Lossless Visible Watermarking Using GA and developed Independent Components Analysis

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ABSTRACT

This paper review present techniques about digital watermarking(visible as well as invisible) and a new approach of lossless watermarking techniques with robust security is explained, This apparent security through the use of mixing matrix as a key between the sender and the recipient, as well as the use of the best mixing matrix through accurate selection using genetic algorithm, this paper introduced a new way of treatment that the cover image and watermark image are not equally sized,like this evolution in the algorithm of ICA .

Experimental expected result shows a good results than other methods .

Keywords: Watermarking, Lossless visible Watermark, genetic algorithm, mixing matrix, ICA

الخلاصة:

ظهرت العلامات المائية كمجال جديد للبحث في محاولة لمنع الاستنساخ الغير القانوني و التمثيل الخاطئ. في هذه البحث، يقدم تقنيات عن العلامة المائية الرقمية (مرئية وكذلك غير مرئية) و اتباع نهج جديد من تقنيات العلامة المائية من دون فقدان مع تحصين امني قوي، وهذا التحصين الأمني واضح من خلال استخدام مصفوفة خلط كمفتاح بين المرسل والمستلم، وكذلك استخدام أفضل مصفوفة خلط من خلال اختيار دقيق لهذه المصفوفة باستخدام الخوارزمية الجينية. الخوارزمية المقترحة تظهر نتائج جيدة مقارنة مع الطرق الأخرى .

الكلمات المفتاحية : علامة مائية مرئية، الخوارزمية الجينية، وخلط مصفوفة،ICA

1. Introduction

The success of the Internet and digital consumer devices has profoundly changed our society and daily lives by making the capture, transmission, and storage of digital data extremely easy and convenient. However, this raises a big concern in how to secure these data and preventing unauthorized use. This issue has become problematic in many areas. For example, there are many studies showing that the music and video industry loses billions of dollars per year due to illegal copying and downloading of copyrighted materials from the Internet(Tsui *et al.*,2008). Now a days, some very crucial issues of digital media are duplication, distribution, editing copyright protection etc. The main reason of these kind of issues is development of internet and multimedia technology. As a solution, Digital watermarking is used very frequently. Hence, digital watermarking becomes very attractive research topic and many may taxonomies for digital watermarking have been proposed. Among these, the most common taxonomies are embedding in spatial and transform domain(Hwang *et al.*,1999).Digital watermarking is the process of embedding information regarding the identity of the owners into an image or any piece of data. It is a special case of information hiding. It is the process of embedding information into digital multimedia content such that the information (the watermark) can later be extracted or detected for a variety of purposes including copy prevention and control. Watermarks are generally used to make it more difficult for people to steal images without giving proper credit. In the recent years due to the growth of Internet it has highlighted the mechanism to protect the ownership of digital media. Digital watermarking has become an active and important area of research and development. Copyright protection for digital information has become easier with the advent of digital watermarking. The information can be textual data about the author, its copyright or image itself. Digital watermarking is a technique which allows an individual to add hidden copyright notices or other verification messages to digital audio, video, or image signals and documents(Jose *et al.*,2012). digital watermarking schemes can be divided into two categories: visible watermarking schemes embedding unobtrusive but visible patterns into works and invisible watermarking systems introducing imperceptible alternations to the cover work in order to hide some messages. Comparisons between the two types of watermarking schemes are summaries in Table(1)(Chuang *et al.*,2007).

Table(1) : Comparing invisible and visible watermarking schemes

Characteristics	Invisible Watermarking	Visible Watermarking
Fidelity	Imperceptible	Unobtrusive but visible
Possible Attacks	Media processing or malicious removal	Malicious removal
Message Form	Arbitrary (any binary representation)	Meaningful patterns
Explicit Extractor	Required	Not required
Message Notifying	Passive	Active
Complexity	Often higher	simpler

Visible digital watermark logo is visible, and it fuses watermark image and original image. In essence, the watermark is not hidden for the visible digital watermarking technology, but the part of sub-image information replaced by the watermark image. It is designed to operate by removing the watermark to recover the original image from the visual point of view so that legitimate users access to free images or data. However, for invisible digital watermark, watermark logo is not visible. It hides the digital watermark information itself which can be extracted by detecting the watermark(Yong *et al.*,2011). In the literature, several techniques have been developed for watermarking.(Mohanty *et al.*,2000) proposed a visible watermarking technique in the discrete cosine transform (DCT Domain). Their scheme proposes a mathematical expression to modify each DCT coefficient by $\bar{C} = \alpha C + \beta W$, where C and W are the DCT coefficients of host image and watermark respectively. The variable α and β are determined by exploiting the texture sensitivity of human visual model (HVS). (Chuang *et al.*,2007) Show that proposed scheme outperforms existing invisible watermarking methods in its capability to practically convey metadata to users of legacy display devices lacking renewal capability. On the other hand, it does not suffer from the annoying quality-degradation problem of visible watermarking schemes.(Hu *et al.*,2006) proposed a removable visible watermarking. The scheme uses a key to determine the unchanged coefficients and the pixel wise varying parameters of the embedder are calculated from those unchanged coefficients. Thus the user with the correct key in the receiver end can recalculate the parameters to remove the visible watermark from the watermarked image.(Liu *et al.*,2010) A novel method for generic visible watermarking with a capability of lossless image recovery is proposed. The method is based on the use of deterministic one-to-one compound mappings of image pixel values for overlaying a variety of visible watermarks of arbitrary sizes on cover images. The compound mappings are proved to be reversible, which allows for lossless recovery of original images from watermarked images. (Yip *et al.*,2006) Propose two lossless visible watermarking algorithms, Pixel Value Matching Algorithm (PVMA) and Pixel Position Shift Algorithm (PPSA). PVMA uses the bijective intensity mapping function to watermark a visible logo whereas PPSA uses circular pixel shift to improve the visibility of the watermark in the high variance region.

This paper is organized as follow: section 2 discuss the concepts of Independent Components Analysis (ICA) algorithm, section 3 explain Genetic algorithm approach, section 4 describe the proposed method , section 5 reviews the experimental results for the proposed algorithm, Conclusions on section 5.

2. Independent Components Analysis (ICA) algorithm :

Blind source separation (BSS) (Haykin *et al.*,2000) is a technique for estimating individual source signals from their mixtures observed by sensors. The BSS of audio signals has a wide range of applications including speech enhancement. Independent component analysis (ICA)(Hyv¨arinen *et al.*,2001) is one of the main statistical methods used for BSS and it achieves separation by using the non-Gaussianity and independence of source signals. In most realistic applications, the number of source signals is large, and the signals are mixed in a convolutive manner with reverberations. This makes the problem difficult.

There are two major approaches to solving the convolutive BSS problem. The first is the time domain approach, where ICA is applied directly to the convolutive mixture model(Douglas and Sun,2003). This approach achieves good separation if the calculation successfully converges to a correct solution, however, it incurs considerable computational cost. Thus it is difficult to obtain a solution in a practical time especially when the number of source signals is large. In this section, we present the basic data model used to define both Independent Component Analysis and the Blind Source Separation problem, and explain how both are related to each other. Consider a random source vector S(n):

$$S = [S_1, S_2, S_3, ..., S_m]^T \tag{1}$$

where, the m components are provided by a set of independent sources that are scalar-valued and mutually statistically independent for each sample value m. The vector S(n) is put to a linear system whose input-output characterization is defined by nonsingular m-by-m mixing matrix A. The resultant is a n-by-1 mixture vector X(n) related to S(n) as follows:

$$X = A \times S = \sum_{i=1}^{n} a(i) s_m(i) \tag{2}$$

where,

$$X = [X_1, X_2, X_3, ..., X_n]^T \tag{3}$$

In real life situation, Source vector S and mixing matrix A both are unknown. Here, only from mixture vector X, we have to find a demixing matrix W (which is the inverse of mixing matrix) so that the source vector S can be recovered from the output vector Y defined as Y = W×X in (4) as:

$$Y = [Y_1, Y_2, Y_3, ..., Y_n]^T \tag{4}$$

This problem is also known as Blind Source Separation, the term Blind mean that we don’t know about the source signals and the only information used in recovering source vectors is contained in performance of the mixture vector X. Here, Source vector S(n), mixture vector X(n) and output vector Y(n) are assumed to be zero-mean vectors and unit variance. s_k = [s_k(l),. . . , s_k(M)]T is the source vector consisting of the M source signals (independent components), where i = 1, . . . M at the index value k. A = [a(l),. . . , a(M)]T is a constant L x M mixing matrix whose columns are the basis vectors of ICA, and n_k denotes possible corrupting additive noise. In blind source separation, the task is to find the waveforms $s_k(i)$ of the sources, knowing only the data vectors x_k and the number M of sources. There is lot of work on both batch type and data-adaptive BSS algorithms. In neural realizations, adaptive learning algorithms that are as simple as possible but yet provide sufficient performance are desirable. In adaptive source separation, an M x L separating matrix B_k is updated so that the M-vector

$$Y_k = B_k x_k \qquad (5)$$

y_k is an estimate of the original independent source signals. In neural realizations, y_k is the output vector of the network, and the matrix Bk is the total weight matrix between the inputs and outputs. The estimate $k_{(i)}$ of the i^{th} source signal may appear in any component $y_k(j)$ of y. The amplitudes of the sources $s_k(i)$ and their estimates $y_k(j)$ are typically scaled so that they have unit variance(Singh *et al.*,2008).

3.Genetic algorithm approach

The genetic algorithm is modeled on a relatively simple interpretation of the evolutionary process; however, it has proven to a reliable and powerful optimization technique in a wide variety of applications. (Holland,1975) was first proposed the use of genetic algorithms for problem solving. (Goldberg,1998) were also pioneers in the area of applying genetic processes to optimization. As an optimization technique, genetic algorithm simultaneously examines and manipulates a set of possible solution. Over the past twenty years numerous application and adaptation of genetic algorithms have appeared in the literature. During each iteration of the algorithm, the processes of selection, reproduction and mutation each take place in order to produce the next generation of solution. Genetic Algorithm begins with a randomly selected population of chromosomes represented by strings. The GA uses the current population of strings to create a new population such that the strings in the new generation are on average better than those in current population (the selection depends on their fitness value). The selection process determines which string in the current will be used to create the next generation. The crossover process determines the actual form of the string in the next generation. Here two of the selected parents are paired. A fixed small mutation probability is set at the start of the algorithm. This crossover and mutation processes ensures that the GA can explore new features that may not be in the population yet. It makes the entire search space reachable, despite the finite population size.

Figure (1)shows the generic implementation of genetic algorithm.

```
1.    Encode solution space
2.    (a) Set pop_size, max_gen, gen=0
      (b) Set cross_rate , mutate _rate ;
3.    initialize population
4.    while max_gen≥ gen
          evaluate fitness
          for ( i=1 to pop_size)
              select  (mate1,mate2)
            If  ( rnd (0,1)≤ cross_rate)
                child=crossover(mate1,mate2)
            If (rnd (0,1)≤ mutate _rate)
                child = mutation();
            repair  child if necessary
          end  for
          Add offspring  to new generation
          Gen = gen+1
      End while
5.    return best chromosomes
```

Figure 1 : A generic genetic algorithm

3.1 Main ingredients of Genetic algorithm

3.1.1 Chromosomes

During the division process of the human cells the chromatin (contained in the nucleus and built from DNA (deoxyribonucleic acid), proteins and RNA (ribonucleic acid)) become shorter and thicker and forms spiral strings – chromosomes. In these chromosomes are the genes, that carry the inherited cell information. Every gene codes particular protein and is independent factor of the genetic information, which determines the appearance of different peculiarities.

For the genetic algorithms, the chromosomes represent set of genes, which code the independent variables. Every chromosome represents a solution of the given problem. Individual and vector of variables will be used as other words for chromosomes. In this work, we use way of encoding is a real number.

From other hand, the genes could be Boolean, integers, floating point or string variables, as well as any combination of the above.

A set of different chromosomes (individuals) forms a generation. By means of evolutionary operators, like selection, recombination and mutation an offspring population is created(Popov ,2005).

3.1.2Crossover Operators

The crossover operator involves the swapping of genetic material (bit-values) between the two parent strings. This operator randomly chooses a locus (a bit position along the two chromosomes) and exchanges the sub-sequences before and after that locus between two chromosomes to create two offspring(Townsend,2003).

In this work, Uniform Crossover is applied. Uniform crossover creates offspring by deciding for each allele of one parent, whether to swap that allele with the corresponding allele in the other parent with $pr._c = 0.5$.

3.1.3 Mutation

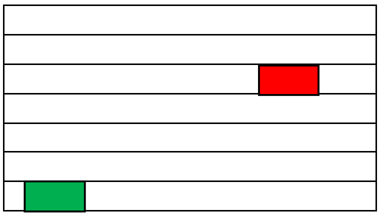
The newly created by means of selection and crossover population can be further applied to mutation. Mutation means, that some elements of the DNA are changed. Those changes are caused mainly by mistakes during the copy process of the parent's genes. In the terms of GA, mutation means random change of the value of a gene in the population Figure (2 a). The chromosome, which gene will be changed and the gene itself are chosen by random as well Figure(2 b) (Popov ,2005).

In this work, each position in a chromosome is mutated with probability ($pr._m$) in the following way. If the value at that position is not zero, then it becomes zero else a new sequence is generated by selecting random points from gang(0.0,1.0).

4 1 3 8 0 7 3 1 3 5 1

↓

4 1 3 8 0 7 3 8 3 5 1



a) Mutation in a chromosome b) mutation places in the population

Figure 2 Mutation in the genetic algorithms

3.1.4 Populations

A population is a collection of individuals. A population consists of a number of individuals being tested, the phenotype parameters defining the individuals and some information about search space. The two important aspects of population used in Genetic Algorithms are:

1. The initial population generation.
2. The population size.

The size of the population raises few problems too. The larger the population is, the easier it is to explore the search space. But it has established that the time required by a GA to converge is O (nlogn) function evaluations where n is the population size. We say that the population has converged when all the individuals are very much alike and further improvement may only be possibly by mutation.

Goldberg has also shown that GA efficiency to reach global optimum instead of local ones is largely determined by the size of the population. To sum up, a large population is quite useful. But it requires much more computational cost, memory and time. Practically, a population size of around 100 individuals is quite frequent, but anyway this size can be changed according to the time and the memory disposed on the machine compared to the quality of the result to be reached(Sivanandam and Deepa,2008).

3.1.5 Selection Strategy

Individuals are selected to reproduce on the basis of their fitness, so that fitter individuals from one generation will contribute proportionately more to the next generation than will individuals of low fitness. There have been many fitness-proportionate selection schemes proposed; perhaps the simplest is "roulette wheel" selection(Mitchell,1996). Under this scheme each individual is allocated a slice of a circular "roulette wheel," of a size proportional to its fitness. The wheel is spun N times for a population of N individuals; the individual under the marker on each spin is selected as a parent for the next generation. Roulette-wheel selection has been criticized on the grounds that in a small population, chance effects can result in disproportionate allocation of offspring to individuals(Mitchell,1996). However, it is easy to implement and has been widely used.

In addition to fitness-proportionate selection, generational replacement in the GA incorporated "elitism," in which the fittest x percent (Generation Gap) of the previous generation is copied unchanged to the next generation. This strategy ensures that fit individuals are not lost due to chance(Chambers ,2001).

In this work, Roulette Wheel Selection (RWS) is applied; here Parents are selected according to their fitness and expected value for each chromosome in the population according to Equation that:

$$e_i = f_i / \sum f_i \qquad (6)$$

4. The Proposed Method :

In this section, we describe the proposed approach to visible watermarking, using Developed Independent Component Analysis, In this way we will use the genetic algorithm to select the best mixing matrix to produce visible watermarking image. The original image can be recovered losslessly from a resulting watermarked image and to select suitable mixing matrix there are two conditions(Chandramouli ,2003)

- Mixing image must be a square
- mixing matrix multiplication by inverse matrix of mixing equal to union matrix.

The proposed approach consists of two processes: embedding process and watermark extraction process.

The embedding algorithm

In this algorithm the results watermarking image that explain by the following algorithm.

Algorithm 1: Generic Visible Watermark Embedding

***Input*:** an image I and a watermark L.

Output: watermarked image W_i

Steps:

1- Convert two images (I , L) to vector , first and the second row represents Images(I , L) respectively .

2- Selection appropriate element of α1, α2 to mixing matrix (A)

where $A = \begin{pmatrix} 1 & 0 \\ \alpha_1 & \alpha_2 \end{pmatrix}$ by using genetic algorithm.

3- Multiplication operation between mixing matrix (A) and vector of images resulting from the first step By using Eq.2 .
4- Convert vector resulting from the multiplication operation to two Images , the first row in the vector represents the Original Image (I) and the second row represents Watermarked Image (W_i) .

In step2 using genetic algorithm to select suitable mixing matrix could give us a good mixing result .

Procedure genetic algorithm

Input : no. of watermark image:=1.

Output: better mixing matrix satisfy the two conditions above.

Steps:

1- Generation:=1

2- Loop (each chromosome in the population)

Randomly choose k_i seed in the rang [0.0, 1.0].

Distribute these seeds in the chromosome.

End Loop

3-Repeat

Loop (each chromosome in the population)

Calculate the fitness value for each chromosome in the population according to Eq. (7).

End Loop

M:= the best individual.

Apply Roulette Wheel Selection to select subpopulation of parents.

Apply uniform crossover with probability($pr._c$) between parents

Apply mutation on child with probability($pr._m$).

new population:=old population.

Generation:= Generation +1 (apply Elitism Behavior).

Until (Generation >Max Generation)

4-Return the **better mixing matrix**.

5-End.

The extracting algorithm:

Note that we received from the previous algorithm is watermarked image W, we are working to restore the original image I, that explain by the following algorithm.

Algorithm 2: Generic Visible Watermark Extracting

Input: an image I and a watermarked image W_i .

Output: Original Image

Steps:

1- Account elements value of inverse mixing matrix Stage . Where $W=A^{-1}$.
2- Convert two images (I , W_i) to vector , first and the second row represents Images(I,W_i) respectively .
3- Multiplication operation between demixing matrix (W) and vector of images resulting from the second step By using Eq($Y = W\times X$).
4- Transformation the results element from step3 to second images that first row represent original image, second row represented watermark image.
5- Original Image and extract watermark .

4.1 The Measurement of fitness

Simulation are performed to evaluate the proposed algorithm above. The simulation is performed using two images. Figure 2 shows the watermark, figure 3 represent the original images. In this work, PSNR is used to evaluate the distortion of the watermarked image with respect to the original image where PSNR is (Kjoelen *et al.*,1998):

$$PSNR = 10\log_{10}\left(\frac{(L-1)^2}{\frac{1}{N\cdot M}\sum_{r=0}^{N-1}\sum_{c=0}^{N-1}\left[\bar{I}(r,c)-I(r,c)\right]^2}\right) \qquad \ldots\ldots\ldots 7$$

Where :

L : the number of gray level

$\bar{I}$: is the watermarked image

I : is the original image

N, M : the image dimensions.

5.Experimental Results:

The proposed system applied several images all of them are in 256 x 256.
Example watermarked images are show below

Figure (3-a) : The Watermark

Figure (3-b) : The Original Image

Figure (3-c) : The Watermarked

Figure (3-d) : The Lossless

For the image in Figure(3-c)

Table 2 The result for watermarked image in figure(3-c)

Example	PSNR	Max Generation of GA	Better Mixing Matrix
1	40.4356	46	$\begin{pmatrix} 1 & 0 \\ 1 & 0.06 \end{pmatrix}$

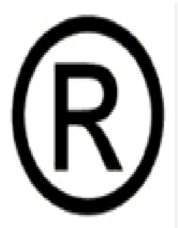


Figure (4-a) : The Watermark

Figure (4-b) : The Original

Figure (4-c) : The Watermarked Image

Figure (4-d) : The Lossless restore image

For the image in Figure(4-c)

Table 3 The result for watermarked image in figure(4-c)

Example	PSNR	Max Generation of GA	Better Mixing Matrix
2	42.4967	40	

			$\begin{pmatrix}1 & 0\\ 1 & 0.06\end{pmatrix}$

0

we have tested the proposed algorithm on a number of images(68 Image). The test image ranges from fairly smooth images to highly textured ones. We evaluate the performance of the algorithm from several aspects such as watermark size, data hiding capacity, watermark transparency, image quality, and security.

The proposed system is moving towards an invisible watermarking when using more accurate mixing matrix , when we apply the following mixing matrix on first example produces:

Table 4 Show the better Mixing Matrix for example 1

Mixing Matrix	PSNR
$\begin{pmatrix}1 & 0\\ 1 & 0.006\end{pmatrix}$	48.2725

Figure (5-a) : The Watermarked Image

Figure (5-b) : The Lossless restore image

And we apply the following mixing matrix on second example produces:

Table 4 Show the better Mixing Matrix for example 2

Mixing Matrix	PSNR
$\begin{pmatrix}1 & 0\\ 1 & 0.006\end{pmatrix}$	52.2354

6. Conclusions

This paper presents a lossless recovery with visible digital watermarking technology, a new method for visible watermarking with a capability of image recovery. The good results dependent on the accuracy of selection the mixing matrix coefficients which selection by using genetic algorithm and the proposed system moving to invisible watermarking when selection more accurate mixing matrix.
Compare with the exist visible watermarking methods(Yong *et al.,*2011) (Liu *et al.*,2010)(Yip *et al.*,2006), The proposed method meets the most requirements.

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