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A Consistent Quality Bit Rate Control for the Line-Based Compression

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Abstract: Emerging technologies such as the Internet of Things (IoT) and the Advanced Driver Assistant System (ADAS) often have image transmission functions with tough constraints, like low power and/or low delay, which require that they adopt line-based, low memory compression methods instead of existing frame-based image compression standards. Bit rate control in the conventional frame-based compression systems requires a lot of hardware resources when the scope of handled data falls at the frame level. On the other hand, attempts to reduce the heavy hardware resource requirement by focusing on line-level processing yield uneven image quality through the frame. In this paper, we propose a bit rate control that maintains consistency in image quality through the frame and improves the legibility of text regions. To find the line characteristics, the proposed bit rate control tests each line for ease of compression and the existence of text. Experiments on the proposed bit rate control show peak signal-to-noise ratios (PSNRs) similar to those of conventional bit rate controls, but with the use of significantly fewer hardware resources.

Keywords: Bit rate control, Low-memory line-based compression, Consistent line quality, Low-power codec

1. Introduction

Growing user demand for immersive images, the advanced technology of cameras and display devices, and the high accuracy requirements of image recognition systems force more and more application systems to use image information, even in the Internet of Things (IoT) systems that require extremely low power consumption. An extremely low-power system can reduce power consumption by compressing large-image data and transmitting the compressed data. The existing image compression standard methods, including High Efficiency Video Coding (HEVC), yield a high compression ratio at the expense of too-high power consumption due to extensive computation and memory access to be adopted. To meet the low-power requirement of IoT systems, line-based low memory–compression methods have been studied [1, 2]. Additionally, a system like the Advanced Driver Assistant System (ADAS), which demands a strict real-time requirement, also relies on line-based low memory–compression methods to transmit image data [3].

Since the characteristic differences between the upper image and the lower image in a frame cause large fluctuations in the compression efficiency of line-based image compression, existing studies often attack two problems in bit rate control (BRC): failure to meet the target compression rate due to the low compression efficiency at the bottom of the image, and poor image quality caused by the rapid changes in line compression ratios. A BRC scheme was proposed in the Joint Photographic Experts Group-Lossless Standard (JPEG-LS) environment [4] that predicts the next target compression ratio based on the slope of the compression ratios of two consecutive lines. However, insufficient accuracy in compression ratio prediction can fail to meet the target compression rate and cause buffer overflow. A BRC scheme based on cumulative compression ratio [5] can effectively achieve the target compression ratio, but consistency in image quality through the whole image is not guaranteed due to its adaptation to the changes of line characteristics. Another existing BRC scheme for JPEG2000 [6] can satisfy the two requirements of target compression ratio and consistent image quality. However, because of the additional computational complexity in predicting the frame-to-frame correlation, this scheme is not suitable for an application that requires low complexity.

In this paper, we propose a line-based BRC scheme that maintains consistent image quality through a frame. The proposed scheme achieves the target compression ratio by adaptively controlling the compression parameter sets that are prepared for the different line characteristics in the images. Moreover, the proposed BRC scheme identifies text lines using signal energy, and adaptively controls bit rates to guarantee a text's readability. The proposed BRC scheme showed better peak signal-to-noise ratios (PSNRs) than the conventional BRCs, and the resulting PSNR is close to the PSNR of a frame memory–based optimization scheme without using any line memory or frame memory. The proposed scheme also generates the resulting images with better text quality by relocating available bits from image areas to text areas.

The conventional line-based BRCs and compression systems are reviewed in Section 2. In Section 3, the proposed line-based BRC is presented. Section 4 compares the experimental results of the proposed BRC to those of existing BRCs. Section 5 concludes this paper.

2. Related Work

Edirisinghe and Bedi [4] proposed a variation of JPEG-LS, the rate control that targeted the cumulative compression ratio of lines. In their compression system, quantization and run-length coding is used for compression. The BRC for Edirisinghe and Bedi's compression system compares the cumulative compression ratio and the target compression ratio before applying the quantization parameter for the next line, to quickly achieve the target compression ratio and to maintain a stable compression ratio. On the other hand, it is hard to detect how much the compression ratios of two consecutive lines are changed with the different quantization parameter, because it only checks the cumulative compression ratio. The compression parameter does not easily adapt to the changes in line characteristics, and image quality can significantly fluctuate through the frame.

Jiang [5] suggested a BRC for differential pulse code modulation (DPCM) based on a near-lossless image codec. In Jiang's BRC, the current line is compressed first, and then, by checking the slope of the compression ratios of two lines that are separated by a certain distance, the frame compression ratio is predicted, and a corresponding quantization level (QL) is determined. However, it is possible for the degree of the slope to change rapidly before the next lines are reached, which produces inaccurate prediction of the compression ratio for the subsequent intermediate lines. Due to this inaccuracy, a risk that the final compression ratio may not meet the target compression ratio arises, and the scheme can over-compress the image at the expense of image quality.

Li et al. [6] proposed an adaptive line-based rate control for line-based JPEG2000. Their adaptive rate control algorithm uses PSNR-related image activity measure (IAM). After a specific number of horizontal lines have been compressed, the IAMs of the previous and current frames are compared to estimate the rate-distortion (R-D) slope threshold of the current frame so as to reduce coding passes. However, this BRC requires much more hardware resources because it is a two-dimensional estimation system. Additionally, obtaining IAMs incurs additional computation cost.

Furthermore, the conventional BRCs [4-6] do not give special treatment to text regions in frames; hence, the legibility of text is not as clear as it should be.

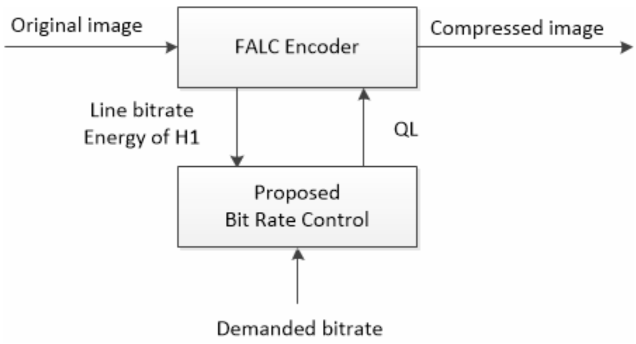


Fig. 1. The proposed bit rate control–based FALC encoder system.

3. The Proposed Scheme

The frequency adaptive line compression (FALC) algorithm recently proposed by Kim et al. [7] is one of the line-based compression techniques for display devices. However, there are no BRC schemes like FALC, and an optimized BRC was used in FALC. The proposed BRC builds on FALC. To adapt to low-power mobile display devices, FALC is based on discrete wavelet transforms (DWTs) and uses low-complexity algorithms, such as predictive coding, frequency selective zero-zone quantization, and frequency component entropy encoding. For fine control of the compression ratio, the number of quantization parameter sets in FALC is extended to 89 from 16. For the proposed BRC to incorporate FALC, a transmission format and a unit called the frequency shuffler (which arranges encoded bits according to the transmission format) are also implemented. The transmission format is designed to minimize the size of the transmission buffer by shuffling frequency components in a predefined order. A high-pass filter is also implemented to detect lines containing text, for appropriate rate control and text quality.

Fig. 1 illustrates the overall structure of the compression system using the FALC encoder with the proposed BRC appended. In the proposed BRC, FALC is set to compress the images at the target compression ratio, which is the minimum compression ratio of the system. The proposed BRC consists of five stages: initialization (INIT), quantization type selection (QTS), quantization level determination (QLD), remaining line processing (RLP), and text line processing (TLP). Fig. 2 depicts the five stages in a flowchart of the proposed BRC. In INIT,

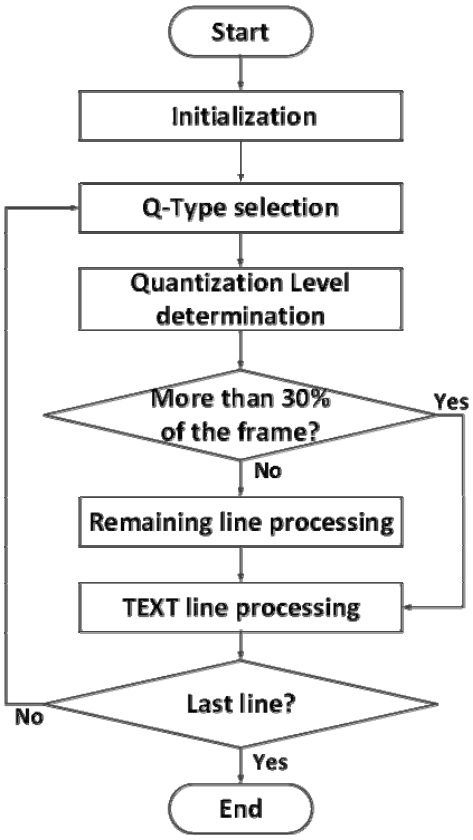


Fig. 2. Flow chart of the proposed bit rate control.

the initial quantization level of the current frame is determined based on the compression ratio of the previous frame, because the current frame is similar to the previous frame in most image sequences. In QTS, the line compression ratio and the local target compression ratio of the current frame are compared to determine the quantization type for the next line. In QLD, the quantization level is determined as the compression state of the line. Next, in RLP, the remaining lines are processed to meet the global target compression ratio. If the proportion of uncompressed lines is less than 30% in the current frame, then the quantization level is controlled to prevent buffer overflow. Finally, in TLP, lines crossing text are identified, and the quantization level is adjusted to improve text legibility. All stages except INIT are repeated until all of the lines have been processed.

3.1 Initialization Stage

In scene changes with a new frame image, the achieved compression ratio can miss the target compression ratio due to the characteristic changes of the whole frame. The proposed method, adaptively adjusts the target compression ratio of the current frame to improve bit rate control accuracy based on the difference between the target compression ratio and the achieved compression ratio of the previous frame. The temporal similarity in the consecutive frames, determines the new target compression ratio of the current frame. The compression ratio of the previous frame is classified into a deficiency state or a surplus state, depending on whether the achieved compression ratio is low or high, compared to the previous target compression ratio. If it is in the deficiency state, the proposed method raises the target compression ratio of the current frame to prevent repetitive overflow.

On the other hand, in the surplus state, the proposed method lowers the target compression ratio of the current frame to prevent degradation of image quality more than necessary. The degrees of increase or decrease for all parameters are determined empirically.

Table 1 shows how the target compression ratio of the current frame is selected. Global target compression ratio (GTCR) means the target compression ratio for the entire image sequence, and frame compression ratio (FCR) is the compression ratio result of the previous frame. Local target compression ratio (LTCR) is the temporal target compression ratio by considering the difference between GTCR and FCR. High_TCR is set higher than GTCR, and Higher_TCR is set higher than High_TCR. Eq. (1) shows the definition of compression ratio.

$$Compression\ Ratio = \frac{Total\ number\ of\ bits\ original\ image}{Total\ number\ of\ bits\ \ compressed\ image} \tag{1}$$

Table 2 shows an example of how the target compression ratio of the current frame is determined when frame overflow is allowed. GTCR is 3.0, High_TCR is 3.05, Higher_TCR is 3.10, and NEAR range is [2.97:3.00]. For case (2-1) in Table 1, previous frame compression ratio (PFCR) is lower than GTCR and within the NEAR range, and previous local target compression ratio (PLTCR) is smaller than High_TCR (3.05). The compression rate is judged as the deficiency state, which is case (1-1) in Table 1, and the target compression ratio of the current frame is determined as High_TCR (3.05). The state for case (2-2) is determined as the deficiency state of PFCR away from the lowest limit of NEAR range, which falls into case (1-2) of Table 1. Since overflow is allowed in this example, LTCR is set as Higher_TCR (3.10). Finally, case (2-3) is determined like case (1-2) in Table 1, because the PLTCR is greater than High_TCR (3.05), whereas PFCR is smaller than GTCR. Since overflow is allowed, LTCR is set as before, even though the frame compression ratio is unable to meet GTCR (3.0) continuously.

3.2 Quantization Type Selection Stage

In the QTS stage, one of four quantization types (Q-Types) is selected to adaptively determine the quantization level of the current line. The four Q-Types are Low-Q, Middle-Q, High-Q, and Super-Q. Each Q-Type has many quantization levels that represent quantization parameters for compression. Super-Q is a special type for images where compression ratios are very low with normal quantization parameters. Table 3 shows the compression ratios of several Q-Types and their quantization levels, where each ratio is the average compression ratio measured with many sample video clips.

Table 1. Local target compression ratio initialization.

Results of previous frame BRCs			New setting of current frame BRCs		
BRC state	Range (PFCR, PLTCR)		Case	Overflow	Current LTCR
	Previous FCR	Previous LTCR			
Deficient (PFCR < GTCR)	In NEAR	PLTCR $\leq$ High_TCR	(1-1)		High_TCR
	Outside NEAR	PLTCR > High_TCR	(1-2)	Allow	Higher_TCR
				Not	LTCR++
Surplus (PFCR $\geq$ TCR)		PLTCR $\leq$ PFCR	(1-3)		LTCR--
		PLTCR > PFCR	(1-4)		PLTCR

(PFCR: previous frame compression ratio, GTCR: global target compression ratio, PLTCR: previous local target compression ratio)

Table 2. An example of initialized local target compression ratio when frame overflow is allowed.

Case	PLTCR	PFCR	Current LTCR
(2-1)	PLTCR $\leq$ 3.05	2.97 $\leq$ PFCR < 3.00	3.05
(2-2)	PLTCR <= 3.05	PFCR < 2.97	3.10
(2-3)	PLTCR > 3.05	PFCR < 3.00	3.10

Table 3. Experiment Parameters.

	High-Q	Middle-Q	Low-Q		Super-Q
QL	CR	CR	CR	QL	CR
0	1.820	2.051	2.511	73	2.554
1	1.888	2.229	2.733	74	2.653
2	1.921	2.306	2.813	75	2.793
3	1.958	2.352	2.854	76	3.049
…	…	…	…	…	…
69	3.437	4.257	4.827	85	4.360
70	3.522	4.302	4.845	86	4.455
71	3.628	4.414	4.970	87	4.561
72	3.663	4.452	5.019	88	4.636

The quantization level number is designed to show that the average compression ratio in the table increases linearly in proportion to the quantization level. However, there are a few non-linear spots, as average values are used. To determine the Q-Type of the next line, the current line compression ratio, the local target compression ratio, and the cumulative compression ratio are considered. However, determining the Q-Type of the next line with only global parameters could cause an inappropriate Q-Type selection. In the proposed BRC, the Q-Type is determined by the current line compression ratio, the quantization level of at least 10 previous lines, and the limit count of Super-Q. Fig. 3 is the pseudocode that determines the Q-Type of the next line. If the limit count meets the UP threshold value (UP_TH), then the Q-Type of the following lines is set to Super-Q. On the other hand, if the limit count meets the DOWN threshold value (DOWN_TH), a Q-Type that has the compression ratio closest to the current line's compression ratio is selected, with the same quantization level as that of the current line. If the number of remaining lines is less than 30%, the limit count for Super-Q is not used, because using the limit count could severely degrade image quality.

```
Algorithm 1: Selection Q-Type

if(Line CR > Line Target CR) then
     {limit_cnt++}

else{limit_cnt--}

if(limit_cnt >= UP_TH) then
        {Q-Type = Super-Q,
         limit_cnt = UP_TH}

else if (limit_cnt <= DOWN_TH) then
        {Search CR of other Q-Type tables
         with the same QL of current line,
         Q-Type = Q-Type that has the CR
         closest to the current Line CR,
         Limit_cnt = DOWN_TH}

else {Q-Type = Q-Type of previous line}
```

Fig. 3. Pseudocode for Q-Type selection (*CR: Compression Ratio).

3.3 Quantization Level Determination

The starting quantization level is empirically set to the starting constant, because videos played in mobile and desktop environments contain a lot of text. From the second frame, the average QL value in the previous frame is set as the starting QL. The starting quantization level is expressed in Eq. (2).

$$Starting\ QL = \begin{cases} starting\ constant & if\ \ first\ frame \\ \dfrac{sum\ of\ all\ line\ QL}{frame\ height} & otherwise \end{cases} \qquad (2)$$

In the QLD stage, the quantization level of the next line is determined by the current line compression ratio (LCR). Before determining the quantization level of the next line, the state of the current line is categorized either as Steady

State or Scene Change State based on the difference between the line compression ratios. In the Steady State, the Q-Types of the previous and the current line are identical, so the quantization level is determined as shown in Eq. (3).

$$QL = \begin{cases} QL+1 & \text{if } current\ LCR < LTCR \\ QL-1 & otherwise \end{cases} \tag{3}$$

The Scene Change State is entered when the current line compression ratio is significantly changed. In the Scene Change State, the Q-Type that was determined in the QTS stage is used. Eq. (4) shows how the quantization level of the next line is determined, and Eq. (5) shows how the step size is calculated.

$$QL = \begin{cases} QL_{Base} - Step & \text{if } Q-Type[QL] < current\ LCR \\ QL_{Base} + Step & otherwise \end{cases} \tag{4}$$

$$Step = \frac{\left| Q-Type[QL] - current\ LCR \right|}{offset} \tag{5}$$

QL_{Base} in Eq. (4) refers to the quantization level that would allow achievement of the local target compression ratio, and *offset* in Eq. (5) is the average slope of all of the compression ratios in the Q-Type table.

3.4 Remaining Line Processing Stage

In the RLP stage, if the proportion of uncompressed lines is less than 30% in the current frame, then the quantization level is adjusted to prevent memory overflow, even if image quality could degrade. The cumulative compression ratio (CCR), the local target compression ratio, and the Q-Type of the current line are considered to adjust the quantization level for the next line. Eq. (6) shows how the quantization level is determined. The parameter α is determined empirically.

$$QL = \begin{cases} QL & \text{if } Type\ of\ current\ line = Super-Q, CCR \geq LTCR \\ QL+\alpha & otherwise \end{cases} \tag{6}$$

3.5 Text Line Processing

Finally, in the TLP stage, quantization level is adjusted to improve text legibility when the frame contains text. Unlike the conventional methods that are based on 2-D DWT, such as Gllavata et al.'s method [8], the proposed method uses a few lines of 1-D DWT. For low-complexity text line processing, the proposed method examines the high frequency energy over several lines—based on research on the high-frequency energy of text [9, 10]. For detecting text lines in the proposed method, the high-frequency signals are selected by an finite impulse response (FIR) high-pass filter of the H1 band of a four-level DWT encoder system. Then, the amount of high-frequency energy is measured and stored in a history buffer that holds the measured energies of two previous lines in order to find a vertical text boundary. If the energy data stored in the history buffer exceeds a text energy (E_{TEXT}) threshold value, the quantization level of the following line is restricted to a certain value, as shown in Eq. (7), to guarantee text legibility. The maximum quantization level for text lines is empirically set to QL_{TEXT}.

$$QL = \begin{cases} QL_{TEXT} & \text{if } E_{history\ buffer} > E_{TEXT}, QL > QL_{TEXT} \\ QL & otherwise \end{cases} \tag{7}$$

4. Experimental Results

In these experiments on the proposed BRC, the target frame compression ratio was set to 3.0. With the given compression ratio, the PSNR of the proposed BRC (where compression ratio is determined at the line level) was compared with BRCs optimized at the frame level. The subjective image quality of the text region was also tested with images that have both graphics and text. Finally, the proposed algorithm was tested with videos.

4.1 Comparison to Existing Works

The proposed BRC was compared to a BRC with a fixed quantization parameter optimized for a whole frame (a frame-optimized BRC), a BRC with optimum line quantization parameters per line (a line-optimized BRC), a BRC with a variable quantization parameter determined by a simple comparison (a baseline BRC), Edirisinghe and Bedi's BRC [4], and Jiang's BRC [5]. The images used in the experiment are Kodak images [11] at resolutions of 768x512 and 512x768. In order to show how well the proposed BRC works at any compression ratio, it was compared with the existing works for three target frame compression ratios: 2.0, 3.0, and 4.0. The frame-optimized BRC uses a single optimum quantization level for the whole frame, which meets the target frame compression ratio. The line-optimized BRC is supposed to use the optimum quantization level for each line while meeting the target frame compression ratio. The baseline BRC increases or decreases the quantization level for each line by only comparing the cumulative line compression ratio with the target frame compression ratio. In addition to comparison with optimized BRCs, the proposed bit rate control was compared with two existing bit rate controls [4, 5] after porting them to be incorporated within FALC. The quantization levels in the optimized BRCs were predetermined through a lot of iterations.

Fig. 4 shows a comparison of the PSNR results of the proposed line-based BRC, the frame-optimized BRC, the line-optimized BRC, the baseline BRC, Edirisinghe and Bedi's BRC [4], and Jiang's BRC [5] at the target frame compression ratio of 3.0.

The results show that the PSNR of the proposed BRC is, on average, higher than the baseline BRC by 1.5771 dB, higher than Edirisinghe and Bedi's BRC [4] by 2.5254 dB, and higher than Jiang's BRC [5] by 6.4309 dB. The average of the baseline BRC includes only the images that meet the target frame compression ratio. The PSNR of the

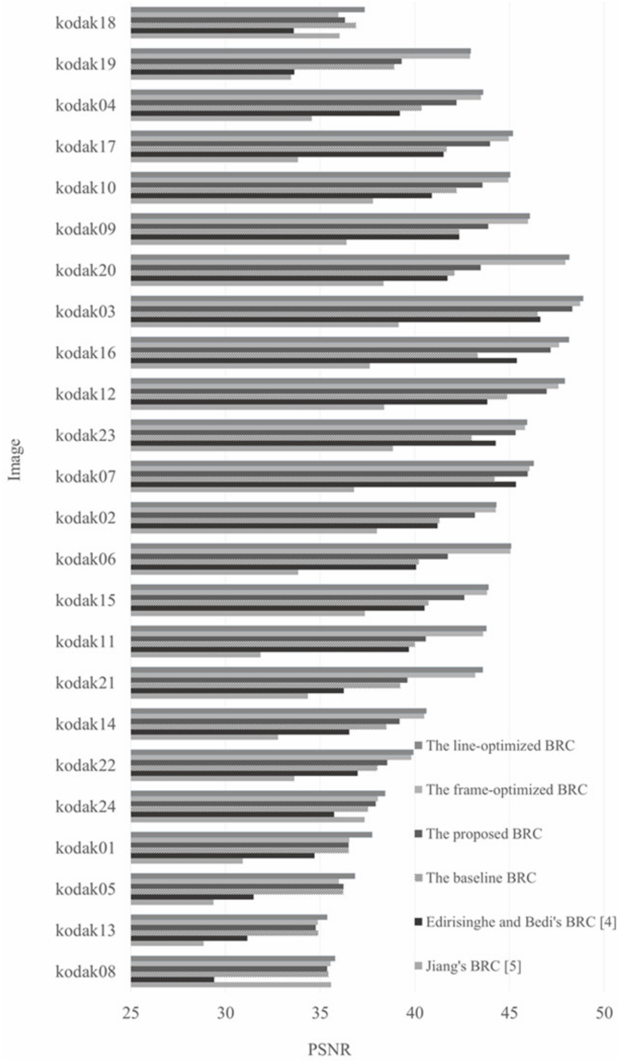


Fig. 4. PSNRs of the BRC performance comparison at the target frame compression ratio of 3.0.

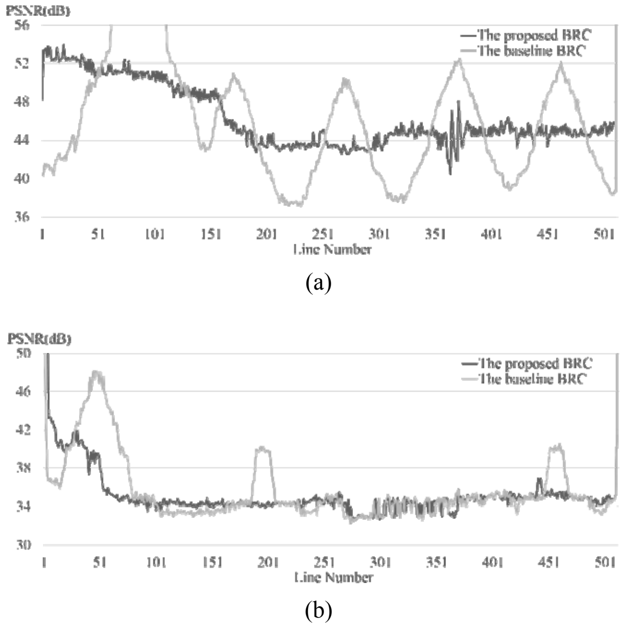


Fig. 5. PSNR results per line of the proposed and the baseline BRC (a) Kodak 23 image, (b) Kodak 13 image.

proposed BRC is, on average, lower than the frame-optimized BRC by 1.4592 dB, and lower than the line-based optimized BRC by 1.5821 dB. The proposed BRC maintains a PSNR close to that of the two optimized BRCs without any omniscient information to meet the target frame compression ratio, and sometimes outperforms the frame-optimized BRC. On the other hand, the baseline BRC does not maintain congruent image quality, as shown in Fig. 5(a). Fig. 5 shows a comparison of the line PSNR results for the proposed BRC and the baseline BRC. There are a few cases in which the baseline BRC outperforms the proposed BRC for images with very low PSNRs, such as Kodak 8 and Kodak 13. However, these images are hard to compress, so there is little room to change quantization level, even with the baseline BRC. If there is a slight chance of quantization level increase, the image quality of the baseline BRC fluctuates, as shown in Fig. 5(b).

Table 4 shows a performance comparison of the proposed line-based BRC and the existing BRCs at the three target frame compression ratios: 2.0, 3.0, and 4.0. For comparison purposes, some parameters related to compression ratio, such as the base quantization level and the local target compression ratio, were set the same as the target frame compression ratio. Each PSNR in the table is the average PSNR of the compressed images that meet the target compression ratio. The average PSNRs of all images are shown in parentheses.

The average frame compression ratios for all BRCs (except the baseline BRC) at the target frame compression ratio of 4.0 meet the corresponding target frame compression ratios. However, Jiang's BRC has higher compression ratios than the other BRCs because of the inaccuracy of target compression ratio prediction with Jiang's BRC. As a result, the reconstructed images with Jiang's BRC have a low average PSNR between 34.9 dB and 35.2 dB. Since the proposed BRC is designed to maintain image quality at a frame compression ratio of 3.0, it is not guaranteed to meet the frame compression ratio of 4.0. However, for images where the frame compression ratio of 4.0 is met, the average PSNR of the proposed BRC is better than Edirisinghe and Bedi's BRC [4] by 2.4 dB. And the subjective image quality with Edirisinghe and Bedi's BRC is degraded in some regions, as shown in Fig. 6.

The comparison of hardware resources for the proposed BRC and other existing BRCs are shown in Table 5. The hardware resources are compared with regard to memory resources and computational resources, such as additions. In Table 5, N represents the height of an image, and K is the number of iterations for optimization. The two optimized BRCs use a frame memory and repeated scanning of the image K times to determine the optimized quantization level while meeting the target compression ratio. On the other hand, the other BRCs (including the proposed BRC) do not use any frame memory, and computational resources are fewer than for optimized BRCs. The proposed BRC needs more computational resources, especially additions, than the baseline BRC, Edirisinghe and Bedi's BRC [4], and Jiang's BRC [5] due

Table 4. BRC performance comparison with different target frame compression ratios.

BRCs	Average frame compression ratio			Number of frames that do not meet the target compression ratio			Average PSNR		
	Target frame compression ratio			Target frame compression ratio			Target frame compression ratio		
	2.0	3.0	4.0	2.0	3.0	4.0	2.0	3.0	4.0
Proposed	2.05	3.01	4.03	0	0	0	52.2	41.3	36.0
Edirisinghe and Bedi's BRC [4]	2.02	3.00	4.01	0	0	0	50.7	38.8	33.5
Jiang's BRC [5]	4.18	4.37	4.47	0	0	4	34.9	35.2	35.2 (34.8)
Baseline	2.04	3.00	3.94	0	0	4	49.0	40.1	37.7 (37.0)
Frame optimized	2.05	3.04	4.03	0	0	0	53.2	42.6	37.0
Line optimized	2.00	3.00	4.00	0	0	0	54.0	42.9	37.4

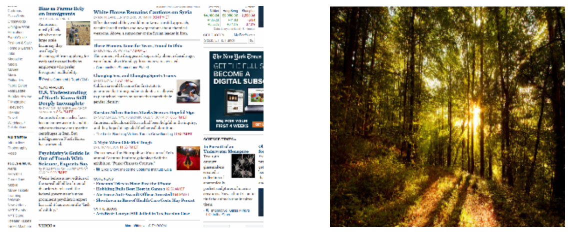
Table 5. Hardware resources for the BRC comparisons.

BRCs	Addition	Shift	Memory
Proposed	26N	N	0
Edirisinghe and Bedi's BRC [4]	11N	0	0
Jiang's BRC [5]	14N	2N	0
Baseline	2N	0	0
Frame optimized	K*2N	0	1 Frame memory
Line optimized	$K*(4N^2 + 10N)$	0	1 Frame memory

Fig. 6. The subjective result of Edirisinghe and Bedi's BRC [4] with low image quality.

(a) (b) (c)

Fig. 7. Results of text line processing (a) original image, (b) processed without our BRC, (c) processed with our BRC.



(a) (b)

Fig. 8. Screenshots of test videos (a) a scene from a video that contains text, (b) a scene from a video without text.

to initialization, quantization type selection, remaining line processing, and text line processing stages. However, subjective and objective image quality from the proposed BRC are better than other BRCs, as shown in Figs. 4 and 6.

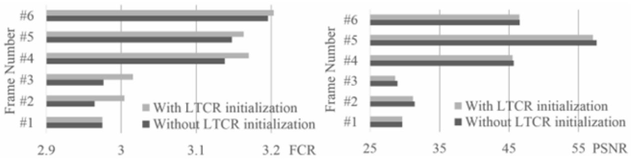
4.2 Image Quality with Text Line Processing

Text line processing in the proposed BRC was evaluated with several images that are composited with images that have many high-frequency components and text in similar proportions. Fig. 7 compares enlarged text regions in the decoded frames, with and without the text line processing applied to the original image. Due to the variation of quantization levels between lines, the text image without the text line processing, seen in Fig. 7(b), is significantly degraded; image quality degradation is barely noticeable in the text image with text line processing seen in Fig. 7(c).

4.3 Experiments with Videos

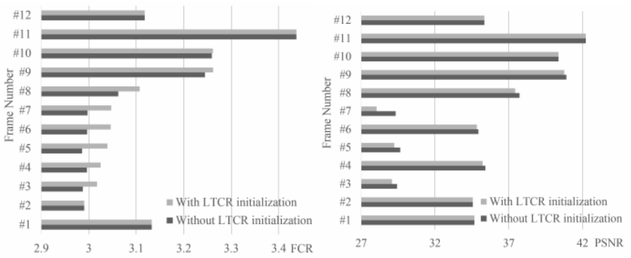
The performance of the proposed BRC was evaluated with videos at 1920x1080 resolution without text and at 1024x874 resolution with lots of text. The image sequences of the test videos were selected so as to make it difficult to meet the frame compression ratio of 3.0. Fig. 8 shows two screenshots from the videos used in the experiment.

Since the compression result of the previous frame is considered at the INIT stage, the performance of the proposed BRC is compared with that of the BRC without adaptive target compression ratio initialization. Figs. 9 and 10 show the frame compression ratio result and PSNR for



(a) (b)

Fig. 9. Frame compression ratio and PSNR results from the BRCs for video with no text (a) frame compression ratio results, (b) PSNR results.



(a) (b)

Fig. 10. Frame compression ratio and PSNR results from the BRCs for video that contains text (a) frame compression ratio results, (b) PSNR results.

BRCs used on image sequences with and without text.

As shown in Figs. 9(a) and 10(a), the frame compression ratios for many frames do not meet the frame compression ratio of 3.0 when the BRC without adaptive local target compression ratio initialization is applied, whereas the frame compression ratio of the proposed BRC mostly meets the frame compression ratio of 3.0, except for one frame. Although the increased frame compression ratio decreases PSNR, the PSNR results with the proposed method are still close to the BRC without the adaptive local target compression ratio initialization, as shown in Figs. 9(b) and 10(b).

5. Conclusion

In this paper, a line-based BRC for display devices is proposed. The proposed BRC determines the compression ratio of each line, and uses little in the way of hardware resources to meet the target frame compression ratio while maintaining image quality. To handle various types of image sequences, the proposed BRC uses several quantization types that consist of appropriate quantization levels. For mobile and desktop environments, a text line-processing algorithm is applied in order to improve the legibility of text in the image.

Experiments show that the PSNR of the proposed method is close to that of an optimized BRC. The proposed BRC also improves the legibility of text, compared to the BRC without text line processing. By using the simple datum of the compression ratio of the previous frame, the proposed BRC successfully maintains the resulting compression ratio at the target frame compression ratio, with little degradation in image quality. The proposed BRC will be further improved with regard to image quality and stability of the compression ratio by using the per-line compression ratios of the previous frame. These issues will be covered in future work.

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