking algorithm based on singular value decomposition and dither-modulation quantization is presented. The watermark is embedded using dither-modulation quantization of the singular values of the blocks of the host audio signal. The watermark can be blindly extracted without the knowledge of the original audio signal. Subjective and objective tests confirm high imperceptibility achieved by the proposed scheme. Moreover, the scheme is quite robust against attacks including additive white Gaussian noise, MP3 compression, resampling, low-pass filtering, requantization, cropping, echo addition and denoising. The watermark data payload of the algorithm is 196 bps. Performance analysis of the proposed scheme shows low error probability rates.

Keywords Audio watermarking · Dither-modulation (DM) · Quantization index modulation (QIM) · Singular value decomposition (SVD)

1 Introduction

Digital watermarking [5] is a recent method of protecting digital multimedia data (audio, image and video) against unauthorized copying. A digital watermark is a signal added to the original signal, which can later be extracted or detected. The

V. Bhat K (✉) · I. Sengupta · A. Das
Department of Computer Science and Engineering,
Indian Institute of Technology, Kharagpur 721302, India
e-mail: vbk@cse.iitkgp.ernet.in, kvivekbhat@gmail.com

I. Sengupta
e-mail: isg@cse.iitkgp.ernet.in

A. Das
e-mail: abhij@cse.iitkgp.ernet.in

Published online: 13 April 2010

watermark is intended to be permanently embedded into the digital data so that authorized users can easily access it. At the same time, the watermark should not degrade the quality of the digital data.

An audio watermarking scheme must satisfy the following requirements [8]: (i) Imperceptibility: It is the perceptual similarity between the original audio signal and the watermarked audio signal. (ii) Payload: This is the number of bits that can be embedded into the audio signal within a unit of time. There should be more than 20 bps data payload for the watermark. (iii) Security: The watermark can be detected only by authorized persons. (iv) Robustness: This stands for the resistance of the watermark against common signal processing and malicious attacks. No algorithm is known to satisfy all of the above requirements. Watermarking algorithms aim at achieving suitable trade-offs among the requirements.

Most of the watermarking algorithms proposed over the last few years focus on digital images and video sequences. Recently, audio watermarking has become an issue of significant interest to the research community. A comprehensive survey on audio watermarking can be found in [6]. Compared to image and video watermarking techniques, embedding of additional bits in an audio signal is a considerably more difficult task. The reason for this is that audio signals are represented by much less samples per time interval compared to images and video. This indicates that the amount of information that can be embedded robustly and imperceptibly is much lower for audio media than for visual media. Moreover, the human auditory system (HAS) is much more sensitive than the human visual system (HVS), implying that the realization of imperceptibility for audio signals is much more difficult than realizing invisibility for images.

Wang et al. [14] propose a digital audio watermarking algorithm based on the discrete wavelet transform (DWT). The watermark information is embedded into low-middle-frequency wavelet coefficients. A scheme of watermark detection is presented by using linear predictive coding (LPC), which does not require the original audio signal during watermark extraction. Wu et al. [15] present a self-synchronized audio watermarking algorithm using quantization index modulation (QIM). The synchronization code and the watermark data are embedded into the low-frequency sub-band in the DWT domain. In [2], Chang et al. propose a DWT-based counter-propagation neural network (CPN). The watermark embedding and extracting procedures are integrated into the proposed CPN. Li et al. [11] propose an audio watermarking method in which the embedding and detection regions are determined by applying content analysis of the music. Xiang and Huang [16] propose a multi-bit audio watermarking method based on two statistical features: the histogram shape and the modified mean value in the time domain. Xiang et al. [17] present another histogram-based audio watermarking scheme, in which the watermark is inserted by shaping the histogram after the DWT. Fan and Wang [7] recently introduce a novel audio watermarking scheme based on discrete fractional sine transform (DFRST). Experimental results show that the audio watermarking methods mentioned above have difficulty in obtaining favorable trade-offs among imperceptibility, robustness and data payload.

Singular value decomposition (SVD) is a useful tool of linear algebra with several applications in image compression, watermarking, and other areas of signal processing. A few years ago, SVD is explored for image watermarking applications [1, 18]. SVD is an optimal matrix-decomposition technique in a least-square sense. It packs maximum signal energy into as few coefficients as possible. SVD has the ability of adapting to variations in local statistics of a given signal, so watermarking schemes using SVD typically have high payload. Most SVD-based watermarking schemes embed watermark bits by modifying the singular values (SVs).

Dither-modulation (DM) quantization [3, 12] has good performance in terms of imperceptibility, data payload, robustness and blind extraction, and has become one of the popular watermarking schemes. DM quantization, combined with other methods, improves watermark extraction when the host signal is not available to the detector. In DM quantization, the host signal is dithered using watermark information. Then, the watermark information is embedded by quantizing the dithered host signal using quantizers selected from a set of possibilities.

In this paper, we present a new audio watermarking scheme using SVD and DM quantization. The advantages of using quantization and singular values (SVs) in watermarking methods are: (i) The QIM method is simple, has low complexity, and achieves good rate-distortion-robustness trade-offs. (ii) Changing SVs slightly does not affect the signal quality, and (iii) SVs do not change much after various types of common signal processing operations.

The rest of this paper is organized as follows. In Section 2, the proposed watermark embedding and extraction procedures are explained. Performance analysis and experimental results pertaining to our scheme are detailed in Sections 3 and 4. Concluding remarks are presented in Section 5.

2 A new audio watermarking scheme based on SVD and DM quantization

Let $A = (A_{ij})_{p\times p}$ be an arbitrary matrix with SVD of the form $A = UDV^T$, where U and V are orthogonal $p \times p$ matrices, and D is a $p \times p$ diagonal matrix with nonnegative elements. Let $u \leq p$ be the rank of the matrix A. The non-zero elements $\lambda_1, \lambda_2, \ldots, \lambda_u$ of D are the SVs of the matrix A.

Let $X = \{x(i), 1 \leq i \leq L\}$ represent a host audio signal of length L samples. $W = \{w(i, j), 1 \leq i \leq M, 1 \leq j \leq M\}$ is a binary image to be embedded within the host audio signal, and $w(i, j) \in \{0, 1\}$ is the pixel value at (i, j).

2.1 Embedding algorithm

The block diagram of our watermark embedding algorithm is shown in Fig. 1. The main steps of the embedding algorithm are described below.

Step 1: The audio signal X is partitioned into non-overlapping 2-D matrix blocks B_j, $j = 1, 2, 3, \ldots, M \times M$, each of size $u \times u$, where $M \times M$ is the number of bits in the watermark image.

Step 2: SVD is applied to each block, and the Euclidean norm of the SVs is computed for each block. Let $\lambda^j = (\lambda_1^j, \lambda_2^j, \ldots, \lambda_u^j)$ be the vector of SVs of the block B_j. The Euclidean norm of this vector is given by

$$n_j = \|\lambda^j\| = \sqrt{\sum_{i=1}^{u} (\lambda_i^j)^2} \tag{1}$$

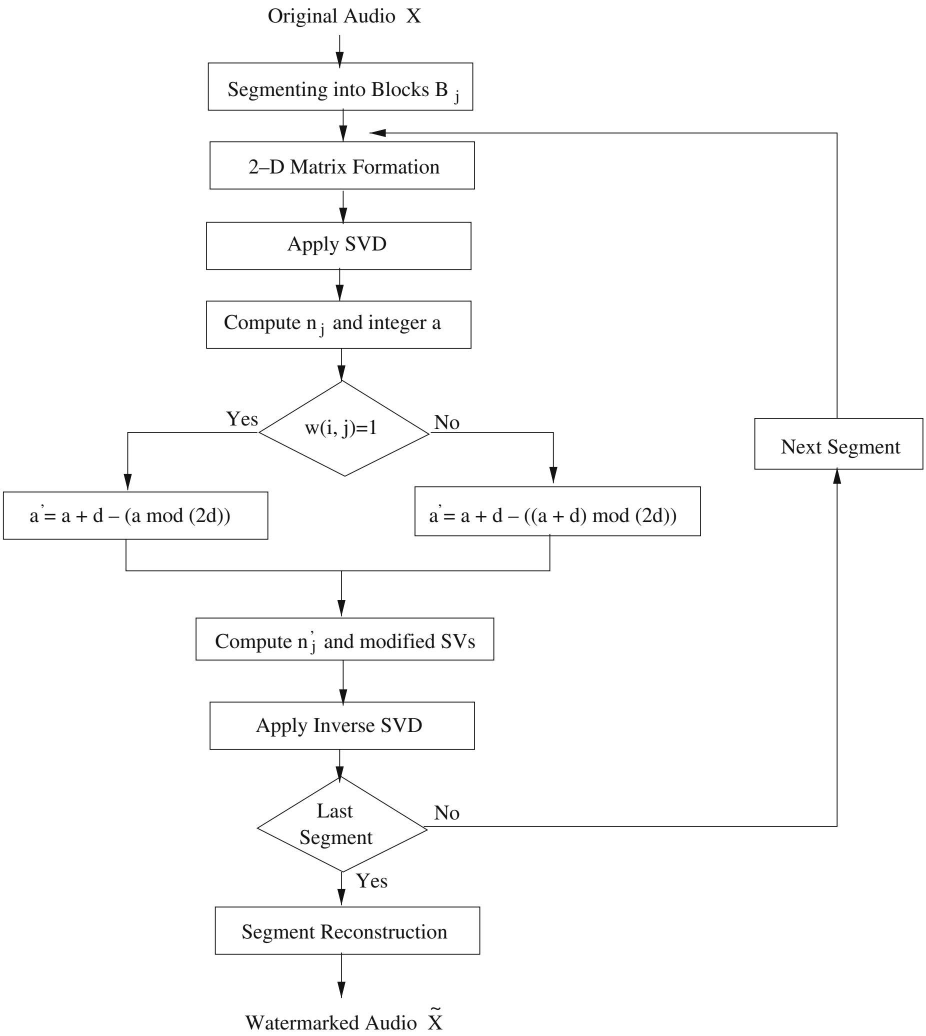


Fig. 1 Watermark embedding

Step 3: The integer $a = \lfloor \frac{n_j}{\Delta} \rfloor$ is computed, where Δ is a user-defined quantization step size (Δ is a positive real number).

Step 4: The watermark bits are embedded by using dither modulation. If the watermark bit $w(i, j) = 1$, then we modify a as follows:

$$a' = a + d - (a \bmod (2d)), \tag{2}$$

where d is a user-defined dither value (d is a positive real number).

Step 5: If the watermark bit $w(i, j) = 0$, then we modify a as follows:

$$a' = a + d - ((a + d) \bmod (2d)). \tag{3}$$

Step 6: We calculate the value $n_j^{'} = \Delta \times a^{'} + \frac{\Delta}{2}$ and compute the modified vector of SVs of the blocks using the following equation:

$$\tilde{\lambda}^j = \lambda^j \times \frac{n_j^{'}}{n_j}. \tag{4}$$

Step 7: The modified matrix of the block $\tilde{B}_j$ is obtained by applying inverse SVD to the modified SVs.

Step 8: The watermarked audio signal $\tilde{X}$ is reconstructed from all the modified blocks $\tilde{B}_j$.

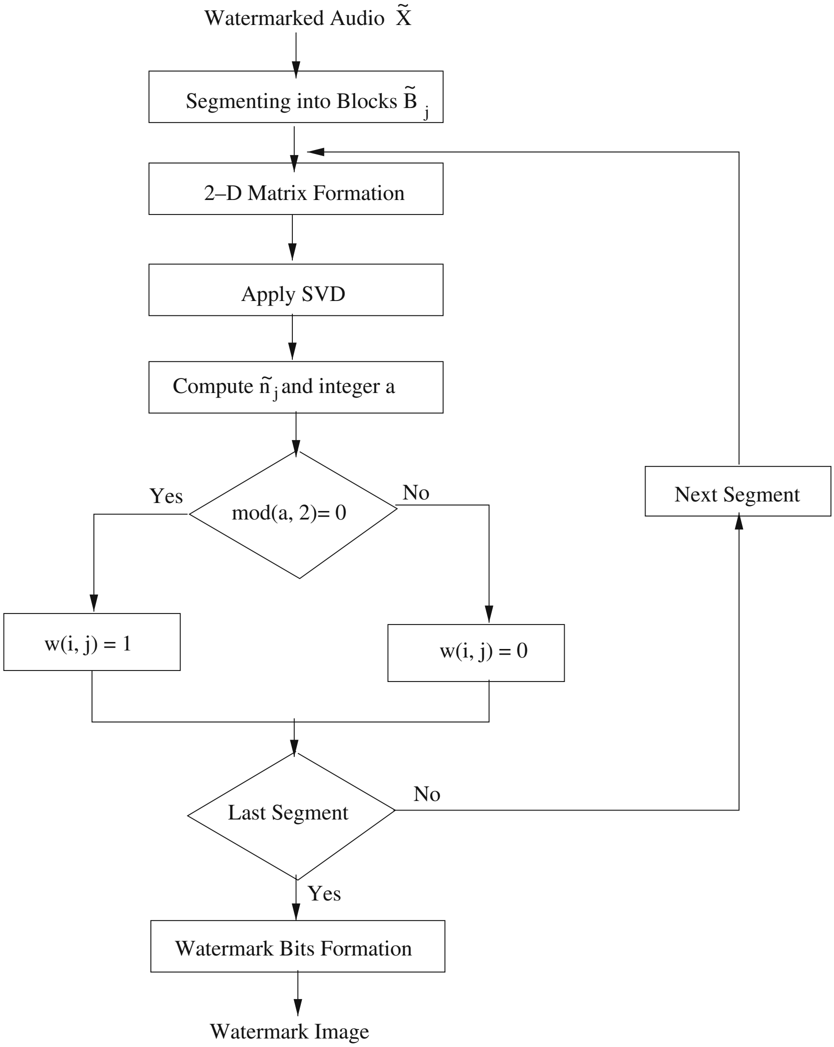


Fig. 2 Watermark extraction

2.2 Extraction algorithm

The block diagram of our watermark extraction algorithm is shown in Fig. 2. The main steps of the extraction algorithm are described below.

Step 1: The watermarked audio signal $\tilde{X}$ is segmented into 2-D matrix blocks $\tilde{B}_j$, $j = 1, 2, \ldots, M \times M$, of size $u \times u$, where $M \times M$ is the number of bits in the watermark image.
Step 2: SVD is applied to each block.
Step 3: The norms $\tilde{n}_j = \|\tilde{\lambda}^j\|$ of the SVs of the blocks are computed.
Step 4: The integer $a = \lfloor \frac{\tilde{n}_j}{\Delta} \rfloor$ is obtained.
Step 5: If $\mathrm{mod}(a, 2) = 0$, then the embedded bit is 1. Otherwise, it is 0.

3 Performance analysis

Two types of errors may occur while searching the watermark sequence: the false positive error and the false negative error. These errors are very harmful because they impair the credibility of the watermarking system. It is rather difficult to give an exact probabilistic model of false positive and false negative errors. Here, we adopt a simplified model based on binomial probability distribution, similar to [7].

3.1 False positive error

The false positive error stands for the situation that an unwatermarked audio signal is declared as watermarked by the decoder. Less false positive error probability implies better watermarking. Let k be the total number of watermark bits, and t the number of matching bits. The false positive error probability P_{f_p} can be calculated as follows:

$$P_{f_p} = 2^{-k} \sum_{t=\lceil 0.8k \rceil}^{k} \binom{k}{t}, \tag{5}$$

where $\binom{k}{t}$ is the binomial coefficient.

Figure 3 plots the false positive probabilities for $k \in (0, 100]$. It demonstrates that the false positive probability approaches 0 when k is larger than 20. In our method, $k = 1{,}024$, hence the false positive probability is close to 0. Indeed, putting $k = 1{,}024$ in (5) gives $P_{f_p} = 1.18 \times 10^{-529}$.

3.2 False negative error

The false negative error is the situation when a watermarked audio signal is declared as unwatermarked by the decoder. Less false negative probability implies better watermarking. The false negative error probability P_{f_n} can be calculated as follows:

$$P_{f_n} = \sum_{t=0}^{\lceil 0.8k \rceil - 1} \left[\binom{k}{t} (p)^t (1-p)^{k-t} \right], \tag{6}$$

where p is the bit error probability of extracted watermark.

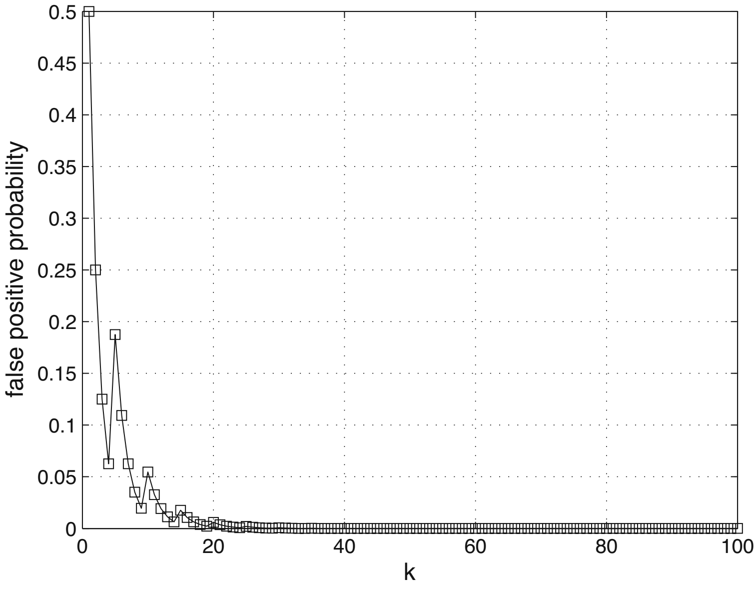


Fig. 3 False positive probabilities under various *k*

From Tables 3 and 4 shown in the next section, we see that the BERs are all less than 0.03, so p is taken to be 0.97 in our scheme. Figure 4 plots the false negative probabilities for $k \in (0, 100]$. It indicates that the false negative probability

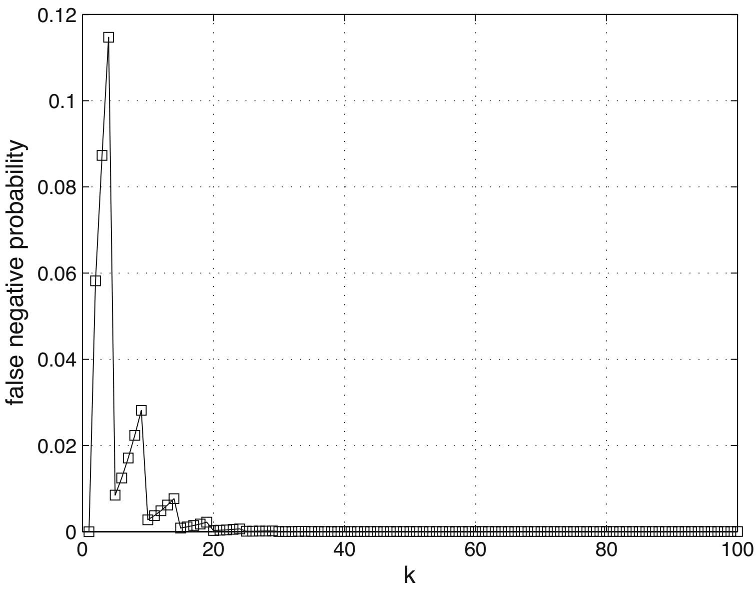


Fig. 4 False negative probabilities under various *k*

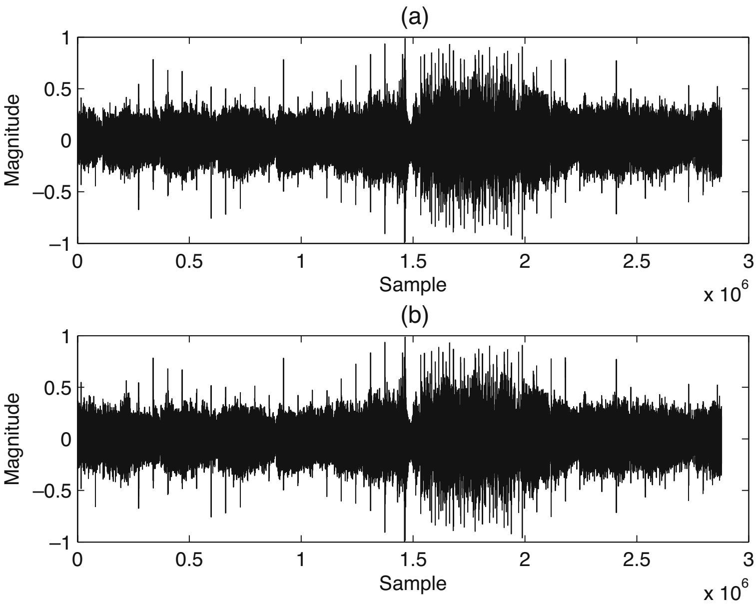


Fig. 5 **a** Pop audio signal **b** Watermarked pop audio signal

approaches 0 when k is larger than 20. In our method, $k = 1{,}024$, hence the false negative probability of our scheme is close to 0. Indeed, putting $k = 1{,}024$ and $p = 0.97$ in (6) gives $P_{f_n} = 1.53 \times 10^{-102}$.

4 Experimental results and comparison

We have performed experimentation using MATLAB 7.1. Five types of audio signals (classical, country, blues, jazz and pop) are used in the experiment. Each such audio signal is a 16-bit mono file in the WAVE format and has 44.1 kHz sampling rate. A short portion of an original pop audio signal and that of the corresponding watermarked audio signal are shown in Fig. 5a, b, respectively. We use a $M \times M = 32 \times 32$ binary image shown in Fig. 6 as our watermark for all these audio signals. The parameters used in the algorithm are set as follows: the audio block size $u \times u$ is 15×15, the fixed quantization step size $\Delta = 0.5$, and the fixed dither value $d = 1$. These parameters have been experimentally selected so as to achieve a good trade-off among the conflicting requirements of imperceptibility, robustness, and payload.

Fig. 6 Binary watermark

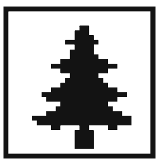


Table 1 Subjective and objective difference grades

SG	ODG	Description of impairments	Quality
5.0	0.0	Imperceptible	Excellent
4.0	−1.0	Perceptible, but not annoying	Good
3.0	−2.0	Slightly annoying	Fair
2.0	−3.0	Annoying	Poor
1.0	−4.0	Very annoying	Bad

4.1 Imperceptibility test

The imperceptibility test is performed by subjective and objective means [4].

4.1.1 Subjective listening test

Subjective listening tests are essential to perceptual quality assessment, since the ultimate judgment is made by human acoustic perception.

In the subjective listening test, five participants are provided with the original and the watermarked audio signals and are asked to report dissimilarities between the two signals, using a five-point subjective grade (SG) shown in Table 1. The average SG scores for our scheme are shown in Table 2. These high SG scores indicate that our scheme provides good imperceptibility of the watermark in the audio signals.

4.1.2 Objective test

The ultimate goal of objective measurement algorithms is to substitute the subjective listening tests by modeling the listening behavior of human beings. The objective measurement metric namely objective difference grade (ODG) does not always correlate very well with the result from subjective listening tests [9]. However a final judgment regarding audio quality has to be based on subjective listening tests [6].

The ODG is the output variable obtained from perceptual evaluation of audio quality (PEAQ) measurement algorithm specified in ITU-R BS.1387 (International Telecommunication Union-Radio-communication Sector) [13]. It corresponds to the subjective grade used in human based audio tests. The ODG ranges from 0.0 to −4.0 (corresponding to imperceptible to very annoying) as shown in Table 1. To measure the ODG between original and watermarked audio signals the software program EAQUAL (Evaluation of Audio Quality) [10] based on ITU-R BS.1387 is utilized. Table 2 presents results of objective test. It is evident that all the ODG scores are within (−1.0, 0.0), which confirm that our watermarked audio signals are perceptually similar to original audio signals.

Table 2 Average SG and ODG scores for different audio signals

Audio file	Average SG	ODG
Blues	4.8	−0.48
Classic	4.9	−0.79
Country	4.6	−0.78
Jazz	4.4	−0.86
Pop	4.5	−0.74

4.2 Robustness test

Normalized correlation (NC) is used to evaluate the correlation between the extracted and the original watermark and is given by

$$NC(W, \tilde{W}) = \frac{\sum_{i=1}^{M} \sum_{j=1}^{M} W(i, j)\tilde{W}(i, j)}{\sqrt{\sum_{i=1}^{M} \sum_{j=1}^{M} W^2(i, j)} \sqrt{\sum_{i=1}^{M} \sum_{j=1}^{M} \tilde{W}^2(i, j)}}, \tag{7}$$

where W and $\tilde{W}$ are the original and the extracted watermarks, respectively, and i, j are indices in the binary watermark image. If $NC(W, \tilde{W})$ is close to 1, then the correlation between W and $\tilde{W}$ is very high. If $NC(W, \tilde{W})$ is close to zero, then the correlation between W and $\tilde{W}$ is very low.

The bit error rate (BER) is used to measure the robustness of our scheme:

$$BER(W, \tilde{W}) = \frac{\text{Number of error bits}}{\text{Number of total bits}} = \frac{\sum_{i=1}^{M} \sum_{j=1}^{M} W(i, j) \oplus \tilde{W}(i, j)}{M \times M}, \tag{8}$$

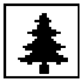
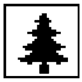
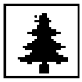
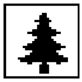
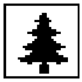
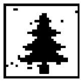
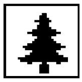
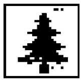
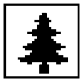
where $\oplus$ is the exclusive or (XOR) operator.

The following signal processing attacks are performed to assess the robustness of our scheme. The audio editing and attacking tools adopted in the experiment are MATLAB 7.1, Adobe Audition 1.0, and GoldWave 5.18.

(A) Additive white Gaussian noise (AWGN): White Gaussian noise is added to the watermarked signal until the resulting signal has an SNR of 20 dB.
(B) Resampling: The watermarked signal, originally sampled at 44.1 kHz, is resampled at 22.05 kHz, and then restored back by sampling again at 44.1 kHz.
(C) Low-pass filtering: A second-order Butterworth filter with cut-off frequency 11,025 Hz is used.
(D) Requantization: The 16-bit watermarked audio signal is re-quantized down to 8 bits/sample and then back to 16 bits/sample.
(E) MP3 compression 64 kbps: The MPEG-1 layer-3 compression is applied. The watermarked audio signal is compressed at the bit rate of 64 kbps and then decompressed back to the WAVE format.
(F) MP3 compression 32 kbps: The MPEG-1 layer 3 compression is applied. The watermarked audio signal is compressed at the bit rate of 32 kbps and then decompressed back to the WAVE format.
(G) Cropping: Segments of 500 samples (5×100) are removed from the watermarked audio signal at five positions and subsequently replaced by segments of the watermarked audio signal attacked with low-pass filtering and additive white Gaussian noise.
(H) Echo addition: An echo signal with a delay of 98 ms and a decay of 41% is added to the watermarked audio signal.
(I) Denoising: The watermarked audio signal is denoised by using the "Hiss removal" function of GoldWave.

The extracted watermarks along with the NC and BER values for the above attacks on a country audio file are summarized in Table 3. The NC values are all

Table 3 Extracted watermark with NC and BER for Country audio

Attack type	Normalized correlation (NC)	Bit error rate (BER(%))	Extracted watermark
No attack	1	0	
AWGN	1	0	
Resampling	0.9994	0	
Low-pass filtering	1	0	
Requantization	1	0	
MP3 64 kbps	0.9923	1	
MP3 32 kbps	0.9879	2	
Cropping	1	0	
Echo addition	0.9943	1	
Denoising	1	0	

above 0.9879 and the BER values are all below 2%. The extracted watermark images are visually similar to the original watermark. This illustrates good robustness of the proposed method for a country audio file.

In Table 4, similar results for Blues, Classic, Jazz, and Pop audio files are shown. The NC values are all above 0.9866 and the BER values are all below 3%, demonstrating the robustness of our scheme on these types of music.

4.3 Payload

The data payload refers to the number of bits that can be embedded into the audio signal within a unit of time and is measured in the unit of bps (bits per second).

Table 4 NC and BER of extracted watermark for different audio files

Audio file	Attack	Normalized correlation (NC)	Bit error rate (BER(%))
Blues	No attack	1	0
	AWGN	1	0
	Resampling	1	0
	Low-pass filtering	1	0
	Requantization	1	0
	MP3 64 kbps	0.9968	0
	MP3 32 kbps	0.9879	2
	Cropping	1	0
	Echo addition	0.9866	3
	Denoising	1	0
Classic	No attack	1	0
	AWGN	1	0
	Resampling	1	0
	Low-pass filtering	1	0
	Requantization	1	0
	MP3 64 kbps	0.9994	0
	MP3 32 kbps	0.9955	1
	Cropping	1	0
	Echo addition	0.9955	1
	Denoising	1	0
Jazz	No attack	1	0
	AWGN	1	0
	Resampling	0.9924	1
	Low-pass filtering	1	0
	Requantization	1	0
	MP3 64 kbps	0.9975	0
	MP3 32 kbps	0.9911	1
	Cropping	1	0
	Echo addition	0.9987	0
	Denoising	1	0
Pop	No attack	1	0
	AWGN	1	0
	Resampling	0.9994	0
	Low-pass filtering	1	0
	Requantization	1	0
	MP3 64 kbps	0.9987	0
	MP3 32 kbps	0.9994	0
	Cropping	1	0
	Echo addition	0.9987	0
	Denoising	1	0

Suppose the length of host audio signal is L seconds, and the watermark data is of size M bits. Then, the data payload DP is defined as follows:

$$DP = \frac{M}{L} \text{ bps.} \tag{9}$$

The data payload of our scheme is 196 bps.

Due to diversity of watermark embedding approaches, a general comparison between our method and several recent methods, sorted by attempted data payload

Table 5 A general comparison of audio watermarking algorithms, sorted by attempted data payload

Algorithm	Payload (bps)	Noise addition BER (%)	Resampling BER (%)	Low-pass filtering BER (%)	MP3 compression BER (%)
Our	196	0 (20 dB)	1 (22.05 kHz)	0 (11.025 kHz)	2 (32 kbps)
In [15]	172	4.98 (16.12 dB)	0 (22.05 kHz)	Not reported	24.18 (32 kbps)
In [7]	86	4.22 (65 dB)	0 (22.05 kHz)	3.71 (20 kHz)	3.47 (48 kbps)
In [2]	86	Not reported	0 (22 kHz)	0 (4 kHz)	0 (56 kbps)
In [14]	10.72	5.13 (36 dB)	13.64 (22.05 kHz)	18.06 (11.025 kHz)	5.71 (128 kbps)
In [11]	4.26	1.56 (Not reported)	0 (22.05 kHz)	0 (8 kHz)	1.56 (32 kbps)
In [16]	3	0 (35 dB)	0 (Not reported)	8.33 (9 kHz)	15 (128 kbps)
In [17]	2	15 (35 dB)	0 (16 kHz)	7.5 (8 kHz)	17.5 (64 kbps)

is given in Table 5. Our comparison is based on reported results of recently published methods and it is given for data payload, noise addition, resampling, low-pass filtering, and MP3 compression. In view of the comparison in Table 5, our proposed watermarking algorithm achieves high embedding capacity and low BER against attacks, such as noise addition, resampling, low-pass filtering and MP3 compression. The performance of our algorithm can be further improved by reducing data payload.

5 Conclusion

In this paper, we propose an audio-watermarking scheme based on SVD and DM quantization. The watermark is embedded by applying DM quantization on the SVs of the audio signal blocks. Extensive experimental works have shown that the proposed watermarking scheme has strong robustness to common signal processing operations. Moreover, the proposed scheme achieves low error probability rates. We have compared performance of our algorithm with other recent audio watermarking algorithms. Overall, our proposed algorithm has high embedding capacity and achieves low BER against attacks, such as noise addition, resampling, low-pass filtering, and MP3 compression.

References

1. Bao P, Ma X (2005) Image adaptive watermarking using wavelet domain singular value decomposition. IEEE Trans Circuits Syst Video Technol 15(1):96–102
2. Chang C-Y, Shen W-C, Wang H-J (2006) Using counter-propagation neural network for robust digital audio watermarking in DWT domain. In: IEEE International conference on systems, man and cybernetics, (SMC'06), vol 2, pp 1214–1219
3. Chen B, Wornell GW (2001) Quantization index modulation: a class of provably good methods for digital watermarking and information embedding. IEEE Trans Inf Theory 47(4):1423–1443
4. Christian N, Jurgen H (1998) Digital watermarking and its influence on audio quality. In: Proceeding of the 105th AES convention, Preprint 4823
5. Cox I, Miller M, Bloom J, Fridrich J, Kalke T (2007) Digital watermarking and steganography. Morgan Kaufmann, USA
6. Cvejic N, Seppanen T (2007) Digital audio watermarking techniques and technologies. Information Science Reference, USA

7. Fan M, Wang H (2009) Chaos-based discrete fractional Sine transform domain audio watermarking scheme. Comput Electr Eng 35(3):506–516
8. Katzenbeisser S, Petitcolas FAP (2000) Information hiding techniques for steganography and digital watermarking. Artech, Boston
9. Keiler F (2006) Real-time subband-ADPCM low-delay audio coding approach. In: Proceeding of the 120th AES convention, Preprint 6748
10. Lerch A (2002) Zplane development, EAQUAL-Evaluate Audio QUALity, version: 0.1.3alpha. http://www.mp3-tech.org/programmer/misc.html
11. Li W, Xue X, Lu P (2006) Localized audio watermarking technique robust against time-scale modification. IEEE Trans Multimedia 8(1):60–69
12. Solanki K, Jacobsen N, Madhow U, Manjunath BS, Chandrasekaran S (2004) Robust image-adaptive data hiding using erasure and error correction. IEEE Trans Image Process 13(12):1627–1639
13. Thielde T et al (2000) PEAQ-The ITU standard for objective measurement of perceived audio quality. J Audio Eng Soc 48(1/2/3):3–29
14. Wang R, Xu D, Chen J, Du C (2004) Digital audio watermarking algorithm based on linear predictive coding in wavelet domain. In: 7th IEEE International conference on signal processing, (ICSP'04), vol 1, pp 2393–2396
15. Wu S, Huang J, Huang D, Shi YQ (2005) Efficiently self-synchronized audio watermarking for assured audio data transmission. IEEE Trans Broadcast 51(1):69–76
16. Xiang S, Huang J (2007) Histogram-based audio watermarking against time-scale modification and cropping attacks. IEEE Trans Multimedia 9(7):1357–1372
17. Xiang S, Kim HJ, Huang J (2008) Audio watermarking robust against time-scale modification and MP3 compression. Signal Process 88(10):2372–2387
18. Yavuz E, Telatar Z (2007) Improved SVD-DWT based digital image watermarking against watermark ambiguity. In: Proceedings of the ACM symposium on applied computing, pp 1051–1055

Vivekananda Bhat K received M.Sc. degree from Mangalore University, Karnataka, India, in 1995 and M.Tech. degree from National Institute of Technology Karnataka, Surathkal, India, in 2003. He is currently working toward Ph.D. degree in the Department of Computer Science and Engineering of the Indian Institute of Technology, Kharagpur, India. Prior to joining Ph.D., he held academic position at National Institute of Technology Karnataka, Surathkal, India. He has four publications in international journal and conferences. His research interests include Digital watermarking and Cryptography.

Indranil Sengupta obtained B.Tech, M.Tech, and Ph.D. degrees in Computer Science and Engineering from the University of Calcutta, India, in 1983, 1985, and 1990, respectively. He joined Indian Institute of Technology, Kharagpur, as a faculty member in 1988, in the Department of Computer Science and Engineering, where he is presently a Professor and the Head of the Department. He also heads the School of Information Technology of the Institute. A Centre of Excellence in Information Assurance has been set up at IIT Kharagpur under his leadership, where a number of security related projects are presently being executed. He has over 24 years of teaching and research experience, and over 100 publications to his credit in international journals and conferences. His research interests include Cryptography and network security, VLSI design and testing, Mobile computing, and Digital watermarking.

Abhijit Das received Bachelor degree in Electronics and Telecommunication Engineering from Jadavpur University, Calcutta, India, in 1991, M.E. and Ph.D. degrees in 1993 and 2000, respectively, in Computer Science and Engineering from the Indian Institute of Science, Bangalore, India. He is currently an Assistant Professor in the Department of Computer Science and Engineering, Indian Institute of Technology (IIT) Kharagpur. Before joining IIT, he held academic positions at the Indian Institute of Technology Kanpur and Ruhr-Universitat Bochum, Germany. He has 12 publications in international journals and conferences. His research interests include Cryptography, Number-theoretic and algebraic computations, and Digital watermarking.