# DWT based Low Power Image Compressor for Wireless Capsule Endoscopy

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Abstract: In WCE literature so far, the stress is on having an image compressor with low power consumption and silicon area. However one needs to consider the image compressor along with the serialiser, the interface between image compressor and transmitter as a single unit. In this paper, we propose the design of a hardware efficient, low power image compression system along with the serialiser for wireless capsule endoscopy. It is based on integer version of discrete wavelet transform and uses low complexity encoders like adaptive Golomb-Rice encoder. An alternative architecture for serialiser is proposed specific to the algorithm which runs at only 8 times instead of 32 times the frequency required at the existing compressors in the literature. The proposed algorithm gives a compression of 91.88 percent at a PSNR of 38.17. The implementation of the compressor plus serialiser in 130nm HS (high speed) standard CMOS process technology consumes 16.9uW of power at 2 frames per second for 256×256 image. Compared to the existing designs at similar power consumption, the proposed scheme reduces the serialiser's frequency by a factor of four besides giving at least 1.5 % higher compression.

## 1 INTRODUCTION

Wireless Capsule endoscopy uses a miniature camera to capture images of the gastrointestinal tract. The whole system is built into a small capsule for minimum invasiveness. The patient ingests a small vitamin size capsule containing CMOS image sensor array, LEDs, battery, and an RF transmitter. It captures images and sends them to an outside workstation where the images can be analysed by gastroentologists. The battery for the capsules runs for about 8-10 hours. A major research thrust is on incorporating additional functionalities like drug delivery and locomotion on to the chip (Bruaene et al., 2015; Koulaouzidis and Iakovidis, 2015; Hale et al., 2014). Introducing these new features reduces the capsule area devoted to the power source, thereby necessitating a decrease in power consumption to lengthen the capsule lifetime. In this paper we focus on designing a low power image compressor along with its interface to the transmitter. Our scheme employs hardware efficient and low complexity methods like integer discrete wavelet transform (Bhanu and Chilambuchelvan, 2012) and adaptive Golomb-Rice encoder (Memon, 1998). We also propose a new architecture for the serialiser which works at 8 times the frequency of the compressor.

The prior works which are based on DCT (Discrete Cosine Transform) divide the image into non overlapping blocks and employ transforms to reduce 2D spatial redundancy in an image. Since the image comes in raster-scan fashion, the above technique necessitates the use of memory for storing few rows of incoming image. The computational resources required to compute these transforms are also high. As a result they are not hardware efficient and consume lot of power. A low memory DPCM (Differential Pulse Code Modulation) based design was proposed in (Khan and Wahid, 2013; Khan and Wahid, 2011a). It used hardware efficient techniques at the cost of low compression rates. Recently, in (Fante et al., 2016), an image compression scheme was proposed which was based on optimal combination of quantisation and subsampling thereby achieving higher compression rate as compared to the previously proposed schemes (Khan and Wahid, 2013; Khan and Wahid, 2011a). However, the serialiser, which runs at 32 times the compressor frequency is the major power consumer and the existing designs did not optimise its power consumption.

In this paper, we treat compressor and serialiser as a unit and propose a new architecture for the

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serialiser which works at 8 times the frequency of the compressor. Furthermore, we employ 1D DWT (Discrete Wavelet Transform) instead of subsampling for achieving higher compression while maintaining good image quality. Although using 2D DWT would have increased the compression, it would have substantially increased the hardware requirements. Using 1D DWT keeps the hardware minimal and increases the compression with good image quality.

This paper is organised as follows – a detailed discussion of the proposed algorithm is given in section 2, performance results are described in section 3, section 4 gives details about the hardware realisation and the power consumption. Finally in section 5 we conclude this paper.

## 2 PROPOSED ALGORITHM

The algorithms proposed by (Khan and Wahid, 2013) and (Fante et al., 2016) are power efficient as they minimize the usage of buffer memory while achieving a very high compression ratio. In this section we will discuss the techniques employed to achieve a better compression ratio along with reduced power consumption. The compression algorithm used takes hardware feasibility into account. We have ensured that the average and minimum PSNR (Peak signal-to-noise ratio) is over the recommended value (Cosman et al., 1994; Philip et al., 2008). The algorithm is designed such that the transmitter has to run at a frequency which is only at 8 times higher than that of the compressor. Our design reduces the serialiser frequency by a factor of 4 as compared to the existing designs((Khan and Wahid, 2011b) and (Fante et al., 2016)). The block diagram of the image compressor and decompressor is shown in the Figure 1 and 2 respectively.

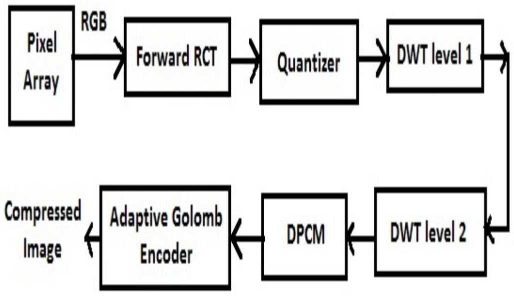


Figure 1: Block Diagram of Image Compressor.

### 2.1 Forward RCT Transform

RCT stands for reversible colour transform. The image obtained from the camera is of RGB888 format.

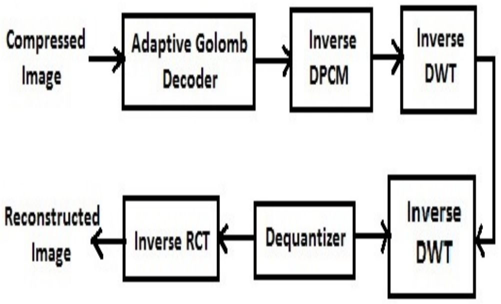


Figure 2: Block Diagram of Image Decompressor.

It is first converted from RGB color space to YUV color space using the following equations:

$$Y = \left\lfloor \frac{R+2G+B}{4} \right\rfloor, U = R-G, V = G-B \qquad (1)$$

Figure 3 shows the R, G and B values of the pixels along the middle row of an image. We see that the Red, Green and Blue channels are highly correlated. We also observe that red is the most dominant color as compared to green and blue. Thus we can safely assume that the signal which is the difference between Green and Blue will contain very less information. Therefore, we transformed the color space from RGB to YUV to de-correlate the image (Fante et al., 2016).

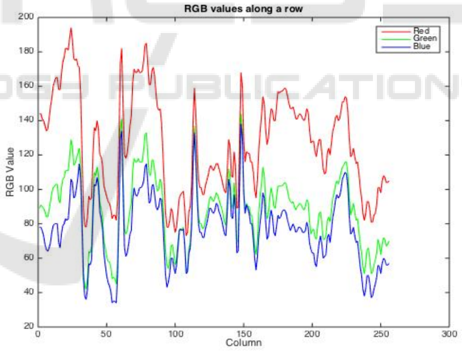


Figure 3: R, G and B value of pixel along middle row.

Table 1 and 2 shows the correlation between different color channels. We can easily see that the correlation in the transformed color space is reduced.

Table 1: Correlation between RGB components.

| Correlation Matrix | Red | Green | Blue |
|---|---|---|---|
| Red | 1 | 0.9626 | 0.9159 |
| Green | 0.9626 | 1 | 0.9864 |
| Blue | 0.9159 | 0.9864 | 1 |

The Y component corresponds to intensity value while U and V represents the chrominance components. It should be noted that the value of Y varies

Table 2: Correlation between YUV components.

| Correlation Matrix | Y | U | V |
|---|---|---|---|
| Y | 1 | 0.6814 | 0.6599 |
| U | 0.6814 | 1 | 0.8554 |
| V | 0.6599 | 0.8544 | 1 |

from 0 to 255 whereas the values of U and V varies from -255 to 255.

## 2.2 Quantisation

The output of RCT forward transform is quantized first – in order to implement a hardware efficient quantization, we ignore the least significant bits. The quantization formula used is:

$$P_q = \left\lfloor \frac{P + Q/2}{Q} \right\rfloor \tag{2}$$

Where $P$ is the value of the pixel, $Q$ is the quantisation value given by $2^l$ where $l$ is the number of bits to be quantised and $P_q$ is the quantised pixel value. In our design we quantized the YUV image by 3 bits. Increasing it to 4 bits resulted in unacceptable PSNR (Peak Signal to Noise Ratio) values while 2-bits quantization reduced the compression ratio. Therefore 3 bits was the sweet spot in our design as shown in Section 3.Quantization also reduces the standard deviation of the data which will further helps us in adaptive Golomb-Rice encoding.

## 2.3 DWT

The algorithm proposed by (Fante et al., 2016) subsamples the U and V component by 4 since U and V contains less information compared to Y. In our implementation,we have used the 5-3 integer DWT to down-sample the data (Jing et al., 2008). The U and V components are successively passed through two DWT blocks while retaining the lower frequency components at each stage. Since images of interest are sparse at higher frequencies, our method achieves compression comparable to the previously employed subsampling approach while retaining a better image quality. For hardware efficiency we implemented the lifting architecture of 5-3 integer DWT (Bhanu and Chilambuchelvan, 2012).

## 2.4 DPCM

DPCM exploits the spatial redundancy of an image. It uses a prediction function which predicts the value of a pixel given the previous values. In our design we use the simplest prediction function i.e. the predicted value is same as the previous value. Better results could have been achieved by using better prediction functions or using 2D prediction scheme at the cost of higher hardware requirements.

## 2.5 Corner Clipper

While the lens of the capsule generates a circular image, the image sensor is rectangular. Due to this all pixels outside the circular region have a value of zero. The Golomb Rice encoder would encode these pixels by using a single bit for each component. As proposed by (Khan and Wahid, 2011a), we use linear cropping to crop these pixels. This process is hardware efficient and increases the Compression Rate.

## 2.6 Golomb Encoder

Golomb Rice encoder was shown to be an hardware efficient entropy encoder for endoscopy images. In (Khan and Wahid, 2011a), Golomb Rice parameter $m = 2^k$ was static but it gave poor compression. In (Fante et al., 2016), this parameter changed on the fly and was determined using a single context to reduce computational complexity. Using such an adaptive Golomb-Rice encoder improved the compression rate. Both of these encoders produced maximum code length of 32. This required the serialiser to work at 32 times the frequency which consumed a lot of power. We investigated the effect of reducing the max code length to 16 bit by limiting the parameter glimit to 16 in the Golomb Rice encoder. Doing this resulted in the decrease in the Compression Rate(CR). But by replacing subsampling by DWT in our algorithm, we were able to achieve an extra bit of quantisation. This helped in decreasing the max code length to 16 without seriously affecting the Compression Rate.

Table 3 summarises the details of our encoders in comparison to the ones proposed by (Khan and Wahid, 2013) and (Fante et al., 2016).

# 3 PERFORMANCE EVALUATION

For evaluation purposes, 120 images were collected from Gastrolab (Gastrolab, 2014). It includes the entire GI tract and thus is a good representative for the entire digestive system. The performance of the proposed compression algorithm is evaluated using Compression Rate(CR) which is given by:

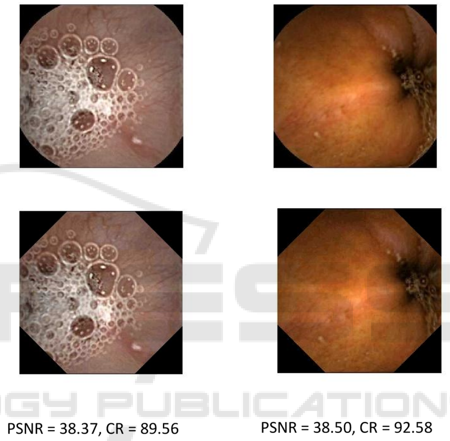
$$CR = \left(1 - \frac{\text{Image Size After Compression}}{\text{Image Size Before Compression}}\right) \times 100 \tag{3}$$

Table 3: Golomb Encoding Comparison Table.

| Aspect | Golomb (Proposed) | Golomb (Fante) | Golomb (Khan) |
|---|---|---|---|
| Parameter k | Dynamically calulated | Dynamically Calculated | static |
| Max Code Length | 16 | 32 | 32 |
| Compression | Medium Compression | Medium Compression | Low Compression |
| Complexity | Medium Complexity | Medium Complexity | Low Complexity |

Table 4: Performance of Algorithm for Different Parameters.

| Quantisation | Golomb-Encoder | CR | PSNR |
|---|---|---|---|
| Q = 1 | Adaptive glimit=16 | 80.06 | 46.56 |
| Q = 2 | Adaptive glimit=16 | 84.99 | 44.49 |
| Q = 4 | Adaptive glimit=16 | 89.22 | 42.27 |
| Q = 8 (Proposed) | Adaptive glimit=16 | 91.88 | 38.17 |
| Q = 8 | Adaptive glimit=32 | 91.95 | 38.17 |
| Q = 16 | Adaptive glimit=16 | 93.38 | 32.87 |


PSNR = 38.37, CR = 89.56

PSNR = 38.50, CR = 92.58

Figure 4: Original (top) and Reconstructed(bottom) images with PSNR and CR value for 2 out of the 120 images.

The proposed image compression algorithm is lossy due to quantisation and DWT where high frequency components are dropped. The quality of the reconstructed image is measured using PSNR which is given by (Korhonen and Junyong, 2012) :

$$\mathrm{PSNR} = 10 \times \log_{10}\left(\frac{\mathrm{MAX}^2}{\mathrm{MSE}}\right) \tag{4a}$$

$$\mathrm{MSE} = \frac{1}{3\mathrm{HW}} \sum_{k=1}^{k=3} \sum_{i=1}^{i=H} \sum_{j=1}^{j=W} (I(i,j,k) - K(i,j,k))^2 \tag{4b}$$

MAX is the maximum possible pixel value which is 255 in our case, as we are using 8 bits per sample. H and W are the height and width of the original image I and K represents the reconstructed noisy image. The algorithm is tested for different values of quantisation and different setting of Golomb encoder. The performance under different settings is tabulated in Table 4.

From the Table 4, we observe that on increasing quantisation, the compression rate increases but the quality of the reconstructed image falls. An optimum tradeoff between the achieved compression and the image quality is achieved at Q = 8. Setting the maximum code length to 16 instead of 32 in Golomb Rice encoder decreases the compression by only 0.07 percent but decreases the power in the serialiser and allows us to design an efficient architecture of the serialiser which can run at 8 times the frequency of the compressor. Thus in our proposed algorithm, we use adaptive Golomb Rice encoder with max code length set to 16 and are able to achieve compression of 91.88 percent at a PSNR of 38.17. In Table 5 we compare the performance of our algorithm with the recent existing works. Our implementation achieves higher compression rate than the previous implementations. Figure 4 shows two images compressed and reconstructed using our algorithm.It can be seen that the reconstructed image quality is very good and it is almost indistinguishable from the original to the human eye.

# 4 HARDWARE REALISATION

## 4.1 Image Compressor

The block diagram of the proposed architecture for the image compressor is shown in Figure 5. The image compressor has three inputs : 8 bit Pixel [7:0], Reset, and CLK. Its output includes a 16 bit code word, code word length and a valid bit. The image compressor accepts the input in RGB format and is used to compress a 256*256 image with 24 bits per pixel at 2 frames per second.

The control unit is the heart of the design and generates the control signals for the entire design. It takes

Table 5: Comparison with Previous Works. In this table, Q stands for quantisation, SS stands for sub-sampling , GR stands for Golomb-Rice, RL stands for Run Length.

| Method | Colour Space | Entropy Encoder | CR | PSNR |
|---|---|---|---|---|
| DPCM + Q + SS (Fante et al., 2016) | YUV | Adaptive GR with code limit = 32 | 90.35 | 40.66 |
| DPCM (Khan and Wahid, 2011a) | YUV | Static GR | 76.64 | 52.60 |
| DPCM + SS (Khan and Wahid, 2011b) | YUV 812 | Static GR | 82.57 | 41.01 |
| DPCM + SS (Khan and Wahid, 2012) | YUV 16:1:1 | Static GR, code limit=32 | 85.72 | 38.37 |
| DCT (Turcza and Duplaga, 2011) | $YC_gC_o$ | Huffman | 91.34 | 36.67 |
| DCT (Turcza and Duplaga, 2013) | $YC_gC_o$ | GR with RL | 91.35 | 38.59 |
| DPCM + Q + DWT (This Work) | YUV | Adaptive GR with code limit = 16 | 91.88 | 38.17 |

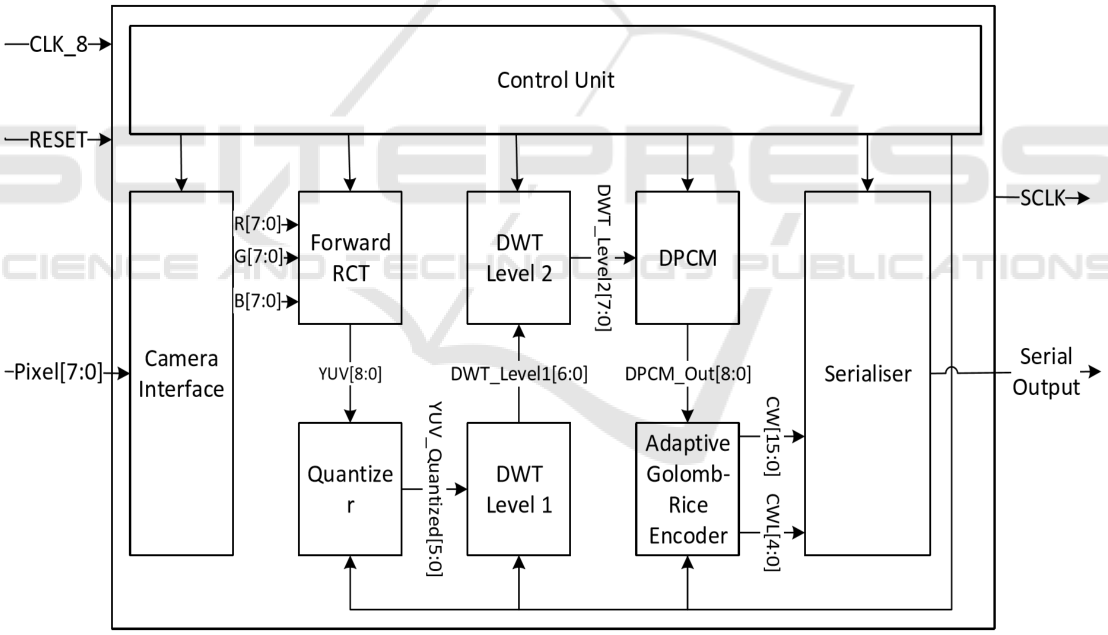


Figure 5: Hardware Architecture of Image Compressor.

CLK and reset as input and generates two separate clocks for the compressor and serialiser. Moreover, it contains a column and a row counter which keeps track of the current pixel being processed and also helps in corner clipping. It further generates the “valid signal” which signifies whether the current output is valid or not. The pixels is encoded using quantisation, DWT transform and Golomb encoding.

The forward RCT module is a purely combinational block and performs colour space transformation from RGB to YUV space. The quantiser performs the 3 bit quantisation on the output of the RCT module. 2 level 1D DWT is used on the quantized U and V values. Lifting architecture is used to implement the 5-3 integer wavelet. The output is encoded using simple DPCM and passed through Golomb encoder. The Golomb encoder involved mapping negative values to positive values, finding parameter k using context variables and encoding the given pixel. It produces a 16 bit code word along with the code word length which is fed to the serialiser. The entire design is hardware efficient and uses simple computations along with no buffer memory. Small sets of registers are used in RGB, DWT , DPCM and Golomb encoder. In total, 229 registers are used in the design of the compressor. The image compressor processes each pixel in 3 cycles and thus for a 256*256 image at 2fps requires a clock frequency of 393.216 KHz.

## 4.2 Serialiser

The Serialiser proposed by (Fante et al., 2016) and (Khan and Wahid, 2013) works at 32 times the frequency of the compressor. It was also mentioned that the serialiser was a major power hog. In order to reduce the consumption of power, first of all we limited the input to the serialiser to 16 bit code by changing the Golomb encoder in the compressor. Secondly, in our algorithm we were effectively sub-sampling the U and V components by 4. This implied that for every 12 clock cycles of the compressor, we sent 4 Y values, 1 U value and 1 V value, whereas in 6 clock cycles no data was produced by the compressor. The pattern of the data produced by the compressor is like : YUVY- -Y- -Y- -, where '-' represents no data. If we consider the worst case scenario, where all these data produced are of 16 bits, then minimum frequency of data transmission required, R, can be calculated as 12*R = 16*6 , which gives R =8. Thus from this calculation, we can observe that we can run the serialiser at 8 times the clock frequency of the compressor.

It must be noted that compressor can output up to 16 bits in 1 compressor clock cycle but the serialiser can send at most 8 bits per compressor clock cycle. Therefore, it is pretty obvious that we need a FIFO to solve our problem. In order to calculate the maximum buffer sizer to prevent overflow we again consider the worst possible scenario by assuming the output of every channel to be 16 bits. In order to prevent overflow we must ensure that after every 12th clock cycle the buffer occupancy is zero. It could be easily seen that for the given pattern of YUV the maximum buffer occupancy that could ever be reached is 40. Therefore by running the FIFO at 8 times the frequency of the compressor and keeping its size at 40 works perfectly fine as a serialiser for our algorithm.

The architecture of the proposed serialiser is given in Figure 6.

We can also adapt the original serialiser architecture proposed in (Khan and Wahid, 2013) for 16 bit Golomb encoder. The power consumption will reduce by more than half since the number of registers will be halved and the frequency of operation is also halved. On comparing the power consumption between proposed serialiser and the original archtecture for 16 bit, we find that original architecture requires lower power. The reason is straightforward, since our architecture has 40 registers operating at 8 times clock frequency, whereas the original architecture has 16 registers operating at clock frequency. Moreover we have a barrel shifter which consumes majority of the combinational power. But the advantage of our serialiser architecture is that the overall frequency of operation is halved. Note that both the serialisers with 16 bit input consume less power as compared to the previous designs (Fante et al., 2016; Khan and Wahid, 2013) which work at 32 times the operating frequency of compressor.

Table 6: Power Consumption of Proposed Compressor with the New Serialiser.

| Supply Voltage | 1.2 Volts |
|---|---|
| Compressor Power | 10.7 uW |
| Serialiser Power | 6.2 uW |
| Total Power | 16.9 uW |
| Dynamic Power | 9.71 uW |
| Leakage Power | 7.21 uW |

Table 7: Power Consumption of Proposed Compressor with the Old Serialiser but operating with 16 bit input.

| Supply Voltage | 1.2 Volts |
|---|---|
| Compressor Power | 11.64 uW |
| Serialiser Power | 2.56 uW |
| Total Power | 14.2 uW |
| Dynamic Power | 7.60 uW |
| Leakage Power | 6.60 uW |

## 4.3 Power Comparison

The proposed image compressor and the serialiser was implemented in Verilog. It was synthesized using Synopsys Design vision and mapped to UMC 130nm CMOS process using High Speed Faraday standard cell libraries. The whole image compressor along with the new proposed serialiser takes 1463 cells. The image compressor with the serialiser proposed in (Fante et al., 2016) adapted for 16 bit takes 1230 cells.The power consumption of the two designs, one with the new proposed serialiser and other one with the serialiser proposed by (Fante et al., 2016) adapted for 16 bit encoder are given in Tables 6 and 7. The layout of the proposed compressor is shown in Figure 7.

The proposed scheme is hardware efficient since the entire design involves simple operations like addition, and shifting and expensive operations like di-

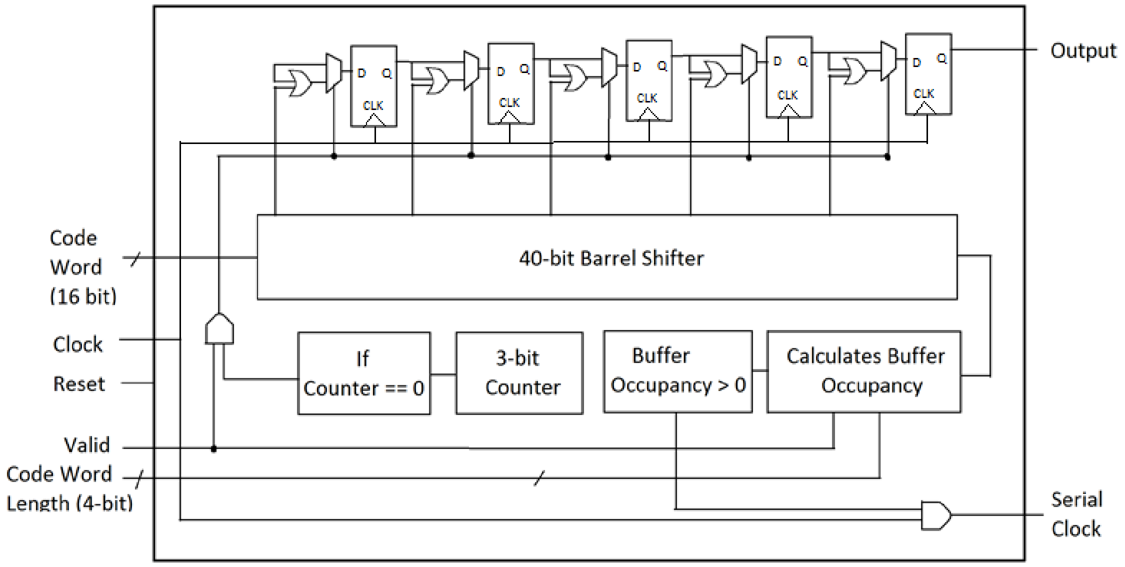


Figure 6: Hardware Architecture of Serialiser.

Table 8: Power Comparison with Previous Works.

| Existing Works | Process Technology | Chip Area ($mm^2$) | Gate Count | Power Consumption (mW) | Frame Rate (fps) (image size) |
|---|---|---|---|---|---|
| ASIC(Khan and Wahid, 2011a) | 0.18 um | 0.0256 | 2k | 0.018 | 2(3*320*240) |
| ASIC(Khan and Wahid, 2012) | 0.18 um | 0.0320 | 2k | 0.042 | 2(3*256*256) |
| ASIC(Khan and Wahid, 2011b) | 0.18 um | 0.0256 | 2k | 0.042 | 2(3*256*256) |
| ASIC (Fante et al., 2016) | 0.13 um | 0.018 | 2.2k | 0.035 | 2(256*256*3) |
| ASIC (Lin and Weng, 2006) | 0.18 um | 0.329 | 31k | 14.92 | 2(512*512*3) |
| Simulation (This Work : with New Serialiser) | 0.13 um | 0.021 | 5.5k | 0.0169 | 2(256*256*3) |
| Simulation (This Work : with 16 bit Old Serialiser) | 0.13 um | 0.019 | 4.9k | 0.0142 | 2(256*256*3) |

vision and multiplication are avoided. The order of computational complexity of our algorithm is O(n), which is similar to the design proposed in (Fante et al., 2016). As compared to their design, we required some more registers in the DWT block, but overall we are increasing the compression at a minimal increase in hardware. By limiting the max length of code to 16 in the Golomb Rice encoder, we simplified the design of the serialiser. If we consider the compressor along with the serialiser as a unit, then we obtain higher compression as compared to previous designs at almost similar hardware complexity and power consumption. Our implementation requires no memory buffer and does not require complex computations.Table 8 compares the power consumption of our design with the previous works.

## 5 CONCLUSIONS

In this paper, we presented a hardware efficient image compressor along with the serialiser for application in

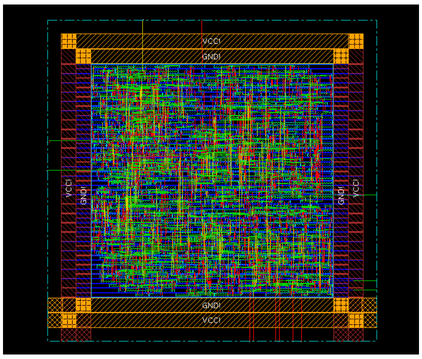


Figure 7: Layout of the Proposed Image Compressor.

wireless capsule endoscopy. It was based on computationally simple techniques like 1D integer wavelet transform, DPCM, color transformation and Golomb Rice encoder. The performance of the algorithm was evaluated on the basis of PSNR and Compression Ratio. Our image compressor was able to achieve a compression of 91.88 percent at a PSNR 38.17. An alternative architecture for the serialiser was also proposed specific to the implemented algorithm which ran at only 8 times the frequency of the compressor. The hardware implementation of the proposed compressor along with two different serialisers using Faraday HS library standard cells in UMC130nm process consumes 14.2uW and 16.9 uW respectively. The architecture is designed for a 256*256 image at 2 frames per second. As compared to the existing DCT based implementations, we get as good a compression ratio but with very low power consumption. In comparison to the DPCM based approaches, our algorithm gives higher compression with similar power consumption. Moreover, we were able to optimize the design of the serialiser so that it works at lower frequency. We believe that the proposed image compressor along with the serialiser is a good candidate for WCE applications as it has a high compression ratio, good reconstructed image quality, low power consumption, and small area.

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