

Performance of Predictive Coders for Wireless Capsule Endoscopy Image Compression



Caren Babu, D. Abraham Chandy

Abstract: *Wireless capsule endoscopy is a medical diagnostic technique developed for the endoscopic examination of the small bowel. The encoder module is the core of the wireless capsule endoscopic system impacting on power and area requirement for the hardware implementation of the capsule. One of the remarkable features of the endoscopic image is that the neighboring pixels are highly correlated. Two predictive coding techniques are considered in this work exploiting the above fact. The first predictive coder i.e., DPCM coder is based on previous horizontal neighboring pixel, whereas the second predictive coder is based on adjacent horizontal and diagonal neighbors. The performance of the predictive coders is tested with 41 small bowel type endoscopic images available in the Gastrolab dataset. The results show that the average compression rate and peak signal to noise ratio attained by DPCM coder and newly tested predictive coder are 66.37 % & 73.03 % and 32.17 dB & 35.55 dB, respectively.*

Keywords: *Compression, DPCM, Endoscopic image, Gastrolab, Predictive coder.*

I. INTRODUCTION

Wireless capsule endoscopy is a medical diagnostic technique capable of examining the digestive tract and to detect various diseases associated with it [1]. Once the capsule enters the body, it passes through the digestive tract, captures real-time images and is designed to be excreted [2]. The capsule which forms the transmitting module comprises of an image sensor, compression module, transmitter as shown in Fig. 1 (a). The receiver module present outside the human body consists of a data recorder and a reconstruction module that performs the reverse operation as that of the transmitter as shown in Fig. 1 (b) [2]. The endoscopic examination may last 8 to 12 hours which generates more than 50,000 images per examination [3]. The comfort and absence of pain are boon to wireless capsule endoscopy compared to wired endoscopy [4]. The data generated due to this examination is enormous and demands compression within the capsule.

The design of a compression module is vital in wireless capsule endoscopy. Many criteria need to be addressed in this

scenario [5]. Firstly, the bandwidth of the network which defines the level to which the amount of data in a video stream has to be minimized. Secondly, the process of identifying the redundancy and reducing the data with the help of any compression technique should take place with minimum delay and computational cost. The constraint on designing the capsule and its operating conditions indirectly affect the performance of the compression module. The major challenge at this point is choosing an appropriate compression scheme for the WCE compression. The synchronization between the transmitter and the receiver is keen to ensure real-time data transfer. The system complexity and hardware design architecture are carefully evaluated in consideration of power consumption, memory usage, and battery life. In addition, the design should be associated with system miniaturization in line with capsule size. Moreover, the compression module should uniformly achieve data reduction for a variety of images of different parts of the GI tract obtained from the endoscopic procedure. It is important that the quality of the reconstructed image is a major concern when it comes to medical diagnosis. A slight de-coloration or irregularity in the video may be an indication of some deformities or disorders that may be associated with the internal organ [6].

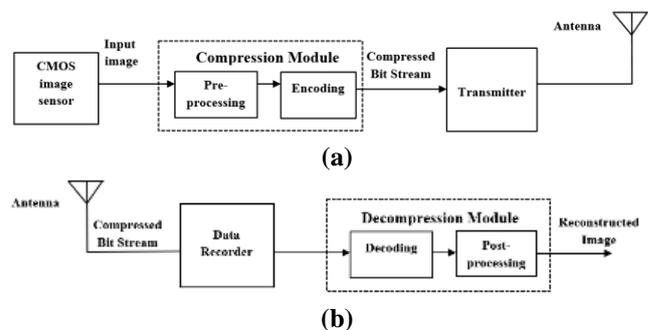


Fig. 1. WCE compression (a) Transmitter (b) Receiver

The main objective of this work is to propose a compression scheme suitable for endoscopic images using predictive coder. In addition, the possibility to replace DPCM coders in WCE compression is also discussed in terms of comparison results. The paper is organized as follows. Section II gives a brief review of related works. Section III explains the methodology and the performance measures used to evaluate the compression scheme. The results obtained are discussed in Section IV and we conclude in Section V.

II. RELATED WORKS

A number of related works reported in the past for compression algorithms for endoscopy.

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The widely accepted image and video compression algorithms are not suitable for WCE due to high computational complexity and large memory demands.

The prior works under lossy compression are based on discrete cosine transform (DCT) [7], [8], discrete wavelet transform (DWT) [9] and compressed sensing [10]. Low quality reconstruction and complex computation are its major drawbacks. In addition, they work with pixel values in a raster-scan pattern which demands memory and thus, puts constraints on battery life and hence, overall WCE system.

The lossless compression, on the other hand, ensures quality reconstruction which is obligatory for medical images and therefore, preferred for WCE compression. The works on lossless WCE compression are categorized based on the input image type. The Bayer Color Filter Array (CFA) image is the image sensor output. A compressor based on JPEG-LS [11], [12], [13] is suitable to be implemented on endoscopic images. These algorithms need buffer memory to store image pixel values which increases the power consumption. Moreover, the algorithms work on Bayer format image data, results in interpolation and hence, an enormous amount of data. The literatures on RGB endoscopic images are scarce and it works on the endoscopic images available from the database [14]. There is a common approach used in literature to perform preprocessing and two-stage encoding. It is reported to have developed a compression algorithm based on neighboring pixel correlation. DPCM based image compression algorithms [5] have lower complexity and do not need a buffer memory is highly acceptable. However, DPCM coders make using of immediate previous neighbors alone and this problem has not been given adequate attention in the literature. Therefore, in this work various predictive coders are tested which effectively considers all the immediate neighbors of a pixel for prediction.

III. METHODOLOGY

Wireless capsule endoscopic image compression includes the preprocessing and encoding stage. The input to the compression module is the endoscopic image and the output is the compressed bit stream. The encoder is designed to be two-stage with a DPCM coder and Golomb Rice coder [5]. In this work, DPCM coder is replaced by a few predictive coder. The design of the encoder determines the efficiency of the compression in terms of power saving, low computation and data reduction. The proposed predictive coder is successful in imparting the above-mentioned outputs goals to guarantee its application in capsule endoscopy. The block diagram of WCE compression is shown in Fig. 2. The preprocessing, predictive coding and Golomb Rice coding are the three important steps in the WCE compression methodology.

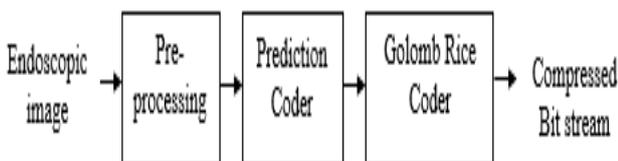


Fig. 2. Stages of WCE compression module

A. Pre-processing

The pre-processing stage involves converting the RGB image into YUV color space. The chrominance-based color spaces prove to be effective in reducing the representation and achieves data reduction [5]. The YUV model is preferred for the compression scenario as the variation of the component values in YUV representation is less compared to the RGB model [15]. The RGB to YUV conversion is present in some capsules and the process is reversible. The conversion involves simple computation and is highly recommended for the implementation inside the capsule. In YUV color space, Y is the luminance component, U and V represent the chrominance components [16] as given by (1)-(3). This model is suggested based on the remark that green color is relatively not visible in such images.

$$Y = 0.299 \times R + 0.587 \times G + 0.114 \times B \quad (1)$$

$$U = -0.147 \times R - 0.289 \times G - 0.436 \times B \quad (2)$$

$$V = 0.615 \times R - 0.515 \times G - 0.100 \times B \quad (3)$$

B. Predictive Coder

The homogenous texture patterns and the absence of sharp edges in the endoscopic images indicate the possibilities of utilizing neighboring pixel correlation for predictive coders [17]. The input to the predictive coder is the YUV converted image from the previous section. Predictive coding (PC) is a lossless technique, where the difference (error) between the component and its prediction is encoded [18]. The neighboring pixel correlation is large for endoscopic images and hence, the error value is of a small range which reduces the number of bits required to code them. This is the motivation behind using predictive coders in this work. All the prediction equations available in [19] are tested and the best yielded one is given in (4). $\check{Z}(x, y)$ represents the prediction value for the pixel located at row x and column y . $Z(x-1, y-1)$, $Z(x, y-1)$, $Z(x+1, y-1)$ denotes neighboring pixel in previous column adjacent to current pixel $Z(x, y)$. The prediction error Δz is then estimated by subtracting original pixel value from the predicted value as given in (5).

$$\check{Z}(x, y) = (Z(x-1, y-1) + Z(x, y-1) + Z(x+1, y-1))/3 \quad (4)$$

$$\Delta z = Z(x, y) - \check{Z}(x, y) \quad (5)$$

DPCM coders [20] utilize the previous pixels within the same row to obtain the prediction value. Therefore, $\check{Z}(x, y)$ in this case, is given by (6) as shown below. It should be followed by obtaining the error value with the help of (5).

$$\check{Z}(x, y) = Z(x-1, y) \quad (6)$$

C. Golomb Rice Coder

The prediction error obtained is converted to bitstream with the help of Golomb Rice coder. Literature shows that Golomb coders are most preferred as stage 2 coders for WCE due to its ease for hardware implementation [21].

The prediction error is mapped to positive values and applied to the Golomb coder details as discussed in our previous work [22]. The resulting bitstream is a sequence of zeros and ones which are then transmitted wirelessly to the receiver end through the channel. At the receiver, the reverse process is carried out to obtain the reconstructed image from the compressed bitstream.

D. Performance Measures

The performance of the compression scheme is evaluated using namely compression rate (CR) and peak signal to noise ratio (PSNR). The compression rate is defined as the ratio of the total bits after compression to total bits before compression as given in (7) and it is expressed in percentage [5]. The total bits before compression is obtained by multiplying the height, width, and number of bits used to represent each pixel in the original input image. The total bits after compression is obtained in a similar manner from the reconstructed image. Thus, CR indicates the relative reduction in the size of data produced by the compression algorithm.

$$CR = \left(1 - \frac{\text{Total bits after compression}}{\text{Total bits before compression}}\right) \times 100 \quad (7)$$

The next parameter is the reconstructed image quality measured using peak signal to noise ratio (PSNR) [23] expressed in dB is formulated in as in (8). The MSE is the mean square error which is calculated using (9) from the original and reconstructed image [24].

$$PSNR = 20 \log_{10} \left(\frac{255}{MSE}\right) \quad (8)$$

$$MSE = \left[\frac{1}{M \times N} \sum_{y=1}^N \sum_{x=1}^M (Z(x,y) - Z'(x,y))^2\right]^{1/2} \quad (9)$$

where, Z (x, y) and Z' (x, y) are original and reconstructed components, respectively. Here, M and N represent the image width and height, respectively.

IV. RESULTS AND DISCUSSION

The experiments were performed on an Intel Pentium IV processor of 2.4 GHz frequency. The compression scheme is implemented using MATLAB 2017. The experimentation is conducted on 41 images available under small bowel type in the Gastrolab dataset [12]. It should be noted that similar images are used in the literature.

Table I illustrates the compression results in terms of CR and PSNR values for the entire images used for experimentation using DPCM and predictive coders. Compared to the existing compression technique using DPCM, the predictive coder proposed in this work is successful in improving the average compression rate from 66.37% to 73.03%. This is a remarkable improvement as far as compression performance is considered. However, there is a slight deterioration in average PSNR value. The reduction in PSNR value is an indication on the accumulation of error at receiver end while reconstruction. However, it can be minimized by reducing erroneous pixel accumulation during reconstruction. It is reported in the literature that a PSNR value above 30 dB is acceptable [25].

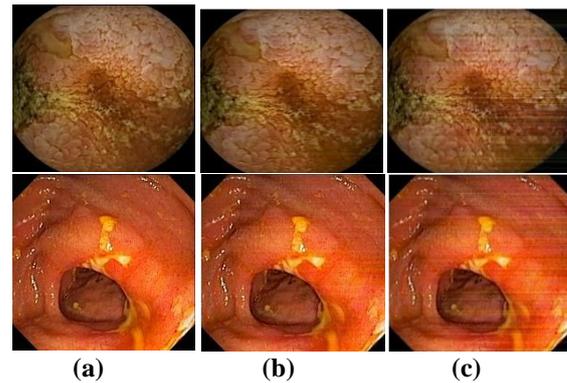


Fig. 3. Reconstruction results (a) input image (b) reconstructed image using DPCM (c) reconstructed image using PC

The reconstructed results are demonstrated with the help of two sample images taken from the dataset as shown in Fig. 3. The visual inspection of a reconstructed image clearly indicates there is no significant quality degradation. The DPCM based coders produce a compression rate of 69.15 % and 47.49%, respectively and PSNR value of 37.24 dB and 35.68 dB, respectively for those two images. On the other hand, the proposed PC result in CR of 75.21% and 61.48% and PSNR of 34.23 dB and 31.45 dB respectively for the same input image. It should be noted that using a predictive coder as a replacement for DPCM coder the CR is improved. The domination in terms of compression rate is quite promising for the application of predictive coders in WCE compression. However, some measures have to be taken to avoid deterioration in PSNR value. The graph shown in Fig. 4 demonstrates the average CR and PSNR values obtained for entire images using DPCM and predictive coders.

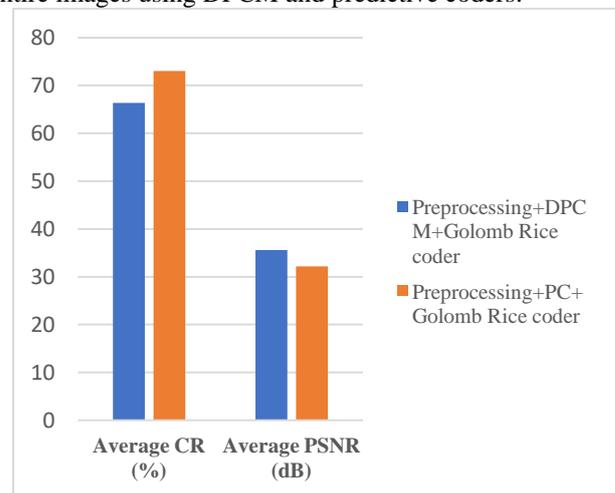


Fig. 4. Performance Comparison

Table I: Compression performance of DPCM and predictive coders

Image_id	CR (%)		PSNR (dB)		Image_id	CR (%)		PSNR (dB)		Image_id	CR (%)		PSNR (dB)	
	DPCM	PC	DPCM	PC		DPCM	PC	Using DPCM	Using PC		Using DPCM	Using PC	Using DPCM	Using PC
1	62.65	71.24	34.2	31.95	15	69.15	75.21	35.24	32.23	29	66.2	73	35.76	31.95
2	69.87	75.13	34.49	32.02	16	66.56	73.85	34.18	31.67	30	74.75	77.94	37.64	32.35
3	64.83	72.31	32.96	31.91	17	75.54	78.38	38.96	32.42	31	64.76	72.42	33.64	33.03
4	65.75	72.75	33.34	31.96	18	77.7	79.61	37.44	32.67	32	61.59	70.36	32.56	32.36
5	66.5	73.16	35.13	32.08	19	69.52	75.11	36.25	32.08	33	67.55	73.93	34.23	32.53
6	51.13	63.51	33.46	31.55	20	77.17	79.4	37.3	32.6	34	65.13	72.55	34.09	32.73
7	47.49	61.48	33.68	31.44	21	77.33	79.45	37.39	32.24	35	65.78	72.85	32.89	32.97
8	43.45	59.43	33.7	31.61	22	76.28	78.73	37.6	32.46	36	72.73	77.17	34.57	32.27
9	41.44	57.76	32.79	31.52	23	78.07	80.26	35.01	32.24	37	61.93	69	36.57	32.17
10	42.75	58.66	33.02	31.47	24	77.17	79.33	35.97	32.41	38	61.5	70.12	36.76	31.97
11	49.81	62.37	34.14	31.62	25	76.28	78.73	37.6	32.46	39	63.27	71.15	36.56	32.14
12	74.55	77.87	39.37	32.79	26	76.43	79.12	35.94	32.07	40	61.7	70.46	36.56	31.95
13	72.73	76.99	39.07	32.44	27	76.87	79.22	37.73	31.87	41	60.07	69.41	36.72	31.97
14	70.84	76.02	36.26	32.44	28	76.14	78.76	36.85	32.03					

The various prediction models tested in this work helps to arrive at the proposed predictive coder in which current pixel is predicted using several of its neighbourhood pixels. this is in contradiction to DPCM coders that depends on previous neighbors alone to predict the current value. This has a significant impact on improving CR. It is noticed that while estimating the error value for DPCM based coder, the value range is larger than the predictive coders. This burdens the DPCM coder in terms of data to be transferred to the receiver. Another observation is that in DPCM coders, the error accumulation due to false prediction in the first element of a row is high. The predictive coders are successful in minimizing this error as dependency on a single erroneous pixel is avoided. Thus, the predictive coders prove itself to be an alternate to DPCM coders in WCE compression with some techniques to compensate the reduced PSNR value. Therefore, the low power compression module design discussed in this work ensures its easy implementation inside the capsule with minimum load.

V. CONCLUSION

This paper presents the performance of two prediction based encoders used in wireless capsule endoscopic image compression system. The encoder analysis for endoscopic images proves that the pixels are highly correlated not only to its immediate previous neighbor, but also to several adjacent pixels leading to desired amount of data reduction. Thus, predictive coders are good in exploiting the redundancy exist in the data. In this work, the second predictive coders is better than DPCM coder. On the other hand, DPCM coder is successful in maintaining better PSNR value. However, the PSNR value attained by the second predictive coder is well above the clinical margin, i.e., 30 dB. In future work, increasing the PSNR can be can be focused. In addition, the identification of appropriate neighboring pixels for the

prediction of each category of the endoscopic image can also be explored.

REFERENCES

1. P. Szczypiński, A. Klepaczko, M. Pazurek, and P. Daniel, "Texture and color based image segmentation and pathology detection in capsule endoscopy videos," Computer methods and programs in biomedicine, vol. 113, no. 1, pp. 396-411, 2014.
2. J. Gerber, A. Bergwerk, and D. Fleischer, "A capsule endoscopy guide for the practicing clinician: technology and troubleshooting," Gastrointestinal endoscopy, vol. 66, no. 6, pp. 1188-1195, 2007.
3. J. Berens and M. Fisher, "Wireless capsule endoscopy color video segmentation," IEEE Transactions on Medical Imaging, vol. 27, no. 12, pp. 1769-1781, 2008.
4. K. A. Fante, B. Bhaumik, and S. Chatterjee, "Design and implementation of computationally efficient image compressor for wireless capsule endoscopy," Circuits, Systems, and Signal Processing, vol. 35, no. 5, pp. 1677-1703, 2016.
5. T. Khan and K. Wahid, "Design of a lossless image compression system for video capsule endoscopy and its performance in in-vivo trials," Sensors, vol. 14, no. 11, pp. 20779-20799, 2014.
6. M. S. Imtiaz and K. A. Wahid, "Color enhancement in endoscopic images using adaptive sigmoid function and space variant color reproduction," Computational and mathematical methods in medicine, vol. 2015, 2015.
7. J. Li and Y. Deng, "Fast compression algorithms for capsule endoscope images," in 2009 2nd International Congress on Image and Signal Processing, 2009: IEEE, pp. 1-4.
8. J. Thoné, J. Verlinden, and R. Puers, "An efficient hardware-optimized compression algorithm for wireless capsule endoscopy image transmission," Procedia Engineering, vol. 5, pp. 208-211, 2010.
9. W. Ding, F. Wu, X. Wu, S. Li, and H. Li, "Adaptive directional lifting-based wavelet transform for image coding," IEEE Transactions on Image Processing, vol. 16, no. 2, pp. 416-427, 2007.
10. J. Wu and Y. Li, "Low-complexity video compression for capsule endoscope based on compressed sensing theory," in 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2009: IEEE, pp. 3727-3730.
11. H. Chen, M. Sun, and E. Steinbach, "Compression of Bayer-pattern video sequences using adjusted chroma subsampling," IEEE Transactions on Circuits and Systems for Video Technology, vol. 19, no. 12, pp. 1891-1896, 2009.



12. X. Chen et al., "A wireless capsule endoscope system with low-power controlling and processing ASIC," IEEE Transactions on Biomedical Circuits and Systems, vol. 3, no. 1, pp. 11-22, 2009.
13. G. Liu, G. Yan, S. Zhao, and S. Kuang, "A complexity-efficient and one-pass image compression algorithm for wireless capsule endoscopy," Technology and Health Care, vol. 23, no. s2, pp. S239-S247, 2015.
14. Gastrolab database <http://www.gastrolab.net/ni.htm>
15. C. Babu, D. A. Chandy, and P. Karthigaikumar, "Novel chroma subsampling patterns for wireless capsule endoscopy compression," Neural Computing and Applications, pp. 1-10, 2019.
16. T. H. Khan and K. A. Wahid, "Subsample-based image compression for capsule endoscopy," Journal of real-time image processing, vol. 8, no. 1, pp. 5-19, 2013.
17. B. Li and M. Q.-H. Meng, "Wireless capsule endoscopy images enhancement via adaptive contrast diffusion," Journal of Visual Communication and Image Representation, vol. 23, no. 1, pp. 222-228, 2012.
18. H. Kobayashi and L. R. Bahl, "Image data compression by predictive coding I: Prediction algorithms," IBM Journal of Research and Development, vol. 18, no. 2, pp. 164-171, 1974.
19. J.-J. Shen, C.-H. Yeh, and J.-K. Jan, "Effective quality improvement of upscaled images by differential image scheme," in 2016 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD), 2016: IEEE, pp. 1887-1892.
20. C. Babu and D. A. Chandy, "DPCM based compressor for capsule endoscopic videos," in 2017 International Conference on Signal Processing and Communication (ICSPC), 2017: IEEE, pp. 89-93.
21. S.-L. Chen, T.-Y. Liu, C.-W. Shen, and M.-C. Tuan, "VLSI implementation of a cost-efficient near-lossless CFA image compressor for wireless capsule endoscopy," IEEE Access, vol. 4, pp. 10235-10245, 2016.
22. C. Babu, D. A. Chandy, and P. Karthigaikumar, "Novel chroma subsampling patterns for wireless capsule endoscopy compression," Neural Computing and Applications, pp. 1-10.
23. P. C. Cosman, R. M. Gray, and R. A. Olshen, "Evaluating quality of compressed medical images: SNR, subjective rating, and diagnostic accuracy," Proceedings of the IEEE, vol. 82, no. 6, pp. 919-932, 1994.
24. A. M. Eskicioglu and P. S. Fisher, "Image quality measures and their performance," IEEE Transactions on communications, vol. 43, no. 12, pp. 2959-2965, 1995.
25. Y. Yuan, B. Li, and M. Q.-H. Meng, "Bleeding frame and region detection in the wireless capsule endoscopy video," IEEE journal of biomedical and health informatics, vol. 20, no. 2, pp. 624-630, 2015.

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