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Reversible Watermarking Based on Complementary Predictors and Context Embedding

Ioan-Catalin Dragoi
Electrical Engineering Dept.
Valahia University of Targoviste, Romania
Email: catalin.dragoi@valahia.ro

Dinu Coltuc
Electrical Engineering Dept.
Valahia University of Targoviste, Romania
Email: dinu.coltuc@valahia.ro

***Abstract*—Two complementary bounds of the predicted pixel are defined and used to compute two estimates of the prediction error. The more suitable value for reversible watermarking among the two estimates is selected for data insertion. A reversible watermarking scheme based on context embedding ensures the detection of the selected value, without the need for any additional information. The scheme is general and works regardless the particular predictor. The proposed scheme is of interest for embedding bit-rates of less than 0.5 bpp. Interesting results are reported for the case of pairwise embedding reversible watermarking. The proposed scheme compares very well with the most efficient schemes published so far.**

I. Introduction

Reversible watermarking provides, at detection, the exact recovery of both the embedded data and the cover image. The recent reversible watermarking algorithms use the prediction error (PE) for data embedding. More precisely, there are two major types of algorithms: prediction error expansion (PEE), and prediction error histogram bin shifting (PE-HS). The basic PEE scheme, [1], enlarges two times the prediction error (i.e., clears the least significant bit of the PE) and adds one bit of data to the enlarged PE. Obviously, the embedding can be done only if the graylevel range is preserved. The PE-HS scheme, [2], embeds data into a selected error bin after a prior shifting of the PE histogram in order to create an adjacent free bin. Obviously, for such PE-HS schemes, the embedding bit-rate for one stage of embedding is controlled by the size of the selected histogram bin. Among the PEE-HS schemes, the most efficient are the ones that embed data into the two-dimensional PE histogram of pixel pairs [3], [4]. The PE-HS schemes are adequate for low embedding bit-rates (about the size of the two largest histogram bins since two bins can be simultaneously embedded). As the embedding bit-rate increases, the PEE schemes become more efficient.

The prediction quality determines the performances of both PEE and PE-HS schemes. For the case of PEE, the embedding is performed by increasing two times the prediction error. An improved prediction not only brings reduced embedding distortions, but also increases the embedding bit-rate, since more pixels can be watermarked. For PE-HS schemes, improved predictions means also both higher peaks in the PE histogram (an increase of the embedding bit-rate) and lower distortion (less shifted pixels in the tails of the histogram).

The improvement of the prediction is a major research topic in reversible watermarking. Initially, efficient predictors developed for lossless compression, like MED, GAP, etc., have been used in reversible watermarking schemes too [1], [5], etc. Then, specially designed causal or non-causal predictors have been proposed. Such a predictor is the simple average on the rhombus composed of the four horizontal and vertical neighboring pixels, [6]. Most of the recent reversible watermarking schemes are based either on the rhombus predictor or on improved versions of the rhombus predictor (see [7]–[9], etc.). Finally, one of the most efficient schemes proposed so far, [10], computes a local least mean squares predictor for each image pixel.

This paper aims at reducing the distortion in the case of large prediction errors. The basic idea is to use two rather close predicted values and to consider their prediction errors. The proposed scheme selects for data embedding the prediction error with smallest absolute value. A reversible watermarking scheme based on context embedding ensures the detection of the selected value, without the need for any additional information. We remind that context embedding schemes split the error between the current pixel and its prediction context in order to minimize the global distortion [5], [9]. This new scheme embeds adaptively either the current pixel or a selected one from its context. The outline of the paper is as follows. The PEE and PE-HS schemes are briefly reminded in Section II. The proposed scheme and the experimental results are presented in Sections III and IV, respectively. Finally, the conclusions are drawn in Section V.

II. PEE and PE-HS reversible watermarking

Both the PEE approach introduced in [1] and the PE-HS one of [2] follow the same watermarking principles. Namely, the embedding proceeds in a fixed order, either raster-scan starting from the upper left corner or two staged based on the local context (introduced in [6]). For each pixel x_i, the predicted value, $\hat{x}_i$, is determined based on its prediction context. Then, the prediction error, e_i, is computed:

$$e_i = x_i - \hat{x}_i \tag{1}$$

The current pixel is modified based on its prediction error:

$$x'_i = x_i + \delta_i \tag{2}$$

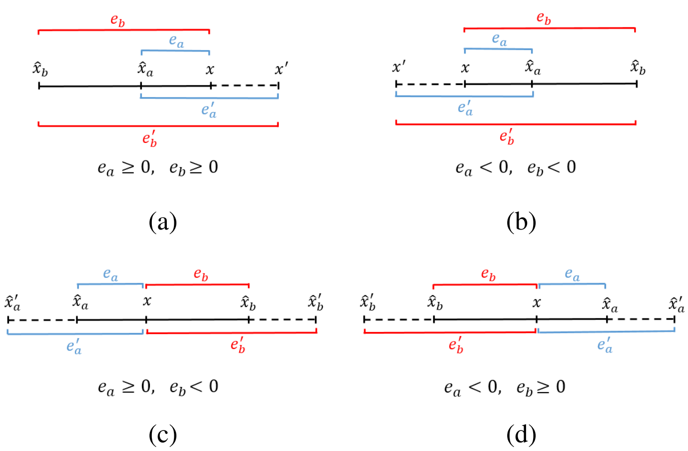


Fig. 1. The proposed watermarking scheme ($|e_a| < |e_b|$): classic embedding if e_a and e_b have the same sign (a,b), context embedding otherwise (c,d).

where δ_i represents the distortion introduced by the reversible watermarking scheme in x_i. For PEE, this distortion is computed as:

$$\delta_i = \begin{cases} e_i + b_i, & \text{if } -T \leq e_i < T, \\ T, & \text{if } e_i \geq T, \\ -T, & \text{if } e_i < -T. \end{cases} \tag{3}$$

where $b_i \in \{0, 1\}$ is the hidden bit inserted in x_i and T is the embedding threshold. Only pixels with $-T \leq e_i < T$ are used for data hiding, the others are shifted to prevent them from overlapping with the marked pixels.

The PE-HS approach distorts the current pixel with:

$$\delta_i = \begin{cases} 0 & \text{if } L < e_i < R, \\ b_i, & \text{if } e_i = R, \\ -b_i, & \text{if } e_i = L, \\ 1, & \text{if } e_i > R, \\ -1, & \text{if } e_i < L. \end{cases} \tag{4}$$

where R and L are the prediction errors selected for watermarking.

At decoding, the pixels containing hidden data are identified based on their PE: $-2T \leq e_i' < 2T$ for PEE and $e_i' \in \{R, L, R+1, L-1\}$ for PE-HS. The watermark is then decoded: $b_i = \text{mod}(e_i', 2)$ for PEE; if $e_i' \in \{R, L\} \Rightarrow b_i = 0$ and if $e_i' \in \{R+1, L-1\} \Rightarrow b_i = 1$ for PE-HS. The original pixel values are restored with $x_i = x_i' - \delta_i$.

III. Proposed Scheme

The proposed scheme is first introduced in the PEE/PE-HS framework presented above (Section III-A), next the complementary predictors based on the rhombus average are presented (Section III-B) and then the 2D pairing version of the proposed scheme is described (Section III-C).

A. Complementary predictors and context embedding scheme

Current reversible watermarking approaches use a single predicted value, $\hat{x}_i$ to estimate x_i. The proposed scheme computes two complementary predicted values, $\hat{x}_a$ and $\hat{x}_b$, for each pixel x_i:

$$\hat{x}_a = \hat{x}_i - \hat{x}_j + x_j, \qquad \hat{x}_b = \hat{x}_i + \hat{x}_j - x_j. \tag{5}$$

where x_j is a neighbor of x_i and $\hat{x}_j$ is the predicted value for x_j. $\pm(\hat{x}_j - x_j)$ acts as a correction coefficient for $\hat{x}_i$. Both $\hat{x}_i$ and $\hat{x}_j$ are computed using classic predictors. Note that for this predictors, x_j cannot be part of the prediction context for x_i and vice-versa.

Next, the prediction errors furnished by $\hat{x}_a$ and $\hat{x}_b$ are computed:

$$e_a = x_i - \hat{x}_a, \qquad e_b = x_i - \hat{x}_b \tag{6}$$

and the error with the smallest absolute value is selected:

$$e_i = \begin{cases} e_a, & \text{if } |e_a| < |e_b| \text{ or } (|e_a| = |e_b| \text{ and } e_a \leq e_b), \\ e_b, & \text{if } |e_a| > |e_b| \text{ or } (|e_a| = |e_b| \text{ and } e_a > e_b). \end{cases} \tag{7}$$

where $|e|$ is the absolute value of e. Note that when e_a and e_b have opposite signs, but have equal absolute values, the negative prediction error is selected because of the asymmetric nature of the embedding scheme.

If $e_a, e_b \geq 0$ (Fig. 1.a) or $e_a, e_b < 0$ (Fig. 1.b), the current pixel x_i is watermarked as for the classical schemes (equation (2)), but with the superior prediction offered by (7). Otherwise, x_j is modified using context embedding:

$$x_j' = \begin{cases} x_j - \delta_i, & \text{if } e_i = e_a \\ x_j + \delta_i, & \text{if } e_i = e_b \end{cases} \tag{8}$$

Contrary to [5] and [9], the entire distortion is inserted in x_j and x_i remains unchanged.

Both $\hat{x}_a$ and $\hat{x}_b$ are computed using x_j (equation (5)) and are directly affected by (8): $\hat{x}_a' = \hat{x}_a \mp \delta_i$, $\hat{x}_b' = \hat{x}_b \pm \delta_i$. This allows the relation between e_a and e_b to be maintained at detection with e_a' and e_b' (see Fig. 1.c–d). x_j was potentially modified by the embedding scheme before x_i was processed. In this case, the secondary modification introduced by (8) can add to the distortion or correct the initial modified value of x_j.

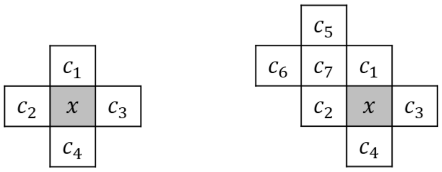
The overflow/underflow problem is solved with an overflow map [1]. The watermarked value (x_i' or x_j') for the current pixel is checked and if overflow/underflow occurred, the position for x_i is stored in the map and corresponding value (x_i or x_j) remains unchanged.

B. Complementary predictors for the rhombus average

The rhombus predictor of [6] estimates x_i as:

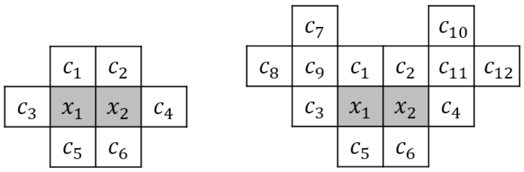
$$\hat{x} = \left\lfloor \frac{c_1 + c_2 + c_3 + c_4}{4} + 0.5 \right\rfloor \tag{9}$$

where $\lfloor x \rfloor$ represents the greatest integer less than or equal to x and c_1, c_2, c_3, c_4 form the prediction context of x_i (Fig. 2.a).



(a) (b)

Fig. 2. The rhombus prediction context (a) and the extended one used by the complementary predictors based on the rhombus average (b).



(a) (b)

Fig. 3. Horizontal pairing: the original prediction context (a) and the one used by the proposed 2D scheme (b).

Let the left upper diagonal neighbor $x_j = c_7$ (Fig. 2.b) be considered for context embedding. The corresponding complementary predictors are:

$$\begin{aligned} \hat{x}_a &= \left\lfloor \tfrac{c_1+c_2+c_3+c_4}{4} - \tfrac{c_5+c_6+c_1+c_2}{4} + 0.5 \right\rfloor + c_7 \\ \hat{x}_b &= \left\lfloor \tfrac{c_1+c_2+c_3+c_4}{4} + \tfrac{c_5+c_6+c_1+c_2}{4} + 0.5 \right\rfloor - c_7 \end{aligned} \tag{10}$$

$\hat{x}_a$ and $\hat{x}_b$ are used to compute e_a and e_b (equations (6)), e_i is then selected with (7) and x_i or c_7 are modified using (2) or (8) based on the relation between e_a and e_b.

Before going any further, let us discuss a simple reversible watermarking example. Let us consider the PEE case with: $x_i = 100$, $\hat{x}_a = 98$, $\hat{x}_b = 96$, $b_i = 1$ and $T = 3$. The prediction errors are computed as $e_a = 2$ and $e_b = 4$. The error with the smallest absolute value, $e_a = 2$, is selected as e_i. The pixel is watermarked: $x'_i = 100 + 2 + 1 = 103$. At detection the errors are $e'_a = 5$ and $e'_b = 7$. The correct error, $e'_i = 5$ (smallest absolute value) is selected and x_i can be restored: $x_i = 103 - \lfloor 5/2 \rfloor - \mathrm{mod}(5, 2) = 100$.

Next, let us consider: $x_i = 100$, $\hat{x}_a = 98$, $\hat{x}_b = 104$, $b_i = 1$ and $T = 3$. The corresponding errors are $e_a = 2$ and $e_b = -4$, $e_i = 2$ is selected. It immediately appears that the embedding in x_i would produce errors at the decoding stage: $x'_i = 103$, $e'_a = 5$, $e'_b = -1$ and $e'_i = -1$ (wrong value) is selected. To avoid this problem, x_j is modified instead of x_i, this affects the predicted values: $\hat{x}'_a = 98 - 3 = 95$, $\hat{x}'_b = 104 + 3 = 107$. At detection we have: $e'_a = 5$ and $e'_b = -7$. The correct value, $e'_i = 5$, is selected.

C. *Complementary predictors and context embedding for the 2D pairing framework*

The reversible watermarking schemes of [3] and [4], based on the 2D prediction error histogram, process the pixels as pairs. The horizontal pixel pairs used by [4] and the corresponding prediction context are presented in Fig. 3.a. The predicted values for each pixel in the pair are computed as:

$$\begin{aligned} \hat{x}_1 &= \left\lfloor \frac{c_1+c_3+\frac{c_2+c_3+c_4+c_6}{4}+c_5}{4} + 0.5 \right\rfloor \\ \hat{x}_2 &= \left\lfloor \frac{c_2+\frac{c_1+c_3+c_4+c_5}{4}+c_4+c_6}{4} + 0.5 \right\rfloor \end{aligned} \tag{11}$$

The $(\hat{x}_1, \hat{x}_2)$ prediction pair is used to determine e_1 and e_2. The (x_1, x_2) pair is then watermarked as follows:

$$x'_1 = \begin{cases} x_1 + \delta_1, & \text{if } e_1 \geq R \\ x_1 - \delta_1, & \text{if } e_1 \leq L \end{cases}, \quad x'_2 = \begin{cases} x_2 + \delta_2, & \text{if } e_2 \geq R \\ x_2 - \delta_2, & \text{if } e_2 \leq L \end{cases} \tag{12}$$

where δ_1 and δ_2 represent the watermarking distortions introduced in x_1 and x_2, respectively.

The prediction context in Fig. 3.a can be easily expanded in order to allow the use of complementary predictors. The expanded context is shown in Fig. 3.b. The prediction errors for c_9 and c_{11} are used for correcting the values of $\hat{x}_1$ and $\hat{x}_2$, respectively:

$$\begin{aligned} \hat{x}_{1a} &= \left\lfloor \frac{c_1+c_3+\frac{c_2+c_3+c_4+c_6}{4}+c_5}{4} - \frac{c_7+c_8+c_1+c_3}{4} + 0.5 \right\rfloor + c_9 \\ \hat{x}_{1b} &= \left\lfloor \frac{c_1+c_3+\frac{c_2+c_3+c_4+c_6}{4}+c_5}{4} + \frac{c_7+c_8+c_1+c_3}{4} + 0.5 \right\rfloor - c_9 \\ \hat{x}_{2a} &= \left\lfloor \frac{c_2+\frac{c_1+c_3+c_4+c_5}{4}+c_4+c_6}{4} - \frac{c_{10}+c_2+c_{12}+c_4}{4} + 0.5 \right\rfloor + c_{11} \\ \hat{x}_{2b} &= \left\lfloor \frac{c_2+\frac{c_1+c_3+c_4+c_5}{4}+c_4+c_6}{4} + \frac{c_{10}+c_2+c_{12}+c_4}{4} + 0.5 \right\rfloor - c_{11} \end{aligned} \tag{13}$$

The horizontal pairing does not allow for the use of the rhombus average for predicting the (x_1, x_2) pair. The predictors used in (11) are estimates for the rhombus average. The latter can be used for predicting c_9 and c_{11}.

Next, e_1 and e_2 are computed with equation (7). Based on e_{1a} and e_{1b}, either x_1 is modified with equation (12) or c_9 with:

$$c'_9 = \begin{cases} c_9 - \delta_1, & \text{if } (e_1 \geq R,\, e_1 = e_{1a}) \text{ or } (e_1 \leq L,\, e_1 = e_{1b}) \\ c_9 + \delta_1, & \text{if } (e_1 \leq L,\, e_1 = e_{1a}) \text{ or } (e_1 \geq R,\, e_1 = e_{1b}) \end{cases} \tag{14}$$

Similarly to x_1/c_9, based on e_{2a} and e_{2b}, either x_2 is modified with (12) or c_{11} with:

$$c'_{11} = \begin{cases} c_{11} - \delta_2, & \text{if } (e_2 \geq R,\, e_2 = e_{2a}) \text{ or } (e_2 \leq L,\, e_2 = e_{2b}) \\ c_{11} + \delta_2, & \text{if } (e_2 \leq L,\, e_2 = e_{2a}) \text{ or } (e_2 \geq R,\, e_2 = e_{2b}) \end{cases} \tag{15}$$

x_1/c_9 and x_2/c_{11} are watermarked with (12), (14) or (15) independent of each-other.

IV. Experimental results

Six graylevel 512×512 images extensively used in reversible watermarking are considered, namely: *Lena, Boat, Elaine, Lake, Mandrill* and *Jetplane*. The test images are presented in Fig. 4.

$$(\delta_1, \delta_2) = \begin{cases} (b_1, b_2), & \text{if } e_1 \in \{R, L\} \text{ and } e_2 \in \{R, L\}, \\ (b_i, b_i), & \text{if } \ e_1 \in \{R+1, L-1\} \text{ and } e_2 \in \{R+1, L-1\}, \\ (b_i, 1), & \text{if } e_1 \in \{R, L\} \text{ and } e_2 \notin \{R, L\}, \\ (1, b_i), & \text{if } e_1 \notin \{R, L\} \text{ and } e_2 \in \{R, L\}, \\ (1, 1), & \text{otherwise.} \end{cases}$$

where $(b_1, b_2) \in \{(0, 0), (0, 1), (1, 0)\}$ and $b_i \in \{0, 1\}$.

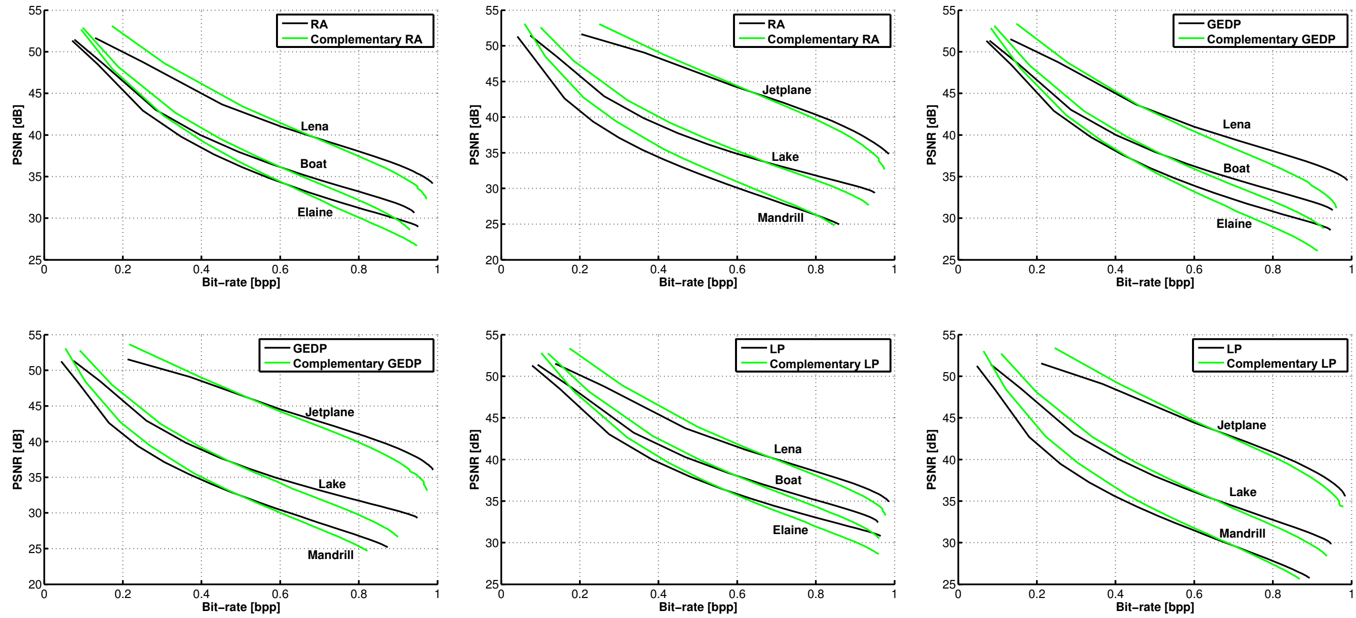


Fig. 5. Bit-rate/PSNR comparison between the rhombus average of [6], the GEDP predictor of [11], the local predictor of [10] and their proposed complementary equivalents using PEE.

Fig. 4. Test images: *Lena, Boat, Elaine, Lake, Mandrill* and *Jetplane*.

The effectiveness of the proposed complementary predictors with context embedding is first evaluated. The rhombus average of [6], the GEBP predictor of [11] and the local prediction of [10] are compared with their complementary counterparts. Note that for the complementary predictors based on local prediction, x_i and x_j were replaced by estimates (the rhombus average) in both the corresponding learning blocks. For a given embedding bit-rate, the watermarking distortion introduced by each scheme is evaluated using the peak signal-to-noise ratio (PSNR) between the original host image and its watermarked version. The results are presented in Fig. 5. The proposed approach outperformed its classic counterparts at bit-rates of up to 0.5 bpp (reaching 0.7 bpp for local prediction). As was previously mentioned, some pixels are modified twice (as x_i and x_j). These pixels can be modified once in each directions (reducing the introduced distortion) or both times in the same direction (which significantly increases the corresponding square error). On average, 0.5 bpp corresponds to an embedding threshold of at most $T = 3$. For these values, the distortions introduced by moving a pixel twice in the same direction are completely compensated by the improved prediction offered by the complementary approach and the correction mentioned above. As the embedding threshold increases, the square errors for the unfavorable pixels increases much faster that the scheme can compensate and the watermarking performance is increasingly affected. Local prediction allows the corresponding complementary predictors to better adapt to an increasingly noisy local context, compensating for the unfavorable pixels at higher embedding threshold.

Both the classic PE-HS and the 2D pairing approaches introduce a distortion of at most ± 1, this is ideal for the proposed scheme. As was previously shown, the distortions of ± 2 (with a square error of 4) caused by the pixels modified twice can be easily compensated by the improved prediction of the proposed scheme. The proposed 2D pairing scheme described in Section III-C is compared with the ones of Sachnev et al. [6], Ou et al. [3], Dragoi et al. [4] and Li et

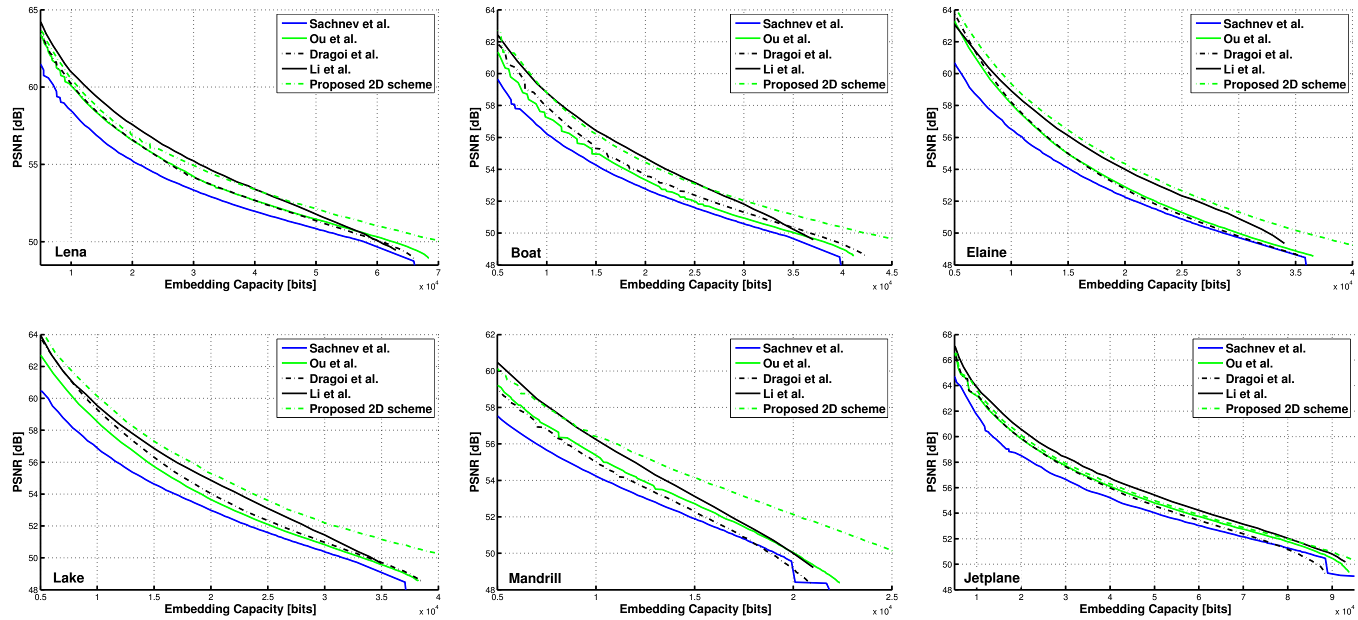


Fig. 6. Capacity/PSNR comparison between the proposed 2D pairing scheme and the ones of Sachnev et al. [6], Ou et al. [3], Dragoi et al. [4] and Li et al [12].

al [12]. The results are presented in Fig. 6. Depending on test image, the proposed approach obtains a maximum capacity for single layer embedding between 25,000 and 95,000 bits (0.1–0.36 bpp). The 2D pairing with complementary predictors and context embedding provides an average increase in PSNR of 2.04 dB, 1.04 dB, 0.99 dB and 0.21 dB compared to [6], [3], [4] and [12], respectively. The most noticeable improvement over the multiple histogram based approach of [12] was obtained on *Mandrill* (an average PSNR of 0.61 dB and a maximum PSNR of 1.7 dB), followed by *Lake, Elaine* and *Boat* with an average PSNR of 0.56 dB, 0.43 dB and 0.06 dB, respectively. For the remaining two images, [12] outperforms the proposed scheme with 0.1 dB (on *Lena*) and 0.3 dB (on *Jetplane*). Both these images have large uniform areas that are easy to predict regardless of the predictor used and the gain in precision of the proposed complementary predictors is lost on such areas.

V. Conclusion

An original reversible context embedding scheme has been proposed. The proposed scheme appears to be very efficient for low embedding bit-rates. Notably good results have been obtained for its use in pairwise reversible watermarking, where the proposed approach compares very well with the scheme of Li et. al, 2015, the most efficient reversible watermarking scheme proposed so far for low embedding bit-rates.

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References

[1] D. M. Thodi and J. J. Rodriguez, ”Expansion Embedding Techniques for Reversible Watermarking”, *IEEE Trans. Image Process.*, vol. 15, pp. 721–729, 2007.

[2] P. Tsai, Y.-C. Hu, and H.-L. Yeh, ”Reversible image hiding scheme using predictive coding and histogram shifting”, *Signal Process.*, vol. 89, no. 6, pp. 11291143, 2009.

[3] B. Ou, X. Li, Y. Zhao, R. Ni and Y.-Q. Shi, ”Pairwise Prediction-Error Expansion for Efficient Reversible Data Hiding”, *IEEE Trans. on Image Processing*, vol. 22, no. 12, pp. 5010–5021, 2013.

[4] I.-C. Dragoi, D. Coltuc, I. Caciula, ”Horizontal pairwise reversible watermarking”, *Proceedings of the* 23^{rd} *European Signal Processing Conference (EUSIPCO2015)*, 56–60, 2015.

[5] D. Coltuc, ”Improved Embedding for Prediction Based Reversible Watermarking”, *IEEE Trans. Inf. Forensics Security*, vol. 6, no. 3, pp. 873–882, 2011.

[6] V. Sachnev, H. J. Kim, J. Nam, S. Suresh and Y. Q. Shi, ”Reversible Watermarking Algorithm Using Sorting and Prediction”, *IEEE Trans. Circuits Syst. Video Technol.*, vol. 19, pp. 989–999, 2009.

[7] X. Li, B. Yang and T. Zeng, ”Efficient Reversible Watermarking Based on Adaptive Prediction-Error Expansion and Pixel Selection”, *IEEE Trans. on Image Process.*, vol. 20, no. 12, pp. 3524–3533, 2011.

[8] X. Li, B. Li, B. Yang and T. Zeng, ”General Framework to Histogram-Shifting-Based Reversible Data Hiding”, *IEEE Trans. on Image Process.*, vol. 22, no. 6, pp. 2181–2191, 2013.

[9] D. Coltuc, I.-C. Dragoi, ”Context embedding for raster-scan rhombus based reversible watermarking”, *roceedings of the first ACM workshop on Information hiding and multimedia security (IH&MMSec 13)*, 215–220, 2013.

[10] I.-C. Dragoi and D. Coltuc, ”Local Prediction Based Difference Expansion Reversible Watermarking”, *IEEE Trans. on Image Processing*, vol. 23, no. 4, pp. 1779–1790, 2014.

[11] W.-J. Yang, K.-L. Chung, H.-Y. M. Liao and W.-K. Yu, ”Efficient reversible data hiding algorithm based on gradient-based edge direction prediction”, *Journal of Systems and Software*, vol. 86, no. 2, pp. 567–580, 2013.

[12] X. Li, W. Zhang, X. Gui and B. Yang, ”Efficient reversible data hiding based on multiple histograms modification”, *IEEE Trans. on Information Forensics and Security*, vol. 10, no. 9, pp. 2016–2027, 2015.