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Steganography in Audio Files by Hermite Transform

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Abstract: This work proposes the use of the Hermite Transform (HT) for imprinting audio files with hidden information. One of the most important aspects of this kind of concealment derives from the amount of data that a host file (audio, images, data, or video) can hold. In this particular case, both the host and the hidden files are audio files. The amount of information that can be hidden-with the suggested technique-occupies half the length of the host file. Furthermore, the use of the Hermite Transform on audio files helps improve the algorithm performance. Experimental results show that our proposal is efficient and effective, because the audio file concealment is imperceptible to human hearing. Performance of our proposal was assessed using correlation and peak signal to noise ratio. The results strengthen the effectiveness of the method.

Keywords: Audio files, Hermite transform, Signal processing, Steganography

1 Introduction

Although Internet is a medium that enables both communication and data transmission through different means-audio, video, texts, and images-, and is employed in many applications, it cannot guarantee the integrity of information during the transmission process; hence it can be corrupted. Since most applications require transmit data in a confidential manner, many security measures have become quite important, functioning as a basis for new techniques related to the protection of data. One of them is steganography [1], which is a technique used for concealing a message that needs to be kept a secret within a public channel: the message goes unnoticed to those individuals that are not aware of the specific data, thus allowing the imperceptible transmission of large quantities of information. Images, audio, or video can be used for masking information in order to ensure important information.

The data secretly hidden or sent is called concealed information, while the digital file hosting is known as host or carrier. In the present paper, both the concealed information and the host are audio files.

Many methods for the concealment [1,2] of audio files have been developed. However-and without taking into account the technique employed-it is important to consider the following elements: perceptive invisibility (the concealed information must go unnoticed to the audience; in this case, hearing); robustness (resistance present in the utilized technique when facing the carrier?s manipulation, such as compression or filtering); and capacity (amount of information that can be hidden in the host without affecting the rest of its characteristics).

A simple technique for hiding data is through the modification of the Least Significant Bits [3]. It requires the modification of those bits whose contribution to the carrier signal are less valuable. Although it constitutes a simple technique, and the changes in the host file are hardly perceptible to the human ear, it is sensible to alterations, which translates into low robustness. It is important to mention that various techniques have been developed, based on the LSB alteration, so as to improve the quantity of bits that can be modified [9], which allows for larger quantities of data to be concealed.

Another technique is proposed in [4], called spread spectrum. In this technique the audio is coded throughout the whole frequency range. This allows the audio to be transmitted over different frequencies that vary according to the spectrum extension method employed. Those techniques that utilize this type of methodology are the

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safest for transmitting a hidden message in an audio file; nevertheless, random noise can lead to data loss.

The different developed techniques can be applied in the spatial and in the transform domain-Fourier Transform, Discrete Cosine Transform (DCT), or Discrete Wavelet Transform (DWT). In the present work, we proposed used the Hermite Transform.

The Hermite transform was originally proposed by Martens [5] and successfully used in [6,7]. This transform allows local processing on visual information. It also shows features that make it an efficient tool in graphic applications; it allows local processing on the visual information. It also incorporates the ”masking” property of human visual system (HCS),it is based on Gaussian functions derivates [8], and is a particular case of the Polynomial transform.

As the Discrete Wavelet Transform (DWT), HT decomposes a signal into a number of coefficients, where the zero-order coefficients represent the average Gaussian measurement, and higher order coefficients contain details. In addition, these coefficients can be generated with and without subsampling. The coefficients containing the details are used to hide the audio file.

In this particular case, we used an audio file (*.wav) of 8 bits, *(A carrier)*, with a sampling frequency of 44100 samples per second and Pulse Code Modulation (PCM). The audio to hide is also an audio file, with the same parameters, *W*.One of the advantages of this work is the amount of information hidden: if the original file size is *A(n,2) (n: rows and 2 columns)*, then the amount of information that will be hidden is *W(n/2,2)*.

The results showed that our proposal is an efficient method when the hidden information and the carrier are audio files. The advantage is that the hidden file results imperceptibly audible when it is embedded in the host audio. Besides, when it is recovered, there is not noticeable audible change, since the sample is very clear.

This paper is organized as follows: in section 2, the mathematical theory of the Hermite Transform is presented. Section 3 describes our proposal of hidden audio files. The experiments and results are presented in Section 4. Finally, the conclusions are detailed in Section 5.

2 The Hermite Transform

The Hermite Transform [5,6,7,8,10] constitutes a particular case of polynomial transform, which is a signal decomposition technique where the signals are locally approximated by polynomials.

2.1 Polynomial Transform

The analysis employing a polynomial transform involves two stages. In the first one, the original signal *L(x)*) is localized by multiplying it by a window function *V(x)*. A complete description of the signal requires the repetition of the localization process at a sufficient number of window positions. From the localized window function *V(x)*, it is possible construct a weighting function *W(x)* (Eq. 1) by periodic repetition:

$$W(x) = \sum_k V(x-kT), \tag{1}$$

where T is the period.

Provided *W(x)* is nonzero for all *x*, we get (Eq. 2):

$$L(x) = \frac{1}{W(x)} \sum_k V(x-kT), \tag{2}$$

Therefore, we are guaranteed that the localized signals *L(x)V(x-kT)* contain enough information about the original signal, for all different window positions *kT*.

The second stage consists in approximating the signal segment-within the window-with a polynomial. As basis functions for the polynomial expansion, we use the polynomials $G_n(x)$ which are orthonormal regarding $V_2(x)$, where n is the degree of the polynomial as Eq. (3) shows:

$$\int_{-\infty}^{\infty} V(x)G_m(x)G_n(x)\,dx = \delta_{nm} \tag{3}$$

The orthonormal polynomials for an arbitrary window function $V_2(x)$ are given by Eq. (4):

$$G_n(x) = \frac{1}{\sqrt{M_{n-1}M_n}} \begin{bmatrix} c_0 & c_1 & \dots & c_n \\ c_1 & c_2 & \dots & c_{n+1} \\ \vdots & \vdots & \dots & \vdots \\ c_{n-1} & c_n & \dots & c_{2n-1} \\ 1 & x & \dots & x^n \end{bmatrix} \tag{4}$$

where the determinant M_n is defined by Eq. (5):

$$\begin{aligned} M_n &= \left|c_{i+j}\right| \\ M_{-1} &= -1 \\ c_n &= \int_{-\infty}^{\infty} x^n V^2(x)\,dx \end{aligned} \tag{5}$$

If $V^2(x)$ is even, $c_{2n+1} = 0$ the expressions G_i are simplified.

Under general conditions [11] for the original signal $L(x)$, by Eq. (6) we get that:

$$V(x-kT)\left[L(x) - \sum_{n=0}^{\infty} L_n(kT)G_n(x-kT)\right] = 0 \tag{6}$$

where $L_n(kT)$ is the direct polynomial transform and is defined by Eq. (7) as follows,

$$L_n(kT) = \int_{-\infty}^{\infty} L(x)G_n(x-kT)V^2(x-kT)\,dx \tag{7}$$

The coefficients $L_n(kT)$ can be derived from the signal $L(x)$ by convolving with the filter functions (8):

$$D_n(x) = G_n(-x)V^2(-x) \tag{8}$$

The inverse polynomial transform equations (2) and (6) is defined by Eq. (9):

$$L(x) = \sum_{n=0}^{\infty} \sum_{k} L_n(kT)P_n(x-kT) \tag{9}$$

where the pattern functions are defined by Eq. (10):

$$P_n(x) = \frac{G_n(x)V(x)}{W(x)} \tag{10}$$

The inverse polynomial transform consists of interpolating the coefficients $L_n(kT)$ with the pattern function $P_n(x)$ and summing over all orders n.

2.2 Hermite Transform

The important parameters that have to be considered in a polynomial transform are the window function and the sampling period. In HT, the applied window has a Gaussian distribution (11):

$$V(x) = \frac{1}{\sqrt{\sqrt{\pi\sigma}}} \exp\left(\frac{x}{2\sigma}^{2}\right) \tag{11}$$

where σ is the standard deviation of the Gaussian function.

The filter functions that are convolved signals are calculated by Eq. (12):

$$D_n(x) = \frac{(-1)^n}{\sqrt{2^n n!}} \frac{(1)}{\sigma\sqrt{\pi}} H_n\left(\frac{x}{\sigma}\right) \exp\left(\frac{-x^2}{\sigma^2}\right) \tag{12}$$

In the special case of the Gaussian window, we obtain the Hermite polynomials [12], which are defined by Eq. (13):

$$H_n(x) = (-1)^n \exp(x^2) \frac{d}{dx^n} \exp(-x^2) \tag{13}$$

The filter function $D_n(x)$, is equal to the nth order derivative of a Gaussian function defined by Eq. (14) as follows:

$$D_n(x) = \frac{(-1)^n}{\sqrt{2^n n!}} \frac{d}{d(\frac{x}{\sigma})^n} \left[\frac{1}{\sigma\sqrt{\pi}} \exp\left(\frac{-x^2}{\sigma^2}\right)\right] \tag{14}$$

The Fourier transform is (15):

$$d_n(\omega) = \frac{1}{\sqrt{2^n n!}} (j\omega\sigma)^n \exp\left(\frac{-\omega^2\sigma^2}{4}\right) \tag{15}$$

The maximum value for $(\omega\sigma)^2$ is $2n$; hence, filters of increasing order successively analyze higher frequencies in the signal. However, for large orders, the frequency peaks move very close together, therefore, sequential filters give only very little additional information.

The pattern functions $P_n(x)$ necessary to recover to the original signal from the coefficients of the Hermite transform are defined by Eq. (16).

$$P_n(x) = \frac{T}{\sqrt{2^n n!}} \frac{1}{\sqrt{2\pi}} H_n\left(\frac{x}{\sigma}\right) \frac{exp(\frac{-x^2}{2\sigma^2})}{W(x)} \tag{16}$$

3 Proposed Algorithm

As we indicated the HT decomposes a signal in different components. The total energy of the original signal is distributed in each of these components. The energy measurement [13] is important when an application of this type (steganography or watermarking) replaces or modifies information of the original signal, because it is important to prevent loss of energy. Therefore, the shortfall of a considerable amount of energy in a signal means that essential information is also lost. In all signals, a large percentage of energy is found at low frequencies. Considering this premise, it was decided to manipulate the components of lower energy for hiding the audio file.

An audio file (*.wav) of 8 bits, with a sampling frequency of 44100 samples per second and Pulse Code Modulation (PCM), was decomposed with HT to determine which were the components of lower energy. Subsequently, the energy of each component was calculated, in order to identify those with lower energy. This exercise was repeated with samples of n audio files to determine if the distribution of energy was similar. Once this was verified, various tests were performed to establish the number of components that had to be modified so that the file hidden would stay imperceptible, allowing at the same time its retrieval.

The following sections describe the procedure for concealing and extracting the secret information.

3.1 Hiding information

1. The audio carrier is read. $A(n,2)$ *(n: rows and 2 columns).*
2. The Hermite Transform coefficients $A(n,2)$ are calculated in order to get: $\hat{A}\left(\frac{n}{2}, 2, nc\right)$.
3. The four coefficients of lower energy of $\hat{A}$ are determined, since this ensures redundancy, and especially, it guarantees that the secret information will be audibly imperceptible.
4. For each of the four components of lower energy, its maximum and minimum value is established for setting a threshold that is used in the concealment process of the audio file. The determination of each

value of threshold is made per component and it corresponds to Eq. (17):

$$threshold = \left| max\left(\hat{A}\left(\frac{n}{2},2,nc\right)\right) - min\left(\hat{A}\left(\frac{n}{2},2,nc\right)\right)\right| \quad (17)$$

5.The audio signal to be hidden $S\left(\frac{n}{2},2\right)$ is read, and separated into two channels (left and right). Only the voice channel $S_1\left(\frac{n}{2},1\right)$ is chosen. It becomes clear that the amount of information that can be hidden in the host audio is $\frac{n}{2}$.

6.To hide the information in each of the Hermite coefficients of lower energy, we use the Eq. (18):

$$\hat{A}\left(\frac{n}{2},1,nc\right) = threshold * S_1\left(\frac{n}{2},1\right) \quad (18)$$

Each modified component will have its respective threshold.

7.The inverse Hermite Transform is calculated to have: $A_{mod}(nx2)$.

8.The new audio file is A_{mod}.

3.2 Extracting information

1.The audio signal, A_{mod}, is read.

2.The Hermite Transform coefficients are calculated to get: $\hat{A}_{mod}\left(\frac{n}{2},\frac{m}{2},nc\right)$.

3.We determined the four lower energy components from $\hat{A}_{mod}$.

4.Extract the hidden information of each low energy component, according to the Eq. (19):

$$S_{mod}\left(\frac{n}{2},1\right) = \frac{Amod\left(\frac{n}{2},\frac{m}{2},nc\right)}{threshold} \quad (19)$$

Therefore, there are four recovery samples, and we can determine which contain the original file without audible changes.

4 Experimental Results

Our proposal was tested in fifty different audio files. First, an audio file was used as host and fifty different samples were concealed. Then fifty host audio files were modified with a single sample. We used correlation and Peak Signal to Noise Ratio to assess the quality or our proposal.

a) Correlation
The correlation r indicates relation between two variables [13], in this case between the host audio and modified audio file (see equation 20).

$$r = \frac{\sum_m\sum_n (A_{mn}-A)(B_{mn}-B)}{\sqrt{\left(\sum_m\sum_n (A_{mn}-A)^2\right)\left(\sum_m\sum_n (B_{mn}-B)^2\right)}} \quad (20)$$

where:

A: original signal
B: carrier signal
$\hat{A}$: original signal average
$\hat{B}$: carrier signal average

b) Peak Signal to Noise Ratio
An objective way to get an answer to the file quality is the Signal to Noise Ratio (SNR) [14]. This relation is defined as the ratio between signal intensity and the noise intensity that accompanies it. For this particular case, the peak signal to noise ratio PSNR [15] was defined by Eq. (21):

$$PSNR = 10log_{10}\frac{NA^2}{\|A-A_{mod}\|^2} \quad (21)$$

where N is the length of the carrier signal, A is the maximum absolute square value of the original signal, and $\|A-A_{mod}\|^2$ is the energy of the difference between the original and the carrier signal.
Table 1 shows the correlation and PSNR values of the original and the carrier signals, as well as, the correlation between the original and the recovered audio final.

The correlation of these components was the same; therefore only one value was included. Besides, all samples extracted from the three components were ”*audibly*” well heard, without noticing that it had been modified. Regarding the audio signal, it is also clear that the correlation is high, as well as the PSNR value, indicating that there was no noise and did not change significantly. Regarding the audible aspect, neither change was noticed with any of the fifty embedded samples.

Figure 1 shows the original audio signal with its two channels. In figure 2 we show the audio signal modified and the original audio signal (only one channel). We only display a sample with length 882000. According to the figures, it is clear that the based audio signal was not modified; consequently its information was not altered. The same applies to audio files that were used as samples.

Figure 3 shows the original audio file to hide and the recovered audio file. For this example we used the sample 7. It can be seen that the recovered sample is very similar to the original file. Once more, the results proved that inaudible modification is shown.

A very important factor to take into account is the amount of information hidden. Its length is exactly half the length of the host audio. It has a lot of information to be hidden without greatly altering the host audio. Besides, the samples can be recovered without significant changes. Another test was performed using fifty host audio files and a single audio file as a samples. In table 2, we can observe the values of correlation and PSNR. As before, for all the tests, the hidden audio and the recovered audio did not show any distortion. From Table 2, we can observe that both hidden information and recovered audio

Table 1: Correlation and PSNR values from fifty different audio files to hide

Sample to hide	PSNR [dB]	Correlation Original and modified file	Correlation Original and extracted file
1	33.1887	0.9908	0.9638
2	30.5079	0.9832	0.9797
3	34.4267	0.9930	0.9503
4	39.1526	0.9976	0.8659
5	35.3001	0.9943	0.9431
6	30.5214	0.9832	0.9805
7	31.1130	0.9853	0.9770
8	33.3408	0.9911	0.9632
9	29.1681	0.9773	0.9847
10	37.3177	0.9964	0.9118
11	33.9464	0.9922	0.9580
12	32.5547	0.9894	0.9689
13	31.4957	0.9865	0.9742
14	32.9015	0.9902	0.9664
15	32.3370	0.9888	0.9692
16	29.9594	0.9810	0.9818
17	32.5839	0.9894	0.9690
18	34.6857	0.9934	0.9498
19	30.8211	0.9843	0.9791
20	34.0892	0.9925	0.9562
21	33.3773	0.9912	0.9628
22	33.1490	0.9907	0.9611
23	33.7856	0.9919	0.9594
24	31.2930	0.9859	0.9766
25	32.4109	0.9890	0.9699
26	29.7428	0.9800	0.9825
27	32.9798	0.9903	0.9651
28	30.8443	0.9844	0.9781
29	34.2274	0.9927	0.9553
30	37.3821	0.9964	0.9106
31	29.0532	0.9767	0.9856
32	28.8593	0.9757	0.9859
33	27.4246	0.9666	0.9901
34	36.7365	0.9959	0.9220
35	32.1196	0.9883	0.9708
36	37.0117	0.9961	0.9165
37	28.2829	0.9724	0.9874
38	35.1583	0.9941	0.9446
39	34.5502	0.9932	0.9517
40	29.1105	0.9770	0.9842
41	33.2302	0.9909	0.9638
42	32.4925	0.9892	0.9694
43	37.6069	0.9966	0.9051
44	31.7822	0.9873	0.9737
45	32.5207	0.9893	0.9691
46	32.1006	0.9882	0.9718
47	32.9583	0.9903	0.9654
48	34.1504	0.9926	0.9556
49	33.4728	0.9914	0.9622
50	29.6188	0.9795	0.9840

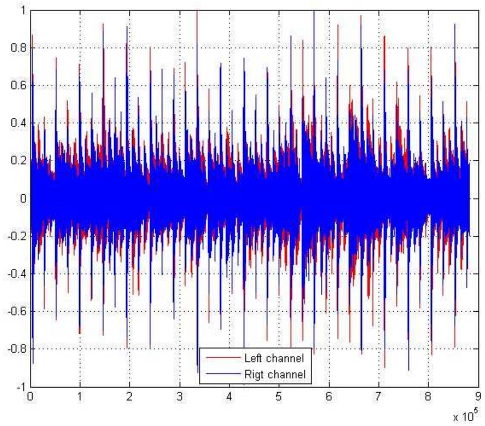

Fig. 1: Original Audio Signal

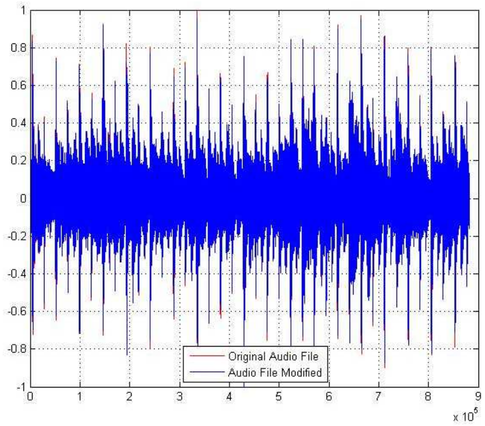

Fig. 2: Original Audio Signal and Audio Signal Modified

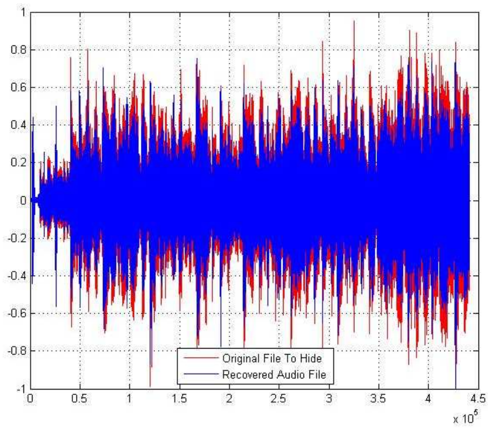

Fig. 3: Original Audio file and recovered audio file

signals did not undergo major modifications, and they show correlation values above 0.9. Furthermore, in most cases, the values of PSNR from the original signal with the signal extracted were above 30 dB.

The columns distribution is the same as in Table 1; only the first column changed because we used fifty different host audio signals and the secret audio was always the same.

Graphically, the changes that took place on both host audio files, such as samples to hide, are shown in figures 4, 5 and 6, respectively. We present the sample number 17. Figure 4 shows the sample which was utilized as host audio. While figure 5 shows the audio signal to hide. Finally, the original and extracted audio files can be seen in figure 6. It can be observed that magnitude variations of the signals did not alter the relevant information; changes are almost imperceptible. Both host and hidden files were clearly audible.

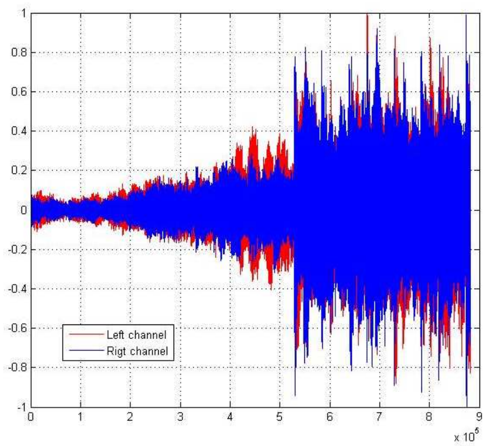

Fig. 4: Host Audio (sample 17)

Finally, in order to determine the efficiency of the used algorithm, Gaussian filter and Gaussian noise were applied on the host file. Since most of the results, regardless of the sample, are similar, we only display those of the sample 17, which was also used for the table 2 and the figures 4, 5, and 6.

a) Gaussian Filter
Linear filtering was performed using a Gaussian filter, size *NxN*. The used average was O, and the deviation standard 0.5. Both parameters remained constant during the test. Table 3 shows the correlation value that exists between the hidden file and the recovered one.
According to Table 3, it is clear that the hidden sample can be recovered in those cases in which the size of the Gaussian window is odd.

Table 2: Correlation and PSNR values (fifty different host samples)

Host	PSNR [dB]	Correlation carrier and modified file	Correlation Original and recovered file
1	33.1887	0.9908	0.9638
2	31.0190	0.9958	0.9176
3	30.7353	0.9860	0.9409
4	30.6613	0.9930	0.9446
5	37.2887	0.9972	0.9748
6	40.8721	0.9987	0.9424
7	37.1974	0.9981	0.8756
8	35.7610	0.9972	0.9600
9	31.7251	0.9968	0.8972
10	31.1076	0.9849	0.9788
11	36.0023	0.9968	0.9767
12	42.7371	0.9986	0.9275
13	30.6202	0.9950	0.9004
14	36.4654	0.9961	0.9677
15	30.8800	0.9933	0.9408
16	32.6046	0.9973	0.8793
17	40.2919	0.9986	0.9963
18	35.8797	0.9952	0.9669
19	36.0385	0.9714	0.9956
20	38.2541	0.9985	0.9527
21	34.5151	0.9948	0.9816
22	28.4119	0.9829	0.9417
23	31.4228	0.9916	0.9726
24	30.5368	0.9964	0.9537
25	41.2302	0.9991	0.9149
26	33.7409	0.9984	0.8493
27	33.1639	0.9950	0.9517
28	32.8457	0.9241	0.9950
29	33.0988	0.9934	0.9983
30	49.6257	0.9995	0.9838
31	34.6433	0.9984	0.9168
32	33.4414	0.9980	0.8947
33	33.8051	0.9984	0.9288
34	36.1315	0.9952	0.8894
35	26.8546	0.9740	0.9854
36	36.0042	0.9916	0.9735
37	30.9360	0.9974	0.8803
38	32.7908	0.9879	0.9874
39	36.2639	0.9923	0.9514
40	29.4254	0.9947	0.8926
41	37.0023	0.9974	0.9470
42	32.5837	0.9956	0.9864
43	38.9638	0.9971	0.9731
44	39.6444	0.9989	0.8942
45	33.0039	0.9952	0.9689
46	34.5592	0.9961	0.9753
47	30.7308	0.9936	0.9653
48	34.0944	0.9957	0.9574
49	32.0207	0.9928	0.9701
50	38.0587	0.9973	0.9570

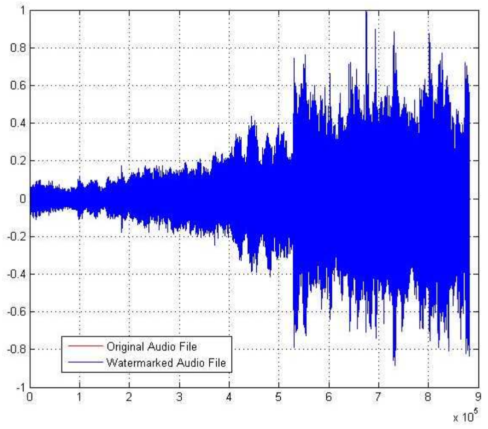

Fig. 5: Original Audio File vs Audio File Modified (sample 17)

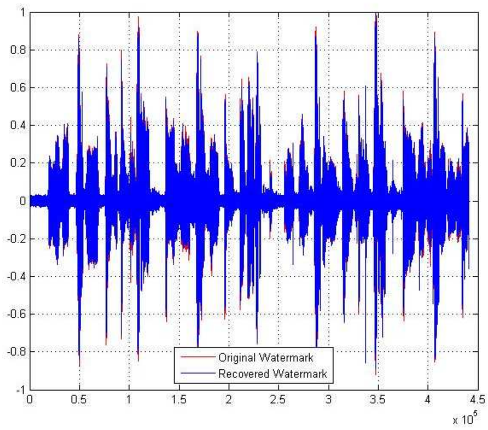

Fig. 6: Recovered Audio File

Table 3: Correlation values of the recovered file against the originally hidden file, after applying the Gaussian filter to the file with the concealed information.

Sample	NxN	Correlation original and extracted file
	2	0.0086
	3	0.9902
	4	0.0083
17	5	0.9902
	6	0.0083
	7	0.9902
	8	0.0083
	9	0.9902

Table 4: Correlation values of the recovered file against the original hidden file, after applying Gaussian noise to the file with the concealed data.

Sample	SNR [dB]	Correlation original and extracted file
	0	0.0168
	10	0.0491
	20	0.1555
17	30	0.4447
	40	0.8415
	50	0.9770
	60	0.9943

b) Gaussian Noise

Gaussian white noise was added, with diverse SNR values (Table 4). The correlation values obtained between the original embedded file and the one recovered for the different SNR values employed can be seen in Table 4.

Experimental results showed that, starting from a noise value of 40 dB, it is possible to retrieve the sampled that was inserted in the host file. Moreover, the sample is audible clear.

5 Conclusions

This paper presents a steganography technique for audio files using the Hermite Transform (HT). An important feature of this method is that the information amount that can be concealment is half the total length of the audio file. Another contribution is the use of HT, that has proved to be useful in digital image applications (watermarking, image fusion, among other, etc.). One of the main advantages of the HT is the use of a Gaussian window for modeling the receptive fields of the human visual system (HSV).

The results of the experiments showed that the hidden audio file did not affect the quality of the original file. First, the hidden audio file was inaudible, and then, the values PSNR were above 30 dB.

In those cases in which a Gaussian filter is applied onto the file with the hidden information, it can be recovered when the size of the filter window is odd. When Gaussian noise is added, even when the correlation values are low, the recovered sample can be audibly distinguished.

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