Effective Digital Audio Watermarking Using Dwt And Neural Networks

Abhijit Patil[1*], Dr. Ramesh Shelke[2]

Abstract

Watermarking is the process in which a digital signal is added with another secret digital signal. Digital audio watermarking has been widely used in many applications such as copyright protection, tamper detection, piracy prevention, content authentication, etc. The audio watermarking process has to satisfy many properties such as robustness, imperceptibility, and security. There are many classical as well as hybrid techniques available in the literature to achieve these properties. However, it's difficult to achieve all the properties at the highest level using a single technique. Echo hiding and pitch shifting approaches are being used from beginning. Some new techniques are being designed that make use of machine learning and deep learning algorithms, "bio-inspired algorithms" such as swarm intelligence algorithms [18], and genetic algorithms, AI-based techniques such as simulated annealing can also be used for optimization in watermarking process. Arnold scrambling and use of cryptographic algorithms can be used for increasing the security of watermarks. However, it is observed that many modern approaches are not giving efficient results in embedding and extraction of watermark with minimum bit error. Finding optimal locations for the watermark bits embedding into host signal is a challenge. In this paper, we are discussing some of the important hybrid and novel techniques used for digital audio watermarking. We proposed and demonstrated the work using a custom-designed simple backpropagation neural network. Our focus is to demonstrate the usefulness of neural network architectures in the subject of study.

Keywords: Audio Watermarking, Neural Network, DWT, Robustness, Imperceptibility, Deep Learning.

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1. Introduction

The main reason for Digital audio watermarking technology being more challenging is that "the human auditory system is extremely more sensitive than the human visual system" [28]. Audio watermarking algorithms are broadly classified into time and frequency domain techniques. Frequency domain techniques are more popular in the research community. Conventional techniques used for watermarking procedure are LSB technique, DCT, DWT, SVD, and or the combination of two or more among these [27-28]. Major group of schemes in the topic of study use spread spectrum techniques [32-34]. There is another group of audio schemes which use patchwork algorithms [14, 35-38]. Few techniques use the synthesized echoes of original signal as a secret message to be embedded [29-31]. However, it is observed that neural network-based techniques are also being used for making the watermarking procedure more robust and secure against the attacks. In recent year many researchers had used deep learning algorithms for watermarking [1-14]. The characteristics that determine the effectiveness of watermarking algorithms are Robustness, Imperceptibility and Security. Through the extensive literature survey it is observed that the neural network and deep learning-based techniques have a great impact on increasing the robustness of the watermark. It has been observed that the neural network-based techniques had shown better results in providing robustness and imperceptibility [1-3, 7-13]. "Artificial neural networks" (ANN), "Convolutional Neural Networks" (CNN), Encoders and decoders, are few of them [1-5]. Bit error rate, Mean Square

***Corresponding Author:-** Abhijit Patil
Address: 1*Ph.D. Scholar, Department of Computer Engineering, PAHER University Udaipur, Rajasthan, India
2Research Supervisor, Department of Computer Engineering, PAHER University, Udaipur, Rajasthan, India
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Error (MSE), and Peak Signal Noise Ratio PSNR) are the important parameters that are used for the comparison of different watermarking algorithms. In this paper, we are discussing the neural network-based techniques used for digital audio water-marking and their effectiveness. We are proposing a neural network-based approach for improving the robustness and imperceptibility of watermarked speech data. The aim of using deep learning techniques in audio watermarking is to make the watermark more robust against the attacks, to improve the strength of watermark [5]. As the audio watermarking is more challenging than image watermarking, deep learning techniques are found to be best suitable if used in combination with DWT, DCT. The traditional techniques are manual and provide the strength to watermark up to some limit. We can improve the robustness and imperceptibility of the watermark if a suitable deep learning technique is used. The rest of the paper is organized as: Section 2 involves a literature survey of different neural network-based approaches used previously. Section 3 contains the implementation of the general framework. Section 4 discusses Experimental results. And finally, section 5 concludes the paper.

2. Literature Review

In audio watermarking the commonly used watermarks are binary message [1], binary image [2],[3],[7],[15], or an audio signal[14]. Whenever an image is used as a watermark, it has to be converted into a one-dimensional binary signal so that it can be properly inserted at the desired positions in the host signal. Deep learning networks such as encoders and decoders are found suitable for inserting the watermark data (bits) at the best positions in the host signal so that they cannot be easily extracted or attacked. These techniques are used in combination with conventional techniques i.e. DWT or DCT. The choice of watermark data (Image or Audio) depends on the type of application it is used. We studied research work carried out in recent years in this area and found some good techniques. Here we are discussing few of them along with a table of comparison.

K. Pavlović et.al.[1] have performed speech watermarking using Encoder, Decoder, and STFT techniques. One Dimensional Binary Message was used as a watermark and the dataset was audio recordings from the parliament of Montenegro. The Audio files of 226 speakers of around 232 minutes per speaker were collected for training which were sampled at 44.1 kHz. They obtained good results with Decoder Accuracy 99.82% and PSNR 57.5dB. G. Wu et.al.[2] have used discrete wavelet transform(DWT) on the audio signal, for selecting the important coefficients which are ready to be trained in the neural network. The concept of watermark memorization in the nerve cells of CPN Counter propagation network was used. The network was designed to be fault tolerant. The architecture is designed with an adaptive number of parallel Counter propagation networks. These parallel networks were able to treat each audio frame separately and the corresponding watermark bits. They found that CPN improves the efficiency for watermark embedding process was improved. Also more correctness in extracting the watermark data. The method was robust and as well as improved the inaudibility of audio watermark. C. Maha et. al. [3] in this paper a blind audio watermarking scheme based on neural network is described. The basis of the method is human psychoacoustic model (HPM) with error correcting code. They used DWT, HPM as a reference model, and BPNN. Along with this they used Hamming Code for increasing the security of the watermark. A binary image of size 32*32 is used as a watermark and the audio file (.wav file) with 44.1 Khz Sampling rate, 16 bits per sample was used for testing the results. They found that the HPM provides better robustness and imperceptibility.

Das et.al.[4] presented the deep learning scheme for embedding an audio watermark into an image. An unsupervised learning approach is used. In this paper “a robust and blind audio-in-image watermarking scheme” is described. They designed a network called as similarity network that is able to recognize the audio watermarks under distortions. The deep network is modelled as “Encoder, Decoder, Embedder, and Extractor Networks”. J. Hu et.al. [8] Used triple forward Neural Network and Wavelet transform for embedding the watermark. Important coefficients the audio signal are found to embed the watermark into it. Later on corresponding algorithms of watermark generation, embedding, and

extraction are used. It is a "non-blind audio watermarking scheme" in which original signal is needed for while extracting the watermark. The watermark is simulated for common signal processing attacks and shown that the algorithm is robust against the attacks. Chuan-Yu Chang et. al. [9] proposed a novel "Fully Connected Counter Propagation Network." (FCNN) for image watermarking. Along with this they performed: Imperceptibility Testing, Robustness testing(for grayscale watermark, for binary watermark), Authenticity testing. Rather than the cover images, the watermark is embedded in synapses of FCNN. Their experimental results shown that the quality of watermarked image was not degraded. As mentioned in the paper, the watermark become robust, because the watermark was stored in the synapses. Jiang Jing et.al. [10] In this paper "a patchwork method for digital watermarking based on Radial Basis Neural Network (RBNN)" is discussed. The method randomly selects two patches using a key, then some constant value is added in one patch and at the same time subtracted from other. M pairs of patches and 2M sets of pseudorandom numbers are used for embedding watermarking information. The watermark is embedded into the sample audio signal. The RBNN is trained using a randomly selected sample from embedded audio signal. The method is based on the wavelet domain. The watermark signals are embedded in approximation coefficients [10]. Quality of watermark is verified using PSNR and ER(Extraction Ratio) parameters. In works of Sarreshtedari et.al. [22] they have used source-channel coding approach for digital self-embedding speech signals. It generates a tamper-proof signal. Hash generation algorithm is used for preserving MSB of speech signal frames. In the works of Huiqin Wang et. al. [12] Neural Network based Controller was used for checking and ensuring the strength of embedded watermark data. Signal to Mask Ratio from psychoacoustic model (SMR), and DCT coefficients are used as the input to the model. [13] H. Yang et. al, here they had used the concept of WSF(Watermark Scaling Factor) and MMF(Minimum Masking Threshold). WSF is determined with the help of signal data and some statistical parameters. An artificial neural network was designed which not only determines watermark scaling factor (WSF), but uses the concept of MMT such that the power spectrum of watermark always remain below MMT. Embedding of the watermark is carried out in DCT domain. The embedded watermark remains robust against few attacks since it depends on secret key, ANN architecture and final weights.

Authors	Paper Title	Method Used	Watermark Used	Dataset Used	Experimental Results / Remarks
[1]K. Pavlović, S. et. al. 2020	"Speech watermarking using Deep Neural Networks"	Encoder, Decoder, STFT	One Dimensional Binary Message.	The audio recording data is taken from parliament of Montenegro and was sampled at 44.1 kHz. (Total 226 speakers and recordings of total 232 minutes duration per speaker)	Obtained Decoder Accuracy 99.82% PSNR 57.5dB
[2] G. Wu and X. Zhou 2008	"A Fast Audio Digital Watermark Method Based on CPNN"	DWT, Counter Propagation Networks	64*64 bit binary image.	16 bit mono audio signal files : i) music.wav and ii) speaker.wav.	Obtained SNR 61.32 and 40.15 for two samples respectively. BER for extracted data 6.2%
[3] C. Maha, E. Maher and B. A. Chokri 2008	"A blind audio watermarking scheme based on neural network and HPM with error correcting code in wavelet domain"	DWT, Human Psychoacoustic Model, BPNN, Hamming Code	A Binary image of size 32*32 pixels.	A Wav file with 44.1 Khz Sampling rate, 16 bits per sample.	Hamming Code provides security and avoids corruption of watermark. HPM gives better robustness and imperceptibility.
[4] Das, Arjon, and Xin Zhong. 2021	"A Deep Learning-based Audio-in-Image Watermarking Scheme."	"Audio-In-Image Watermarking" "WM Network (Encoder, Decoder, and Embedder, and Extractor Networks)", Similarity Network	"Speech Commands Dataset"	Image, "rescaled 128 × 128 Microsoft COCO Dataset"	Root Mean Squared Error (RMSE) and SSIM parameters are used for verification. High fidelity and robustness was obtained.
[7] C. Chang, W. Shen and H. Wang 2006	"Using Counter-propagation Neural Network for Robust Digital Audio Watermarking in DWT Domain"	DWT based Counter Propagation Network, Synchronization Code.	Binary image of 32 * 32 size.	16 bits mono-track audio music with sampling rate 44.1KHz Audio file of frame size 512.	

[8] J. Hu, X. Qiu and D. He 2008	"Digital Audio Watermarking Algorithm based on Neural Networks"	Multi Layer Feed Foreword network in DWT Domain	Black and white image.	Audio signal with 8 bits/sample, 44.1kHz sample rates. 3-grade Daubechies-4 wavelet to decompose the audio signal.	No distortion in original watermark, Robust against low pass filtering, resampling,and compression attacks
[9] C Yu Chang et. al.	"A neural-network-based robust watermarking scheme."	FCNN	(Used for Image Watermarking)	(Used for Image Watermarking)	(For Image Watermarking)
[12] H. Wang et. al. 2006	"New Audio Embedding Technique Based on Neural Network"	NN Controller, Masking Level, Dimensionality Reduction, Signal to ask ratio.	Binary Image of Size 256 * 256	Audio File of duration 4 Seconds and sampling frequency 22.05KHz.	Robustness is checked against noise, low pass filtering and resampling attacks. There is some distortion in extracted watermark.
[13] H. Yang, et. al. 2002	"An artificial neural network-based scheme for robust watermarking of audio signals."	Simple ANN with Discrete Cosine Transform, Concept of WSF(Watermark scaling Factor), and MMt(Minimum Masking Threshold are used.	Audio Signal	A3dsplash.wav (with sampling rate: 44.1KHz, and bit rate: 705kbps with mono) This signal is divided into 131 frames. Every frame containing with 1024 samples. Each frame is further segmented into 32 sub bands with 32 samples.	Produced Good Imperceptibility. MSE level obtained was -37dB

Table1: Literature Review of Neural Network Based Techniques for Audio Watermarking

3. Proposed Method

Audio Watermarking is carried out in two steps: i) Embedding and ii) Extraction. The host audio signal used is an audio file of 90 minutes duration, and the watermark is 180*180 binary image. We used backpropagation neural network for watermark embedding and extraction process along with DWT. Our framework takes two sources of input which are

i. The watermark image and,

ii. The audio file (Which has to be watermarked)

We used a sample lecture audio file as host signal for input. We had divided the 90 minutes audio files into small chunks whose size can be set from 10 seconds to 5 minutes to increase the processing speed. We used binary image of size 50 by 50 as a watermark. While processing, we take a 2D binary image (watermark).. Then this image is converted into binary using open cv2. For the second input i.e. audio signal we had taken a sample audio file of lecture recording. For pre-processing we used DWT as the standard and most efficient technique. DWT is applied to these chunks for obtaining the lower frequency components. In next step analysis of the chunks is done for each frame. Then, the custom built Neural Network embeds binary bits of watermark in the audio signal. For the decoding process the second neural network decodes back the watermark from the audio. DWT is applied again on the 10 second chunks and they are converged/merged back as well. We had used python programming and the required libraries for demonstrating the experimental results.

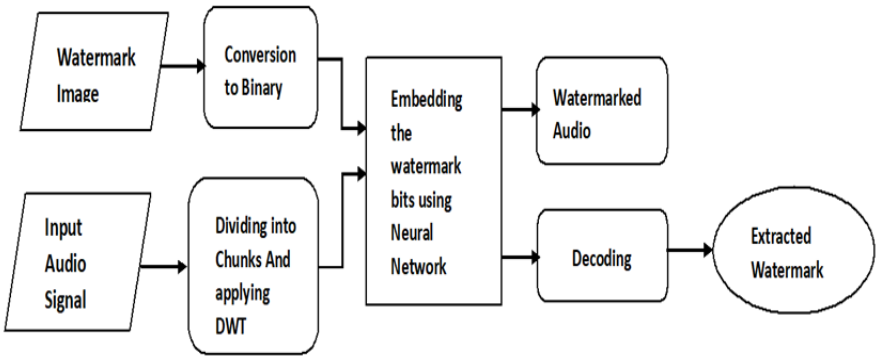

Fig 1 : Flow Diagram of Proposed Work

3.1. *Input Processing*

The first step in our system is to process the watermark image. For the proposed project we have taken the JPG image as sample watermark with the dimensions of 180 x 180 pixels. The JPG image is converted into binary format which is embedded in the audio signal.

First we convert it into Grayscale by setting a threshold of 128. Further, we had converted the image into binary of size 50 by 50 to use as the watermark. All these preprocessing steps are carried out using cv2 and numpy. Hence the watermark is hereby converted into a numpy array of 50 x 50 dimension. The audio file that has to be watermarked is first sampled at rate of 44.1 KHz. We down sample the given audio file to 16 KHz using an external library librosa. We divided the whole input audio file of 90 mins into chunks of length 10 seconds to 5 minutes for testing the experimental results. Hence we have the input watermark in the binary form and the audio down sampled into 16 KHz.

3.2. *Encoding using Neural Network*

In order for successful embedding of our watermark in the audio file, our Neural Network uses the lowest significant bits of the audio data for embedding the watermark inside it. In simple terms, the embedding process efficiently replaces the Lowest Significant bit of each byte in the audio file (in our case the binary watermark data). Logical AND and Logical OR operations are used here for hiding the secret data(watermark) inside audio file.

3.3. *Training the Network*

The neural network does some logical calculations and completes the watermarking process. The developed neural network has two input features and one output feature. The learning rate is set at 0.01. Sigmoid function is used as an Activation function. The model is trained at 100000 epochs.

3.4. *Decoding the Network*

After the encoding process, in order to decode the audio and extract the watermark from it the encoded audio is first converted into a byte array. The LSB is extracted from the byte array the extracted bytes is the matrix of pixel values of our watermark image. By plotting this matrix we can visualize the watermark image.

4. Results and Discussion

The proposed neural network does all the logical calculations and completes the watermarking process. The developed neural network has two input features and one output feature. The learning rate is set at 0.01. The Sigmoid function is used as an Activation function. The model is trained at 100000 epochs.

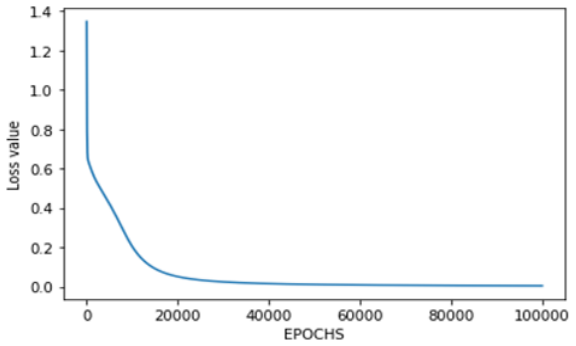

Fig 2 : Graph showing Training of the Model for 100000 epochs and reduction in loss

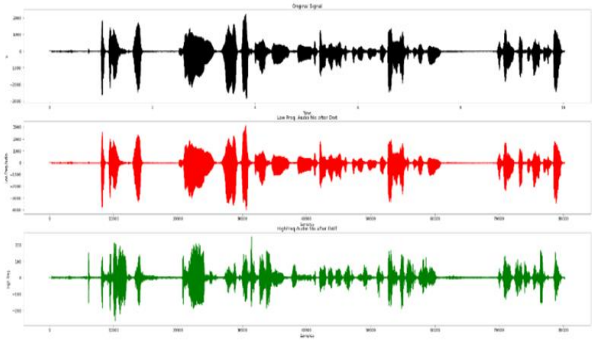

Fig 3: Audio Signal before applying DWT.(Color codes used : Black- Original Audio, Red-Low Frequency Component, Green-High Frequency Component.)

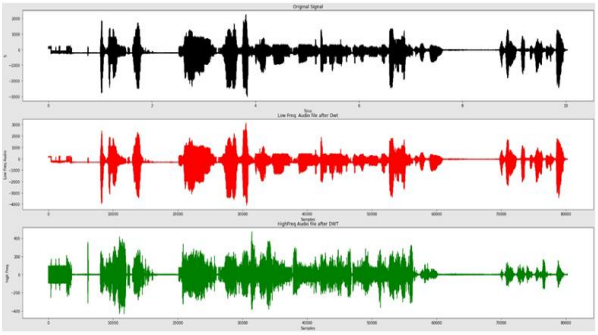

Fig 4: Audio Signal after applying DWT.(Color codes used : Black- Original Audio, Red-Low Frequency Component, Green-High Frequency Component.)

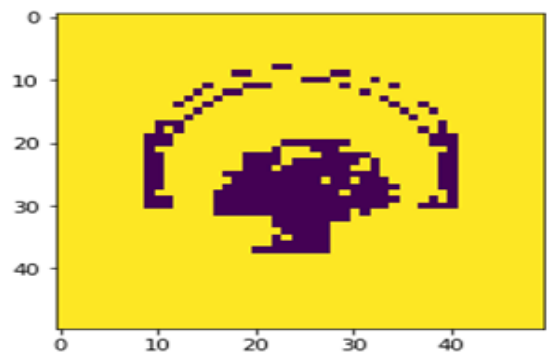

Fig 5: Sample Watermark Image

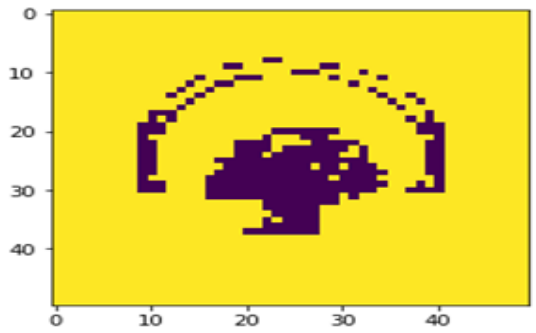

Fig 6: Extracted Watermark Image (After Decoding).

5. Conclusion

In this paper we discussed various neural network based approaches used for digital audio watermarking. Also, we designed a simple backpropagation neural network and used it along with DWT for embedding and extraction of watermark into audio signal. The experimental results shown that the watermark is successfully embedded into audio signal such that it is difficult for the attacker to remove it or tamper it. Bit Error Rate is found very low. There is a negligible amount of bit loss in the extracted watermark and we achieved robustness at higher level. We simulated the obtained output signal for robustness and imperceptibility and found that the watermark is robust against the common signal processing attacks such as noise attacks. The imperceptibility is also found to be good. We tested the results with 20 different persons to check the imperceptibility, none of the user was able to differentiate between original and watermarked audio. Thus, in this paper we discussed many algorithms based on neural networks and demonstrated a simple method using backpropagation network with DWT domain for digital audio watermarking. In future work, we will try to make the watermark more secure by using security algorithms. We will design a network such that, instead of using small chunks and then integrating them together at the output side, we will be able to collect a single audio file as the output.

Conflicts of Interest

"We the authors/ co-authors of this manuscript declare that there is no conflict of interest regarding the publication of this paper."

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