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RESEARCH ARTICLE

Reversible Watermarking for Data Embedding into Images using DHS and IIC

D.Maladevi[1], V.Rajaram[2], K.Thaiyalnayaki[3]

[1,2,3] Sri Venkateswara college of Engineering, Chennai, Tamilnadu, India

Abstract— ***A reversible watermarking scheme is one of the improvements in histogram shifting modulation that modifies local precision of image content. In existing schemes large number of images can't be hidden i.e. capacity is less and distortion is more so we propose dynamic histogram shifting to insert large number of images into a single host images and with the less distortion. For the same capacity, achieved Peak Signal-to-noise ratio (PSNR) is more than 63dB. Invariant image classification is to classify the parts of the images and embedder, extractor remain synchronize with the watermarked image. Classification of original images derives from image itself.***

Keywords –PSNR; reversible watermarking/lossless watermarking; DHS; IIC

I. INTRODUCTION

For about twelve years, several lossless watermarking strategy have been proposed for assuring images of delicate content, like healthcare or defence images, for which any changes may impact their interpretation [1]. These concepts allow the end user to recover absolutely the authentic image from its watermarked version by extracting the watermark. Thus it becomes possible to restore the watermark content, for example security attributes like digital signature, at any time without adding new image distortions [2], [3]. In present days they are using the solution of Expansion Embedding modulation and Histogram shifting modulation [7] modulation. There are two main concepts with these modulations is to neglect underflows and overflows. Overflow is the process of reducing the image distortion while it is in watermarked. Underflow is the process of avoiding negative grey level values. There are two types of classes involved like carrier and non carrier classes. Carrier classes are those where a pixel belongs to highest peak point of histogram, Non carrier are those where classes is a pixel belongs to lowest peak point of histogram.

In order to improve the security via internet[1] where crucial application of the internet is applied in healthcare environment for various activities like transmit and receive ERP via emails among healthcare institution. It contains a private material of patient information related to medicals.There are different types of watermarking like visible and invisible watermarking. Visible watermarking is visible to the user and it is not authenticated, security is less. Invisible watermarking cannot be seen by the viewer. The output signal does not change much when compared to the original signal. The watermarked signal is almost similar to the original signal. As the watermark is invisible, the imposter cannot crop the watermark as invisible watermarking. Invisible watermarking is more robust to signal processing attacks when compared to visible watermarking.

II. DYNAMIC HISTOGRAM SHIFTING

In spatial domain [7], the basic assumption of Histogram Shifting modulation consists of shifting a pixel of the histogram with a limited magnitude, in order to create a space near the histogram maximum. Pixels are more generally modelled 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, i.e., ’0’ or ’1’.

Prediction-errors that encode the content belongs to the carrier-class, another prediction-errors is noncarriers. This predicate is static for the entire image and cannot consider the local specification of the image because prediction is acting as a low-pass filter; most of the prediction- error carriers are located inside the mild image regions. Highly smooth regions contain noncarriers. The basic concept of our proposed scheme is thus to increase carriers in such a region by adapting the carrier-class depending on the local context of the pixel. Also consider that the objective is only at modulating the prediction-errors leaving intact their immediate neighbourhood. Because of the local stagnant of the image they can consider without too much risk that adjoining prediction-errors have the similar behaviour. Assuming the prediction-error neighbourhood so as to define the location of the prediction-error is dynamic. To define the carrier-class for the histogram limits to which the infinite values of prediction-errors. Using their mean-value will result in predicting centered on zero.

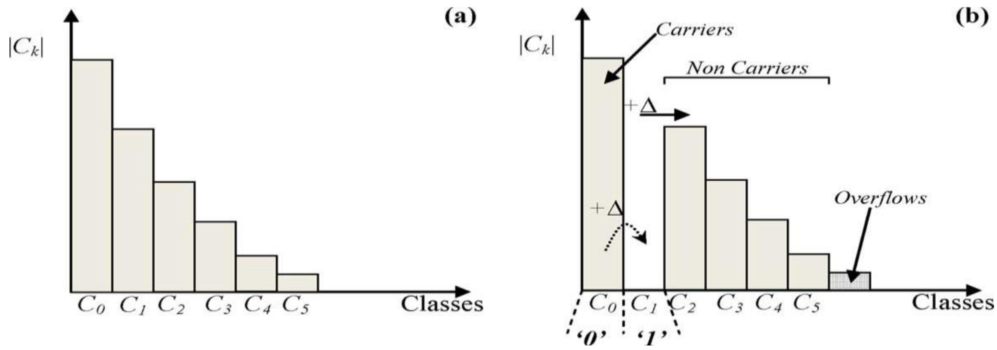

Fig.1. (a) Original dynamic histogram (b) Dynamic histogram of the watermarked data

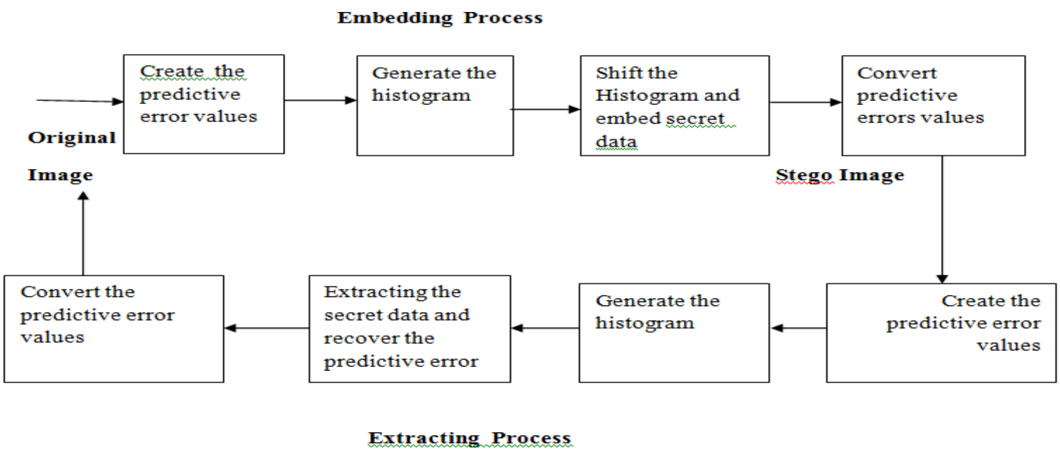

Fig.2. Architecture of reversible watermarking image authentication based on DHS and prediction error

Based on our approach, the reference class is resolved dynamically for each prediction-error of the picture. They allow us to compensate the prediction-error in smooth regions and give us the capability to embed data in such areas where another method fail to do so. The location is computed independently of and will be salvage by the extractor: Embedder and extractor remain harmonized without having to embed some extra-overhead. DHS modulation requires to performing the watermarking of the image in several purposes. One fourth of the image pixels are watermarked is to ensure that their prediction-error neighbourhood remains stable. The most of the methods functioning with HS enforced to pixel prediction-errors. The modulation gives no advantages regarding overflows and underflow modulations can increase in performance by enforcing EE modulation on the prediction-error simply shifting the carrier and the same capacity there by reducing the distortion**.**

III. INVARIANT IMAGE CLASSIFICATION

Invariant image classification is a process of identifying various sets of image regions. These regions are separately watermarked taking advantage of the most pertinent HS modulation. The difference between the two regions as HS is directly enforced to the pixels or enforced dynamically to pixel prediction-errors respectively. A reference picture is derived from the picture itself under the two following constraints:

i) Image remains unchanged after it has been watermarked into, i.e., and have the same reference picture.

ii) Keeps the properties of an image signal so as to serve a image classification process.

The PHS and DPEHS only modulate one pixel value within one block of the picture.

$$C^{q1} = D \,.\, C^{q} = D \,.\, C^{q}{}_{w} = D \,.\, C^{q} \qquad (1)$$

Once these constraints are fulfilled the watermark extractor will salvage exactly .They allows us to indicate each block of the image by some simple measures extracted from its block of reference (e.g., maximum and minimum values). Such a block characterization is the basis of our classification process. Assume the first classification process whose aim is for healthcare images is to segregate regions that will be PHS or DPEHS watermarked. This merely difference between the black background of the image from the human (anatomical) object. Based on the fact that PHS and DPEHS are parameterized by a shift of magnitude which is equal to threshold value, i.e., if the pixel belongs to the PHS region otherwise to the DPEHS region. From here on, they will also assume as part of the image background, blocks. The reason is the healthcare image background sometimes contains pixels corresponding to some annotations or markers. From that standpoint, it can distinguish between different parts of the image and the extractor will be able to salvage them easily. Our scheme uses this approach not only for classifying image regions where to enforce PHS or DPEHS but also for governing underflow and overflows. Watermark does not have some extra-overhead data.

IV. Results and Discussions

1) Predictive error algorithm

a) Predictive error value: Read and resize the image and using grey scale image then assign the values for rows and columns for eg: imgresize(imread(‘aa.jpg’),[5 5])

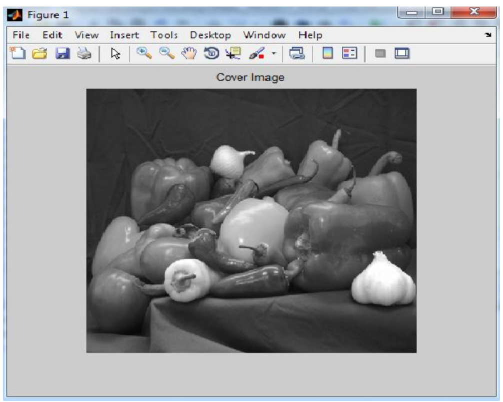

Fig. 3. Original image

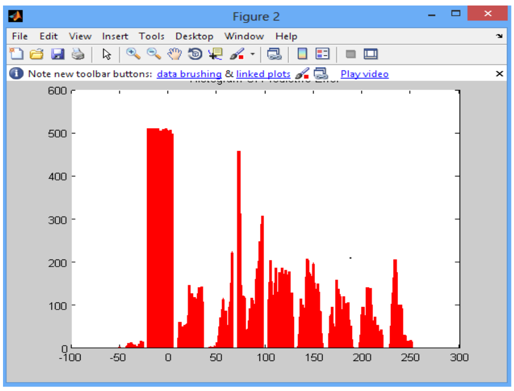

Fig.4. Predictive error for original image

b) Then find out predictive error value for odd columns. So that we are using 3 formulas to find out the predicted values for odd column

D(i,j)=h(i,j)-h(i,j+1) for finding first odd columns

D(i,j)=h(i,j)-(h(i,j-1)+h(i.j+1)/2) for finding middle odd columns

D(i,j)=h(i,j)-h(i,j-1) for finding last odd columns

c) Separate the odd columns of the predictive error values, eg

$$C = \begin{bmatrix} -28 & 18 & -43 \\ -73 & -32 & -55 \\ -55 & -69 & 0 \\ -35 & 33 & 19 \\ -29 & 11 & -24 \end{bmatrix}$$

d) Draw the dynamic histogram shifting graph, find the two peak point i.e. two condition must satisfy, like one is positive and another one is negative value.

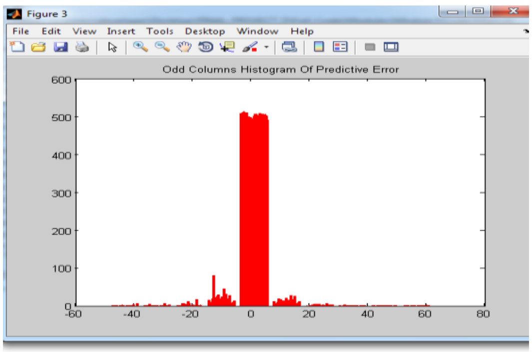

Fig 5. Odd column histogram of predictive error

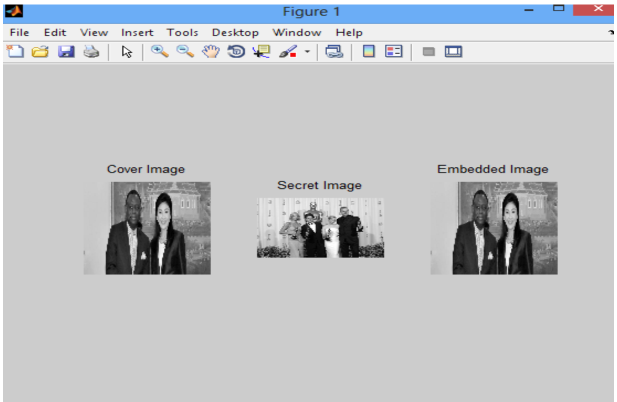

Fig.6. Embedding process

2) Embedding process

a) Make a histogram shifting based on peak and zero points. Then the secret image converted into binary sequence. For example 200 is converted into binary numbers like 10001000,0 takes the value is 1,-1 takes the value is -2(just increment by 1).so that we should free the space of 1 and -2 so have to shift the next position of each values. Finally we get distortion less embedded image.

b) After that binary sequence embedded into predictive error values and the PSNR value will be increased. Finally we get distortion less embedded image.

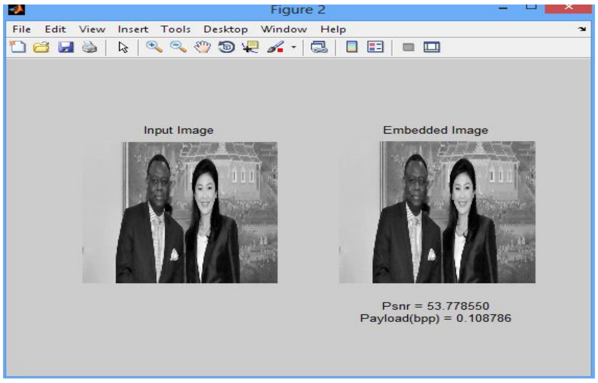

Fig 7. Embedded image of PSNR

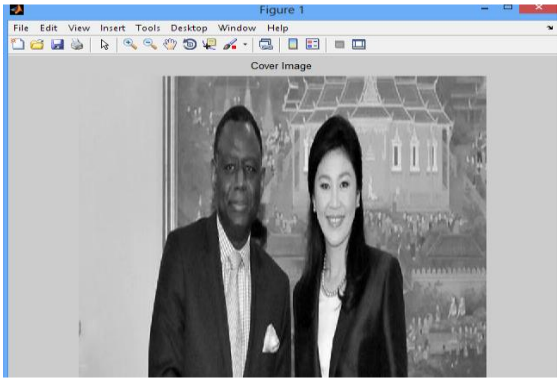

Fig 8. Cover image of the extraction process

3) Extracting Process

Finally we find predictive error values for embedded image. Then recover the binary values from embedded image's Predictive error values. Then binary sequence converted into secret image.

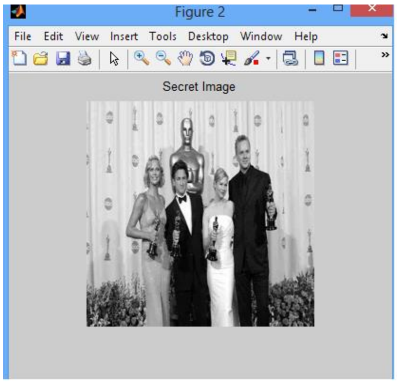

Fig 9.secret image

Hiding more images in a original images

1. Predictive error for original images

a) Read and resize the image and using grey scale image then assign the values for rows and columns for eg: imgresize(imgread('aa.jpg'),[5 5])

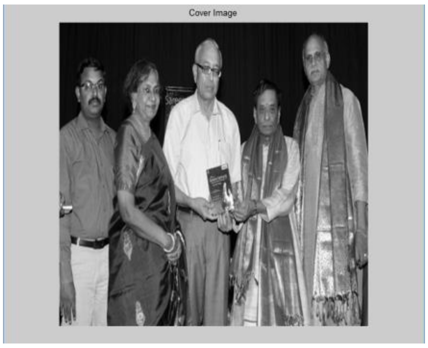

Fig. 10. Original image

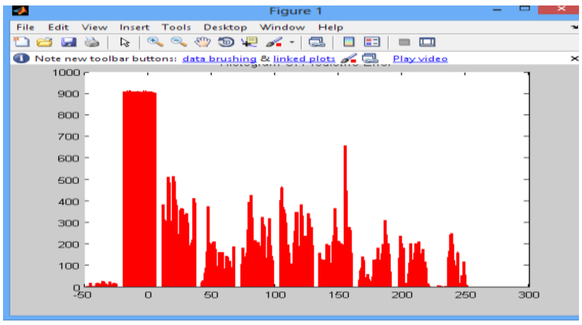

Fig.11. Predictive error for original image

b) Then find out predictive error value for even columns. So that we are using 3 formulas to find out the predicted values for odd column

D(a,b)=h(a,b)-(h(a,b-1)+h(a.b+1)/2)

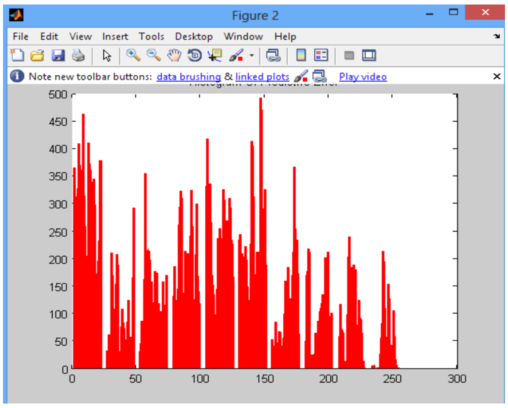

Fig 12. Odd column histogram of predictive error

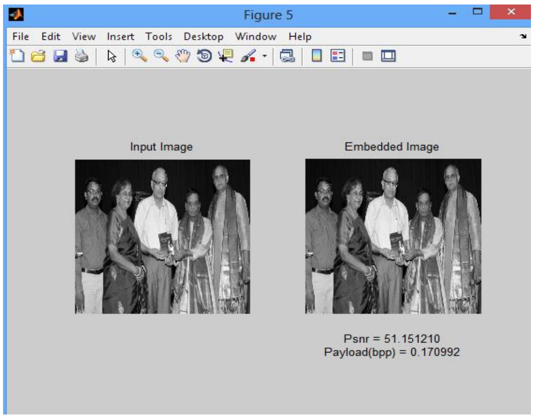

Fig.13. Embedded image of PSNR

c) Draw the dynamic histogram shifting graph, find the two peak point i.e. two condition must satisfy it like one is positive and another one is negative values

2) Embedding process

a) Make a histogram shifting based on peak and zero points. Then the secret image converted into binary sequence. For example 200 is converted into binary numbers like 10001000,0 takes the value is 1,-1 takes the value is -2(just increment by 1).so that we should free the space of 1 and -2 so have to shift the next position of each values. Finally we get distortion less embedded image.

3) Extracting Process

Finally we find predictive error values for embedded image. Then recover the binary values from embedded image's Predictive error values. Then binary sequence converted into secret image.

Fig.14. original image of extracting process

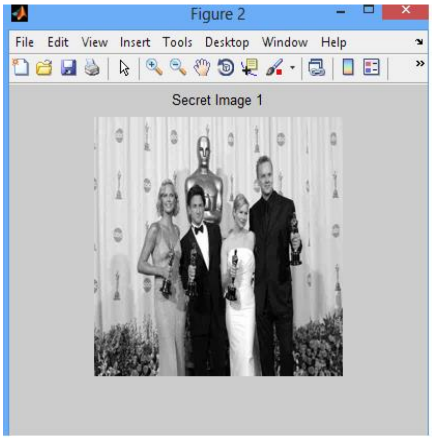

Fig.15. secret image 1

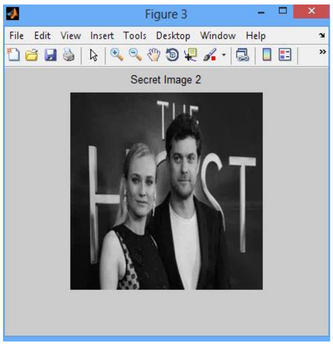

Fig.16. secret image 2

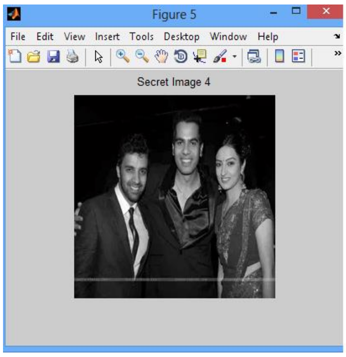

Fig.17. secret image 3

V. CONCLUSION

A reversible watermarking schemes which originally identifies the parts of the images that are watermarked using two technique of HS modulations: PHS and DPHS enforcing HS on pixels may be efficient and of lesser complexity than enforcing it on prediction-errors. The embedder and extractor remain integrated because the extractor will salvage the same reference image. Reversible watermarking is based on dynamic prediction error, histogram shifting can still be improved by further hiding more images in a single original image and also further reducing the distortion and also improve the security of the original image. PSNR values are increased.

REFERENCES

[1] H. M. Chao, C. M. Hsu,S.B.chi, and S. G. Miaou, 'A data-hidding technique with authentication, integration, and confidentiality for electronic patient records', IEEE Trans. Inf. Technol. Biomed, vol. 6, pp. 46–53,Mar. 2002.

[2] J. Tian, 'Reversible data embedding using a difference expansion', IEEE Trans. Circuits Syst. Video Technol, vol. 13, no. 8, pp. 890–896,Aug. 2003.

[3] L. Kamstra and H. J. A. M. Heijmans, 'Reversible data embedding into images using wavelet techniques and sorting', IEEE Trans. Image Process, vol. 14, no. 12, pp. 2082–2090,Dec. 2005.

[4] F. Bao, R. H. Deng,B.C.Ooi, andY. Yang, 'Tailored reversible watermarking schemes for authentication of electronic clinical atlas', IEEE Trans. Inf. Technol. Biomed, vol. 9, no. 4, pp. 554–563,Dec. 2005.

[5] G. Coatrieux, L. Lecornu, 'Reversible watermarking for knowledge digest embedding and reliablility control in medical images', IEEE Trans on IT in biomedicine,vol.13,no. 2,pp. 523-741,Mar. 2009.

[6] V. Sachnev, H. J. Kim, J. Nam, S. Suresh, and Y.-Q. Shi , 'Reversible watermarking algorithm using sorting and prediction', IEEE Trans Circuit Syst. Video Technol, vol. 19, no. 7, pp. 989–999,July. 2009.

[7] G. Coatrieux, C. Le Guillou, J.-M. Cauvin, and C. Roux, 'Reversible watermarking for knowledge digest embedding and reliability control in medical images',IEEE Trans. Inf. Technol. Biomed, vol. 13, no. 2, pp. 158–165,Feb. 2009.

[8] L. Luo, Z. Chen, M. Chen, X. Zeng, and Z. Xiong , 'Reversible image watermarking using interpolation technique', IEEE Trans. Inf. Forensics Security, vol. 5, no. 1, pp. 187–193,Mar. 2010.

[9] Hui-Yu Huang National Formosa University, Taiwan, 'A loseless data hiding technique based on wavelet transform', IEEE Trans.on Machine Vision Applications,vol.8,no. 2,pp. 523-145,Sept. 2011.

[10] D. Coltuc,Dan, Yue Xiao and Shaoqian Li, 'Improved embedding for prediction-based reversible watermarking ',IEEE Trans. Inf. Forensics Security, vol. 6, no. 3, pp. 873–882,Sept. 2011.

