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Development of a Lossless Compression Algorithm using Content-based Classification of Image Block for Wireless Capsule Endoscopic Image

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Abstract: - In this paper, the development of a lossless image compression algorithm for wireless capsule endoscopy using content-based classification of image block is presented along with the simulation results, which shows the effectiveness of the methodology and also represents a significant advancement in medical imaging technology. This algorithm offers a pragmatic solution for reducing data size and transmission rates in wireless capsule endoscopy systems while maintaining high diagnostic image quality. By classifying image blocks based on content, the algorithm can efficiently prioritize informative regions within the images, enhancing the reliability and trustworthiness of the resulting images. The algorithm's performance has been validated through simulations and evaluations, demonstrating its utility in real-world applications. Overall, this development has the potential to significantly improve the efficiency and effectiveness of wireless capsule endoscopy systems, leading to better patient outcomes and enhanced medical diagnostics.

Keywords: Lossless, Endoscopic, Image, Reliability, Medical.

I. Introduction

Advancements in capsules endoscopy systems have ushered in new methods and capabilities, revolutionizing the diagnosis of gastrointestinal disorders and diseases by providing a comprehensive view of the entire digestive tract. Despite these advancements, challenges such as the need to enhance image qualities, low frame rates during transmission, and limited battery life persist [1].

A crucial component of capsule endoscopy systems is the image compression unit, which plays a pivotal role in improving the diagnosis process by increasing frame rates. To address these challenges, this work proposes a high-precision compression algorithm designed to achieve a high compression ratio. By exploiting similarities between frames, the algorithm aims to compress data more efficiently, potentially overcoming these challenges and enhancing the overall performance of capsule endoscopy systems [2].

Endoscopy is a medical procedure used to diagnose various digestive diseases by visually examining different parts of the digestive systems, viz., the esophagus, colons, & smaller intestine. Traditional wired endoscopy involves inserting a long, flexible cable into the digestive tract, making it uncomfortable and painful, especially for young patients. To address this, wireless endoscopy capsules (WCEs) were introduced, such as those by Given Imaging Incorporated. However, WCEs may have limitations, including limited fields of views, lower resolutions, & lower frames rate compared to traditional pushed endoscopies [3].

II. Part-1 & Part-2

Various methods, including WCEs, have attempted to address this issue by separation of the two pixel of very same color. Their compression unit is a crucial component of their endoscopic capsuled systems, and several methods have been developed to improve its performance. These approaches can be broadly categorized into two main groups, viz., Part-1 & Part-2. The Fig. 1 gives a pictorial representation of a typical endoscopic system that for getting the endoscopic images of the patients [10].

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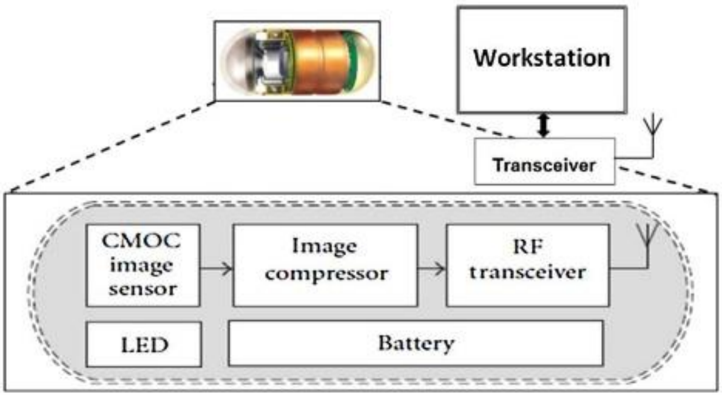

Figure 1. Pictorial representation of a typical endoscopic system

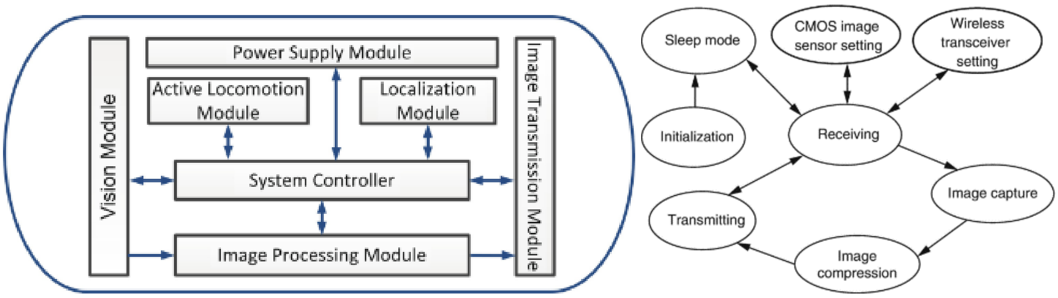

Figure 2. Sensors usage in the endoscopic device

The sensors which are used in the endoscopic device are shown in the Fig. 2. The works are being carried out in 2 parts, viz., part-1 & 2 respectively, which are interpreted as follows one after the other below. The Fig. 2 gives the sensors usage in the endoscopic device used in the hospital [11].

Part-I includes lossless and near-lossless methods, such as JPEG LS dependent method, that offers adequate image's qualities, but, tend to have low compression ratios (CR) and frame rates. The compressive ratios are defined as their ratios of the sizes in the uncompressed image, Im_in, to the sizes in their compression based images, Im_out, and is given by the equation [12]

$$\text{Compression Ratio (CR)} = \text{Im\_in}/\text{Im\_out}$$

Among these lossless methods, our method achieved the best compression rate of > 10% compared to all the methods [13].

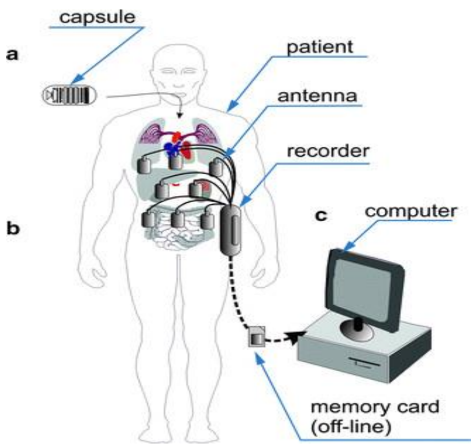

Figure 3. How an endoscopic device is inserted into the mouth & the data is being captured

Part-II encompasses compression methods used for wireless capsule endoscopy (WCE) images, which fall under the category of lossy algorithms. These methods primarily rely on the discrete cosine transforms [DCT]. Example of such lossy method could be seen in literature, which offer higher compressive rate. However, because of their efficiency in compressions, the method often produces lesser-qualities image. While the lossy method offer higher frame rate, achieving higher image resolutions remains a challenge. The lesser correlations b/w neighboring pixel in color filter array (CFA's) image makes traditional JPEG dependent algorithm being ineffective. Therefore, there is a need for modified versions of JPEG-based methods to address this issue. The Fig. 3 shows how an endoscopic device is inserted into the mouth & the data is being captured along with the wireless transmission of the data to the surgeon [14].

III. Design criteria information

Endoscopy is a medical procedure used to diagnose various digestive diseases by visually examining different parts of the digestion systems, viz., the esophagus, colons, & smaller intestines. Traditional wired endoscopy involves inserting a long, flexible cable into the digestive tract, making it uncomfortable and painful, especially for young patients. To address this, wireless endoscopy capsules (WCEs) were introduced, such as those by Given Imaging Incorporated. However, WCEs may have limitations, including limited fields of views, lesser resolutions & lesser frames rate compared to traditional pushed endoscopic images [15].

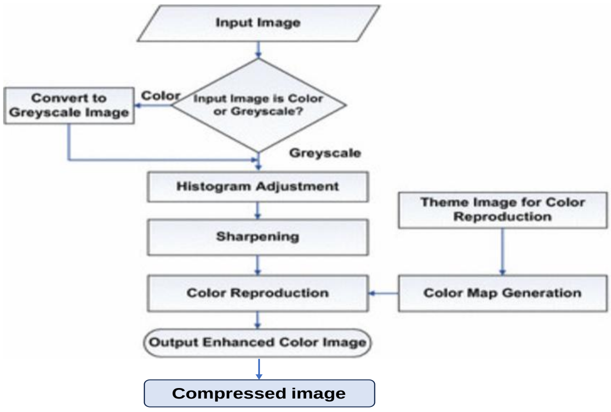

Figure 4. Flow-chart used for the process of image compression of endoscopic captured image

IV. Developed Algorithm

To enhance diagnostic accuracy in capsule endoscopy, an increase in the number of transmitted frames is necessary, as low frame rates may result in missed areas of the digestive tract. However, this approach comes with the drawback of increased data transmission, which is limited by the available power resources. To address these limitations, we proposed a compression methodology solely dependent upon the similarity of consecutive frames instead of relying merely on spatial similarity. This method aims to maintain a high frame rate without significantly increasing the data transmission rate. The block diagram of our developed algorithm is illustrated in Fig. 4 [24].

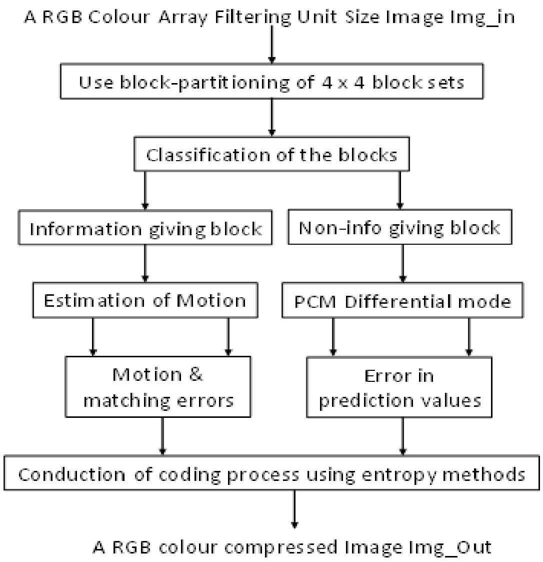

Figure 5. Block diagram of the proposed methodology used for compression of endoscopic images.

In traditional capsule endoscopy systems, real-time data compression is often impractical, leading to the storage of some images on a chip memory. Our proposal differs by leveraging the higher similarity among consecutive frames that arises from increasing the frame rate. This concept draws from techniques used in video compression and is optimized here for capsule endoscopic images. By focusing on temporal similarities, our algorithm aims to achieve higher compression ratios while maintaining diagnostic image quality, thus enabling more efficient use of limited data transmission bit-rates [23].

V. Block modules

In the Blocking module of wireless capsule endoscopy (WCE), where color filter array (CFA) images are utilized, an initial step involves modifying their color of the image in their image / video databases before they are inserted into the module. This modification process entails retaining only one color channel for each pixel and discarding the other channels. To facilitate the comparison of multiple frames, each frame is divided into blocks. The size of these blocks is determined by different factor, including their overall size of the image, the presence of edges and patterns within the image, & the degrees of similarities b/w the frame. Finding their optimal blocks size is crucial and is typically achieved through an iterative search process to identify the size that provides the best results [21].

VI. Classification of the blocks

The Block Classification process in wireless capsule endoscopy (WCE) aims to optimize the efficiency of block analysis by focusing on informative regions while avoiding unnecessary computations for non-informative parts. In endoscopy images, certain areas, such as dark and smooth regions, do not provide significant diagnostic information. To identify these non-informative regions, a gradient is calculated for each block using a simple (3 × 3) Sobel filter. This filter computes gradients in both the x & y directions, denoted as GG_x and GG_y, respectively. The absolute value of the found out gradients is then compared using a predefined threshold. Blocks with gradients below the threshold are labelled as non-informative [smooth] & their data are compressed using Differential Pulse-Code Modulation (DPCM). Conversely, blocks with gradients above the threshold undergo motion estimation [18].

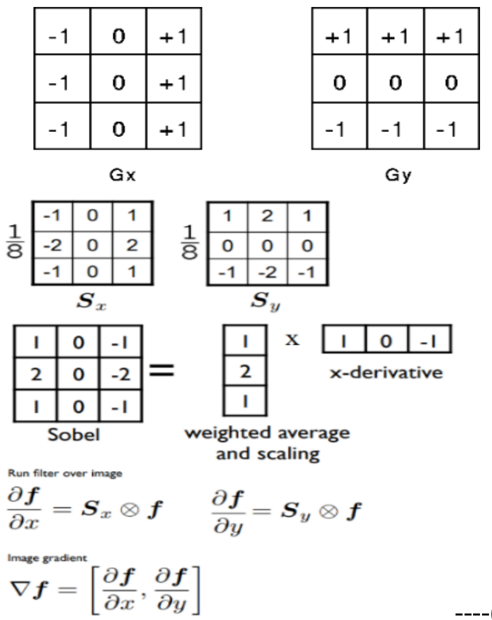

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Figure 6. Sobel standard filter's template usage for computing the gradients along the directions of x & y

The mathematical model used for the development of the Sobel operator is shown in the Fig. 6. To distinguish smooth blocks and facilitate their identification at the receiver, their motion-vector [MV] values $\{x$ & $y\}$ are set to 4's & 0's, respectively. This process helps reduce the computational load by focusing on analyzing only the informative blocks, which contain relevant diagnostic information. By efficiently categorizing blocks based on their gradients and motion characteristics, the Block Classification process improves the overall efficiency and accuracy of the WCE system. This approach ensures that resources are allocated effectively, optimizing the compression and transmission of data while maintaining the quality of diagnostic information extracted from endoscopy images [17].

VII. ESTIMATING THE MOTION OF THE IMAGES

In the Motion Estimation Module, also known as the search module, the compression process begins by directly compressing the first frame using JPEG-LS. Subsequently, for each block in the second frame, a search is conducted within a specified area of the previous frame to find the best matching block. The selection of the best block is based on minimizing the mean of the square of the errors (MSE) b/w their existing block set & every block set well within the searched areas. Their blocks within the min. MSE's are then chosen as the best match. Additionally, the module computes the difference between the selected block and the current block, storing both the difference and their x & y position w.r.t. their blocks which are selected in a motion vector (MV) array [16].

VIII. CODING USING ENTROPY METHODS

For removing statistical redundancy in wireless capsule endoscopy (WCE) images, Entropy Coders are utilized. While a separately developed JPEG or their JPEG based LS blocks could be used for compression of the error data, such an elaborate module may not be practical for endoscopy images. Instead, a simpler approach using a Golomb Rice entropy decoder is deemed sufficient. The Golomb-Rice code word for a integer value which is x ≥ 0 & consisting of 2 vital part, viz., a unary representation of the x divided by 2k value, which is then followed using the k based LSB's of the x values, where the value of k is ≥ 0 & will be an integral parametric variable of the code. In this context, a customized Golomb Rice algorithm, where the first step involves converting signed input data to unsigned data, followed by the selection of an optimized k parameter to achieve the best encoding results. The k parameter is adaptively adjusted based on the local statistics of the input data [9].

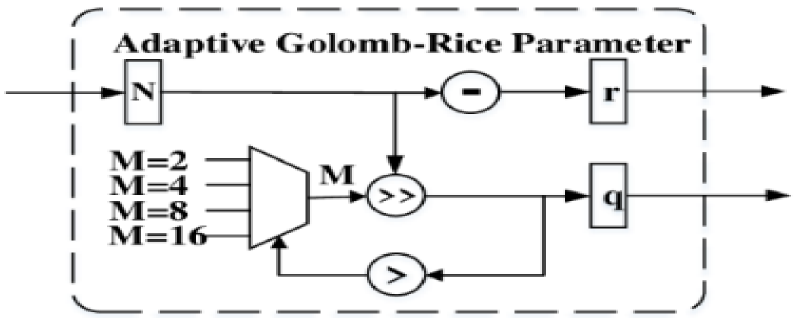

Figure 7. Methodology of the Golomb-Rice Parameter used in the process.

IX. ENDOSCOPIC IMAGE DATABASES USED

Four numbers of databases are used in our work which provides valuable resources for researchers and developers working on endoscopic image analysis and related medical imaging tasks.

- DB1: Endoscopic Image Database for Disease Recognition (EID4DR): A dataset containing endoscopic images for various gastrointestinal diseases, such as oesophageal cancer, gastric cancer, and ulcerative colitis.
- DB2: Kvasir-SEG: A dataset containing images from gastroscopy procedures for semantic segmentation tasks, particularly focusing on polyp segmentation.
- DB3: ASU-Mayo Clinic Gastrointestinal Tract Image Database: A database containing images from various parts of the gastrointestinal tract, including the oesophagus, stomach, and colon, for research in gastrointestinal endoscopy.
- DB4: Hospital Images: Collection of various images of small bowel tumors & polyps in large intestine part from an endoscopic device.

X. EXPERIMENTATION RESULTS

This section presents the experimental results of the proposed algorithm, which were evaluated using 4 databases. In the case of the video database, 10 frames per second were extracted from the video and converted into color filter array (CFA) images for analysis. The Figure Nos. 8-11 / 12-15 illustrates the input images, color-filter dependent image & the error based images w.r.t. their capsule's endoscopic data for database sets – 1 & 2 respectively. Similarly, the Figure Nos. 16-19 / 20-23 depicts the corresponding images for the endoscopy datasets 3 & 4 respectively [6].

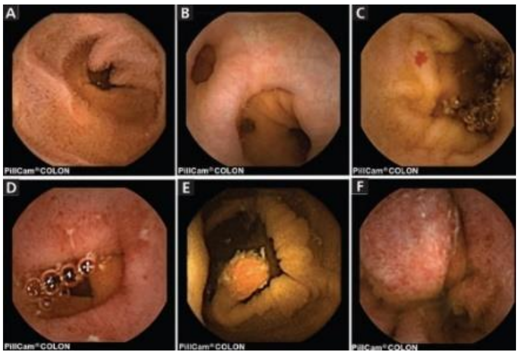

Figure 8. Wireless Capsule endoscopy of small bowel captured by the device (DB1).

The captured image from the endoscopic device is shown in the Fig. 8 with the parameters {a} normalized {b} diverticulas {c} angiodysplasias {d} erosion of Crohn diseases {e} a 10 millimeter pedunculated type of polyps {f} ulceratives colites with the image being taken from the database 1. The Fig. 9 gives the CFA filtered array image obtained after filtering operations. The error image before Golomb Rice entropy encoding usage is shown in the Figs. 10. The final compressed image with good resolution (DB1) after the incorporation of the Golomb Rice entropy encoding usage is shown in the Fig. 11 [2].

Similarly, for the colon image & that of the gastro-intestinal part taken from the database 2, the results are shown in the Figs. 12-15 respectively. Similarly, for the colon image & that of the gastro-intestinal part taken from the database 3, the results are shown in the Figs. 16-19 respectively. Results are also observed for standard images taken from the dataset 4 respectively w.r.t. the small bowel tumors & polyps in large intestine part and is shown in the Figs. 20-23. The justification w.r.t. all the 4 databases still frames are conducted and analyzed and presented as conclusive remarks at the end [1].

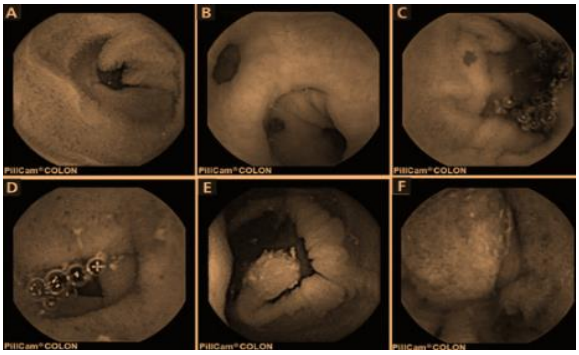

Figure 9. CFA filtered array image obtained after filtering operations (DB1)

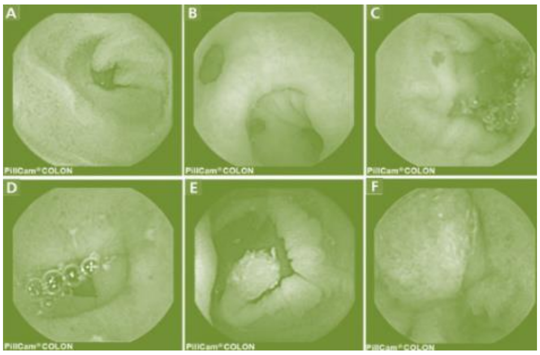

Figure 10. The error image before Golomb Rice entropy encoding usage (DB1)

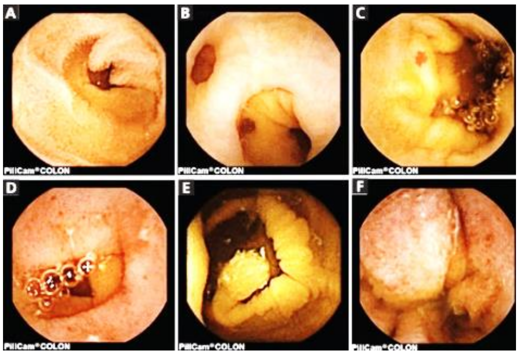

Figure 11. The final compressed image with good resolution (DB1)

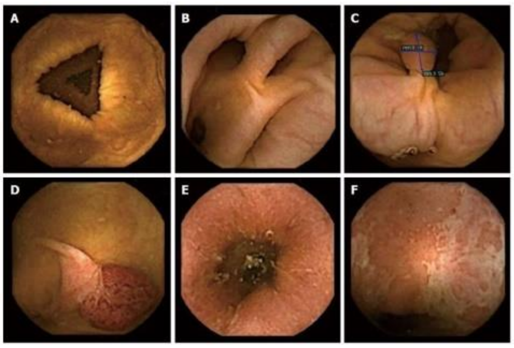

Figure 12. Wireless Capsule endoscopy of colon captured by the device (DB2).

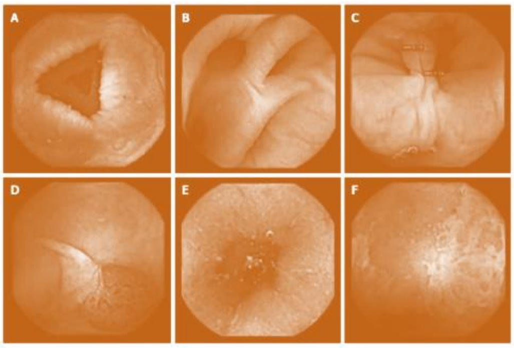

Figure 13. CFA filtered array image obtained after filtering operations (DB2)

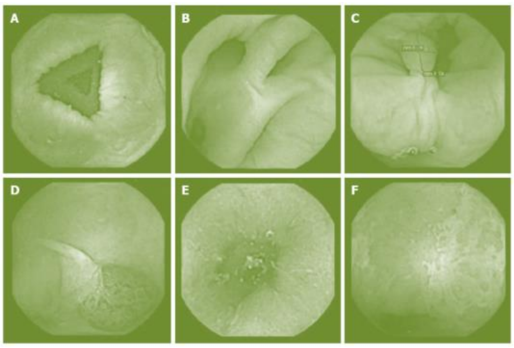

Figure 14. The error image before Golomb Rice entropy encoding usage (DB2)

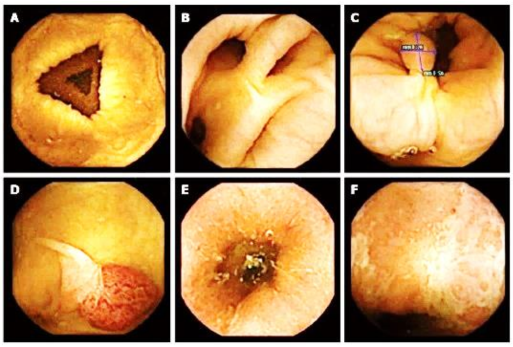

Figure 15. The final compressed image with good resolution (DB2)

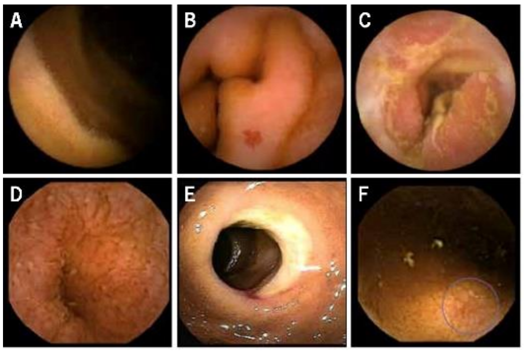

Figure 16. Wireless Capsule endoscopy of gastro-intestinal part captured by the device (DB3).

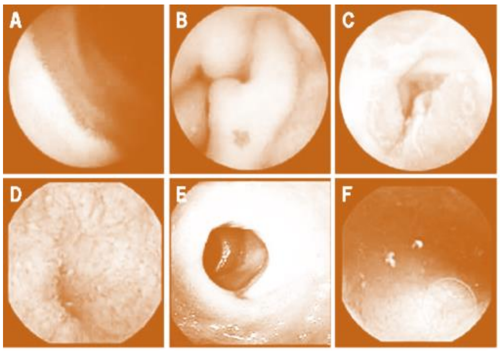

Figure 17. CFA filtered array image of gastro-intestinal part obtained after filtering operations (DB3)

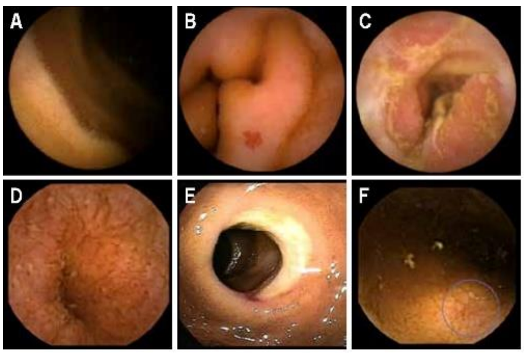

Figure 18. The error image of gastro-intestinal part before Golomb Rice entropy encoding usage (DB3)

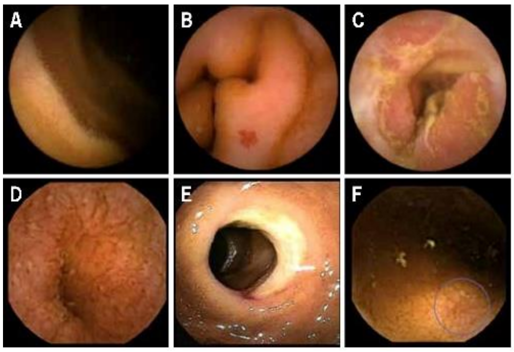

Figure 19. The final compressed image of gastro-intestinal part with good resolution (DB3)

Figure 20. Wireless Capsule endoscopy of the small bowel tumors & polyps in large intestine captured by the device (DB4).

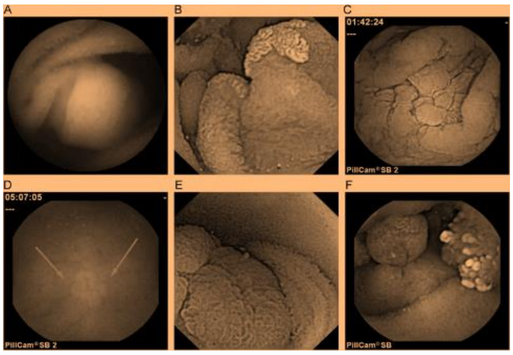

Figure 21. CFA filtered array image of the small bowel tumors & polyps in large intestine after filtering operations (DB4)

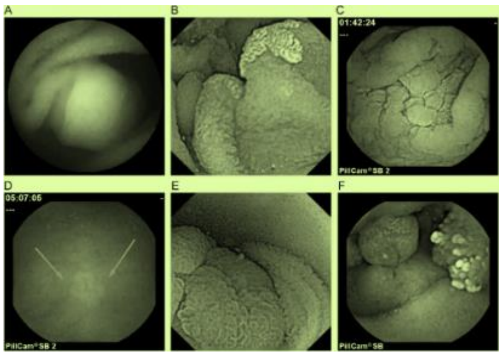

Figure 22. The error image of the small bowel tumors & polyps in large intestine before Golomb Rice entropy encoding usage (DB4)

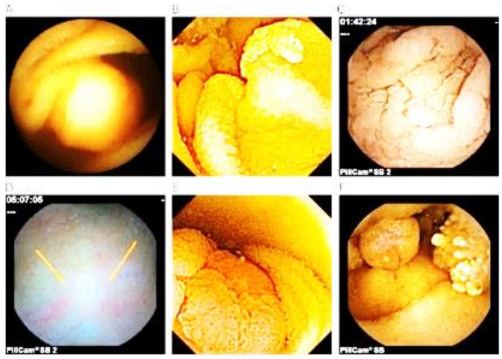

Figure 23. The final compressed image of the small bowel tumors & polyps in large intestine with good resolution (DB4)

XI. Parameters used in the algorithm

In the algorithm discussed, several key parameters are defined to optimize its performance. For instance, a threshold value of 10 is set to identify smooth (non-informative) blocks within the images. Additionally, the block size is selected as (5 × 5), considering the dimensions of the images in the database [214], which are (480 × 480) pixels. To find the best-matched block, an optimal search area is determined as $[(2 \times N) + 1]$, where N represents the lengths in their blocks. Consequently, their searched areas w.r.t. this experiment is defined as (11 × 11) pixels, ensuring a sufficiently large region is examined for block matching.

These parameter choices are crucial for the algorithm's effectiveness in accurately identifying and compressing informative regions within the images. The threshold value helps differentiate between informative and non-informative blocks, allowing for efficient compression by focusing on relevant image data. Similarly, the block size and search area are carefully selected to ensure that the algorithm can effectively analyze and match blocks between consecutive frames, facilitating the efficient encoding of motion information. By fine-tuning these parameters based on the characteristics of the input images, the algorithm can achieve optimal compression performance while maintaining the diagnostic quality of the endoscopic images.

Overall, the selection of these parameters reflects a balance between computational efficiency and compression quality in the algorithm. By considering the specific requirements and constraints of the given dataset, these parameter choices aim to maximize the compression ratio while minimizing the loss of important diagnostic information. Through this approach, the algorithm demonstrates its adaptability and effectiveness in the context of wireless capsule endoscopy, offering a practical solution for efficient image compression in medical imaging applications.

XII. Justification of the Results

In evaluating the compression efficiency of the algorithm, the compression ratio (CR) is utilized as a key metric. The CR is determined by considering the sizes of both the error images and motion based vector, as depicted in the pictorial representation as shown in Figure No. 8-23 respectively. While motion vectors contribute additional data to the compression algorithm, their size is relatively small compared to that of the error images, as there is only one motion vector per block.

Considering the database 1, in a scenario involving 40 frames from the first database [DB1], the CR achieved with the removing of spatial redundancy and using the smooth module is 10.12 which is more than 50% compression ratio compared to the other methods. Considering the database 3, in a scenario involving 40 frames from the first database [DB2], the CR achieved with the removing of spatial redundancy and using the smooth module is 10.93 which is more than 50% compression ratio compared to the other methods. Considering the database 3, in a scenario involving 40 frames from the first database [DB3], the CR achieved with the removing of spatial redundancy and using the smooth module is 11.61 which is more than 50% compression ratio compared to the other methods. Considering the database 4, in a scenario involving 40 frames from the first database [DB4], the CR achieved with the removing of spatial redundancy and using the smooth module is 11.98 which is more than 50% compression ratio compared to the other methods.

TABLE I. COMPARISON OF THE AVG. COMPRESSION RATIOS FOR CAPSULE ENDOSCOPIC IMAGES FOR THE DB1 TO DB4 WITH THE PROPOSED METHOD

Proposed algorithm	[2]	[4]	[6]	[8]	[10]	Database
10.12	6.43	5.43	3.44	6.34	4.21	DB1
10.93	5.23	4.44	5.56	6.75	6.44	DB2
11.61	6.34	5.56	6.67	5.68	7.23	DB3
11.98	6.76	7.78	7.65	6.76	5.87	DB4

Comparing these results with those of other methods on the capsule endoscopy image database, it is evident that the proposed algorithm outperforms existing methods. For instance, the method introduced in [2] [4] [6] [8] [10] achieves a CR of 6.43, 5.43, 3.44, 6.34, 4.21. Similarly, the results are observed for other database images. These comparisons highlight the superior compression performance of the algorithm, showcasing its effectiveness in reducing data size while maintaining diagnostic image quality. Overall, these results demonstrate the algorithm's ability to achieve high compression ratios, making it a promising solution for efficient image compression in wireless capsule endoscopy applications.

XIII. CONCLUSIONS

In this research, we proposed a compression method tailored for wireless capsule endoscopy (WCE) systems, achieving relatively high compression ratios. Simulations of the proposed method demonstrated its strong performance, validating its suitability for practical applications. The design objective was to prioritize simplicity and high performance. By utilizing color filter array [CFA] image & searching of each color in their designated region, the number of comparisons required for full search was reduced from 100 to merely 10^{+}. Additionally, by the optimization of a variety of aspects of their algorithms, a nearest lossless method was developed. Considering an instance, quantization in their predictive error & the reductions in their blocks based searches within searched areas were implemented to decrease hardware requirements and lower power consumption. The flexibility to adjust block sizes and search areas offers further opportunities for reducing hardware complexity and energy usage.

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