Compressive Sampling of Color Retinal Image Using Spread Spectrum Fourier Sampling and Total Variant

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This research was financially supported by the Directorate of Research and Community Service, Telkom University.

ABSTRACT This paper proposes compressive sampling (CS) framework for color retinal image (CRI) compression, which relies on spread spectrum Fourier sampling (SSFS) and total variant (TV)-based reconstruction method with three loop of RGB color space, referred to as RGB-TV. In CS, two steps of process are performed, i.e., compression and CS reconstruction. In compression steps, SSFS is performed to get compressed signal from original CRI with a high compression ratio (CR). While in CS reconstruction, TV-norm and TV proximal operator are exploited for problem optimization to recover original CRI from a compressed signal. In addition, signal-to-noise ratio (SNR), structural similarity (SSIM), and processing time are investigated for the performance metrics of the proposed RGB-TV. The computer simulation result shows that the proposed RGB-TV with a set of CRI of size 512 by 512 can compressed until CR = 10 which obtains mean SNR 22 dB, SSIM 0.84, and processing time 2.2 seconds.

INDEX TERMS Color retinal image, compressive sampling (CS), RGB, spread spectrum (SS), total variant (TV).

I. INTRODUCTION

FOR many years, the application of retinal image in medical imaging was studied by researchers, i.e., automatic cataract classification [1], diabetic retinopathy [2], cholesterol level detection [3]–[5], automatic vessel segmentation [6], and retinal prosthesis [7]. These applications demand a lot of retinal images to analyze and require efficient compression techniques for retinal image storage. In addition, because monitoring such retinal images is a complex undertaking, retinal images must meet stringent quality requirements in order for clinical data to be accurate and dependable. This challenge can be mitigated with the use of effective retinal image compression algorithms [8].

In medical image compression (MIC), various lossy and lossless compression framework were developed. The lossless MICs were proposed, such as a segmentation-based lossless image coding [9], wavelet-based compression scheme [10], adaptive predictive multiplicative autoregressive [11], advanced video coding scheme (H.264/AVC) [12], symmetry-based technique for scalable lossless compression [13], minimum rate predictors [14], and end-to-end optimized learning framework with intra-slice and inter-slice redundancy [15]. In addition, the lossy MICs were developed, i.e., a wavelet-based compression using distortion-constrained adaptive vector quantization [16], optimized volume of interest coding [17], high efficiency video coding [18], and lossy-to-lossless data compression scheme [19]. Moreover, in this paper, a compression framework based on sparse sampling and compressive sensing is proposed for medical images.

Compressive sensing [20] or compressive sampling (CS) [21] or compressed sensing [22] was proposed as an approach to sampling a sparse signal with number of sample is less than the Nyquist theorem and the sampled signal can be recovered using a reconstruction method. Many CS applications in different fields were developed, such as geoscience and remote sensing [23], antennas and wireless propagation [24], signal processing [25], intelligent
This article is organized as follows. Section II describes the related works. Section III presents CS for compression. Section IV presents the proposed RGB-TV. Section V presents retinal images, performance metrics, and experiment scenario. Experiment results are shown in Section VI. Last, Section VII describes the conclusion of this paper.

II. RELATED WORKS

The previous CS framework was proposed using wavelet-based sparsity basis [20]. Then, a new sparsity basis approach was proposed using the average of multiple sparsity basis prior for radio astronomy images and referred to as sparsity averaging reweighted analysis (SARA) [35]. In addition, double concatenated SARA (DC-SARA) was proposed to enhance SARA by using a group of SARA basis and BP regularization for the reconstruction of the CS [36]. Next, a generalize version of DC-SARA was proposed and referred to as M-BRA [31]. Furthermore, a TV-based SARA was proposed for CT images was proposed to reduce the processing time of BP in SARA [37]. Last, MIC for the retinal images was proposed by using CS framework based on BP and average sparsity model [34].

III. CS FOR COMPRESSION

Throughout this article, the sparse signal and the compressed signal are denoted by \( x \) and \( y \), respectively. Fig. 2 shows the illustration of CS, i.e., compression and CS reconstruction for color retinal image (CRI).

A. COMPRESSION

In compression, a signal \( x \in \mathbb{C}^{n \times 1} \) is sampled by a sensing matrix \( \Phi \in \mathbb{C}^{m \times n} \) to get a compressed signal \( y \in \mathbb{C}^{m \times 1} \) with less \( m \)-number of samples. The compression process in CS is defined as

\[
y = \Phi x.
\]  

Suppose an CRI is represented by two-dimensional signal \( I \), then \( I \) is reshaped to one-dimensional signal \( s \in \mathbb{R}^{n \times 1} \). The requirement of CS as follows, first, if \( s \) is sparse, then \( x = s \), while if \( s \) is not sparse, then \( s \) is transformed by sparsity basis \( \Psi \) to a sparse signal \( x \) or \( x = \Psi s \). The compression becomes

\[
y = \Phi \Psi s,
\]  

where where \( \Psi \in \mathbb{C}^{n \times n} \) and \( s \in \mathbb{C}^{n \times 1} \) represents the sparsity basis and \( \Phi \) represents the compression matrix, respectively.
B. CS RECONSTRUCTION

In CS reconstruction, a signal reconstructed signal \( \hat{x} \) is recovered from \( y \) and known \( \Phi \) and the reconstruction process can modeled by a convex problem as

\[
\min \| \hat{x} \|_1 \text{ s.t. } \| y - \Phi \hat{x} \|_2 \leq \varepsilon, \tag{3}
\]

where \( \hat{x} \), \( \| \cdot \|_2, \ell_2 \) norm, \( \varepsilon \), and \( \| \cdot \|_1 \) represent the reconstructed sparse signal, \( \ell_2 \) norm upper bound, and \( \ell_1 \) norm. From Eq. (1), suppose \( \Phi, \Psi, \) and \( y \) are known, then the optimization problem becomes

\[
\hat{s} = \min_s \| s \|_1 \text{ s.t. } \| y - \Phi \Psi \hat{s} \|_2 \leq \varepsilon. \tag{4}
\]

Furthermore, \( \hat{I} \) can be reconstructed for CRI.

C. CS PERFORMANCE METRICS

In CS, compression ratio (CR) is the ratio of \( x \) and \( y \) as shown in Fig. 2 and defined as

\[
\text{CR} = \frac{n}{m}, \tag{5}
\]

where \( n \) and \( m \) are the dimension size of \( \Phi \).

The signal to noise ratio (SNR) is calculated from an original image \( s \) and a result image \( \hat{s} \) and determined as

\[
\text{SNR} = \frac{1}{3} \sum_{l=1}^{3} 10 \log_{10} \left( \frac{\| s_l \|_2^2}{\| s_l - \hat{s}_l \|_2^2} \right), \tag{6}
\]

where \( l \) is color layers of CRI.

The structural similarity (SSIM) is a perceptual metric that represents the loss of quality in data compression based on contrast, luminance, and structural of the image which are defined as follows

\[
\text{con}(s, \hat{s}) = \frac{2\sigma_s \sigma_{\hat{s}} + C_2}{\sigma_s^2 + \sigma_{\hat{s}}^2 + C_2}, \tag{7}
\]

\[
\text{lum}(s, \hat{s}) = \frac{2\mu_s \mu_{\hat{s}} + C_1}{\mu_s^2 + \mu_{\hat{s}}^2 + C_1}, \tag{8}
\]

\[
\text{struc}(s, \hat{s}) = \frac{\sigma_{s \hat{s}} + C_3}{\sigma_s \sigma_{\hat{s}} + C_3}, \tag{9}
\]

where \( \sigma_s \) and \( \mu_s \) denote local standard deviation and mean of the pixel in original CRI. \( \sigma_{\hat{s}} \) and \( \mu_{\hat{s}} \) denote local standard deviation and mean of the pixel in result image. \( \sigma_{s \hat{s}} \) denotes cross-covariance between \( s \) and \( \hat{s} \). Next, SSIM defined as

\[
\text{SSIM}(s, \hat{s}) = [\text{con}(s, \hat{s})]^{\alpha} \cdot \left[ \text{lum}(s, \hat{s}) \right]^{\beta} \cdot \left[ \text{struc}(s, \hat{s}) \right]^{\gamma}. \tag{10}
\]

Let \( C_3, C_3 = C_2 \), and \( \alpha = \beta = \gamma = 1 \) are assumed as default, SSIM becomes

\[
\text{SSIM}(s, \hat{s}) = \left( \frac{2\sigma_s \mu_{\hat{s}} + C_1}{\mu_s^2 + \mu_{\hat{s}}^2 + C_1} \right) \left( \frac{2\sigma_{\hat{s}} + C_2}{\sigma_s^2 + \sigma_{\hat{s}}^2 + C_2} \right). \tag{11}
\]

IV. PROPOSED RGB-TV

Suppose an \( N \times N \times 3 \) pixels of CRI with RGB format, this paper proposes RGB-TV which is consist of CS and reconstruction as shown in Fig. 3. In CS steps as shown in Fig. 3(a), first, an original CRI is represented by an unsigned integer matrices \( I \in \mathbb{Z}^{N \times N \times 3} \), then the original CRI is separated to RGB layer \( I_l \in \mathbb{R}^{N \times N} \). Second, RGB loops is performed. For each loop, in SS Fourier sampling, \( I_l \in \mathbb{Z}^{N \times N} \) image is reshaped to a signal \( x \in \mathbb{R}^{n \times 1} \) with \( n = N \times N \) as \( k \)-sparse input signal and \( m \) sample is measured to obtain measured vector where \( k < m < n \) as the CS rule or \( 0 < \frac{m}{n} < 1 \). The RGB loops is finished when all R,G, and B layers are sampled. In reconstruction as shown in Fig. 3(b), a compressed image is reconstructed from the measured vector. Then, RGB loops are performed to each measured vector. For each loops, TV-based reconstruction is performed to recover image form compressed image. Then, end of loop condition is checked, if the loop is not B layer, then continue to next loop. Last if the loop is B layer loop, the process is finished with the result RGB images and reconstructed image is obtained. Algorithm 1 describes the step of reconstruction.

A. SSFS

SSFS is a process to sample a CRI to get compressed signal using a masking matrix (denoted as \( M \)) and spectrum matrix (denoted as \( A \)) in a domain of discrete Fourier transform matrix (denoted as \( F \)). The SSFS is a CS using \( \Phi = MFA \), where \( M \in \mathbb{R}^{m \times n} \) is a rectangular binary matrix, \( F \in \mathbb{C}^{n \times n} \) is a complex matrix, and \( A \in \mathbb{R}^{n \times n} \) is a diagonal matrix. In
Algorithm 1: RGB-TV

Input: Measured vector $y$, SS mask $\Phi$, and $\varepsilon$
Output: Reconstructed retinal Image $\hat{s}$

for $l \leftarrow 1$ to 3 do
    Initialization $t = 1$;
    while $t < t_{\text{max}}$ and $\alpha > \varepsilon$ do
        Compute the projection onto the $L_2$-ball
        $\min_{\hat{x}} \|x - \hat{x}\|_2^2$ s.t. $\|y - \Phi \hat{x}\|_2 \leq \varepsilon$;
        Compute TV norm $\|\hat{x}\|_{TV}$;
        Compute the TV proximal operator
        $\min_{\hat{x}} \|x - \hat{x}\|_2^2 + \lambda \|\hat{x}\|_{TV}$;
        Update $\alpha = \frac{\|\hat{x}(t) - \hat{x}(t-1)\|_{TV}}{\|\hat{x}(t-1)\|_{TV}}$;
        $t \leftarrow t + 1$;
    end
    $s_l = \hat{x}$;
end

addition, MFA can be the inverse transformed that considers $1_M \in \mathbb{R}^M$ and defined as

$$F^T M^T 1_M.$$  \hspace{1cm} (10)

In SSFS [38], a noise with input signal-to-noise ratio (ISNR) is considered and the CS process becomes

$$y = \Phi x + w,$$  \hspace{1cm} (11)

where $w$ represents the noise and the ISNR is determined as

$$\text{ISNR} = 10 \log_{10} \left( \frac{\|\Phi x\|_2}{\|w\|_2} \right)^2.$$  \hspace{1cm} (12)

B. TV RECONSTRUCTION

In reconstruction process, to reconstruct $x$ according to $\Phi$, the problem of TV proximal operator [39] is defined as

$$\min_{\hat{x}} \|x - \hat{x}\|_2^2 + \lambda \|\hat{x}\|_{TV},$$  \hspace{1cm} (13)

where $\hat{x}$ is a reconstructed signal from TV.

V. EXPERIMENT

This section presents experiment to investigate the performance of proposed RGB-TV. First, retinal images are presented. Second, experiment scenario is presented. Last, hardware and software specifications are elaborated.

A. CRI

In this paper, real CRI data is considered from patient at TelkomMedika hospital, Bandung, Indonesia. The acquisition was acquired by one expert operator from the patients who had high cholesterol. The CRI data consist of 90 images with *.bmp format, RGB colored channel, 660 × 603 pixels, and 8 bit pixel depth. Furthermore, to make a fair comparison of different CMI methods, $N \times N$ with $N = 64, 128, 256, 512$ are investigated in this paper.

B. EXPERIMENT SCENARIO

This section presents experiment scenario, first, an $N \times N$ pixels of CRI is considered as original image. Second, CS is performed according to CR for CRI compression to get compressed vector. Third, reconstruction is performed by using RGB-TV as presented in Algorithm 1 to recover reconstructed image from compressed vector. Last, performance metrics are calculated to investigated the
original and reconstructed CRI. Furthermore, the effect of parameters are presented as follows

- Performance metrics with regards to CR, where \( N = 64 \) is considered as fixed resolution and the different CRs are investigated.
- Performance metrics with regards to ISNR, where \( N = 64 \) is considered as fixed resolution, \( CR = 0.5 \) is considered, and ISNR is investigated.
- Performance metrics with regards to \( N \), where \( 128 \times 128, 256 \times 256, \) and \( 512 \times 512 \) pixels are investigated.

The performance between the proposed RGB-TV, RGB-BPSA [34], RGB-BP with state-of-the-arts with Haar basis [20], Daubechies 8 (Db8) basis, and curvelet basis are compared.

C. HARDWARE AND SOFTWARE SPECIFICATIONS

This paper implement the RGB-TV for CRI using MATLAB R2020b with personal computer specifications as follows: processor Intel(R) Core(TM) i-8700 CPU @ 3.20GHz with RAM 16GB. This specifications are required to validate the processing time results to make fair comparison with other CMI methods.

VI. EXPERIMENT RESULTS

This section presents the results of experiment scenario from Section V-B to show the performance of RGB-TV. The performance between the proposed RGB-TV, RGB-BPSA [34], RGB-BP with state-of-the-arts with Haar basis [20], Daubechies 8 (Db8) basis, and curvelet basis are compared.

A. COMPRESSION RATIO (CR)

Fig. 4 shows the effect of CR to SNR results of proposed RGB-TV, RGB-BPSA [34], RGB-BP-Haar [20], RGB-BP-Db8, and RGB-BP-Curvelet. X and Y-value refer to \( CR = 2, 4, 6, 8, 10 \) and SNR in dB, respectively. The results show that the proposed RGB-TV outperforms all CS benchmarks. Targeting \( SNR > 20 \) dB, RGB-TV achieves at all CR conditions while RGB-BPSA achieves \( CR < 9 \). In addition, the result of RGB-TV and RGB-BPSA at \( CR = 2 \) are obtained a similar SNR results, then a detailed results of SNR are presented in Table 1 and Fig. 6. The boxplot results of SNR with \( CR = 2, 4, \) and \( 6 \) are shown in Fig. 6(a), (b), and (c), respectively. The SNR results in boxplot graphs show that the proposed RGB-TV outperforms all CMIs at \( CR = 4 \) and \( 6 \) with highest median value of SNR as shown in solid red lines. The median value of RGB-TV at \( CR = 2 \) is lower than RGB-BPSA but the minimum value of RGB-TV is higher than RGB-BPSA. From Fig. 6, it is validated that RGB-TV outperforms RGB-BPSA at higher CR and more convergence than RGB-BPSA. Same trends also presented in Table 1 where the mean SNR of the proposed RGB-TV is the best results at all CR conditions.

Next, Fig. 5 shows the results to investigate the SSIM of RGB-TV with regards to \( CR = 2, 4, 6, 8, 10 \). X-value corresponds to CR and Y-value corresponds to SSIM. The results show that the proposed RGB-TV outperforms all benchmark CMIs. Suppose to aim SSIM > 0.8, the proposed RGBV-TV achieves at \( CR \leq 10 \) while RGB-BPSA achieves at \( CR \leq 9 \). A detailed results of SSIM at \( CR \leq 6 \) are presented in Table 2 and Fig. 7 to show the difference of the proposed and BPSA results at \( CR \leq 6 \). The boxplot results of SSIM with \( CR = 2, 4, \) and \( 6 \) are shown in Fig. 7(a), (b), and (c), respectively. The SSIM results in boxplot graphs show that the proposed RGB-TV outperforms all CMIs at \( CR = 4 \) and \( 6 \) with highest median value of SSIM as shown in solid red lines. The median value of RGB-TV at \( CR = 2 \) is lower than RGB-BPSA but the maximum values of RGB-TV is higher than RGB-BPSA. From Fig. 7, it is validated that RGB-TV achieved better visual than RGB-BPSA at higher CR and more convergence than RGB-BPSA. In addition, Table 1 shows that the proposed RGB-TV is the best SSIM results at \( CR > 4 \) with higher mean SSIM and lower standard deviation.

Last, Fig. 8 shows processing results to analyze the performance of proposed RGB-TV, RGB-BPSA, RGB-BP-Haar, RGB-BP-Db8, and RGB-BP-Curvelet. The fastest processing time result is RGB-BP-Haar but RGB-BP-Haar
obtains the second worst SNR and SSIM results. The longest processing time is RGB-BPSA which is achieved ∼ 3.4 seconds at CR = 10. The processing time of RGB-TV is half times of RGB-BPSA and it is validated that RGB-TV outperform all CMIs in the view of SNR, SSIM, and processing time.

B. EFFECT OF ISNR

The effect of ISNR to SNR results are shown in Fig. 9(a). Targeting SNR ≥ 30 dB, both RGB-TV and RGB-BPSA are achieved at ISNR ≥ 23 dB. It is shown that RGB-TV and RGB-BPSA are obtained a similar SNR results, then a detailed results of SNR are presented in Fig. 10. The boxplot results of SNR at ISNR = 10, 30, and 50 dB are shown in Fig. 10(a), (b), and (c), respectively. For all ISNR condition, the proposed RGB-TV outperforms RGB-BPSA
with higher median, minimum, and maximum values in the boxplot results.

The effect of ISNR to SSIM results are shown in Fig. 9(b). Targeting SSIM ≥ 0.98 dB, both RGB-TV and RGB-BPSA are achieved at ISNR ≥ 30. The SSIM of RGB-TV and RGB-BPSA are saturated around 0.98 at ISNR ≥ 40, the SSIM of RGB-BP-Db8 is saturated around 0.97 at ISNR ≥ 30 dB, the SSIM of RGB-BP-Haar is saturated around 0.958 at ISNR ≥ 30 dB, and the SSIM of RGB-BP-Curvelet is saturated around 0.937 at ISNR ≥ 30 dB. It is shown that RGB-TV and RGB-BPSA are obtained a similar SSIM results, then a detailed results of SSIM are presented in Fig. 11. The boxplot results are presented to show the detail SSIM results of RGB-TV and RGB-BPSA. The results show that the median value of RGB-TV outperforms RGB-BPSA at ISNR = 10 dB, while RGB-BPSA outperform RGB-TV at ISNR = 30 and 50 dB. The maximum value of RGB-TV outperforms RGB-BPSA at all ISNR conditions and it is validated that the visual quality results of RGB-TV outperforms RGB-BPSA.

In addition, Table 3 presents the mean and standard deviation results of SSIM with regards to ISNR. The results show that RGB-TV outperforms RGB-BPSA at all ISNR conditions with higher mean and lower standard deviation.

Last, Fig. 9(c) shows processing results to analyze the performance of RGB-TV. RGB-TV and RGB-BPSA are compared where RGB-TV outperforms RGB-BPSA with less processing time at all ISNR conditions.

C. THE EFFECT OF RESOLUTIONS

Fig. 12(a) shows the effect of resolutions to ASNR. The highest ASNR = 42.53 dB is achieved by 256 × 256 at CR = 2 while the lowest ASNR = 24.96 dB is achieved by 64 × 64 at CR = 10. Targeting ASNR > 30 dB, 64 × 64 achieves ASNR ≥ 31.40 dB at CR ≤ 8, ASNR ≥ 32.22 dB is achieved by 128 × 128 at CR ≤ 10, and 256 × 256 achieves ASNR ≥ 37.24 dB at CR ≤ 10.

Fig. 12(b) shows the effect of resolutions to SSIM. The highest SSIM = 0.9941 is achieved by 245 × 256 at CR = 2 while the lowest SSIM = 0.8961 is achieved by 64 × 64 at CR = 10. Targeting SSIM > 0.950, 64 × 64 achieves...
SSIM $\geq 0.9612$ at $\text{CR} \leq 8$, SSIM $\geq 0.9612$ is achieved by $128 \times 128$ at $\text{CR} \leq 10$, and $256 \times 256$ achieves SSIM $\geq 0.9846$ at $\text{CR} \leq 10$.

Fig. 12(c) shows the effect of resolutions to processing time results. The fastest processing time $= 4.04$ seconds is achieved by $64 \times 64$ at $\text{CR} = 10$ while the longest processing time $= 44.33$ seconds is achieved by $128 \times 128$ at $\text{CR} = 8$.

VII. CONCLUSION

This paper proposed CS framework for compression of color retinal image using spread spectrum (SS) Fourier sampling and three loops of RGB layers based on TV reconstruction. The proposed CS is referred to as RGB-TV and compared to the recent RGB-BPSA [34]. RGB-TV outperforms the state-the-arts of CS using BP (i.e., curvelet, haar, and db8 sparsity basis) and RGB-BPSA. Computer simulation results demonstrated that the proposed RGB-TV achieved better visual quality and faster processing time for CS reconstruction of CRI with resolution of $64 \times 64$ pixels.

For future works, sparse bayesian learning (SBL) [40] can be considered as a new framework for CMI and an investigation of efficient multitask structure-aware SBL to color retinal images.

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L. Novamizanti et al.: CS of Color Retinal Image Using SS Fourier Sampling and TV

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