Journal of The Institute of Electronics and Information Engineers Vol.52, NO.9, September 2015 http://dx.doi.org/10.5573/ieie.2015.52.9.106
ISSN 2287-5026(Print) / ISSN 2288-159X(Online)

논문 2015-52-9-13

# 컬러 영상의 압축 센싱을 위한 경계보존 필터 및 시각적 가중치 적용 기반 그룹-희소성 복원

# ( Visually Weighted Group-Sparsity Recovery for Compressed Sensing of Color Images with Edge-Preserving Filter )

Viet Anh Nguyen*, Chien Van Trinh*, 박 영 현*, 전 병 우**

( Viet Anh Nguyen, Chien Van Trinh, Younghyeon Park, and Byeungwoo Jeon©)

## 요 약

본 논문에서는 컬러 영상의 압축 센싱 복원 기술에 인지시각시스템의 특성을 접목해 복원 영상의 화질을 향상 시키는 방법을 연구하였다. 제안하는 그룹-희소성 최소화 기반 컬러 채널별 시각적 가중치 적용 방법은 영상의 성긴 특성뿐만 아니라 인지시각시스템의 특성을 반영할 수 있도록 설계되었다. 또한, 복원 영상에서의 잡음을 제거하기 위하여 설계한 경계보존 필터는 영상의 경계 부분에 대한 디테일을 보존함으로써, 복원 영상의 품질을 향상 시키는 역할을 한다. 실험 결과, 제안하는 방법이 최신의 그룹-희소성 최소화 기반 방법들보다 평균 0.56 ~ 4dB 더 높은 PSNR을 달성함으로써, 객관적 성능을 향상시킬 수 있음을 확인하였으며, 주관적 화질 또한 기존 방법들에 비해 뛰어나다는 것을 복원된 영상 간 비교를 통해 확인하였다.

## Abstract

This paper integrates human visual system (HVS) characteristics into compressed sensing recovery of color images. The proposed visual weighting of each color channel in group-sparsity minimization not only pursues sparsity level of image but also reflects HVS characteristics well. Additionally, an edge-preserving filter is embedded in the scheme to remove noise while preserving edges of image so that quality of reconstructed image is further enhanced. Experimental results show that the average PSNR of the proposed method is 0.56 ~ 4dB higher than that of the state-of-the art group-sparsity minimization method. These results prove the excellence of the proposed method in both terms of objective and subjective qualities.

**Keywords** : Compressed sensing, Group-sparsity recovery, Color, Edge-Preserving Filter

## Ⅰ. Introduction

Compressed sensing (CS) is a new signal acquisition paradigm that enables sampling of signals at a rate much lower than the Nyquist/Shannon rate[1~3]. Therefore, it can reduce sampling cost much, i.e., complexity and memory requirement. It is also promising in image sensing, especially for high resolution image that normally produces large data volume. In this context, much efforts have been made to improve the performance of CS recovery for images. However, most of them work on improving the quality of CS recovery for gray-scale image, and only few approaches actually focus on color images.

* 학생회원, ** 정회원, 성균관대학교 정보통신대학
(Sungkyunkwan University, College of Information & Communication Engineering)
© Corresponding Author(E-mail: bjeon@skku.edu)

※ 이 논문은 2011년도 정부(미래창조과학부)의 재원으로 한국연구재단의 지원을 받아 수행된 연구임 (No. 2011-001-7578).

Received ; June 13, 2015 Revised ; July 29, 2015
Accepted ; September 3, 2015

Note that it is proved[4] that CS recovery solution for gray-scale images does not work well for color images since the correlation between three RGB color channels are not sufficiently exploited.

CS scheme for color image is first proposed in [5] by combining Bayer color filter with the existing single-pixel CS. In the framework, three color components are sensed separately, but are jointly recovered. Following the same sensing scheme[5], the work [4] proposed a scheme utilizing group-sparsity minimization to account for the high correlation between the three color channels. It performs much better than that [5] in terms of both objective and subjective qualities, however, it still leaves space for further improvement since it only focuses on pursuing the sparsity of image signal thus lacking in caring characteristics of image (e.g., its structures) as well as the human visual system (HVS).

In order to overcome the aforementioned problems while noticing that energy of natural images is mostly concentrated on low frequency coefficients, the work [6] proposed a group-sparsity based hard thresholding method (GIHT) that kept low frequency RGB-grouped coefficients in zigzag scan order, while setting the rest to zero. The number of preserved coefficient groups was chosen as a half of number of measurements which is defined as a multiplication of measurement rate ( $R$, $0 < R < 1$ ) with resolution of original signal. In that way, important low frequency coefficient groups (in terms of energy) were preserved and updated more accurately, expecting to give better quality of reconstructed image. However, it still does not reflect various perceptual sensitivity of each transform coefficient. Additionally, when the measurement rate increases, number of preserved coefficient groups also increases, so insignificant grouped coefficients (i.e., the ones with more noises than image information) may still be kept.

In this paper, to improve the quality of reconstructed image in objective and subjective qualities as well, we propose executing visual weighting in the group-sparsity minimization. The visually weighting scheme is designed to reflect various perceptual sensitivity of each transform coefficient group. A large weight is assigned for visually significant coefficient groups, while small weight is assigned for visually less significant coefficient ones. The weighting process is applied to group-sparsity smoothed $l_{2,0}$-norm minimization (GSL20)[4], which is one of the representative group-sparsity minimization techniques for color images, forming the proposed method named HVS_GSL20. The proposed method not only pursues sparsity of image signal, but also addresses HVS characteristics in the CS recovery. Moreover, human eye is well known for its low pass filter characteristics, so the proposed weighting process is expected to smooth images. Therefore, in order to preserve edges of image better, we incorporate it with an edge-preserving filter, named bilateral filter[7]. By this way, the quality of reconstructed image is further enhanced.

The rest of this paper is organized as follows. Section II represents fundamental background of CS for color images. Section III describes the proposed method of visually weighted group-sparsity minimization with edge-preserving filter. Experimental results are presented in Section IV. Finally, Section V draws some conclusions.

## Ⅱ. Background

It is shown[1] that a finite-dimensional signal $X \in R^N$ having sparse or compressible representation in a sparsity domain (e.g., DCT or DWT) can be exactly recovered with an overwhelming probability from a small number of M measurements ( $M \ll N$ ). In CS, the measurement rate is defined as $R = \frac{M}{N}$ . Projecting X using a measurement matrix $\Phi$ gives the measurement vector as:

$$Y = \Phi X \quad (1)$$

More specifically, in color images, the measurement vector can be represented as:

$$Y_C = \Phi_C X_C \quad (2)$$

where $Y_C = [Y_R^T Y_G^T Y_B^T]^T$, $Y_R$, $Y_G$, and $Y_B$ are respective measurement vector of R, G, and B channels, $\Phi_C$ is a block diagonal measurement matrix, $\Phi_C = diag(\Phi_R, \Phi_G, \Phi_B)$, and $X_C = [X_R^T X_G^T X_B^T]^T$. It satisfies some conditions, e.g., restricted isometric property and incoherence condition[8]. In case an image is not apparently sparse in spatial domain, but has a compressible representation in a transform domain (e.g., DCT) of s after transforming by $X = \Psi s$, (2) can be recast as:

$$Y_C = A s_C \quad (3)$$

where $A = diag(\Phi_R \Psi, \Phi_G \Psi, \Phi_B \Psi)$ and $s_C = [s_R^T s_G^T s_B^T]$ ; $s_R$ , $s_G$ and $s_B$ are transform coefficients of R, G, and B channel, respectively. Since the correlation among the channels is non-trivial, so the transform coefficients of each channel corresponding to the same index (i.e., frequency location of transform) should be also correlated. Therefore, in order to guarantee all three high-valued coefficients corresponding to the same index survive in the process of CS recovery, the transform coefficients of all channels of the same index are grouped together to form a single row vector. Now, the transform coefficients vector can be represented as $b = [b_1, \ldots, b_N]^T$, where $N$ is the number of transform coefficients of each color channel. A straight forward way to find a solution of (3) is to minimize the $l_{2,0}$-norm as following:

$$\min \| b \|_{2,0} \ \ s.t. \ \ Y_C = Ab \quad (4)$$

where $\| b \|_{2,0} = \sum_{m=1}^{N} I(\| b_m \|_2 > 0)$ and $I(\| b_m \|_2 > 0) = 1$ only if $\| b_m \|_2 > 0$ . [9] has reported an approach to overcome NP-hardness of the problem of (4). Next, we will discuss how to address HVS characteristic in the approach to enhance the quality of reconstructed image.

## Ⅲ. Visually Weighted Group-sparsity Recovery With Edge-Preserving Filter

### 1. Visually weighting matrices of R, G, and B channels

Human eye is more sensitive to low frequency coefficients than high frequency ones. By noting the idea of taking the characteristic of HVS into account by having weighting matrix in quantization process of JPEG, it is already proposed to have a perceptual weighting matrix for CS[10] also, but it is done only for luminance component. In this paper, we extend the same idea to all color components by using three quantization tables of color components designed by [11]. The visually weighting matrix for each color component is calculated as:

$$w_{i,j}^k = \frac{1}{q_{i,j}^k} \quad (5)$$

where $k = \{1,2,3\}$ represents R, G, and B channel, respectively; $w_{i,j}^k$ is a weight value given to the corresponding DCT coefficient of color component at frequency position $(i,j)$; $q_{i,j}^k$ is the corresponding element in quantization matrix of color component k. (5) shows that those perceptually more sensitive coefficients are assigned with larger weights (or vice versa). Next we will show how to apply this visually weighting scheme to group-sparsity minimization to enhance the quality of reconstructed image.

### 2. Visually weighted group-sparsity minimization

To overcome the NP-hard problem in solving (4), authors of [4] adopted the similar idea in [9] to form the group-sparsity smoothed $l_{2,0}$-norm (GSL20) minimization. In this method, the non-smooth-norm function is replaced by a smooth zero-mean Gaussian function where smoothness can vary depending on the value of $\sigma$, $f_\sigma(b_m)=e^{(-\|b_m\|_2^2/2\sigma^2)}$, $m=1,\ldots,N$. However, the smooth function $f_\sigma(b_m)$ does not reflect perceptual sensitivity of transform coefficients; therefore, by assigning large weights to perceptually significant coefficients, and small weights to visually less significant coefficients, we not only enhance the sparsity of image in transform domain but also reflect perceptual characteristics well. The proposed visually weighted function (HVS_GSL20) is defined as:

$$f_\sigma(w_m \odot b_m)=e^{(-\|b_m \odot w_m\|_2^2/2\sigma^2)}, m=1,\ldots,N \quad (6)$$

where $w_m=[w_{Rm},w_{Gm},w_{Bm}]$ represents weight values of each color component; "$\odot$" denotes element-wise multiplication. Note that:

$$\lim_{\sigma\to 0} f_\sigma(w_m\odot b_m)=\begin{cases}1\,;\ \|w_m\odot b_m\|_2^2=0\\0\,;\ \|w_m\odot b_m\|_2^2\neq 0\end{cases} \quad (7)$$

Therefore, by replacing the smooth function $f_\sigma(w_m\odot b_m)$ by the non-smooth $l_{2,0}$-norm function, the problem in (4) becomes:

$$\max_b \lim_{\sigma\to 0} f_\sigma(w_m\odot b_m)\ such\ that\ Y_C=Ab \quad (8)$$

Since $f_\sigma(w_m\odot b_m)$ is smooth, so (8) can be solved by the gradient-based method. As explained above, the sparsity degree of weighted transform coefficients $(w_m\odot b_m)$ is higher than that of transform coefficients (b) without any weighting process; therefore, according to (7), when $\sigma$ approaches to zero, the visually weighted GSL20 function($f_\sigma(w\odot b)$) becomes spikier (like $l_{2,0}$-norm) than the GSL20 function ($f_\sigma(b)$). As a result, the group of visually significant coefficients is likely to be recovered more exactly. Table 1 summarizes the proposed HVS_GSL20 algorithm.

표 1. 제안하는 HVS_GSL20 복원 방법
Table 1. The proposed HVS_GSL20 recovery.

| |
|---|
| **Input**: measurement vector $Y_C$; measurement matrix $A$; visually weighting matrix $w=[w_1,\ldots,w_N]$; initial $b^{(0)}$; $\sigma_{\min}=10^{-5}$; $\sigma=c\max(\|b_m\|_2^2)$; $k_{\max}$ and constant $\mu$ |
| **Output**: recovered group correlated coefficients $b_{(reco)}$ |
| **While** $(\sigma>\sigma_{\min})$ and $(k<k_{\max})$ **do** |
| 1. Maximize (8) |
| a. Initialize $g=b^{(k-1)}$ |
| b. Let $\Delta g=[g_1 e^{-\|g_1\odot w_1\|_2^2/2\sigma^2},\ldots,g_N e^{-\|g_N\odot w_N\|_2^2/2\sigma^2}]^T$ |
| c. Update: $g=g-\mu\Delta g$ |
| d. Project: $g=g-A^T(Ag-Y_C)$ |
| 2. Set $b^{(k)}=g$; update $\sigma$; $k=k+1$ |
| **End of while** |
| **Output**: $b_{(reco)}, X_{C(reco)}$ |

### 3. Visually weighted group-sparsity smoothed $l_{2,0}$-norm minimization with edge-preserving filter

Human eye is well known as a low pass filter, so the visually weighting process is expected to smooth image. Additionally, in CS recovery, recovered image suffers much from noise especially when image is sampled at a low measurement rate (since we need to recover N dimensional signal from much lower M dimensional signal). Therefore, in order to further remove noise but still preserve edges of image, we let the image go through a filtering process before being estimated by visually weighted group-sparsity minimization. For this, the bilateral filter[7] is employed since it can smooth image while preserving edges relatively well. The procedure of the proposed method is depicted in Figure 1. After an initialization, image is filtered in spatial domain by a bilateral filter. Then, the filtered image is converted to transform domain (DCT). Solution is updated by projecting it into a feasible set (as step 1.d in Table 1). Then, the groups of correlated transform coefficients are recovered by HVS_GSL20 recovery. This iteration is performed until a stopping criterion is satisfied ( $\sigma \leqq \sigma_{\min}$ or $k \geqq k_{\max}$ ).

## Ⅳ. Experimental Results

### 1. Test conditions

In order to evaluate the performance of the proposed visually weighted group-sparsity minimization, we use four test color images (Lena, Mandrill, Jet, and House). Each image is block-based sensed with a random Gaussian measurement matrix which satisfies the RIP condition and the incoherence condition with transform matrix (DCT) with an overwhelming probability. Block size of 32x32 is used. Each color component is sensed at the same measurement rate ranging from 0.1 to 0.5. Image is reconstructed block by block. The parameters of a bilateral filter are chosen by heuristic experiments such as: window size of bilateral filter is set to 5, and spatial domain and intensity domain standard deviation of a bilateral filter is set to 0.5 and 0.1, respectively. Performances of the proposed methods (HVS_GSL20 and EP_HVS_GSL20) are compared with the group-sparsity minimization techniques GSL20[4] and GIHT[6] in both terms of objective and subjective qualities.

### 2. Objective quality

As shown in Table 2, the proposed HVS_GSL20 and EP_HVS_GSL20 perform much better than GSL20; the average PSNR gains of HVS_GSL20 are about 1.18dB (Lena), 0.56dB (Mandrill), 2.04dB (Jet), and 1.92dB (House). It shows that by applying the HVS characteristics to GSL20, groups of correlated transform coefficients are recovered more exactly. With the help of the bilateral filter, we can enhance

표 2. 복원 성능 비교 (PSNR, dB)

Table 2. Recovery performance comparison(PSNR, dB).

| Image | Recovery | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 |
|---|---|---|---|---|---|---|
| Lena | GSL20 [4] | 22.9 | 26.9 | 29.2 | 31.1 | 32.8 |
| | GIHT [6] | 25.6 | 28.1 | 30.3 | 31.9 | 33.4 |
| | HVS_GSL20 | 23.9 | 28.4 | 30.7 | 32.3 | 33.5 |
| | EP_HVS_GSL20 | 25.9 | 30.3 | 32.5 | 34.1 | 35.6 |
| Mandrill | GSL20 [4] | 18.0 | 19.4 | 20.4 | 21.5 | 22.7 |
| | GIHT[6] | 18.0 | 19.2 | 20.5 | 21.7 | 22.8 |
| | HVS_GSL20 | 18.7 | 19.9 | 20.9 | 22.1 | 23.2 |
| | EP_HVS_GSL20 | 19.7 | 21.2 | 22.3 | 23.5 | 24.8 |
| Jet | GSL20 [4] | 21.3 | 25.8 | 28.5 | 30.8 | 32.9 |
| | GIHT[6] | 23.9 | 27.2 | 29.7 | 31.8 | 33.9 |
| | HVS_GSL20 | 22.6 | 27.4 | 30.9 | 33.4 | 35.2 |
| | EP_HVS_GSL20 | 24.3 | 29.7 | 32.9 | 35.3 | 37.1 |
| House | GSL20 [4] | 19.7 | 23.7 | 26.0 | 28.2 | 30.3 |
| | GIHT[6] | 22.1 | 24.7 | 26.9 | 28.7 | 30.8 |
| | HVS_GSL20 | 21.1 | 25.3 | 28.2 | 30.5 | 32.4 |
| | EP_HVS_GSL20 | 22.8 | 26.9 | 29.5 | 31.5 | 33.1 |

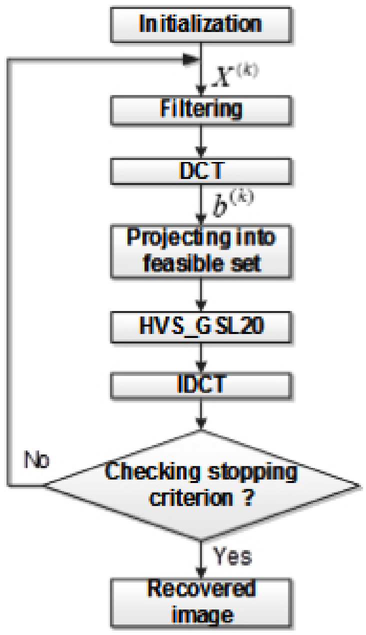


그림 1. 에지-보존-필터 활용 시각적 가중치 그룹-희소성 최소화 (EP_HVS_GSL20)

Fig. 1. Edge-preserving-filter-aided visually weighted group-sparsity minimization (EP_HVS_GSL20).

smoothness while still preserving edges of image. As a result, the quality of reconstructed image is further improved. In the same manner, in comparing with GSL20, the average PSNR gains of EP_HVS_GSL20 is 3.1dB (Lena), 1.9dB (Mandrill), 4dB (Jet), and 3.18dB (House) when the bilateral filter is incorporated to HVS_GSL20. Additionally, in


그림 2. 측정율 0.2, 블록크기 32x32에서 복원된 Lena 및 Mandrill 영상
Fig. 2. Reconstructed Lena and Mandrill images at sub-rate 0.2, block size 32x32.

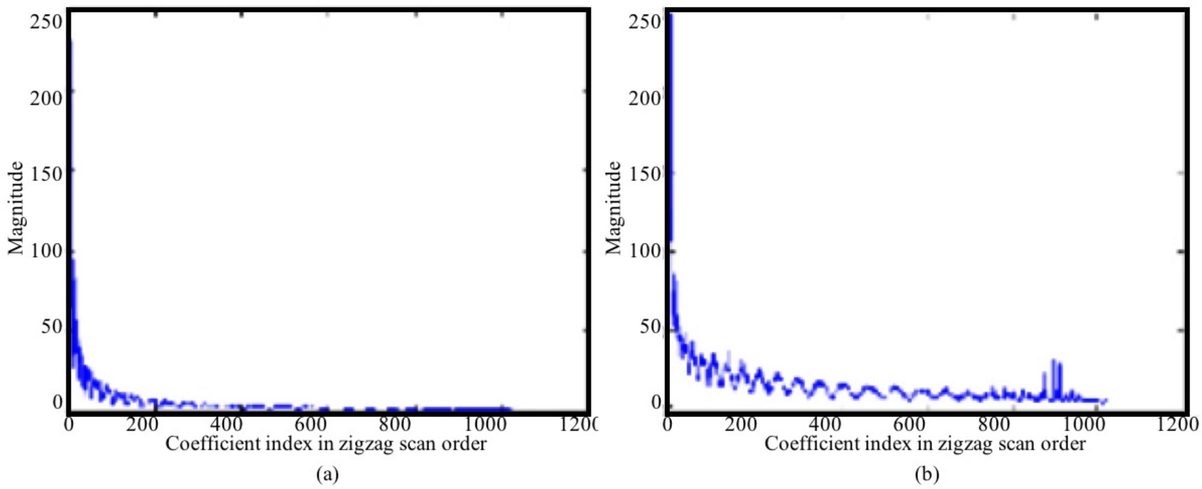


그림 3. 에너지 분포 (a) Lena 영상 (b) Mandrill 영상
Fig. 3. Energy distribution (a) Lena image and (b) Mandrill image.

comparison with GIHT, the objective quality of the proposed HVS_GSL20 is higher (for sub-rates 0.2 to 0.5), i.e., average PSNR gains of HVS_GSL20 is 0.3dB (Lena), 0.5dB (Mandrill), 1.1dB (Jet), and 1.3dB (House); however, at sub-rate 0.1, PSNR of HVS_GSL20 scheme is lower, except in case of Mandrill image. It can be explained by using energy distribution of Lena and Mandrill image as illustrated in Figure 3. In Mandrill image (it is textured image), energy is spread in both low frequency and high frequency coefficients. Therefore, by just keeping low frequency coefficients and replacing the rest of them to zero, GIHT does not offer good recovery quality in Mandrill image. Besides, in Lena image (it is smooth image), most energy is concentrated in low frequency coefficients. Note that, in GIHT, the number of preserved coefficient groups is chosen as a half of number of measurements; therefore, when measurement rate increases, the number of preserved coefficient groups increases, results in insignificant coefficients (whose amount of noise is higher than amount of image information) may still be kept. In contrast, by assigning visual weights that reflect well various perceptual sensitivity of each transform coefficient, the proposed HVS_GSL20 can offer better recovery quality for various types of image (e.g., smooth or detail).

### 3. Subjective Quality

Figure 2 compares the reconstructed images of the proposed HVS_GSL20, EP_HVS_GSL20, and the anchor methods GSL20 and GIHT at sub-rate 0.2. We use the Feature Similarity index for color images (FSIMc)[12] to evaluate subjective quality, the higher FSIMc value means the better subjective quality (it ranges from 0 to 1). By the proposed visually weighting process, visually significant coefficients are recovered more exactly, leads to blocking artifacts (it is caused by mismatch of dominant transform coefficients between two neighboring blocks[13]) are mitigated much in the reconstructed image of HVS_GSL20. Therefore, the proposed HVS_GSL20 offers higher FSIMc index than GSL20 and GIHT. Furthermore, as shown in those reconstructed images of EP_HVS_GSL20, with the help of the bilateral filter, we can reduce much high frequency oscillatory artifacts (which occurs due to low measurement rate[14]) as well those appear in the reconstructed images of HVS_GSL20. As a result, EP_HVS_GSL20 gives the highest FSIMc index.

## V. Conclusions

This paper addresses HVS characteristics to group sparsity minimization for color images. The proposed HVS_GSL20 not only pursues sparsity of image in transform domain but also takes into account human visual system characteristics. Moreover, by incorporating a bilateral filter with HVS_GSL20, we reduced noise in reconstructed image while preserving the structure of image. Experimental results verified the superiority of EP_HVS_GSL20 over existing methods of GIHT and GSL20 in both terms of objective and subjective qualities. In the future, we will take more investigations to HVS characteristics and utilize them in both CS sampling and recovery process to enhance quality of reconstructed image.

## REFERENCES

[1] D. L. Donoho, “Compressive sensing,” *IEEE Trans. Inform. Theory*, vol. 52, pp. 1289-1306, 2006.
[2] S. Park, H. N. Lee, S. Park, "Introduction to Compressed Sensing," *The Magazine of the IEEK*, vol. 38, pp. 19-30, 2011.
[3] H. Lee, S. Kwon, B. Shim, "Reweighted L1-Minimization via Support Detection," *Journal of the Institute of Electronics Engineers of Korea*, Vol. 48, no. 2, pp. 134-140, Mar. 2011.
[4] A. Majumdar and R. K. Ward, “Compressed sensing of color images,” *Jour. Signal Process.*, vol. 90, pp. 3122-3127, 2010
[5] P. Nagesh and B. Li, “Compressive imaging of color images,” Proc. of IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP), pp. 1261-1264, 2009.
[6] V. A. Nguyen, K. Q. Dinh, C. V. Trinh, and B. Jeon, “Smoothed group-sparsity iterative hard thresholding recovery for compressive sensing of color image,” *Journal of the Institute of Electronics and Information Engineers*, vol. 51, pp. 849-856, 2014.
[7] C. Tomasi and R. Manduchi, “Bilateral filtering for gray and color images,” Proc. of Int. Conf. Computer Vision, pp. 839-846, 1998.
[8] E. Candes and J. Romberg, “Sparsity and incoherence in compressive sampling,” Inverse Prob., vol. 23, pp. 969-985, 2007.
[9] Mohimani, M. Babaie-Zadeh, C. Jutten, “A fast approach for overcomplete sparse decomposition based on smoothed l0norm,” *IEEE Trans. Signal Process.*, vol. 57, pp. 289-301, 2009.
[10] A. Nguyen, K. Q. Dinh, C. V. Trinh, and B. Jeon, “HVS based iterative hard thresholding recovery for compressive sensed image,” Proc. of IEEE Int. Conf. Systems, Signal and Image Process. (IWSSIP), 2014.
[11] A. Peterson, H. Peng, J. H. Morgan, and W. B. Pennebaker, “Quantization of color image components in the DCT domain,” Proc. SPIE, Human Vision, Visual Process., vol. 1453, pp. 210-222, 1991.

[12] L.Zang, D. Zang, X. Mou, D. Zang, “FSIM: A feature similarity index for image quality assessment,” *IEEE Trans. Image Process.*, vol. 20, pp. 2378-2386, 2011.
[13] H. T. Kung and S. J. Tarsa, “Partitioned compressive sensing with neighbor-weighted decoding,” Proc. of Int. Conf. Military Comm. (MILCOM), pp. 149-156, 2011.
[14] K. Q. Dinh, H. Shim, and B. Jeon, “Deblocking filter for artifact reduction in distributed compressed video sensing,” Proc. of Visual Comm. Image Process. (VCIP), pp. 1-5, 2012.

## 저 자 소 개

Viet Anh Nguyen(학생회원)
2011년 Hanoi Univ. of Sci. and Tech. 학사 졸업.
2013년 성균관대학교 전자전기 컴퓨터공학과 석사 졸업.
<주관심분야 : 영상압축, 압축센싱>

박 영 현(학생회원)
2011년 성균관대학교 전자전기 공학부 학사 졸업.
2011년～현재 성균관대학교 전자전기컴퓨터공학과 석박사 통합과정.
<주관심분야 : 영상압축, 압축센싱>

Chien Van Trinh(학생회원)
2012년 Hanoi Univ. of Sci. and Tech. 학사 졸업.
2014년 성균관대학교 전자전기 컴퓨터공학과 석사 졸업.
<주관심분야 : 영상압축, 압축센싱>

전 병 우(정회원)
1985년 서울대학교 전자공학과 학사 졸업.
1987년 서울대학교 전자공학과 석사 졸업.
1992년 Purdue Univ. School of Elec. 박사 졸업.
1993년～1997년 삼성전자 신호처리연구소 선임/수석연구원.
1997년～현재 성균관대학교 정보통신대학 교수.
<주관심분야 : 멀티미디어 영상압축, 영상인식, 신호처리>