

Information Entropy for Color Image Format Conversion

Gwanggil Jeon

*Department of Embedded Systems Engineering, Incheon National University
119 Academy-ro, Yeonsu-gu, Incheon 406-772, Korea
gjeon@incheon.ac.kr*

Abstract

In this paper, we propose a method which implements Shannon's information theory on entropy evaluation and use the results for weight decision. We assume that there are two conventional methods, LA and ELA. Using Shannon's information theory we obtained entropy values which are used as weights for choosing interpolation method. The original image is downsampled to be low resolution image, where we apply Shannon's entropy evaluation equation. Finally, result image is obtained by weighted interpolation between LA and ELA. Simulation results show the proposed method gives satisfactory results.

Keywords: *Color image, entropy theory, information, downsampling, edge map*

1. Introduction

In general, high-resolution display devices have been swiftly released. However, some broadcasting systems still adopt interlaced scanning format to compromise between frame rate and transmission bandwidth requirements [1-4]. Due to the usage of interlacing scanning format, above devices suffer from unwanted subjective artifacts such as interline flickers, line crawling, and field aliasing. Therefore, deinterlacing methods are requested [5-7].

There are three categories of deinterlacing methods. One is single field methods which uses only one field, therefore it does not exhibit interline flickers. However, due to its halved resolution, result images look blurred. The other two methods are motion adaptive or motion compensated methods. These methods normally give better performance than the previous one. However, they request more computations and they may exhibit unwanted visual artifacts (interline flickers). In this paper, we proposed a method which uses only one field.

The entropy is a assessment of uncertainty [8-12]. Shannon generated a way to allot a score of uncertainty to a probabilistic variable. The entropy is an important component of information theory. Shannon very firstly presented entropy in the year of 1948, which was published in [8]

The information is the thing that we can obtain from the event when uncertainty is reduced. For example, when one flips a coin, one may be not sure which side will be shown. However, after the coin is flipped, the uncertainty becomes zero, because one will know the results, either head or tail. This process is called information. Therefore, we can make a decision that entropy is the process of determine vagueness.

In this paper, we implement Shannon's entropy on test images and obtain entropy map. This entropy map will be used as weights. In Section 2, we review the Shannon's entropy and explain the proposed method with flowchart. Section 3 shows the simulation results and conclusion remarks are shown in Section 4.

2. Proposed method

In information theory, entropy is an evaluation of order and disorder. In other words, the degree of order is uncertainty connected with a random variable. This concept was introduced by Claude E. Shannon in his 1948 [8], and we assume Shannon's entropy is a measure of the information.

The Shannon's entropy stands for an absolute boundary on the best available lossless compression of any image processing, communication, under certain constraints. Thus, one may deal with signals to be encrypted as a sequence of identically-distributed and independent random variables. In communication, the Shannon's source coding theorem (or noiseless coding theorem) indicates that, in the limit, the average length of the smallest capable representation to encrypt the signals in a provided alphabet is their entropy divided by the logarithm of the number of symbols in the target alphabet.

The Shannon's entropy of A is obtained as,

$$H(A) = - \sum_{i=1}^n P(a_i) \log_2 P(a_i). \quad (1)$$

Now we extend Eq. (1) to make more definitions [8] by adding entropy of B ,

$$H(B) = - \sum_{j=1}^m P(b_j) \log_2 P(b_j). \quad (2)$$

$$H(A|B) = - \sum_{i=1}^n \sum_{j=1}^m P(a_i|b_j) \log_2 P(a_i|b_j), \quad (3)$$

$$H(A, B) = - \sum_{i=1}^n \sum_{j=1}^m P(a_i, b_j) \log_2 P(a_i, b_j), \quad (4)$$

$$H(A, B) = H(A) + H(B|A) = H(B) + H(A|B) \quad (5)$$

These are known as conditional entropy, and each form can be reformulated in different way.

Figure 1 shows the flowchart of the proposed method. The propose method has following steps.

- (1) Obtain original images
- (2) Downsample original images to obtain resolution images
- (3) Shannon's entropy application approach to obtain edge map
- (4) Obtain line average (LA) or edge based line average (ELA) methods results
- (5) Assess the edge map in each pixel location, apply suitable method
- (6) Result images are obtained

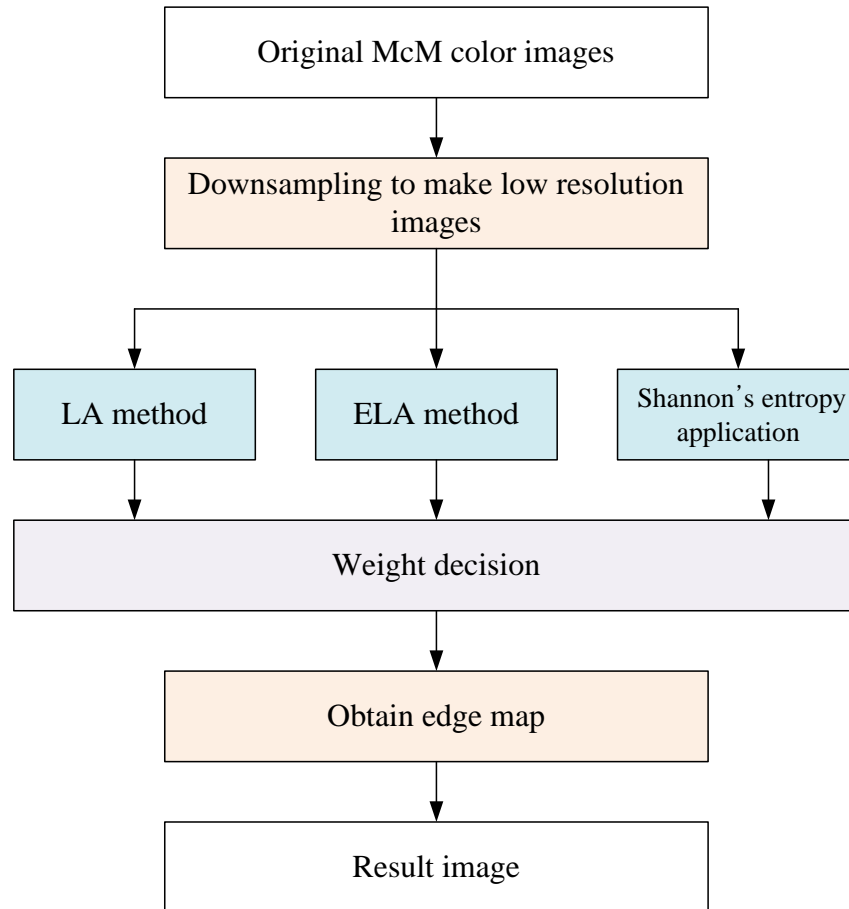


Figure 1. Flowchart of the entropy method.

We supposed that there are two traditional deinterlacing methods: LA and ELA. We first downsmapled the original image with the factor of two, and we obtained low-resolution image. The Shannon's entropy application is applied on low-resolution image, and we obtained entropy map which is known as edge map. The maximal and the minimal values of edge map are 1 and 0. When edge map value (EMV) is bigger than the pre-determined threshold value T , then we employed LA method for system. On the other hand, when EMV is smaller than the pre-determined threshold value T , then we employed ELA method for system. This rule can be represented as

$$\begin{aligned} &\text{if } EMV \geq T, \\ &\quad \text{employed method} = LA \\ &\text{else} \\ &\quad \text{employed method} = ELA \end{aligned} \tag{6}$$



Figure 2. Original #10 McM image.

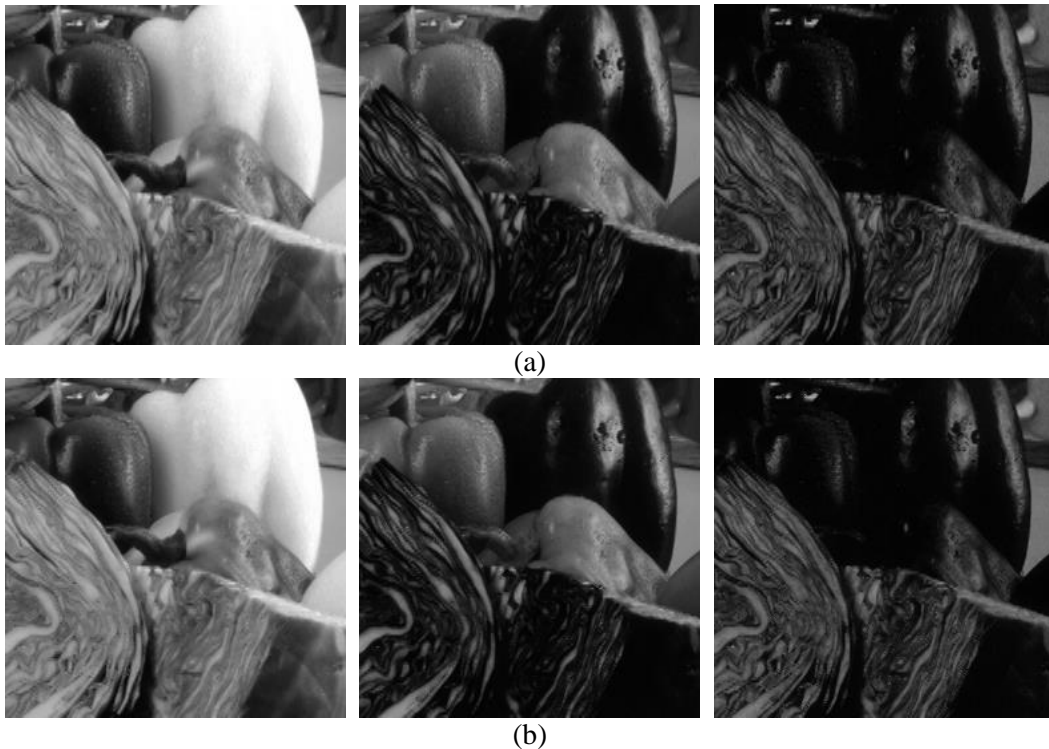


Figure 3. (a) Original #10 McM image, comparison between (a) LA method and (b) entropy method. Note that the left image shows red channel, mid image shows green channel, and the right image shows the blue channel.

We set $T=0.2$, which was obtained empirically. Figures 2 and 3 show result images of conventional LA method and the proposed method. Figure 2 shows the #10 original McM image. Figure 3(a) shows final results images of LA method, where red, green, and blue channels are shown from left to right. In the same manner, Figure 3(b) shows final results images of the proposed method, where red, green, and blue channels are shown from left to right.

3. Simulation results

In this section, a performance comparison is made for objective and visual excellences for the different deinterlacing methods including the presented one. To conduct simulation, we

separated the frame into two fields and then we applied deinterlacing methods. The adopted images were 18 McM images with the size of 500x500 (PNG format).

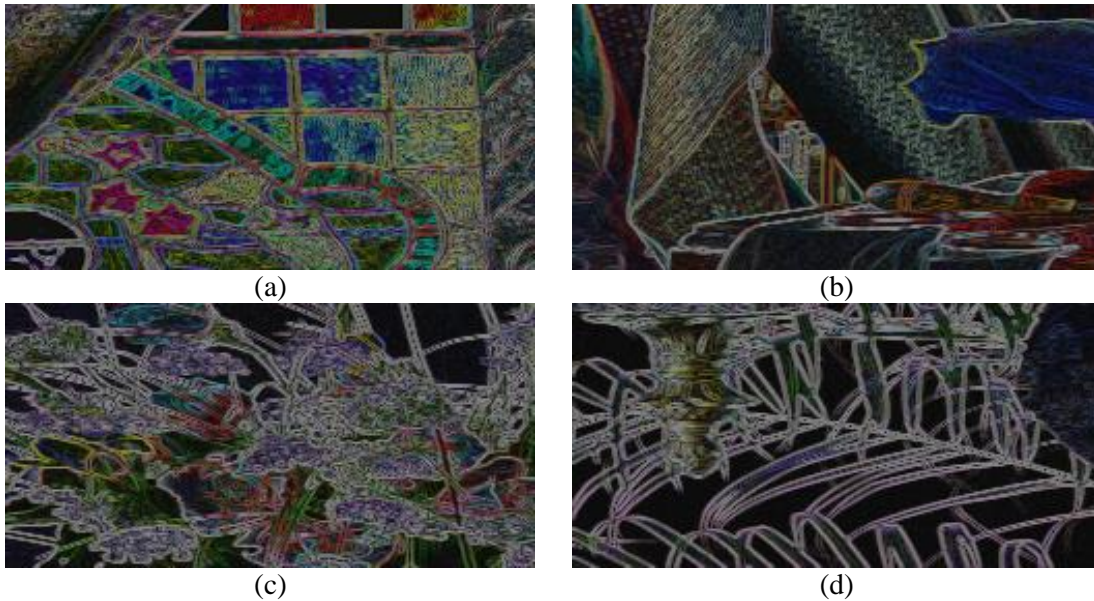


Figure 4. Detected entropy maps for McM images #1-#4.

Four standard test images were used: #1 to #4 for visual assessment. Figure 4 shows examples of edge map for #1 to #4 images. Figures 5-8 exhibits the visual performance using four images. By comparison, we can clearly see that the proposed approach has better visual effect, and the edge we obtained is smoother and sharper than the other one.

To assess objective image quality, we calculated average CPSNR (Figure 9) and CMSE (Figure 10) of 18 McM images. Figures 11-13 show a comparison of LA, ELA, and the proposed method in red, green, and blue channel cases. As to objective performance, the presented method achieves the best PSNR results than the other methods.

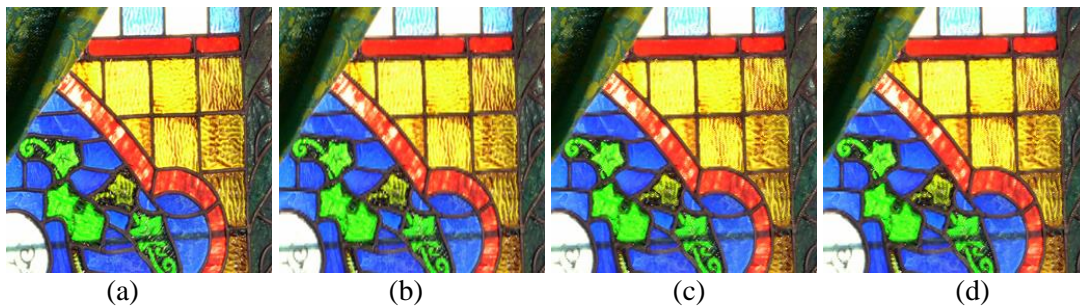


Figure 5. (a) Original McM image #1, results images by (b) LA, (c) ELA, and (d) entropy method.

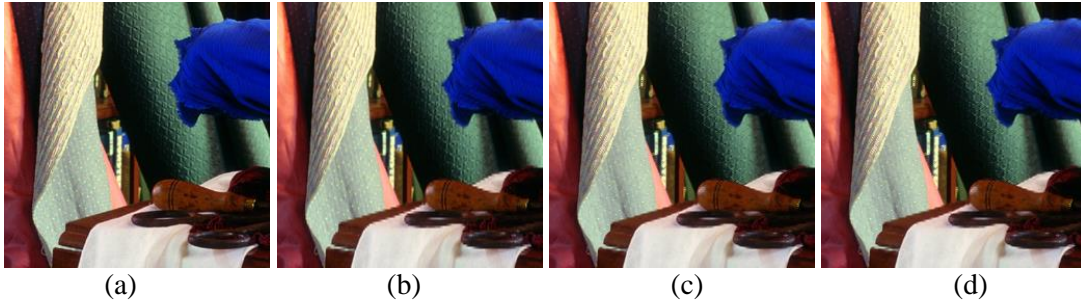


Figure 6. (a) Original McM image #2, results images by (b) LA, (c) ELA, and (d) entropy method.



Figure 7. (a) Original McM image #3, results images by (b) LA, (c) ELA, and (d) entropy method.

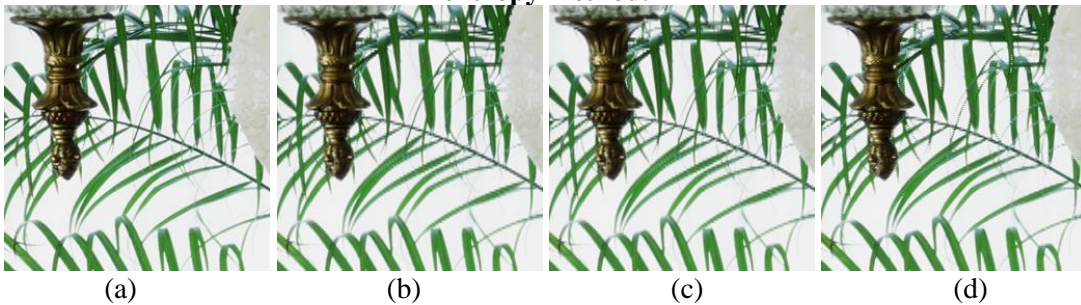


Figure 8. (a) Original McM image #4, results images by (b) LA, (c) ELA, and (d) entropy method.

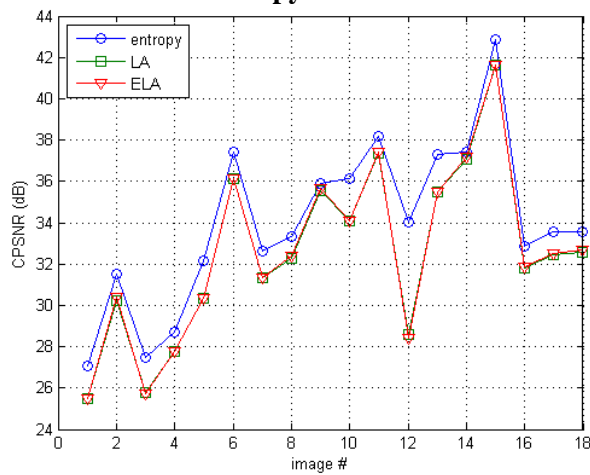


Figure 9. Performance analysis: CPSNR result for R, G, B channels.

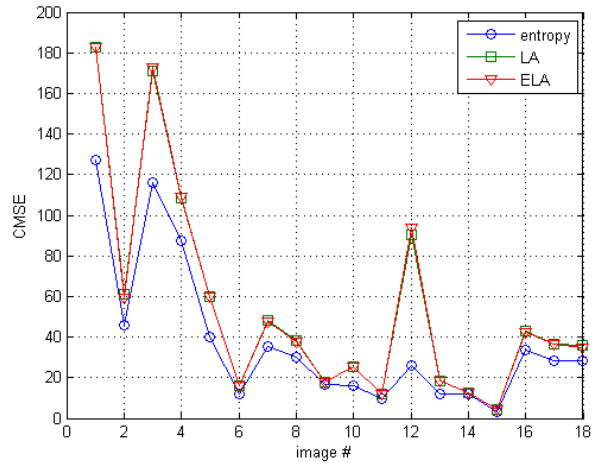


Figure 10. Performance analysis: MSE result for R, G, B channels.

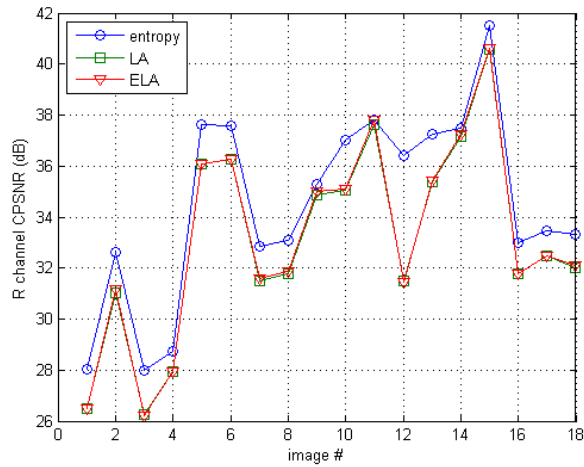


Figure 11. Performance analysis: PSNR result for R channel.

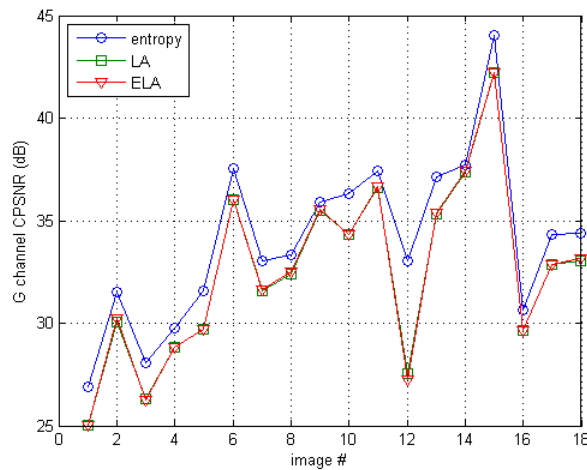


Figure 12. Performance analysis: PSNR result for G channel.

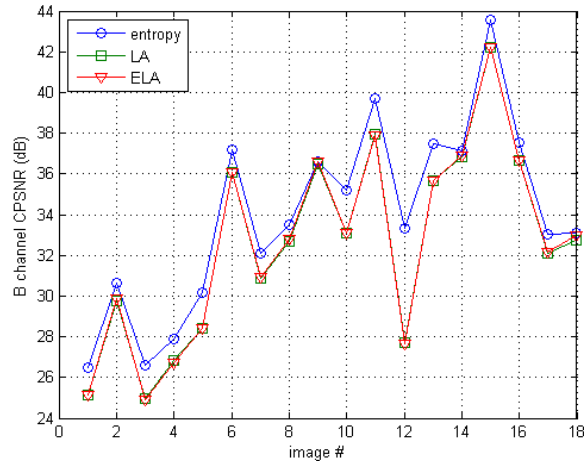


Figure 13. Performance analysis: PSNR result for B channel.

4. Conclusions

In this paper, we proposed a method which implements Shannon's information theory and generated entropy map to employ weight assignment for conventional methods. We supposed that our system employed two traditional methods, and each method was used based on the results of edge map which was generated by Shannon's information theory. The experimental results indicated that the presented approach showed better visual or objective quality than conventional methods.

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References

- [1] E. B. Bellars and G. D. Haan, "De-interlacing: A Key Technology for Scan Rate Conversion", Elsevier, Amsterdam, (2000).
- [2] G. D. Haan and E. B. Bellars, "Deinterlacing—an overview," Proceedings of the IEEE, vol. 86, no. 9, (1998) September, pp. 1839-1857.
- [3] T. Jeong, Y. Kim, K. Sohn, and C. Lee, "Deinterlacing with selective motion compensation," Opt. Eng., vol. 45, no. 7, (2006) July, pp. 077001.
- [4] T. Chen, H. R. Wu, and Z. H. Yu, "Efficient deinterlacing algorithm using edge-based line average interpolation," Opt. Eng., vol. 39, no. 8, (2000) August, pp. 2101-2105.
- [5] W. Kim, S. Jin and J. Jeong, "Novel intra deinterlacing algorithm using content adaptive interpolation," IEEE Trans. Cons. Elect., (2007) August, vol. 53, no. 3, pp. 1036-1043.
- [6] D.-H. Lee, "A new edge-based intra-field interpolation method for deinterlacing using locally adaptive-thresholded binary image," IEEE Trans. Cons. Elect., vol. 54, no. 1, (2008), pp. 110-115.
- [7] P.-Y. Chen and Y.-H. Lai, "A low-complexity interpolation method for deinterlacing," IEICE Trans. Inf. and Syst., vol. E90-D, no. 2, (2007) February.
- [8] C. Shannon, "A mathematical theory of communication. Bell system technical journal, vol. 27, (1948).
- [9] G. Chaitin, "On the Length of Programs for Computing Finite Binary Sequences", J. ACM, vol. 13, no. 4, (1996), pp. 547-569.
- [10] P. Gacs, "On the symmetry of algorithmic information", Soviet Mathematics Doklady, (1974).
- [11] L. Levin, "Laws of Information Conservation (Nongrowth) and Aspects of the Foundation of Probability Theory. Prob. Peredachi Inf., vol. 10, no. 3, (1974).
- [12] A. Renyi, "On Measures of Entropy and Information", In Berkeley Symposium Mathematics, Statistics, and Probability, (1960).

Authors

Gwanggil Jeon, he received the BS, MS, and PhD (summa cum laude) degrees in Department of Electronics and Computer Engineering from Hanyang University, Seoul, Korea, in 2003, 2005, and 2008, respectively.

From 2008 to 2009, he was with the Department of Electronics and Computer Engineering, Hanyang University, from 2009 to 2011, he was with the School of Information Technology and Engineering (SITE), University of Ottawa, as a postdoctoral fellow, and from 2011 to 2012, he was with the Graduate School of Science and Technology, Niigata University, as an assistant professor. He is currently an assistant professor with the Department of Embedded Systems Engineering, Incheon National University, Incheon, Korea. His research interests fall under the umbrella of image processing, particularly image compression, motion estimation, demosaicking, and image enhancement as well as computational intelligence such as fuzzy and rough sets theories. He was the recipient of the IEEE Chester Sall Award in 2007 and the 2008 ETRI Journal Paper Award.

