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# Reversible Watermarking Based on Optimal Dynamic Histogram Shifting

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### Abstract:

A new reversible watermarking scheme have been proposed for protecting the images of sensitive content. This scheme makes use of a classification process for identifying parts of the image that can be watermarked using two modulations. This classification is based on a reference image derived from the image itself aprediction ofit which has the property of being invariant to the watermark insertion. A new feature selection algorithm based on particle swarm optimization (PSO) is proposed. The proposed PSO-based feature selection algorithm is utilized to search the feature space for the optimal feature subset where features are carefully selected according to a well defined discrimination criterion. This scheme offers high capacity and image quality preservation in medical and natural images. Experimental results show that the PSO-based feature selection algorithm was found to generate excellent recognition results with the minimal set of selected features.

Keywords— classification, particle swarm optimization.

#### **I. INTRODUCTION**

**R**eversible watermarking is also known as lossless watermarking. It completely removes the watermark and exactly recovers the original signal or image. The direct approach to reversible watermarking uses lossless compression to substitute parts of the host with their compressed versions and the watermark data. For about ten years several reversible watermarking schemes have been proposed for protecting images of sensitive contentlike medical or military images. For which any modification may impact their interpretation. These methods allow the user to restore exactly the original image from its watermarked version by removing the watermark. Thus it becomes possible to update the watermark content at any time without adding new image distortions.If the reversibility property relaxes constraints of invisibility it may also introduce discontinuity in data protection. In fact, the image is not protected once the watermark is removed. Soeven though watermark removal is possible its imperceptibility has to be guaranteed as most applications have a high interest in keeping the watermark in the image as long as possible taking advantage of the continuous protection watermarking offers in the storage, transmission and also processing of the information. This is the reason why there is still a need for reversible techniques that

introduce the lowest distortion possible with high embedding capacity.

Since the introduction of the concept of reversible water-marking several methods have been proposed. Among these solutions, most recent scheme use Expansion Embedding (EE) modulation, Histogram Shifting (HS) modulation more recently their combination also used. One of the main concern with these modulations is to avoid under-flows and overflows. Indeed with the addition of a watermark signal to the image, caution must be taken to avoid gray level value under flows such as negative and over flows such as greater than d bit depth image in the watermarked image while minimizing at the same time image distortion. Basically EE modulation is a generalization of Difference Expansion modulation which expands the difference between two adjacent pixels by shifting to the left its binary representation, thus creating a new virtual least significant bit (LSB) that can be used for data insertion.

Then EE has been applied in some transformed domains such as the wavelet domain or to prediction-errors. EE is usually associated with LSB substitution applied to samples that cannot be expanded due to the signal dynamic limits or in order to preserve the image quality. In Histogram Shifting (HS) modulation it adds gray values to some pixels in order to shift a range of classes of the image histogram and to create a gap near the histogram maxima. Pixels which belong to the class of the histogram maxima such as carrier-class then shifted to the gap or kept unchanged to encode one bit of the message 0 or 1. Other pixels such as noncarriers are simply shifted. Instead of working in the spatial domain several schemes apply HS to some transformed coefficients or pixel prediction-errors histograms of which are most of the time concentrated around one single class maxima located on zero. This maximizes HS capacity and also simplifies the reidentification of the histogram classes of maximum cardinality at the extraction stage. In order to reduce the distortion while preserving the capacity some preprocessing has been suggested in order to identify pixels transformed coefficients or prediction-errors that do not belong to the histogram maxima classes such as non-arriver classes. Different schemes working with predictionerrors do not watermark pixels within a neighborhood of high variance. These pixels belong to histogram classes that are shifted without message embedding. Recent scheme suggest defining the set of carrierclasses as the classes which minimize for a given capacity image distortion. The set of carrier-classes is uniquely defined for the whole image and the execution time of this approach is rather high.

In this none of the previous methods takes full advantage of the pixel neighborhood. This method proposed to adapt dynamically the carrierclasses by considering the local specificities of the image. The local neighborhood of each predictionerror is used in order to determine the most adapted carrier-class for message insertion.

A new feature selection algorithm based on particle swarm optimization (PSO) is used. PSO is a computational paradigm based on the idea of collaborative behavior. The algorithm is applied to coefficients extracted by two feature extraction techniques: the discrete cosine transforms (DCT) and the discrete wavelet transform (DWT). The proposed PSO-based feature selection algorithm is utilized to search the feature space for the optimal feature subset where features are carefully selected according to a well defined discrimination criterion. Evolution is driven by a fitness function defined in terms of maximizing the class separation. Furthermore this scheme makes use of a classification process for identifying parts of the image that can be watermarked with the most suited reversible modulation. This classification is based on a reference image derived from the image itself a prediction of it which has the property of being invariant to the watermark insertion.Experimental results show that the PSO-based feature selection algorithm was found to generate excellent recognition results with the minimal set of selected features.

# II. RELATED WORKS

A.Difference Expansion

The DE embedding technique involves pairing the pixels of the host image I and transforming them into a low-pass image L containing the integer averages I and a high-pass image H containing the pixel differences h. If a and b be the intensity values of a pixel-pair then I and h are defined as

l=[(a+b)]	/2]		(1)
h=a-b			(2)

This transformation is invertible so that the gray levels a and bcan be computed from 1 and h

a=l+[(h+i)/2](3)

b=l-[h/2](4)

An information bit i is embedded by appending it to the LSB of the difference h thus creating a new LSB. The watermarked difference  $h_{\rm w}$  is

 $h_w=2h+I$  (5)

The resulting pixel gray-levels are calculated from the differenceh<sub>w</sub>and integer average l using.

For an image with n-bit pixel representation the gray levels

Satisfya,  $b {\ensuremath{\mathbb{C}}}[2^n\text{-}1]$  if and only if h and l satisfy the following

Condition:

 $h \in \mathbb{R}_{d}$  (l) = [0, min (2(2<sup>n</sup>-1-l), 2l+1)(6)

Where  $R_d$  (I) is called the invertible region. Combining  $h_w$  and |h| we obtain the condition for a difference to undergo DE

 $2h+i \in R_d(1)$ (7)This condition is called the expandability condition for DE. A difference that satisfies the expandability condition, given a corresponding integer average, is called an expandable difference. Apart from the DE embedding technique this algorithm also uses an embedding technique called LSB replacement. In the LSB-replacement embedding technique the LSB of the difference is replaced with an information bit. This is a lossy embedding technique since the true LSB is overwritten in the embedding process. However in this scheme the true LSBs of the differences that are embedded by LSB-replacement are saved and embedded with the payload, to ensure lossless reconstruction. The LSB of a difference can be flipped without affecting its ability to invert back to the pixel domain if and only if

# $2 [h/2]+i \in R_d (l) (8)$

This is called the changeability condition. A difference satisfying the changeability condition, given a corresponding integer average, is called a changeable difference. An expandable difference is also a changeable difference. A changeable location remains changeable even after its LSB is replaced, whereas an expandable location may not be expandable after DE but it remains changeable.

Let D be the common domain of the highpass and low-passImages H and L respectively. Each element of D is associated with a difference and an integer-average. Expandable locations and changeable locations are subsets of D. The subset of with corresponding changeable differences is denoted by C and is called the set of changeable locations. An important subset of containing the locations with expandable differences is denoted by E and is called the set of expandable locations. Using a selection criterion depending on the size of the payload E is partitioned into  $E^1$  and the set difference. The differences C/E<sup>1</sup>at are expansion embedded. The differences at are  $C/E^1$  modified by LSB replacement. In order to ensure reconstruction, the original LSBs are saved and embedded along with the payload. To enable reconstuction, a binary location mapindicating the selected locations,  $E^1$  is created and losslessly compressed. A bitstream is formed by concatenating the compressed location map, the saved LSBs and the payload and this bitstream is then embedded into the high-pass image. The locations of are traversed in a predefined order and the bits are embedded into the changeable locations C. The watermarked image is calculated from the modified high-pass image and the low-pass image. The major drawback of this scheme is the lack of capacitycontrol which results from having to embed the compressedlocation map along with the payload. The locations selected for expansion embedding determine the location map so the compressibility of the location map depends on the set .Since it is impossible to predict the size of the compressed location map while selecting the locations to embed it is difficult to determine the capacity. Also at low embedding rates the compressibility of the resulting location map is low resulting in a large fraction of the selected capacity to be allotted towards embedding the compressed map.

# B. Histogram Shifting

Difference expansion of the differences in the selected locations expands the histogram of the inner region, and the modified differences now occupy the range [ $-2\Delta$ -2]. Comparing this range with the range of the differences that constitute the outer regions that they overlap in the range. An

appropriate histogram shift of the outer regions would cancel

all overlap between the two regions. In order to achieve this thenegative differences and the nonnegative differences of the outer regions should be shifted left and right respectively, by at least  $\Delta$ +1.

A histogram shift can be easily reversed if  $\Delta$  is known. The histogram shifting has been restricted to expandable differences lying in the outer regions. Histogram shifting causes a smaller change in these differences than difference expansion. Therefore, it is

not necessary to check whether a histogramshift might cause overflow or underflow. Histogram shifting along with DE also eliminates the need to have a location map of the selected expandable locations. The amount of auxiliary information embedded is also significantly reduced. In addition the computational intensity required for histogram shifting is much less than that required for the compression or decompression engine.

# C. Expansion Embedding

Expansion embedding is the technique of embedding a bitinto a feature element by expanding the feature element to create a vacant position that is generally at the least significant position and inserting the bit into the vacant position. The magnitude of the feature element doubles in the process of creating a vacancy at the LSB. The distortion resulting from expansion embedding primarily depends on the magnitude of the feature elements that are expanded. Therefore, it is desirable that most of the elements of the feature set have small magnitudes.

Difference expansion can be considered as a specific case of expansion embedding where the features that are expanded are the pixel differences. A difference operator exploits the correlation only in the pairing direction. This scheme discusses recursive or multiple embedding for his DE scheme, in which the method is applied to an image more than once, with the pairing done in a different direction for each embedding. The idea being that each pass of embedding decorrelate the image in the pairing direction. However every pass decreases the correlation not just in the embedding direction but also of the neighborhood. Thus multiple embedding does not effectively exploit the correlation inherent in a neighborhood. The performance of expansionembedding reversible watermarking can be improved by generating features that decorrelate the image. The classes of integer transforms are appealing because they can be perfectly inverted. Difference expansion is one such class of expansion embedding based on integer transforms. Expansion Embedding propose using a predictor instead of a difference operator to create the feature elements into which expansion embedding is done. A predictor operates on a neighborhood of a given pixel to predict the value of the pixel. A predictor better exploits the correlation inherent in the neighborhood of a pixel. The prediction errors are the feature elements into which expansion embedding is done. One of the advantages of this approach is that it significantly increases the number of feature elements in the feature set. The other important advantage of this approach is that a predictor generatesfeature elements that are smaller in magnitude than thefeature elements by the difference operator.

#### i. Prediction-Error Expansion

The embedding process involves computing the prediction error (PE) from the neighborhood of a pixel, and embedding the information bit in the expanded prediction error. The difference between the pixel intensity and its predicted intensity is the prediction error p. Embedding a bit in results in the watermarked value PE

$$P_{w}=p\pm I \tag{9}$$

#### ii. Basic HS Modulation Principles

The basic principle of Histogram Shifting modulation consists of shifting a range of the histogram with a fixed magnitude  $\Delta$  in order to create a gap near the histogram maxima. Pixels or samples with values associated to the class of the histogram maxima are then shifted to the gap or kept unchanged to encode one bit of the message 0 or 1. The samples that belong to this class as carriers. Other samples called non carriers are simply shifted. At the extraction stage the extractor just has to interpret the message from the samples of the classesC0 andC1 and invert watermark distortions. In order to restore exactly the original datathe watermark extractor needs to be informed of the positions of samples that have been shifted out of the dynamic range. This requires the embedding of an overhead and reduces the watermark capacity.

#### iii. Dynamic Histogram Shifting

Prediction-errors that encode the message belong to the carrier-class $C_C$ =[- $\Delta$ , $\Delta$ ] other predictionerrors are non carriers. This predicate is static for the whole image and does not consider the local specificities of the image signal. Because prediction acts as a low-pass filter most predictionerror carriers are located within smooth image regions.Highly textured regions contain non carriers. The basic idea of this proposal is thus to gain carriers in such a region by adapting the carrier-class $C_C$  depending on the local context of the pixel or of the predictionerror to be watermarked. Dynamic Histogram Shifting modulation to achieve this goal.

#### **III.PROPOSED SCHEME**

The proposed scheme using following architecture and the classification process.

Proposed scheme relies on two main steps. The first one corresponds to an invariant classification process for the purpose of identifying different sets of image regions. These regions are then independently watermarked taking advantage of the most appropriate HS modulation. From here decided to distinguishing two regions where HS is directly applied to the pixels or applied dynamically to pixel prediction-errors respectively. This process is based on our medical image data set for which PHS may be more efficient and simple than the DPEHS in the image black background while DPEHS will be better within regions where the signal is non-null and textured. Now the basic concept of the invariance property of our classification process before detailing how it interacts with PHS and DPEHS is explain.

This scheme introduces some constraints on DPEHS in order to minimize image distortion and then present the overall procedure our scheme follows.. Different schemes working with predictionerrors do not watermark pixels within a neighborhood of high variance. These pixels belong to histogram classes that are shifted without message embedding. Recent scheme suggest defining the set of carrierclasses as the classes which minimize, for a given capacity, image distortion.



Fig :Architecture of proposed system. A. Invariant Image Classification

This classification process exploits a reference image derived from the image Iitself under the two following constraints: i)  $\hat{I}$  unchanged after I has been water-marked into  $I_w$  and have the same reference image ii) Îkeeps the properties of an image signal so as to serve a classification process.

Even though PHS and DPEHS only modulate one pixel value within one block of the image. Let us consider a more general framework where we watermark  $B^k$ , the k<sup>th</sup> block of the image by adding or subtracting a watermark pattern W. Considering linear algebra the invariance constraint can be expressed as

$$\hat{B}^{k} = A.B^{k} = A.B^{k}_{w} = A.(B^{k} \pm W)$$
 (10)

At the same time in order to ensure that  $B^k$  keeps the signal properties of an image it can be designed as a predicted version or a low pass filtered version of B.

# B. Preprocessing

In preprocessing, first the original input image is read from the database. Next converts the input image RGB to the grayscale intensity image by eliminating the hue and saturation information while retaining the luminance. After conversion resize the image by using bicubic interpolation.



Fig: Gray scale image C. PSO based optimal feature selection

Particle swarm optimization (PSO) is a population-based stochastic optimization technique. Each particle makes use of its individual memory and knowledge gained by the swarm as a whole to find the best solution. All of the particles have fitness values, which are evaluated by fitness function to be optimized, and have velocities which direct the movement of the particles. The initial swarm is generally created in such a way that the population of the particles is distributed randomly over the search space. At every iteration, each particle is updated by following two best values calledpbest and gbest. Each particle keeps track of its coordinates in the problem space which are associated with the best solution the particle has achieved so far. This fitness value is stored and called pbest. When a particle takes the whole population as its topological neighbor, the best value is a global best value and is calledgbest.

D. Watermarking

Watermarking is a recognizable image or pattern that appears as various shades of lightness or darkness when viewed by transmitted light or when viewed by reflected caused by thickness or density variations.

## E. Data extraction

Considering a specific run into the image possibly based on a secret key, pixels are classified into PHS region or DPEHS region. One part of the message is embedded in the PHS region along with some overhead in case of overflows or underflows. The rest of the message is embedded into the pixels. At the extraction stage, in the case the matrix A is predefined, the only parameter the extract or needs to know is the histogram shifting amplitude  $\Delta$ . Data extraction is conducted independently in each region and pass. The extractor will retrieve by itself the values of  $T_{min}$ ,  $T_{max}$ ,  $T_{std}$  and  $T_c$ .

## **IV. EXPERIMENTAL RESULTS**

TABLE I THE COMPARISON ASSESSMENT OF CAPACITY AND DISTORTION OF LEENA IMAGE

Δ=1		Use of ½ of the image I		Use of whole image I	
		С	PSNR	С	PSNR
Leena	[11]	0.04	58.51	0.09	55.29
	[12]	0.08	56.78	0.11	54.58
	proposed	0.078	58.543	0.15	55.72

Results are given in terms of capacity and image distortion depending on the pixel shifting magnitude  $\Delta$  and the number of times the algorithm goes through the image. Results for natural images are given where we compare our technique with the four other schemes proposed. Presented curves have been obtained making varying  $\Delta$  and the number of embedding passes progressively. This method provides a better capacity or distortion compromise than any of these methods for low and medium capacities.

## V. CONCLUSION

A new reversible watermarking scheme which originality stands in identifying parts of the image that are watermarked using HS modulations and optimal feature selection algorithm based on particle swarm optimization(PSO). This scheme offers very good compromise in terms of capacity and image quality preservation in both medical and natural images.

## REFERENCES

- [1] G. Coatrieux, C. Le Guillou, J.-M.Cauvin, and C. Roux, "Reversible watermarking for knowledge digest embedding and reliability controlin medical images," *IEEE Trans. Inf. Technol. Biomed.*, vol. 13, no. 2,pp. 158–165, Mar. 2009.
- [2] F. Bao, R. H. Deng,B.C.Ooi, andY. Yang, "Tailored reversible watermarkingschemes for authentication of electronic clinical atlas," *IEEETrans. Inf. Technol. Biomed.*, vol. 9, no. 4, pp. 554–563, Dec. 2005.
- [3] H. M. Chao, C. M. Hsu, and S. G. Miaou, "A data-hidding techniquewith authentication, integration, and confidentiality for electronic patientrecords," *IEEE Trans. Inf. Technol. Biomed.*, vol. 6, no. 1, pp.46–53, Mar. 2002.
- [4] G. Coatrieux, L. Lecornu, B. Sankur, and C. Roux, "A review of imagewatermarking applications in healthcare," in *Proc. IEEE EMBC Conf.*, New York, 2006, pp. 4691– 4694.
- J. M. Barton, "Method and Apparatus for Embedding AuthenticationInformation Within Digital Data," U.S. Patent 5 646 997, 1997.
- [6] J. Tian, "Reversible data embedding using a difference expansion,"*IEEE Trans. Circuits Syst. Video Technol.*, vol. 13, no. 8, pp. 890– 896,Aug. 2003.
- [7] Z. Ni, Y. Q. Shi, N. Ansari, and S.Wei, "Reversible data hiding," *IEEETrans. Circuits Syst. Video Technol.*, vol. 16, no. 3, pp. 354–362, Mar.2006.
- [8] G.Xuan,Y.Q.Shi,C.Y.Yang,Y. Z. Zheng, D. K.Zou, and P. Q. Chai, "Lossless data hiding using integer wavelet transform and thresholdembedding technique," in *Proc. Int. Conf.Multimedia and Expo*, 2005, pp. 1520– 1523.
- [9] D.M. Thodi and J. J. Rodriquez, "Expansion embedding techniques forreversible watermarking," *IEEE Trans. Image Process.*, vol. 16, no. 3,pp. 721–730, Mar. 2007.
- [10] W. Pan, G. Coatrieux, N. Cuppens, F. Cuppens, and C. Roux, "An additiveand lossless watermarking method based on invariant image approximation and Haar wavelet transform," in *Proc. IEEE EMBC Conf.*, Buenos Aires, Argentina, 2010, pp. 4740–4743.

- [11] V. Sachnev, H. J. Kim, J. Nam, S. Suresh, and Y.-Q. Shi, "Reversiblewatermarking algorithm using sorting and prediction," *IEEE Trans.Circuit Syst. Video Technol.*, vol. 19, no. 7, pp. 989–999, Jul. 2009.
- [12] H. J. Hwang, H. J. Kim, V. Sachnev, and S. H. Joo, "Reversible watermarkingmethod using optimal histogram pair shifting based on predictionand sorting," *KSII, Trans. Internet Inform. Syst.*, vol. 4, no. 4,pp. 655– 670, Aug. 2010.
- [13] L. Kamstra and H. J. A. M. Heijmans, "Reversible data embeddinginto images using wavelet techniques and sorting," *IEEE Trans. ImageProcess.*, vol. 14, no. 12, pp. 2082– 2090, Dec. 2005.
- [14] L. Luo, Z. Chen, M. Chen, X. Zeng, and Z. Xiong, "Reversible imagewatermarking using interpolation technique," *IEEE Trans. Inf. ForensicsSecurity*, vol. 5, no. 1, pp. 187–193, Mar. 2010.
- [15] D. Coltuc, "Improved embedding for prediction-based reversible watermarking,"*IEEE Trans. Inf. Forensics Security*, vol. 6, no. 3, pp.873–882, Sep. 2011.
- [16] C. C. Lin, W. L. Tai, and C. C. Chang, "Multilevel reversible datahiding based on histogram modification of difference images," *PatternRecognit.*, vol. 41, pp. 3582– 3591, 2008.
- [17] C. H.YangandM.H.Tsai, "Improving histogram-based reversible datahiding by interleaving predictions," *IET Image Process.*, vol. 4, no. 4,pp. 223–234, Aug. 2010.
- [18] C. De Vleeschouwer, J.-F.Delaigle, and B. Macq, "Circular interpretationofbijective transformations in lossless watermarking for mediaasset management," *IEEE Trans.Multimedia*, vol. 5, no. 1, pp. 97– 105,Mar. 2003.