IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 25 May 2023, accepted 23 June 2023, date of publication 28 June 2023, date of current version 14 July 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3290916

RESEARCH ARTICLE

Area-Ware Adaptive Image Compression

HOSEUNG KIM[1], MINHO PARK[2], SEONGHU HONG[3], AND CHANG-SUNG JEONG[4], (Member, IEEE)

[1]Department of Visual Information Processing, Korea University, Seoul 02841, South Korea
[2]School of Computing, KAIST, Daejeon 34141, South Korea
[3]VD Business, Samsung Electronics Company Ltd., Suwon 16677, South Korea
[4]Department of Electrical Engineering, Korea University, Seoul 02841, South Korea

Corresponding author: Chang-Sung Jeong (csjeong@korea.ac.kr)

ABSTRACT Recently, compression is essential to reduce large traffic generated from video or image-based services such as OTT, IOT, smart city, and self-driving cars. The high data compression reduces data traffic, but causes information loss and data quality deterioration. In this paper, we shall propose a new efficient compression method which increases the compression ratio while maintaining the image quality by partitioning the image into 5 different areas each with the different quantization values according to their priority such as intensity, location, size and correlation. We exploit different compression ratio for each of the areas divided based on saliency map according to their visual priority order in order to fully reflect the visual reaction degree of human visual system. We shall show that our method dramatically increases data preservation and compression efficiency by compressing each area with the different quantization values while using the less memory.

INDEX TERMS Computer-vision, object detection, image compression, image segmentation, clustering.

I. INTRODUCTION

Recently, as the demand and supply of services based on image and video such as OTT, IOT, smart city and autonomous vehicles have increased, the traffic of image signals has increased significantly due to high multimedia resolution [1], [2], [3], [4], [5]. Standardized groups such as Joint Picture Experts Group(JPEG) and Joint Video Experts Team(JVET) have established image and video compression standard such as JPEG2000 [6], [7] and high efficiency video coding (HEVC) [8], [9] in order to reduce the image traffic on the network, and announced a new compression standard, Versatile Video Coding(VVC) in 2020 [10], [11], [12]. Compression standards have been developed to remove temporal and spatial redundancy of image signal and express the image with the less number of bits while maintaining similar quality to original signal.

Current image compression algorithms employ a block-based compression method, but this approach demands substantial memory and computation as the resolution heightens. Block division produces various result according division methods. The block-based methods using deep learning perform poorly if the feature and vector of the data used to train the model differ from the actual application. Moreover, divided many block generate noise around block boundary during the image compression process. To solve this problem, many methods using CNN filter of various size and direct utilization of block division information in deep learning network have been proposed [13], [14].

The human visual system reacts strongly to area with high difference in texture, color and contrast of image. This area is called a salient area [15]. In computer vision, it is defined as area with higher difference of brightness, color and orientation compared to around area. The saliency map is an image which shows the salient area into gray scale intensity. It was first introduced for situational recognition and image resizing [16]. Later, it has since been used extensively in object tracking, clustering, area segmentation, and automatic extraction of objects of interest from multimedia data, such as images and video.

In this paper, we shall propose a new compression method which increases the compression ratio while maintaining the image quality by partitioning the image into 5 different areas each with the different quantization values according to

The associate editor coordinating the review of this manuscript and approving it for publication was Yongjie Li.

their priority such as intensity, location, size and correlation. We exploit different compression ratio for each of the areas divided based on saliency map according to their visual priority order in order to fully reflect the visual reaction degree of human visual system. Object areas are partitioned into a set of object clusters each of which consists of adjacent object areas. We use a hierarchical clustering algorithm [17], [18] which does not specify the number of clusters, while the most widely used K-means clustering algorithm [19] has the disadvantage of specifying the number of clusters. Clusters are evaluated and automatically classified into 5 areas according to the importance of the object areas included in the cluster. We shall show that our method dramatically increases data preservation and compression efficiency by compressing each area with different quantization according to its intensity, location, size and correlation while using the less memory.

Our paper is organized as follows: In Chapter 2, we describe about related works. In Chapter 3, we present our compression method in detail, and in chapter 4, explain about the performance evaluation for our method. In Chapter 5, we give a conclusion.

II. RELATED WORK

A. SALIENCY MAP

The saliency map is commonly used in computer vision and cognitive psychology to study visual attention and to understand how the human visual system processes information. It can also be used to train machine learning models and to evaluate their performance [20]. It is a visualization method used to identify the most significant areas in an image or video. It finds important pixel or area on image according to color, intensity and shape similar to object recognition or human attention. Then, result image is represented into grayscale intensity according to importance of pixel or area.

There are two main categories of saliency map algorithms: bottom-up and top-down. Bottom-up algorithms are based on the physical properties of the input data, such as color, contrast, and texture, while top-down algorithms use prior knowledge and high-level information about the task and the scene.

The results of the saliency map can be further processed and combined with other methods, such as object detection and segmentation, to improve the accuracy and robustness of computer vision algorithms. Moreover, saliency maps are an important topic in the field of computer vision and cognitive psychology, and their contribution to the understanding of visual attention and the development of computer vision algorithms makes various applications.

We shall use saliency map to extract object area, and evaluate object area by calculating grayscale intensity weight as well as its location and size weights.

B. JPEG

JPEG (Joint Photographic Experts Group) is a commonly used image compression format. It uses lossy compression, which means that some image information is lost during the compression process in order to reduce the file size. The compression ratio can be adjusted, allowing a trade-off between image quality and file size. This makes JPEG particularly useful for compressing images for digital photography and web applications, where file size and loading time are important considerations. The JPEG format supports 24-bit color, it suitable for photographs and other high-color images and not suitable for images with large areas of solid color or text. Despite these limitations, JPEG remains a popular format for storing and sharing digital images, due to its widespread support and compatibility with a wide range of devices and software applications [21], [22].

FIGURE 1. Example of saliency map.

The compression algorithm works by dividing an image into pixel blocks, transforming each block into the frequency domain using a Discrete Cosine Transform (DCT), and then quantizing the DCT coefficients [23]. This results in a much smaller representation of the image data, which can then be further compressed using entropy encoding techniques.

We shall use method to increase the compression ratio while maintaining the image quality of the visually interesting area as much as possible by changing the compression ratio of each evaluated area according to the priority.

FIGURE 2. Example of JPEG.

C. HIERARCHICAL CLUSTERING

Hierarchical clustering is a type of unsupervised machine learning technique used for grouping similar data points into clusters. It is clustering which builds a hierarchy of clusters by successively merging or splitting existing clusters.

There are two main types of hierarchical clustering: Agglomerative and Divisive. Agglomerative clustering starts with individual data points as separate clusters and merges them into larger clusters. Divisive clustering, on the other hand, starts with all data points as a single cluster and splits it into smaller clusters.

One advantage of hierarchical clustering is which can be used to produce cluster between randomly distributed data. Additionally, it is a flexible technique which can be applied to a wide range of datasets, including both continuous and various data types [24].

However, hierarchical clustering can be computationally expensive, especially for large datasets, and it can also be sensitive to the choice of linkage method used to define the distance between clusters. Despite these limitations, hierarchical clustering remains a widely used and powerful for clustering and exploratory data analysis.

We shall use hierarchical clustering to create clusters according to the distance and importance of object areas on the image.

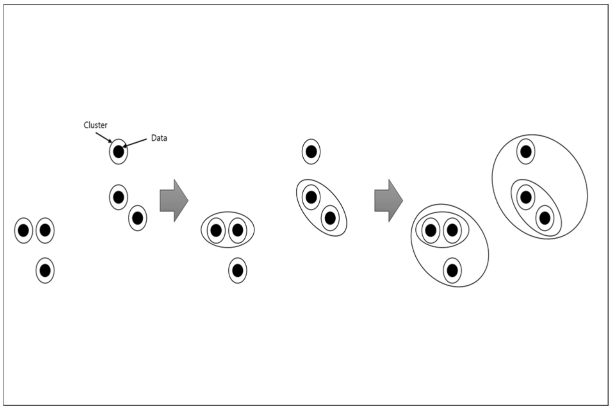


FIGURE 3. Example of hierarchical clustering.

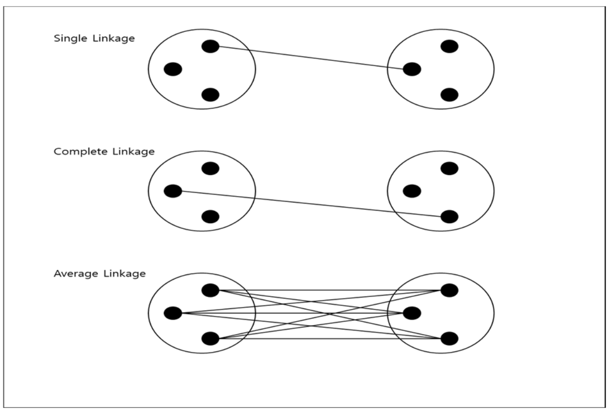


FIGURE 4. Example of measurement method for clustering.

III. AREA-WARE IMAGE COMPRESSION

A. OVERVIEW

In this paper, we propose an efficient image compression method which exploits different compression ratio for each of the areas divided based on saliency map: major object area, minor object area, major interest area, minor interest area and background area.

Our method consists of the following four steps.

First, we extract all the object areas each of which is composed of connected adjacent pixels with the strong grayscale in the saliency map.

Second, we find, for each object area M, its priority by calculating, for each pixel in M, its weights for its intensity, location and size, and then averaging them, and then classify M into major and minor object areas.

Third, we find an interest area for each object cluster area, and then classify it into major and minor interest areas.

Fourth, we find a background area which is obtained by excluding all the object cluster areas from the image.

In the next subsection, we shall explain about object area, object cluster area, interest area and background area more in detail.

B. OBJECT AREA

The saliency map is an image which indicates human visual response intensity with gray scale according to the differences of brightness, color and direction of pixels. It is mainly used to detect object areas in a similar way as human visual systems.

Since a pixel has higher gray scale intensity in the saliency map as its difference of color, brightness and direction increases with respect to its neighboring pixels, we uses the saliency map for extracting object area which consists of connected pixels with high gray scale intensity as follows:

First, a saliency map is created using the chrominance and luminance values of the YUV format image [25].

Second, we execute binarization using the median value of the gray scale values greater than zero in the salience map, since result using average value depends on the number of pixels with low or zero brightness values in the image.

Third, we eliminate noises by repeatedly executing erosion and dilation mask operations, and connect adjacent pixels.

Fourth, we find every object area which consists of those pixels connected in the saliency map, and label each object area.

C. OBJECT AREA PRIORITY

Priority of each object area is evaluated by calculating gray scale intensity weight in the saliency map as well as its location and size weights, since a larger object located more close to the center of the image tends to be recognized as distinguished one [26], [27].

First, the gray scale intensity weight for each object area M is calculated by finding the average of gray scale intensity for those pixels in M of the saliency map.

Second, the location weight for each object area M is calculated by the distance between the center of M and the center of the image.

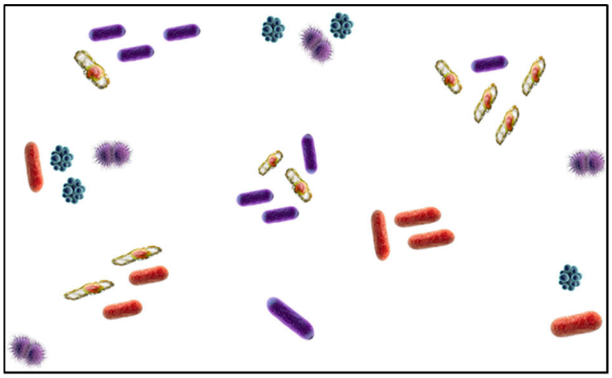
Third, the size weight for each object area M is calculated by finding the number of pixels in M.

Forth, the priority of each object area M is obtained by the average value of the gray scale intensity weight, location weight and size weight for M in saliency map.

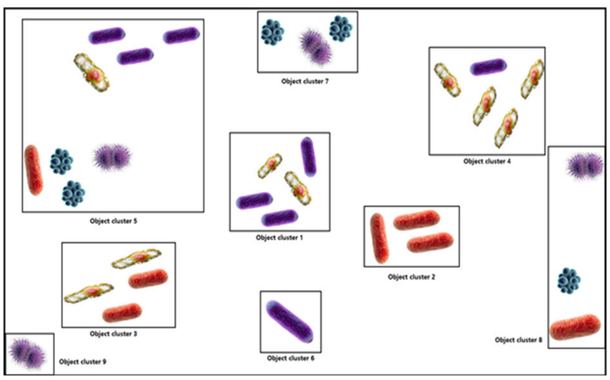
D. OBJECT CLUSTER

Object areas are partitioned into a set of object clusters each of which consists of adjacent object areas. Although the K-means clustering algorithm is widely used, it has the disadvantage of specifying the specification of the number of clusters. We shall use a hierarchical clustering algorithm which does not specify the number of clusters as follows.

Initially, we start from the clusters each of which contains one object area. The average distance is suitable to automatically complete the clustering if number of object area is random. Let D be the average distance between object areas partitioned in the cluster. Next, we repeatedly find, for each cluster C from the highest priority to lower one, its nearest object area N among the ones with its distance from C less than D, and insert N into C until there remains no such object areas. The priority of the cluster C is obtained by calculating the average priority of object areas in C.



a) Test image



b) Clustering result

FIGURE 5. Clustering result of the test image.

Let $C = \{O_1, O_2, \ldots, O_n\}$ be the object clusters. We classify each object cluster O_i into major if its priority average of object areas in O_i is greater than the threshold; otherwise minor.

E. AREA CLASSIFICATION

The input image is classified into 5 areas: major object area, minor object area, major interest area, minor interest area and background area as follows:

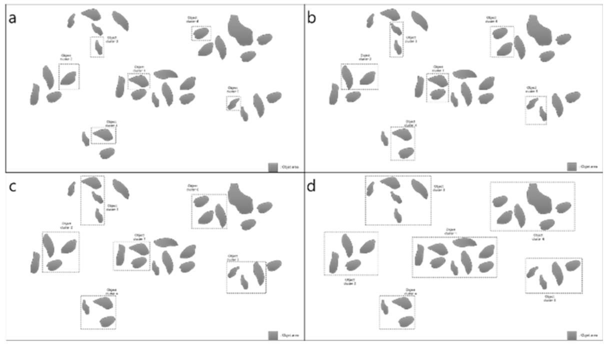


FIGURE 6. Example of the clustering process.

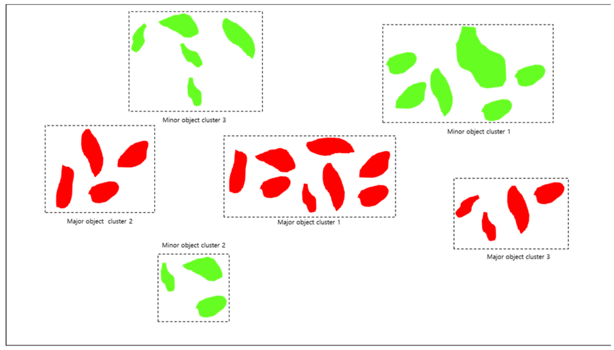


FIGURE 7. Example of classification into major and minor cluster.

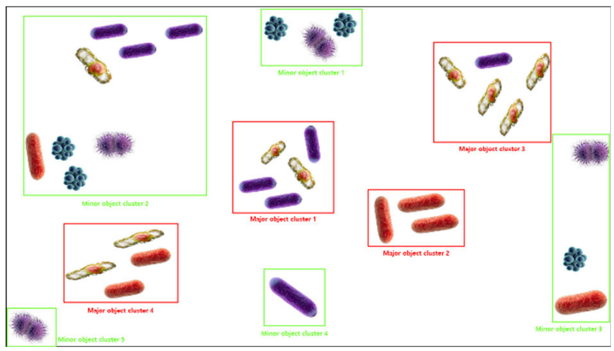


FIGURE 8. Classification result into major and minor cluster of test image.

1) Each object area is major object area if it belongs to major object cluster; otherwise minor.
2) We define, for each major object cluster MOC, its major cluster area by the minimum enclosing rectangle for all the object areas in MOC.
   Similarly, we define, for each minor object cluster MOC, its minor cluster area by the minimum enclosing rectangle for all the object areas in MOC.
3) We define, for each major cluster area MCA, its major interest area by the area obtained by eliminating all the object areas from MCA.
   Similarly, we define, for each minor cluster area MCA, its minor interest area by the area obtained by eliminating all the objects areas from MCA.

4) A background area is defined as the one obtained by excluding all the object areas and interest areas from the image.

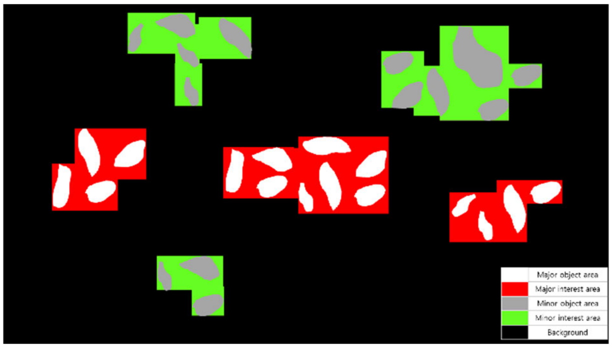


FIGURE 9. Example of classification into 5 type areas.

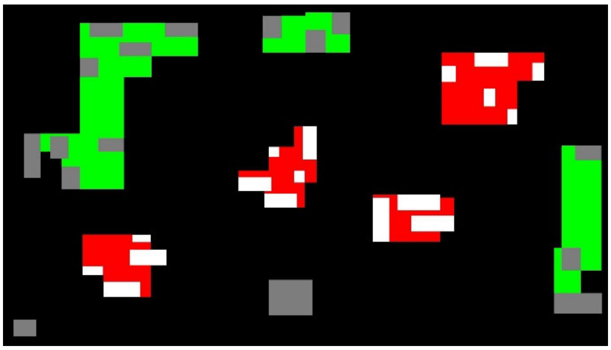


FIGURE 10. Classification result into 5 type areas of test image.

F. IMAGE COMPRESSION

We shall divide the image into 5 areas in their visual priority order starting from the highest: major object area, minor object area, major interest area, minor interest area and background area.

Then, we use 5 different compression ratio for each area according to its priority order which fully reflects the visual reaction degree of human visual system, i.e. the lowest compression ratio for major object area, the higher compression ratio for minor object area, major interest area, minor interest area and the highest compression ratio for the background.

IV. PERFORMANCE EVALUATION

Four images are used as input images: Bacteria(FHD), Balloon 1(4K), Balloon 2(HD) and Bird(HD).

We shall use five cases of quantization values for each of 5 areas as shown Table 1. Standard JEPG uses the same compression ratio for all the areas as shown in Table 2.

Our method sequentially increases the compression ratio according to their visual priority. The previous method, standard JPEG uses the median value of each test case to compare the compression results of the entire image. Figure 12 shows the ratio for each areas of 4 images obtained by applying our method to them.

We compare PSNR (Peak Signal-to-Noise Ratio) and number of bits in addition to file size to evaluate the compression result.

PSNR is measured in decibels (dB) and is a ratio of the peak signal power to the noise power. Higher PSNR values indicate better image quality, while lower values indicate more distortion or loss of information.

Generally, images with more bits per pixel will have higher quality and greater color depth. However, higher bit depths also result in larger file sizes, so there is a trade-off between image quality and file size.

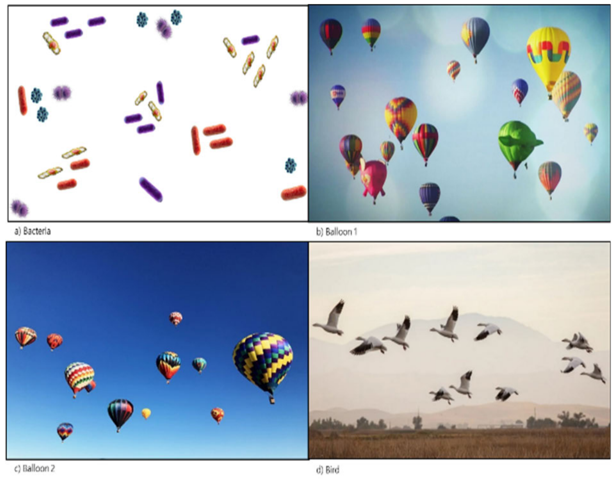


FIGURE 11. Test image.

TABLE 1. Quantization value of each area using our method.

	Quantization value				
	case Ⅰ	case Ⅱ	case Ⅲ	case Ⅳ	case Ⅴ
Major Object Area	1	1	1	1	1
Minor Object Area	2	4	6	8	10
Major Interest Area	3	5	8	10	20
Minor Interest Area	5	10	15	20	30
Background Area	10	20	30	40	50

TABLE 2. Quantization value of each area using standard JPEG.

	Quantization value				
	case Ⅰ	case Ⅱ	case Ⅲ	case Ⅳ	case Ⅴ
All Area	3	5	8	10	20

A. FILE SIZE

We compare the file size between our method and standard JPEG as shown in Figure 13. Bacteria image has the largest file size, since it contains the object areas higher than those of other images even though its background area ratio is more than 50%.

Balloon 1 has the smallest background area ratio. However, it has the file size smaller about than standard JPEG by 14%

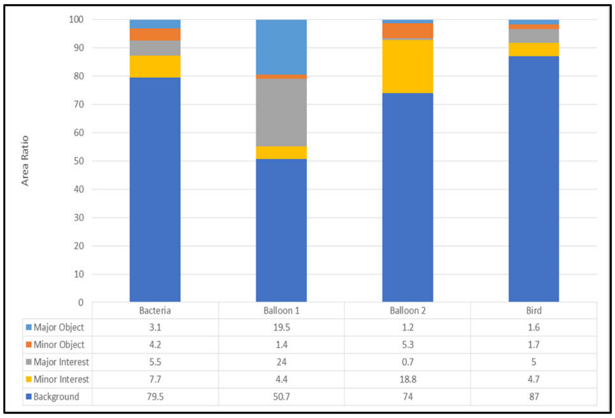


FIGURE 12. Ratios of each area for 4 images.

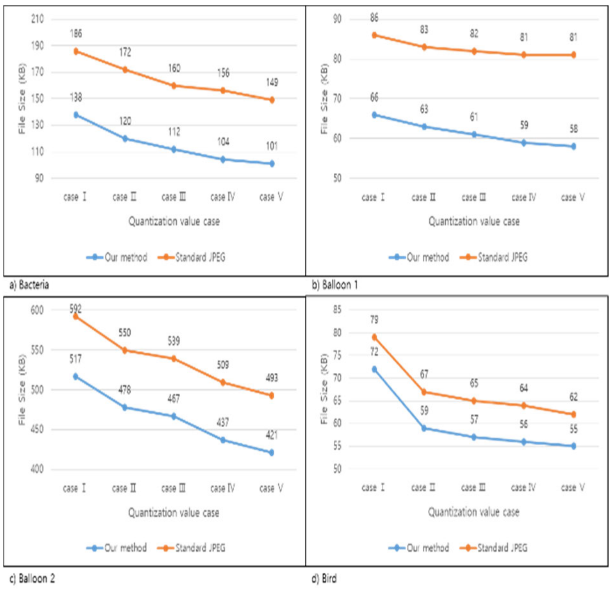


FIGURE 13. File size for four images w.r.t standard JPEG.

while maintaining the image quality of major object and major interest areas almost similar to the original image. Balloon 2 has the smallest file size except Bird, since the ratio of minor object areas and minor object areas is higher than those of other images, thus sharply increasing the compression efficiency. Bird has the smallest file size, since it has the highest ratio of background area ratio. It shows that compression efficiency increases as the ratio of background area does.

In average, our method decreases the file size by about 20% for 4 images with respect to standard JPEG as shown in Figure 14.

B. PSNR

We compare PSNR between our method and standard JPEG [28], [29], [30]. Figure 15 shows that PSNR in our method is higher than that in standard JPEG for all the images.

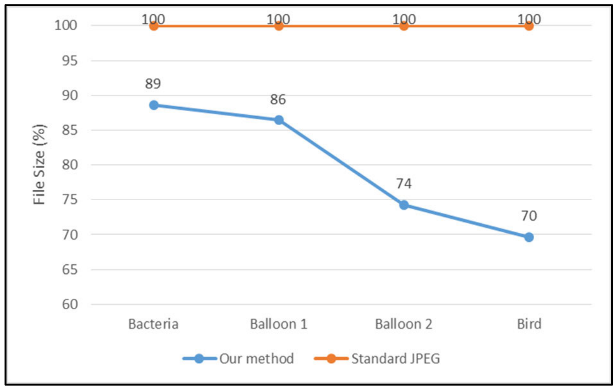


FIGURE 14. File size ratio for 4 images w.r.t standard JPEG.

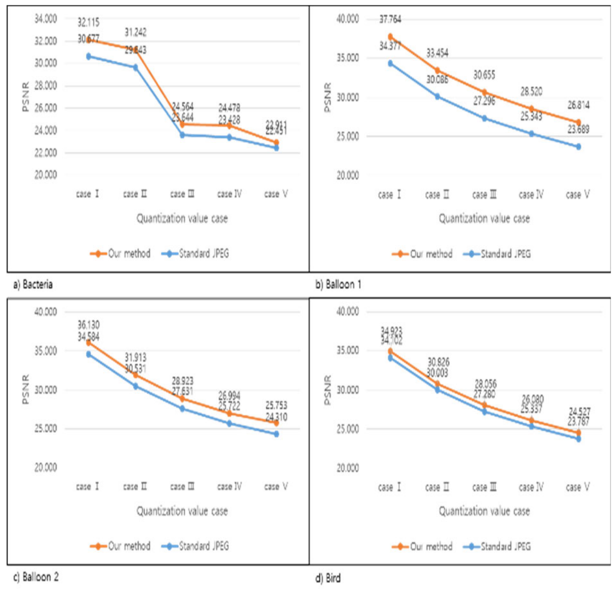


FIGURE 15. PSNR for four images w.r.t standard JPEG.

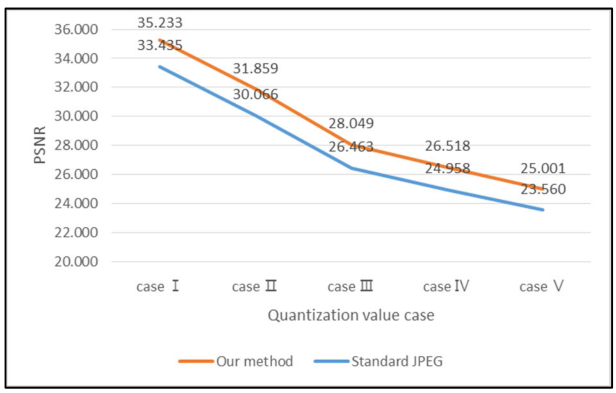


FIGURE 16. Average PSNR w.r.t standard JPEG.

In average, PSNR in our method is higher than standard JPEG by about 10 % as shown in Figure 16.

We compare PSNR between 4 images as shown in Figure 17. Bacteria image has the largest decrease in PSNR,

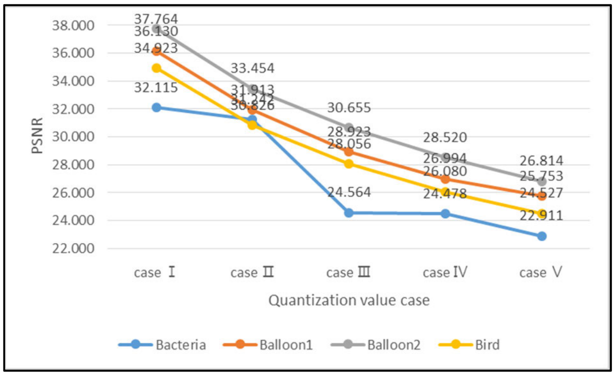


FIGURE 17. PSNR for four images.

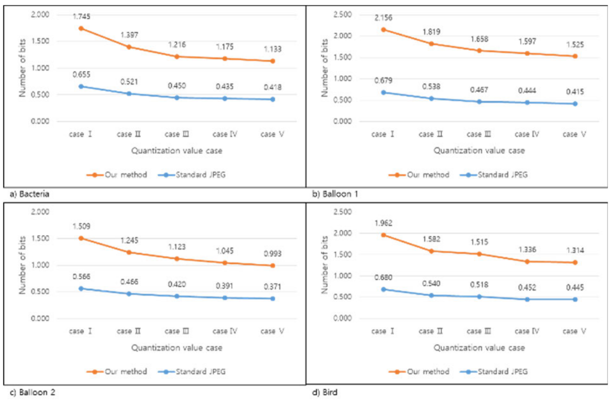


FIGURE 18. Number of bits for four images w.r.t standard JPEG.

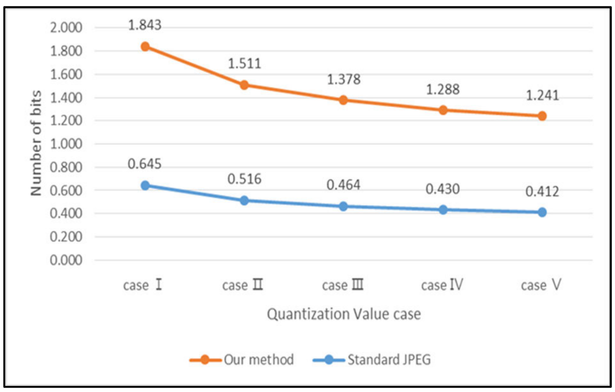


FIGURE 19. Average Number of bits w.r.t standard JPEG.

since the number of object area is higher than other images and image quality difference is increased by the wide boundary between object areas and background area.

In Balloon 1 and Balloon 2, the PSNR is decreased according to the quantization value of background area. It maintains a higher PSNR than standard JPEG by increasing the compression ratio of the background area while maintaining the image quality of the major object area, minor object area, major interest area and minor interest area. Bird has the highest ratio of background area. It shows result similar to standard JPEG used one quantization value.

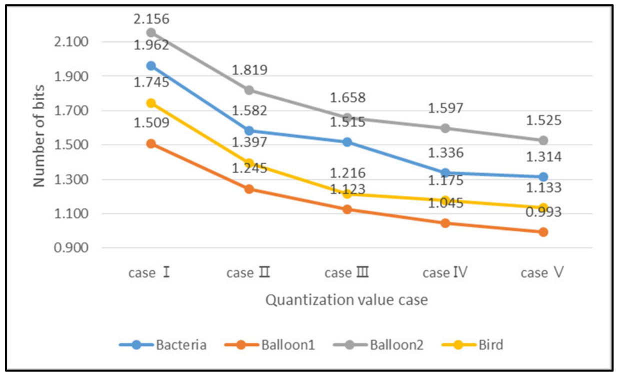


FIGURE 20. Number of bits for four images.

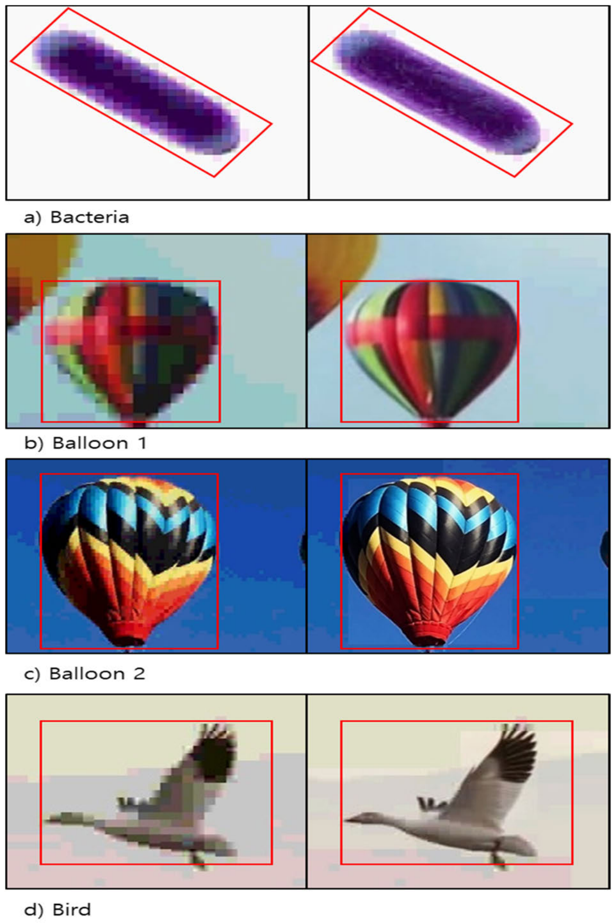


FIGURE 21. Image quality comparison for 4 images w.r.t standard JPEG.

C. NUMBER OF BITS

We compare the number of bits per pixel between our method and standard JPEG [31], [32], [33]. Figure 18 shows that number of bits in our method is higher than that in standard JPEG for all the images.

Our method decreases the overall file size by about 300% with respect to standard JPEG as shown in Figure 19.

We compare number of bits per pixel between 4 images as shown in Figure 20. Bacteria image has the largest number of bits except Balloon 1, since it contains the object areas higher than those of other images even through the ratio of background area more than 50%. It shows that number of bits improves according to number of object area. Balloon 1 image has the largest number of bits since it contains the smallest ratio of background area and maintains the image quality of major object areas similar to the original image. In Balloon 2 image and Bird image, the number of bits is decreased according to the quantization value while maintaining the quality of object areas and interest areas.

D. IMAGE QUALITY

Next, we evaluate our method in terms of image quality with respect to standard JPEG. As shown in Figure 21, standard JPEG shows the image quality degradation for the object area, while our method almost preserves the original quality by decreasing the compression ratio for the object areas with the higher priority.

V. CONCLUSION

In this paper, we have proposed the efficient image compression method which exploits different compression ratio for each of 5 areas divided based on saliency map. We shall divide the image into 5 areas in their visual priority order: major object area, minor object area, major interest area, minor interest area and background area. We use 5 different compression ratio for each area according to its priority order which fully reflects the visual reaction degree of human visual system, i.e. the lowest compression ratio for major object area, the higher compression ratio for minor object area, major interest area, minor interest area and the highest compression ratio for the background. Object areas are partitioned into a set of object clusters each of which consists of adjacent object areas. Unlike the commonly used K-means clustering algorithm, which requires specifying the number of clusters, we utilize a hierarchical clustering algorithm that eliminates this necessity. Clusters are evaluated and automatically classified into 5 areas according to the importance of the object areas included in the cluster.

We have shown that our method dramatically increases data preservation and compression efficiency by compressing each area into different quantization according to intensity, location, size and correlation while using the less memory and decreasing the image degradation. The file size in our method decreases by about average 20%, PSNR increases by about average 10%, and the number of bits per pixel increases by about average 300% with respective to standard JPEG. The evaluation performance about number of bits per pixel shows more performance improvement compared to other performance evaluations by maximizing the compression of the background area and minimizing the compression of the object area.

Also, we evaluate our method in terms of image quality with respect to standard JPEG. Our method almost preserves the original quality by decreasing the compression ratio for the object areas with the higher priority while standard JPEG shows the image quality degradation for the object area. Therefore, our method improves the overall compression performance while using the less memory and decreasing the image degradation.

Our method can be used to efficiently manage massive image data sets created by high-resolution image and video service such as OTT, IOT, smart city and self-driving car. Moreover, image communication traffic can be efficiently reduced by maximizing the compression ratio while maintaining the image quality for the major object and interest areas of the image. For future works, we shall improve the compression efficiency for detail such as different sizes and distribution of object areas.

REFERENCES

[1] J. H. Lee, "The growth and impact of OTT on video viewing behavior," *Asian-Pacific J. Convergent Res. Interchange*, vol. 6, no. 1, pp. 41–50, Jan. 2020.
[2] A. Ahmad and L. Atzori, "MNO-OTT collaborative video streaming in 5G: The zero-rated QoE approach for quality and resource management," *IEEE Trans. Netw. Service Manag.*, vol. 17, no. 1, pp. 361–374, Mar. 2020.
[3] A. Rahman, M. S. Hossain, N. A. Alrajeh, and F. Alsolami, "Adversarial examples—Security threats to COVID-19 deep learning systems in medical IoT devices," *IEEE Internet Things J.*, vol. 8, no. 12, pp. 9603–9610, Jun. 2021.
[4] S. Y. Jang, Y. Lee, B. Shin, and D. Lee, "Application-aware IoT camera virtualization for video analytics edge computing," in *Proc. IEEE/ACM Symp. Edge Comput. (SEC)*, San Francisco, CA, USA, Oct. 2018, pp. 132–144.
[5] M. S. Hossain and G. Muhammad, "Emotion-aware connected healthcare big data towards 5G," *IEEE Internet Things J.*, vol. 5, no. 4, pp. 2399–2406, Aug. 2018.
[6] M. Rabbani and R. Joshi, "An overview of the JPEG 2000 still image compression standard," *Signal Process., Image Commun.*, vol. 17, no. 1, pp. 3–48, Jan. 2002.
[7] W. B. Pennebaker and J. L. Mitchell, *JPEG: Still Image Data Compression Standard*. New York, NY, USA: Springer, 1992.
[8] G. J. Sullivan, J. Ohm, W. Han, and T. Wiegand, "Overview of the high efficiency video coding (HEVC) standard," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 22, no. 12, pp. 1649–1668, Dec. 2012.
[9] F. Bossen, B. Bross, K. Suhring, and D. Flynn, "HEVC complexity and implementation analysis," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 22, no. 12, pp. 1685–1696, Dec. 2012.
[10] B. Bross, Y. Wang, Y. Ye, S. Liu, J. Chen, G. J. Sullivan, and J. Ohm, "Overview of the versatile video coding (VVC) standard and its applications," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 31, no. 10, pp. 3736–3764, Oct. 2021.
[11] B. Bross, J. Chen, J. Ohm, G. J. Sullivan, and Y. Wang, "Developments in international video coding standardization after AVC, with an overview of versatile video coding (VVC)," *Proc. IEEE*, vol. 109, no. 9, pp. 1463–1493, Sep. 2021.
[12] A. Wieckowski, J. Ma, H. Schwarz, D. Marpe, and T. Wiegand, "Fast partitioning decision strategies for the upcoming versatile video coding (VVC) standard," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Sep. 2019, pp. 4130–4134.
[13] D. Mishra, S. K. Singh, and R. K. Singh, "Deep architectures for image compression: A critical review," *Signal Process.*, vol. 191, Feb. 2022, Art. no. 108346.
[14] D. Maleki, S. Nadalian, M. Mahdi Derakhshani, and M. A. Sadeghi, "BlockCNN: A deep network for artifact removal and image compression," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. Workshops*, Salt Lake City, UT, USA, Jun. 2018, pp. 2555–2558.
[15] J. Feng, Y. Wei, L. Tao, C. Zhang, and J. Sun, "Salient object detection by composition," in *Proc. Int. Conf. Comput. Vis.*, Barcelona, Spain, Nov. 2011, pp. 1028–1035.
[16] L. Itti, C. Koch, and E. Niebur, "A model of saliency-based visual attention for rapid scene analysis," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 20, no. 11, pp. 1254–1259, Nov. 1998.

[17] F. Murtagh and P. Contreras, "Algorithms for hierarchical clustering: An overview," in *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 2, no. 1. Chichester, U.K.: Wiley, Jan./Feb. 2012, pp. 86–97.
[18] F. Murtagh and P. Contreras, "Algorithms for hierarchical clustering: An overview, II," in *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 7, no. 6. Chichester, U.K.: Wiley, Nov./Dec. 2017.
[19] A. Likas, N. Vlassis, and J. J. Verbeek, "The global K-means clustering algorithm," *Pattern Recognit.*, vol. 36, no. 2, pp. 451–461, Feb. 2003.
[20] M. Brahimi, M. Arsenovic, S. Laraba, S. Sladojevic, K. Boukhalfa, and A. Moussaoui, "Deep learning for plant diseases: Detection and saliency map visualization," in *Human and Machine Learning: Visible, Explainable, Trustworthy and Transparent*. 2018, pp. 93–117.
[21] H. H. Y. Tong and A. N. Venetsanopoulos, "A perceptual model for JPEG applications based on block classification, texture masking, and luminance masking," in *Proc. Int. Conf. Image*, Chicago, IL, USA, 1998, pp. 428–432.
[22] L. Yuan and T. Ebrahimi, "Image transmorphing with JPEG," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Quebec City, QC, Canada, Sep. 2015, pp. 3956–3960.
[23] R. J. Cintra and F. M. Bayer, "A DCT approximation for image compression," *IEEE Signal Process. Lett.*, vol. 18, no. 10, pp. 579–582, Oct. 2011.
[24] M. F. Balcan, Y. Liang, and P. Gupta, "Robust hierarchical clustering," *J. Mach. Learn. Res.*, vol. 15, no. 1, pp. 3831–3871, Dec. 2014.
[25] L. Goffman-Vinopal and M. Porat, "Color image compression using inter-color correlation," in *Proc. Int. Conf. Image Process.*, Rochester, NY, USA, 2002.
[26] D. J. Bora, "Importance of image enhancement techniques in color image segmentation: A comprehensive and comparative study," 2017, *arXiv:1708.05081*.
[27] D. Kaur and Y. Kaur, "Various image segmentation techniques: A review," *Int. J. Comput. Sci. Mobile Comput.*, vol. 3, no. 5, pp. 809–814, 2014.
[28] S. Winkler and P. Mohandas, "The evolution of video quality measurement: From PSNR to hybrid metrics," *IEEE Trans. Broadcast.*, vol. 54, no. 3, pp. 660–668, Sep. 2008.
[29] D. R. I. M. Setiadi, "PSNR vs SSIM: Imperceptibility quality assessment for image steganography," *Multimedia Tools Appl.*, vol. 80, no. 6, pp. 8423–8444, Mar. 2021.
[30] U. Sara, M. Akter, and M. S. Uddin, "Image quality assessment through FSIM, SSIM, MSE and PSNR—A comparative study," *J. Comput. Commun.*, vol. 7, no. 3, pp. 8–18, 2019.
[31] I. Avcibas, B. Sankur, and K. Sayood, "Statistical evaluation of image quality measures," *IEEE Trans. Image Process.*, vol. 10, no. 2, pp. 313–316, Feb. 2001.
[32] H. R. Wu and K. R. Rao, *Digital Video Image Quality and Perceptual Coding*. Boca Raton, FL, USA: CRC Press, 2017.
[33] H. M. Yasin and A. M. Abdulazeez, "Image compression based on deep learning: A review," *Asian J. Res. Comput. Sci.*, vol. 8, pp. 62–76, May 2021.

HOSEUNG KIM received the B.S. degree from the Department of Computer Software Engineering, Dongeui University, Busan, South Korea, in 2014, and the M.S. degree from the Department of Visual Information Processing, Korea University, Seoul, South Korea, in 2016, where he is currently pursuing the Ph.D. degree. His research interests include image processing and parallel computing environment.

MINHO PARK received the B.S. degree from Sungkyunkwan University, in 2013, and the M.S. and Ph.D. degrees from the School of Computing, KAIST, in 2015 and 2020, respectively. He is currently an Engineer with SEMES. His research interests include data science, software optimization, and databases.

SEONGHU HONG received the M.S. degree from the Department of Electrical and Computer Engineering, Korea University, Seoul, South Korea, in 2018. He is currently a Researcher with VD Business, Samsung Electronics Company Ltd., Seoul. His research interests include parallel distributed processing, computer graphics, embedded computing, machine learning, and deep learning.

CHANG-SUNG JEONG (Member, IEEE) received the B.S. degree from Seoul National University, in 1981, and the M.S. and Ph.D. degrees from Northwestern University, in 1985 and 1987, respectively. He was a Professor with POSTECH, from 1982 to 1992. He was an Associate Researcher with UCSC, from 1998 to 1999. He is currently a Professor with the Department of Electrical and Computer Engineering, Korea University. His research interests include distributed parallel computing, grid computing, ubiquitous computing, networked virtual computing, and development of highly intensive applications, such as stereo image processing and 3-D visualization on collaborative grid and ubiquitous computing environment.