

Medical Image Compression using Adaptive Prediction and Block based Entropy Coding

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ABSTRACT

Evolution of medical imaging has turned out as a boon for medical industry as it provides efficient diagnosis and monitoring of diseases. Compression of medical images helps accommodation of large medical data in limited storage space and fast transmission. The main aim of this paper is to compress medical images with no loss of clinical data using a lossless and adaptive prediction technique. The paper presents a prediction scheme adaptive to gradients defined in four directions. The proposed prediction scheme is based on the idea that the causal pixel in the direction of least gradient value contributes maximum in prediction. Before entropy encoding, the residual errors obtained are grouped on the basis of maxplane coding which further enhances coding efficiency. The proposed work is compared with basic DPCM technique and state of the art CALIC scheme. Experimental results show compression ratio for proposed method for medical images on average is 9.65% and 30.38% better than the CALIC scheme and basic DPCM method respectively while bit rates for proposed method is 6.51% and 30.86% better than CALIC scheme and DPCM method respectively.

General Terms

Gradients, Lossless Compression, Medical Image Compression, Predictive Coding.

Keywords

adaptive prediction, bit rate, compression ratio, gradient estimation.

1. INTRODUCTION

An image is a two dimensional representation of three dimensional world, stored in electronic form[1]. With the evolution of technology, digital imaging has become an essential part of our lives. Digital imaging has signified its worth in the variety of fields. Medical imaging, a branch of digital imaging, has revolutionized the healthcare industry in last three decades, allowing the medical experts in clinical diagnosis, treatment and disease monitoring. DICOM (Digital Imaging and Communication in Medicine) system produces medical images, which are visual representation of interior of the body. Medical images are obtained from various sources like MRI, CT scan, PET, radiography, ultra sonography, etc [2].

Substantial amount of medical images are generated from different medical centers which becomes difficult to be maintained in a limited storage space. In telemedicine applications, medical images are transmitted over the network for medical expert advice which requires high transmission speed [3]. The limited storage space and fast transmission has lead to the need of reducing the size of images through compression. Compression can be carried out by lossy as

well as lossless techniques. The medical images consist of significant amount of diagnostic data, which needs to be preserved while compressing, as any loss of data may lead to severe damage of human life [4],[5]. So, lossless compression is preferred for medical images. The prediction based coding technique predicts current data from already known data and the residual is encoded further. Predictive coding provides good compression ratio with low computation complexity and are simpler to implement [6], [7].

The main aim of the paper is to retain the clinical data and increase the compression ratio without increasing computation complexity. The paper proposes to compress medical images using predictive scheme adaptive to gradients defined in four directions. Before entropy coding of residual, the errors are maxplane coded. The maxplane obtained is separated into blocks and mean for all the blocks are determined. Errors belonging to the blocks with same mean value are grouped together and entropy encoded.

The whole paper is organized as follows. Section 1 briefly introduces the framework for medical image compression. Section 2 presents literature survey done for detailed understanding for the proposed work. Section 3 describes detailed background of CALIC algorithm and GAP prediction method. Section 4 presents proposed method for efficient compression of medical images. Results and Conclusion are given in Section 5 and 6 respectively.

2. LITERATURE SURVEY

Various lossless compression techniques are proposed and developed in past years which can be grouped under dictionary based coding, predictive coding, transform coding, etc.

Prediction based coding method removes spatial redundancy effectively by prediction of pixels in spatial domain. Prediction can be made using different predictors like Median Edge Detector (MED), Gradient Adjusted Predictor (GAP), Minimum Mean Square Error (MMSE), etc. MED is a simple predictor which roughly predicts the edge direction [8]. GAP is a gradient based non linear predictor [9]. It utilizes horizontal and vertical gradient which gives information of local edges and the prediction is adapted according to the sharpness of the edges.

The residual between original intensity value and predicted value is further entropy encoded. Entropy coding mostly utilizes techniques like Run length coding [10], Huffman coding [11], Arithmetic coding[12]. Arithmetic coding method provide with higher compression ratio but involves more compression and decompression time [13]. Arithmetic coding does not perform well for images with more local variations in pixel values. Huffman coding provides best

trade-off between compression ratio and time for compression-decompression while it can be realized with simpler software and hardware. Prediction based coding method produce good compression ratio at less computational cost [14].

DPCM [15] is a differential encoding compression method which predicts the current sample value based on the past sample values and encodes the difference between them. DPCM gives good compression ratio for images with high correlation between neighboring pixels.

Low Complexity Lossless Compression for Images (LOCO-I) is a compression technique with low computation cost and low complexity. It utilizes MED predictor and defines the context, based on local image gradients surrounding the pixel. Joint Photographic Experts Group Lossless Standard (JPEG-LS) [17], [18] is a standard based on LOCO-I using MED for prediction and Golomb codes for entropy coding.

CALIC (context adaptive lossless image compression) [19], [20], [21] is a context based compression method which makes use of GAP predictor. GAP adaptively predicts the pixel value depending upon the edges present around the pixel. It defines the context on the basis of local texture defined by gradients and previous prediction errors which tend to give higher compression rate.

S.M. Guo *et al.* in [22] proposed a highly efficient and easy to implement lossless compression method. This method proposes to centralize the prediction error values based on sign bits and perform maxplane coding enhancement which produce high compression ratio.

H. Tang *et al.* in [23] propose a lossless image compression by forming an adaptive prediction based on local texture defined by selection and comparison of gradients in four different directions. Context modeling is performed on the prediction errors fetching good results.

3. BACKGROUND

3.1 Context based, Adaptive, Lossless Image Codec

CALIC is an efficient context based lossless coding scheme which uses two step prediction/ residual approach. CALIC performs encoding and decoding in raster scan order by one-pass coding scheme. It predicts and forms the context with the previous two scan lines of current pixels. CALIC operates in binary mode and continuous tone mode. In continuous tone mode, image goes through four major processes given as-

1. GAP, gradient-adjusted prediction
2. Context selection and quantization
3. Context modeling of prediction errors
4. Entropy coding of prediction errors

3.2 Gradient Adjusted Prediction

GAP is employed in the context-based, adaptive, lossless image (CALIC) scheme [9]. It predicts the current pixel by the local gradient information. Gradients are defined using the seven neighboring pixels as n, w, nw, ne, nn, ww and nne, surrounding the current pixel 'I'. The first step is to estimate the local horizontal and vertical gradient, given as-

$$gh = |w-ww| + |n-nw| + |ne-n|$$

(1)

$$gv = |w-nw| + |n-nn| + |ne-nne|$$

The difference between the gradients is used as the criterion to choose the predicted value among seven predictors. Gradient adjusted prediction 'I' for current pixel 'I' is determined by the following pseudo code as-

```

if (gv-gh>80) //sharp horizontal edge
    I(i,j) = w
elseif (gv-gh<-80) //sharp vertical edge
    I(i,j) = n
else
    { I(i,j) = (w+n)/2+(ne-nw)/4
    if (gv-gh>32) // horizontal edge
        I(i,j) = (I(i,j) + w)/2;
    elseif (gv-gh>8) //weak horizontal edge
        I(i,j) = (3 I(i,j) + w)/4;
    elseif (gv-gh<-32) // vertical edge
        I(i,j) = (I(i,j) + n)/2;
    elseif (gv-gh<-8) //weak vertical edge
        I(i,j) = (3 I(i,j) + n)/4;
    }

```

4. PROPOSED METHODOLOGY

The paper presents an efficient compression technique for medical images using adaptive prediction and block based error quantization. The paper proposes to compress the medical images losslessly without increasing computational complexity. Sequential coding scheme is used which performs raster scan on the image. The coding process uses an adaptive prediction scheme based on gradients in four different directions. The prediction error obtained is maxplane encoded. The detailed explanation of the method is given in following sections-

4.1 Adaptive Gradient Based Prediction

The paper proposes to give an improved prediction based on gradients which are defined in four different directions. A template with 9 neighboring pixels as shown in Fig.1

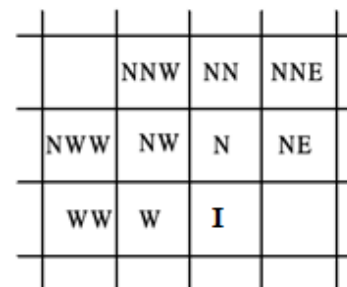


Fig 1: A causal template showing 9 neighbor pixels around current pixel 'I'

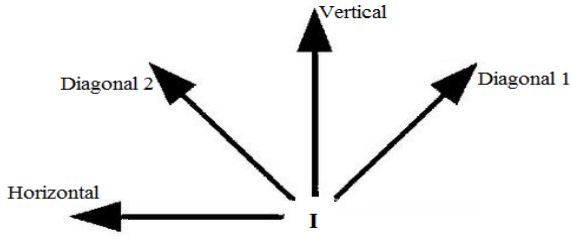


Fig 2: Four directions for which gradients are defined

Gradients are defined in vertical, horizontal, and two diagonal directions as shown in Fig. 2. The system can robustly determine any kind of local edges present with the help of gradients in four directions. Gradient estimation in a direction is done by addition of absolute difference between causal pixels in the target direction.

Each absolute difference in a gradient has different contribution to the prediction as per their distance from the current pixel. So, the gradient in one direction is calculated as a weighted sum of neighboring distances along this direction.

To reduce the computational complexity, the weights are defined as the reciprocal of Manhattan distance from the target pixel to the closest pixel of the neighbor distance. For example, the Manhattan distance of *NWW* to the current pixel is 3 and the distance from *NW* is 2, then the weight of $|NWW-NW|$ is $1/2$. The weighted gradients in horizontal, vertical, diagonal 1 and diagonal 2 are given in (2a), (2b), (2c) and (2d) respectively.

$$d1=2/|W-WW|+2/|N-NW|+2/|N-NE|+|NN-NNE| \quad (2a)$$

$$d2=2/|W-NW|+2/|N-NN|+2/|N-NE|+|NE-NNE| \quad (2b)$$

$$d3=2/|W-N|+2/|N-NNE|+|WW-NW|+|NW-NN| \quad (2c)$$

$$d4=2/|W-NWW|+2/|N-NNW|+|NE-NN| \quad (2d)$$

The sum of weights must be normalized to 1, so that the four gradients can be compared. The corresponding normalized gradients are defined in (3a), (3b), (3c) and (3d).

$$d1'=d1/7 \quad (3a)$$

$$d2'=d2/5 \quad (3b)$$

$$d3'=d3/6 \quad (3c)$$

$$d4'=d4/5 \quad (3d)$$

Each normalized gradient is added with 1 as shown in (4), so as to avoid the estimation of gradients to 0.

$$D_i=d_i'+1 \quad \text{for } i=1-4 \quad (4)$$

So the final four weighted, normalized gradient estimation with addition of 1 are shown in (5a), (5b), (5c) and (5d).

$$d1=(2/|W-WW|+2/|N-NW|+2/|N-NE|+|NN-NNE|) /7+1 \quad (5a)$$

$$d2=(2/|W-NW|+2/|N-NN|+2/|N-NE|+|NE-NNE|) /5+1 \quad (5b)$$

$$d3=(2/|W-N|+2/|N-NNE|+|WW-NW|+|NW-NN|) /6+1 \quad (5c)$$

$$d4=(2/|W-NWW|+2/|N-NNW|+|NE-NN|) /5+1 \quad (5d)$$

The causal pixel in the direction of the lowest estimated gradient has highest contribution in the corresponding prediction. In this paper, the two corresponding causal pixels in the directions with minimum estimated gradients are utilized to get improved prediction.

The prediction is determined by assigning the “closest” pixel with the weight corresponding to the second contributing gradient in the sense of gradient measure, while the second closest pixel with the weight corresponding to the most contributing gradient. The weights are then normalized so that their sum equals to 1.

The corresponding causal pixel for a specific gradient is the immediate neighbor of the current pixel in the direction in which the gradient is defined. The causal pixel for the gradients D_1 , D_2 , D_3 and D_4 are W , N , NE and NW respectively. The smallest two gradients amongst D_1, D_2, D_3 and D_4 are selected as given in (6).

$$D_{min} = \min (D_i) \quad (6)$$

$$D_{min2} = \min (D_i | D_i \neq D_{min}) \quad \text{where } i=1-4$$

Hence, the adaptive prediction can be made by-

$$\hat{I} = \frac{D_{min} C_{min2} + D_{min2} C_{min}}{D_{min} + D_{min2}} \quad (7)$$

4.2 Maxplane Coding

After prediction, Maxplane coding of residual error is done by obtaining maxplane. The residual between Image (I) and Prediction (\hat{I}) given by (8) is given as

$$\text{Error: } e(x, y) = I(x, y) - \hat{I}(x, y) \quad (8)$$

Maxplane indicates the maximum number of bits required to represent an error value. The maxplane for the residual error given by (9) can be estimated as

$$\text{If } e(x,y) = 0 \quad (9)$$

$$H(x, y) = 0$$

Else

$$H(x, y) = \log_2 [|e(x, y)|] + 1$$

4.3 Maxplane grouping

The maxplane image obtained by (9) is divided into blocks having same size. For example, $X \times Y$ image can be divided into $M \times N$ blocks of $T \times P$ size each.

Maxplane values in each block are averaged. The blocks with same mean value are grouped together. The mean for all the

blocks will be in the range 1 to 8 which means 8 groups will be formed all together.

4.4 Entropy Encoding

Entropy Encoding for each group is done separately which provides with good compression results. Encoding can be done with Arithmetic coding or Huffman coding.

5. RESULT AND IMPLEMENTATION

The performance of the proposed method is evaluated on a set of medical images having MRI, CT scan and X-ray images as displayed in Fig 3. Each set of MRI, CT scan and X-ray images contain different categories of medical data related to Head, Brain, Heart, Hand, Knee, Chest, Abdomen and Bladder.



Images are initially resized to size of 256×256 pixels for ease of implementation. The quality of the compressed images has been assessed in terms of Compression ratio and Bit-rate (bpp) as expressed by (10) and (11) respectively.

$$\text{Compression Ratio} = \frac{\text{Original Image Size}}{\text{Compressed Image Size}} \quad (10)$$

$$\text{Bit Rate} = \frac{\text{Compressed Image Size}}{\text{Number of Pixels}} \quad (11)$$

The efficiency of the proposed method is evaluated on comparison with basic DPCM method and state of the art CALIC method. Compression ratio and Bit rates for three methods are compared in Table 1 and Table 2 respectively.

Table 1: Comparison of Compression Ratio

Type	Image	DPCM	CALIC	Proposed
MRI images	Head_mri	1.5412	1.676	1.788
	Brain_mri	2.017	2.489	2.792
	Heart_mri	1.721	1.993	2.251
	Hand_mri	1.810	2.145	2.445
	Knee_mri	1.590	1.901	2.080
	Chest_mri	1.531	1.791	1.951
	Abdomen_mri	1.411	1.631	1.795
	Bladder_mri	1.644	1.948	2.151
CT scan images	Head_ct	1.368	1.464	1.579
	Brain_ct	1.699	1.941	2.135
	Heart_ct	1.881	2.089	2.356
	Hand_ct	2.326	2.847	3.171
	Knee_ct	1.674	1.981	2.182
	Chest_ct	1.777	2.069	2.311
	Abdomen_ct	1.598	1.797	2.001
	Bladder_ct	1.633	1.941	2.100
X-Ray images	Head_xray	1.697	2.188	2.352
	Brain_xray	2.098	2.508	2.732
	Heart_xray	1.829	2.184	2.318
	Hand_xray	1.642	2.253	2.527
	Knee_xray	1.987	2.426	2.626
	Chest_xray	2.009	2.620	2.878
	Abdomen_xray	1.660	1.994	2.124
	Bladder_xray	2.020	2.385	2.484

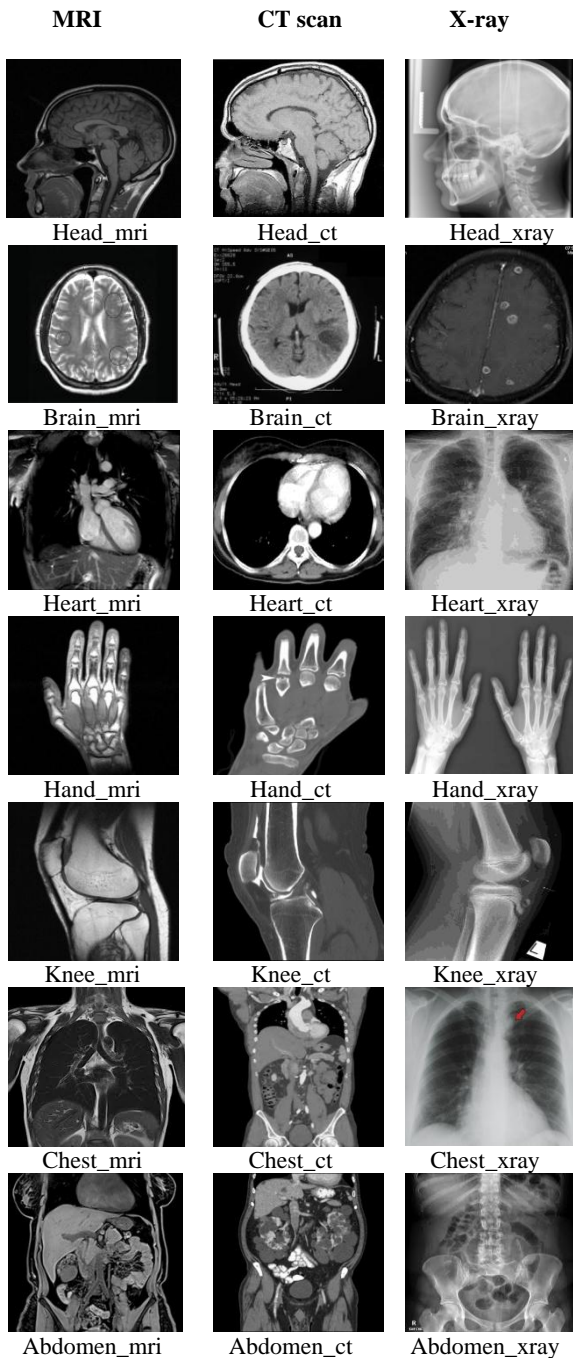


Table 2: Comparison of Bit Rate

Type	Image	DPCM	CALIC	Proposed
MRI images	Head_mri	5.189	4.772	4.476
	Brain_mri	3.966	3.213	2.649
	Heart_mri	4.648	1.014	3.555
	Hand_mri	4.421	3.729	3.272
	Knee_mri	5.032	4.208	3.846
	Chest_mri	5.224	4.467	4.100
	Abdomen_mri	5.668	4.906	4.457
	Bladder_mri	4.867	4.106	3.720
CT scan images	Head_ct	5.847	5.466	5.065
	Brain_ct	4.709	4.121	3.747
	Heart_ct	4.254	3.830	3.395
	Hand_ct	3.439	2.811	2.523
	Knee_ct	4.778	4.039	3.667
	Chest_ct	4.503	3.867	3.462
	Abdomen_ct	5.005	4.451	3.999
	Bladder_ct	4.900	4.122	3.810
X-Ray images	Head_xray	4.716	3.656	3.402
	Brain_xray	3.814	3.190	2.928
	Heart_xray	4.375	3.664	3.451
	Hand_xray	4.874	3.551	3.166
	Knee_xray	4.027	3.298	3.047
	Chest_xray	3.983	3.053	2.780
	Abdomen_xray	4.821	4.013	3.766
	Bladder_xray	3.961	3.355	3.220

6. CONCLUSION

The paper presents a new adaptive prediction algorithm based on gradient estimation which defines the local texture more robustly. Further, the maxplane coding scheme and grouping of blocks with same mean value leads to better compression. The results of our experiments performed on the test sets of medical images are encouraging. The proposed method is applied on set of medical images that include MRI images, CT scan images and X-Ray images. Each category contains eight images belonging to different categories. Thus, the proposed technique is applied on total 24 images. In all images, the proposed method has given the best results when compared with basic DPCM technique and state of the art Context Adaptive Lossless Image codec (CALIC) method. Comparison is done on the basis of compression ratio and bit rate. It has been observed that the compression ratio for proposed method is approximately 30.38% better than DPCM and 9.68% better than CALIC while the bit rates obtained for proposed method are 30.86% better than DPCM and 6.51% better than CALIC. The results obtained prove that the proposed method provides comparatively better results in terms of bit rate and compression ratio for medical images.

7. REFERENCES

- [1] D. Theckedatth, "Introduction to Image Processing," in *Image Processing using MATLAB codes*, 5th ed., India.
- [2] S. B. Gokturk, C. Tomasi, B. Girod and C. Beaulieu, "Medical image compression based on region of interest, with application to colon CT images," *Engineering in Medicine and Biology Society, 2001. Proceedings of the 23rd Annual International Conference of the IEEE*, 2001, pp. 2453-2456 vol.3.
- [3] S. Wong, L. Zaremba, D. Gooden and H. K. Huang, "Radiologic image compression-a review," in *Proceedings of the IEEE*, vol. 83, no. 2, pp. 194-219, Feb 1995.
- [4] I. Daubechies, "Orthonormal bases of compactly supported Wavelets," *Commun. Pure Appl Math.*, vol 41, pp. 909-996, Nov 1988.
- [5] S. G. Mallat, "A theory for multiresolution signal decomposition: the wavelet representation," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 11, no. 7, pp. 674-693, Jul 1989.
- [6] Yao-Tien Chen, Din-Chang Tseng and Pao-Chi Chang, "Wavelet-based medical image compression with adaptive prediction," *2005 International Symposium on Intelligent Signal Processing and Communication Systems*, 2005, pp. 825-828.
- [7] J. Rissanen, "Universal coding, information, prediction, and estimation," in *IEEE Transactions on Information Theory*, vol. 30, no. 4, pp. 629-636, Jul 1984.
- [8] M. J. Weinberger, G. Seroussi and G. Sapiro, "LOCO-I: a low complexity, context-based, lossless image compression algorithm," *Data Compression Conference, 1996. DCC '96. Proceedings*, Snowbird, UT, 1996, pp. 140-149.
- [9] Xiaolin Wu and N. Memon, "CALIC-a context based adaptive lossless image codec," *Acoustics, Speech, and Signal Processing, 1996. ICASSP-96. Conference Proceedings., 1996 IEEE International Conference on*, Atlanta, GA, 1996, pp. 1890-1893 vol. 4.
- [10] S. Golomb, "Run-length encodings (Corresp.)," in *IEEE Transactions on Information Theory*, vol. 12, no. 3, pp. 399-401, Jul 1966.
- [11] D. A. Huffman, "A Method for the Construction of Minimum-Redundancy Codes," in *Proceedings of the IRE*, vol. 40, no. 9, pp. 1098-1101, Sept. 1952.
- [12] G. Langdon and J. Rissanen, "Compression of Black-White Images with Arithmetic Coding," in *IEEE Transactions on Communications*, vol. 29, no. 6, pp. 858-867, Jun 1981.
- [13] A. Moffat, R. Neal and I. H. Witten, "Arithmetic coding revisited," *Data Compression Conference, 1995. DCC '95. Proceedings*, Snowbird, UT, 1995, pp. 202-211.
- [14] A. Moffat, R. Neal and I. H. Witten, "Arithmetic coding revisited," *Data Compression Conference, 1995. DCC '95. Proceedings*, Snowbird, UT, 1995, pp. 202-211.
- [15] N.D. Memon and K. Sayood, "Lossless image compression: A comparative study," in *Proceedings of SPIE*, vol. 2148, pp. 8-20, March 1995.

- [16] B. Carpentieri, M. J. Weinberger and G. Seroussi, "Lossless compression of continuous-tone images," in *Proceedings of the IEEE*, vol. 88, no. 11, pp. 1797-1809, Nov. 2000.
- [17] G. Langdon, A. Gulati and E. Seiler, "On the JPEG model for lossless image compression," in *Data Compression Conference, 1992. DCC '92.*, Snowbird, UT, USA, 1992, pp. 172-180.
- [18] X. Wu and N. Memon, "Context-based, adaptive, lossless image coding," in *IEEE Transactions on Communications*, vol. 45, no. 4, pp. 437-444, Apr 1997.
- [19] H. Hu, "A Study of CALIC," M.S. Dissertation, Dept. of Computer Science and Electrical Engg., Maryland Univ., Baltimore County, Dec 2004.
- [20] S. M. Guo, C. Y. Hsu and J. S. H. Tsai, "Efficient image compression based on error value centralization by sign bits," *TENCON 2013 - 2013 IEEE Region 10 Conference (31194)*, Xi'an, 2013, pp. 1-5.
- [21] H. Tang, S. I. Kamata, "A gradient based Predictive coding for lossless image coding, " in *ICICE Transactions on Information and Systems*, vol. E89, no. 7, pp. 2250-2256, July 2006.
- [22] J. Oliver and M. P. Malumbres, "Low-Complexity Multiresolution Image Compression Using Wavelet Lower Trees," in *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 16, no. 11, pp. 1437-1444, Nov. 2006.
- [23] S. A. Martucci, "Reversible compression of HDTV images using median adaptive prediction and arithmetic coding," *Circuits and Systems, 1990., IEEE International Symposium on*, New Orleans, LA, 1990, pp. 1310-1313 vol.2.
- [24] Xin Li and M. T. Orchard, "Edge-directed prediction for lossless compression of natural images," in *IEEE Transactions on Image Processing*, vol. 10, no. 6, pp. 813-817, Jun 2001.
- [25] B. Meyer and P. E. Tischer, "Grey level image compression by adaptive weighted least squares," in *Proceedings of Data Compression Conference 2001*, Snowbird, Utah, USA, March 2001, pp. 503.