Efficient Reversible Data Hiding in Video Frames based on MNP

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Abstract-ThispaperproposesaReversibleDataHiding(RDH)onvideoframesthatusesanewpredictornamedasMatched NeighbourPredictor(MNP).InspiredbythePredictionErrorExpansiontechnique(PEE),theMatchedNeighbourPredictoris proposed.Inpredictionerrorexpansiontechnique,apredictedimageisestimatedfromthehostimageandthepredictionerroris estimatedbyobtainingthedifferencebetweenthehostimageandthepredictedimage.IntheproposedMNPtechniquethe predictedimageisestimatedbychoosingthreeconsecutiveframesofthevideo.Thedistortionbetweenfirst/thirdframeand secondframeisusedtocheckwhetherthedatacanbeembeddedornot.Theproposedmethodproducesalowpredictionerror comparedtotraditionalpredictorandthedataisembeddedbyexpandingthepredictionerror.Theperformanceoftheproposed algorithmwasmeasuredusingthemetricssuchasembeddingrate(bpp)andPSNR(Peaksignaltonoiseratio).

Index Terms— Embedding rate, Prediction Error Expansion, Reversible Data Hiding, Video frames

1. Introduction

Datahiding embeds messages into digital multimedia such as image, audio, video through an imperceptible way, which is mainly used for copyright protection, integrity authentication, and covert communication. Some special signals of a kind that medical imagery, military imagery and law forensics are so precious that cannot be damaged. To protect these signals, reversible data hiding (RDH) is developed.SeveralresearchesaredoneonRDH whichincludesthepopularstate-of-artsuchasdifferenceexpansion,predictionerrorandhistogramshifting.RDH algorithms are well established; even the schemes approaching theoretical optimum have also appeared. As for RDH, the first step is to generate a host sequence with the small entropy such as prediction errors (PEs) , and then the users reversibly embed messages into the host sequence by modifying its histogram Thehistogram shifting[6]methodestimatesthehistogramanditestimatestheintensitytohidethedata.Thehistogramstotheleftofbinare shiftedtothelefttoembedthedata.Indifferenceexpansionapairofpixelischosenandthedifferencebetweenthepixelsof thepairisusedtoembedthedata.Thequalityofimagehighlyreducesifthedifferenceislargeformorenumberofpairs.

RDH is for the most partused for media annotation and integrity authentication, but its application is now extended by scholars. With RDH we can restore both embedded messages and host image, this make the host image like storage disk which can be erasable. However, marked image produced from RDH is hard to resist detection. If we endow RDH with detectability, and then such RDH algorithms called able to be turned the other way roundsteganography can be applied for convert storage [11]–[13]. Besides convert storage, we can also regard RDH as one tool to do many able to be turned the other way roundimage operations. To be detailed, after operating image to the desired target, we can explore the auxiliary parameters for restoring the original image from the target image, and then reversibly embed the parameters into the target image to get the reversible operated image. At the receiver’s side, we take out these auxiliary parameters and the target image from the able to be turned the other way round operated image, and further restore the original image from the target image with the extracted parameters.

Thepredictionerrorexpansiontechniqueinitiallyestimatesapredictedimagefromthehostimage,andthedifference betweenthepredictedimageandhostimagegivesthepredictionerror.Thedataisembeddedbytheexpansionofprediction error.SeveralRDHalgorithm[7]-[10]havebeenproposedusingthepredictionerrors,toachievebetterperformance.Since colorisapowerfulvisualdescriptors,thereareseveraldataembeddingalgorithmsincolorspacethatincludesthree-color-channelbasedalgorithms[11]-[12],chrominancebasedalgorithm[13]-[14]andluminancebasedalgorithms[15]-[16].Itisnot possibletorecoverthehostcolorimagefromthemarkedcolorimageinthesealgorithms.Inordertoachievethepropertyof reversibility, researches started to work on prediction error that has sharper histograms and thereby reducing the total distortion.Afterembeddingthedata,thecolormarkedimageappearstobeanoisyimagewhencomparingthehostimage.

In[17]ZhangetalproposedaReversibledatahidingwithGrayscaleinvariance.Thismethodsatisfiesthepropertyofgray scaleinvariance.i.e.thegrayscaleversionofRGBimagebeforeandafterembeddingremainsthesame.ThismethodusesRand Bchanneltoembedthedatawhilegreenchannelisusedforadjustmenttosatisfythepropertyofgrayscaleinvariance.This methodpredictsthepredictedimageusinganewpredictorfromwhichthepredictionerrorisestimatedbyobtainingthe differencebetweenthehostimageandpredictedimage.Thedataisembeddedonthepredictionerrorbyexpandingit.After embeddingthedatathegreenchannelisadjustedtomaintaintheoriginalgrayversion.Similartodataembedding,thedata extractionalgorithminitiallyextractsthedatafromtheRandBchannel.TheoriginalRandBchannelsarethenreconstructed formthemarkedRandBchannels.FinallytheGchannelisreadjustedtoobtaintheoriginalhostimage.

TherestofthepaperisconstructedasfollowssectionIIshowstheproposedRDHalgorithmonvideo.SectionIIIshowsthe experimentalresultsandanalysisoftheproposedRDHalgorithmandfinallysectionIVdepictstheconclusionoftheproposed work.

I. Proposed RDHAlgorithm

Theproposedreversibledatahidingonvideowasderivedfromthepredictionerrorexpansiontechnique.Let$m$represents the binary message to embed on the video. Let represent the prediction errors. Letrepresent the pixels of predicted image, Prepresents the pixels of host image. The prediction error can be estimated from the host image and predicted image as,

$$e_{i,j} = P_{i,j} - P'_{i,j} \quad (1)$$

Where(i, j)representsthepositionofpixel.TheproposedReversibledatahidingalgorithmhastwomajormodule ssuchas

- Data Embedding
- DataExtraction

A. DataEmbedding

Fig1showstheblockdiagramoftheproposeddataembeddingalgorithm,whereitusesframe2asreferenceframefor estimatingthepredictionerrorandframe1and3isusedforembeddingthedata.

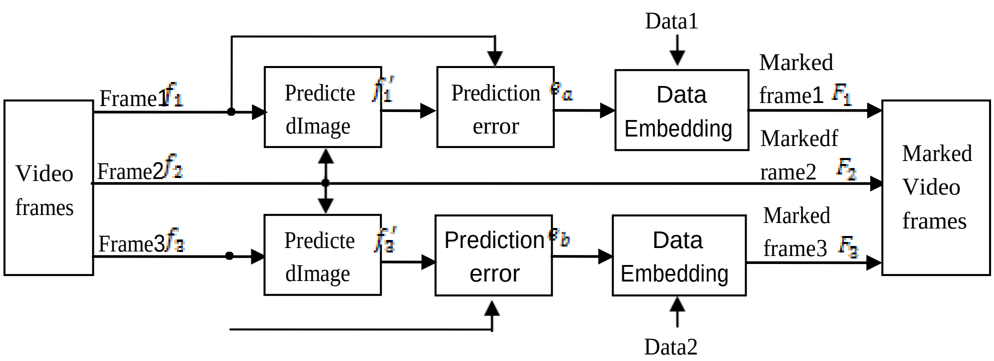


Fig. 1. Block diagram of Proposed Data embedding

Letf_1, f_2, f_3represents any three consecutive frames of a video, where each frame has R, G, B componentsrepresentedby$f_1 = [f_{1R}, f_{1G}, f_{1B}], f_2 = [f_{2R}, f_{2G}, f_{2B}]$ *and* $f_3 = [f_{3R}, f_{3G}, f_{3B}]$.

Thepredictedimageisestimatedforframe1andframe3byusingframe2asreferenceframe.Fig2showstheestimationof predictedimageduringdataembeddingbykeepingframe2asreferenceframe.Thepredictedimageofredcomponentof frame1iscalculatedusingmatchedneighbourpredictor(MNP)asfollows,

r_1'	r_2'	r_3'

r_1	r_2	r_3
r_8	$r_{i,j}$	r_4
r_7	r_6	r_5

Frame 1 or 3

r_8'	$r_{i,j}'$	r_4'
r_7'	r_6'	r_5'

Frame 2 or Reference

Fig. 2. Estimation of predicted image during data embedding

Let$D_\tau$representsadistortionthreshold.ThepredictionimageischosenifthedistortionD_{ij}islessthanthedistortion threshold $D_\tau$ie.$D_{ij} < D_\tau$.

$$D_{ij} = \sqrt{(r_1 - r_1')^2 + (r_2 - r_2')^2 + \cdots (r_3 - r_3')^2} \quad (2)$$

IfthedistortionD_{ij}islessthanthedistortion threshold $D_\tau$ie$D_{ij} < D_\tau$.thenthepredictedimageof$P_{ij} = r_{ij}$is$P_{ij}' = r_{ij}'$.Ifthe distortionD_{ij}isgreaterthanorequaltothedistortionthreshold$D_\tau$ie$D_{ij} \geq D_\tau$thenthepixel$P_{ij} = r_{ij}$shouldnotbeusedfor embedding. Let f_{1R}'represents the predicted image off_{1R} . Similarly the predicted images of green and blue channels are estimated.Letf_{1G}', f_{1B}'represents the predicted image of green and blue channelsf_{1G} andf_{1B}respectively.

$$f_1' = [f_{1R}', f_{1G}', f_{1B}'] \quad (3)$$

Similarlythepredictedimageofthirdframeisestimatedbykeepingframe2asreferenceframe.Letthepredictedimageof third frame is representedas,

$$f_3' = [f_{3R}', f_{3G}', f_{3B}'] \quad (4)$$

Thepredictionerrorofframe1iscalculatedas,

$$e_a = f_1 - f_1' \quad (5)$$

Thepredictionerrorofframe3iscalculatedas,

$$e_b = f_3 - f_3' \quad (6)$$

Thedata1isembeddedonthepredictionerror$e_a$andthedata2isembeddedonthepredictionerrore_b.Let$m_a$represents thesetofdatatobeembeddedone_a(i.e.data1)and$m_b$bethesetofdatatobeembeddedone_b(i.e.data2).Themodified predictionerrorafterembeddingthedataontwoframeswillbe,

$$e_a' = 2e_a + m_a \quad (7)$$

$$e_b' = 2e_b + m_b \quad (8)$$

The first frame after embedding (marked video frame 1) will be,

$$F_1 = f_1' + e_a' \quad (9)$$

Similarly the third frame after embedding will be,

$$F_3 = f_3' + e_b' \quad (10)$$

Thesecondmarkedvideoframeissameasthatofsecondhostvideoframe.

$$F_2 = f_2 \quad (11)$$

A. DataExtraction

r_1	r_2	r_3
r_8	$R_{i,j}$	r_4
r_7	r_6	r_5

Marked frames 1 and 3

r'_1	r'_2	r'_3
r'_8	$r'_{i,j}$	r'_4
r'_7	r'_6	r'_5

Marked frame 2 or reference frame

Fig . 3. Estimation of predicted image during data extraction

Fig 4 shows the block diagram of the proposed data extraction algorithm. The data extraction process is similar to data embedding. Fig 3 shows the estimation of predicted image during data extraction.LetF_1, F_2, F_3representsthethreeconsecutivemarkedvideoofframesrepresentedas$F_1 = [F_{1R}, F_{1G}, F_{1B}], F_2 = [F_{2R}, F_{2G}, F_{2B}]$ *and* $F_3 = [F_{3R}, F_{3G}, F_{3B}]$.

Similartodataembedding,thepredictedimageforframe1andframe3canbeestimatedbykeepingframe2asreference frame.ThedistortionD_{ij}canbecalculatedusing(2).IfD_{ij}islessthanthedistortion$D_\tau$thendataisavailableinthelocation(i,j). If $D_{ij}$is greater than the distortion threshold D_τ then the data is not available in the location(i,j). Let $F'_1$and F'_3represents the predicted image frames of marked frame$F_1$and F_3respectively.

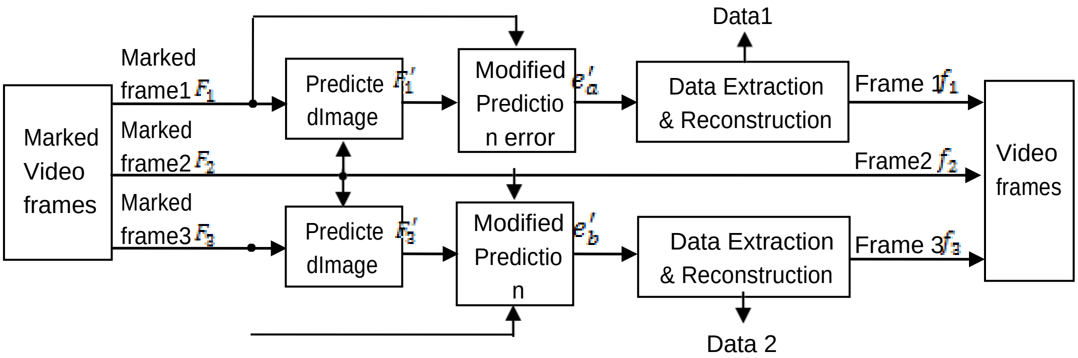


Fig. 4. Block diagram of Proposed Data extraction

The modified prediction errors of marked frame1 and frame3 can be estimatedas,

$$e'_a = F_1 - F'_1 \quad (12)$$

$$e'_b = F_1 - F'_3 \quad (13)$$

From the modified prediction errors data 1 can be recovered using,

$$m_1 = e'_a mod\ 2 \quad (14)$$

Similarly, the data 2 can be recovered using.

$$m_2 = e'_b mod\ 2 \quad (15)$$

Fromthemodifiedpredictionerrors e'_aande'_bthepredictionerrors $e_a$and$e_b$canbecalculatedas,

$$e_a = \left\lfloor \frac{e'_a}{2} \right\rfloor \quad (16)$$

$$e_b = \left\lfloor \frac{e'_b}{2} \right\rfloor \quad (17)$$

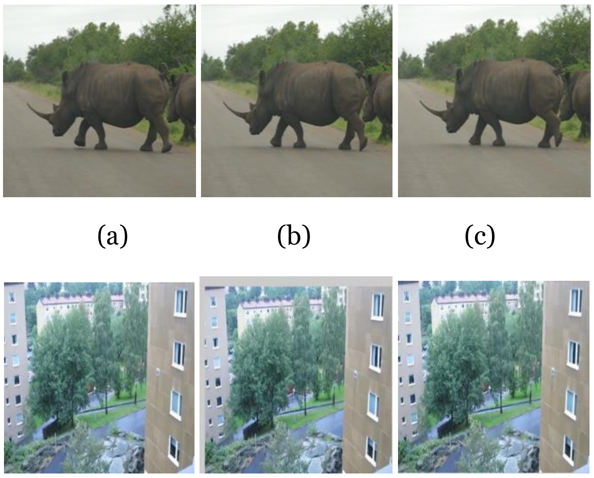
where$\lfloor . \rfloor$representthefllooroperation.Fromthepredictionerrors,thehostvideoofframe1andframe3canberecoveredas,

$$f_1 = F_1' + e_a \qquad (18)$$
$$f_3 = F_3' + e_b \qquad (19)$$

Thesecondframe$f_2$willbesameasthatofmarkedvideoframeF_2(i.e.$f_3 = F_2$)

III. ExperimentalResults

Thesimulationoftheproposedworkwasdoneusing MATLABandtheperformanceoftheproposedworkwastestedusing two‘video1’and‘video2’eachhaving 2000 frames.Theframesizeofeachvideosare 510*510. Fig5showstheframeofvideo1andvideo2.A 512*512 8bitgrayscaleimageLena,BarbaraandBaboonareusedasdatawhichisshowninfig(6). Theperformanceoftheproposedmethodwasanalyzedusingthemetricssuchasembeddingrateand PSNR.



(a) (b) (c)

(d) (e) (e)

Fig. 5. Three consecutive frames of video 1 and video 2 (a)-(c) frame 1, frame 2 and frame 3 of video 1 (d)-(e) frame 1, frame 2 and frame 3 of video 2

(a) (b) (c)

Fig6:Secretimages(a)Lena(b)Barbara(c)Baboon

Theembeddingratecanbecalculatedusing,

$$embedding\ rate(bpp) = \frac{c}{3 \times M \times N \times L} \qquad (20)$$

where$C$ istheembeddingcapacityi.e.numberofbitstobehidden,$M \times N$istheframesizeand$L$isthetotalnumberof framesrequiredtohide Cbits.ThePSNRbetweenhostframeandmarkedframefortheproposedmethodwascalculatedusing therelation,

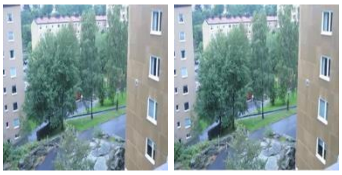
$$PSNR = 10 \times \log\left(\frac{255^2}{MSE}\right) \qquad (21)$$

where,

$$MSE = \frac{1}{3 \times M \times N} \sum_{z=1}^{3} \sum_{x=1}^{M} \sum_{y=1}^{N} [f(x,y,z) - f(x,y,z)]^2 \qquad (22)$$

Where f(x,y,z) representsthehostvideoframeand F(x,y,z) representsthemarkedvideoframeof f(x,y,z).

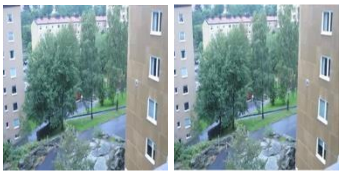
(a) (b)



(c) (d)

Fig7:MarkedvideoframesforthesecretimageLena(a)-(b)frames1and3forvideo1(c)-(d)frames1and3forvideo2

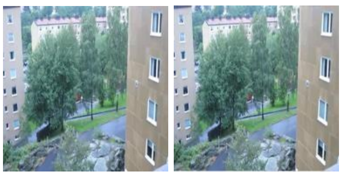
(a) (b)



(c) (d)

Fig8:MarkedvideoframesforthesecretimageBarbara(a)-(b)frames1and3forvideo1(c)-(d)frames1and3forvideo 2

(a) (b)



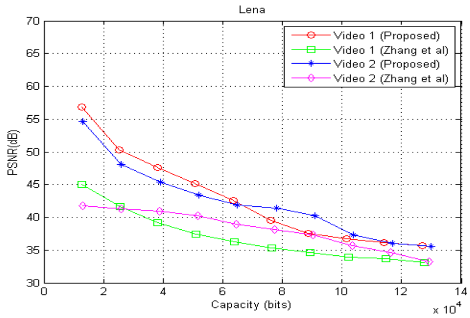
(c) (d)

Fig9:MarkedvideoframesforthesecretimageBaboon(a)-(b)frames1and3forvideo1(c)-(d)frames1and3forvideo 2

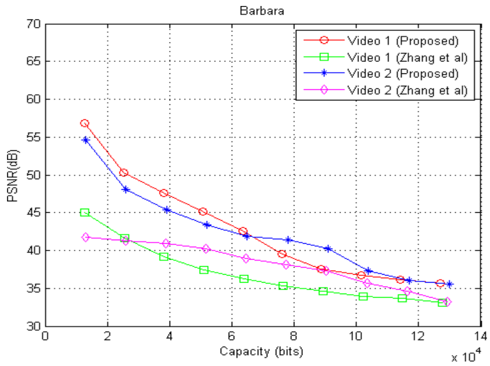
Fig7,fig8fig9showsthemarkedvideoframes1and3fortwovideos,video1andvideo2withdifferentsecretimageslike Lena,BarbaraandBaboon.TheperformanceoftheproposedmethodwascomparedwiththetraditionalZhanget.almethod [17].Table1showstheCapacity,embeddingrate(bpp)andPSNRofoneframefortheproposedRDHalgorithm.

TABLE 1: Capacity, Embedding Rate And PSNR Measurement

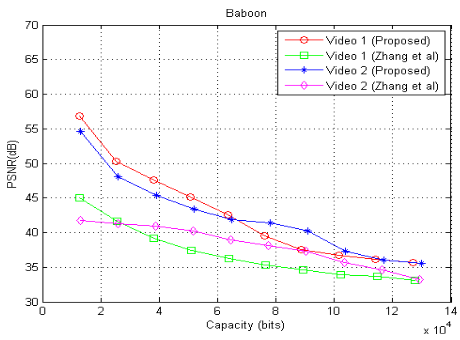
Secret images	Metrics	Proposed RDH		Zhang et al [17]	
		Video 1	Video 2	Video 1	Video 2
Lena	Capacity	127548	129924	126810	129150
	bpp	0.1621	0.1652	0.1612	0.1642
	PSNR(dB)	35.52	35.57	33.06	33.21
Barbara	Capacity	127548	129924	126810	129150
	bpp	0.1621	0.1652	0.1612	0.1642
	PSNR(dB)	35.63	35.44	33.34	33.18
Baboon	Capacity	127548	129924	126810	129150
	bpp	0.1621	0.1652	0.1612	0.1642
	PSNR(dB)	35.72	35.52	33.47	33.09



(a)



(b)



(c)

Fig10:PSNRcomparisonofProposedandZhanget.almethod(a)Secretimage'Lena'(b)Secretimage'Barbara'(c)Secret image'Baboon'

ThecapacityandembeddingrateoftheproposedmethodwasslightlygreaterthanthetraditionalZhanget.almethod [17].ButthePSNRoftheproposedmethodwasaround2dBgreaterthantheZhanget.almethod.Fig10showsthegraphical comparisonofproposedmethodandZhanget.almethodontwotestvideos'Video1'and'Video2'.Foraparticularvideoframe, thePSNRslightlychangesforchangeinsecretimage.ThenextsectionshowstheConclusionoftheproposedwork.

IV. Conclusion

ThispaperproposedaReversibledatahidingonvideoframesusingMatchedNeighbourPredictor(MNP).TheMNPpredictorchoosesthreeconsecutiveframesandselectsecondframeasreferenceframe.Thedistortionismeasuredbetweenfirst/third frameandsecondframe.Thedistortionlevelwilldecidewhetherthedatacanbeembeddedinthecenterpixelornot.Ifthe distortionisgreaterthanthethreshold,thendatacannotbeembeddedinthecenteroftheneighbourhood.Theproposed algorithmwasimplementedusingMATLABandtheperformancewasverifiedusingthemetricssuchasembeddingrateand PSNR.TheproposedmethodprovidesahighqualitymarkedvideoframeswhencomparedtothetraditionalZhanget.al method.i.e.theproposedmethodprovidesaPSNR2dBgreaterthantheconventionalZhanget.almethod.

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