A PARTIAL ACQUISITION TECHNIQUE OF SAR SYSTEM USING COMPRESSIVE SAMPLING METHOD

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Abstract. In line with the development of Synthetic Aperture Radar (SAR) technology, there is a serious problem when the SAR signal is acquired using high rate analog digital converter (ADC), that require large volumes data storage. The other problem on compressive sensing method, which frequently occurs, is a large measurement matrix that may cause intensive calculation. In this paper, a new approach was proposed, particularly on the partial acquisition technique of SAR system using compressive sampling method in both the azimuth and range direction. The main objectives of the study are to reduce the radar raw data by decreasing the sampling rate of ADC and to reduce the computational load by decreasing the dimension of the measurement matrix. The simulation results found that the reconstruction of SAR image using partial acquisition model has better resolution compared to the conventional method (Range Doppler Algorithm/RDA). On a target of a ship, that represents a low-level sparsity, a good reconstruction image could be achieved from a fewer number measurement. The study concludes that the method may speed up the computation time by a factor 4.49 times faster than with a full acquisition matrix.

Keywords: *partial acquisition technique, synthetic aperture radar, compressive sampling*

1 INTRODUCTION

Synthetic aperture radar (SAR) is a active remote sensing technology that produce high resolution images of earth surface from a moving platform during day night and all weather (Curlander and McDonough 1991; Skolnik 2008). One of main challenges to obtain high-resolution images is, that a backscatter signal is sampled at least 2 times the highest frequency of the radar signal as a theory Shannon/Nyquist thus requiring a high rate of Analog Digital Converter (ADC) (Cumming and Wong 2005). This causes the volume of SAR raw data is getting bigger and also requires a great power. This conventional approach is not only complicated and expensive, but also the work of onboard components of a SAR sensor system becomes heavy on the limited onboard memory capacity and downlink transmission. To solve this problem, many techniques have been proposed to compress SAR data. One of most used compression techniques is block adaptive quantization (BAQ). BAQ technique (Kwok and Johnson 1989) aims to estimate the input signal statistics and match quantizer adaptively according to the statistics of input signal and adopt on onboard satellite such as SIR-C (Kwok and Johnson 1989). The BAQ technique, used also for other SAR satellite like TerraSAR-X and COSMO-SkyMed. Other techniques are used such as Down-Sampling BAQ (DSBAQ) on ALOS2 PALSAR 2 (Kankaku *et al.* 2011), Flexible Dinamic BAQ (FDBAQ) on Sentinel-1 (Attema *et al.* 2010).

Unlike conventional compression methods above, the theory of compressive sensing (CS) (Candes and Tao 2006; Donoho 2006; Candes and Wakin 2008) proposed a new approach, where CS can recover certain signals from the measurement/sampling much less than the Nyquist sampling rate theory. Scheme of CS for radar imaging system was introduced from reseachers (Baraniuk and Steeghs 2007; Patel *et al.* 2010) and which states that the radar system with CS can reduce the sampling rate of the ADC on the receiver and eliminate the need of match filter on the radar receiver. The use of random sampling on the radar transmitter was proposed by (Liu and Boufounos 2011) without any changes to the system hardware. All the above research requires the radar signal is sparse and compressible.

Sparse representation model of SAR signals stated that the raw data can be represented as a sparse signal in a certain basis. Herman (Herman and Strohmer 2009) proposed a sparse representation model in the form of a linear equation with All top sequence. Wei (Wei *et al.* 2010) described the SAR signal by separating the sparse target and the acquisition matrix of SAR signal. Another approach is the establishment of the linear model of the SAR raw data based on the Born Approximation (Cheney and Borden 2009; Sun *et al.* 2014).

This paper emphasizes the partial acquisition technique of the SAR system that was not done in the previous paper. The main objectives of the study are to reduce the data storage volume by decreasing the sampling rate of ADC and to reduce the computational load using the partial acquisition technique. The partial acquisition technique was carried out by dividing the dimension of the full acquisition matrix of SAR signal in smaller blocks. This technique can emphasize on the reduction of the number of calculations from the matrix equations. Therefore, the acceleration of the processing time can be obtained. The dimension reduction of the measurement matrix is limited by determination of acceptable the quality of reconstruction.

2 MATERIALS AND METHODOLOGY

2.1 Linear Model of Received SAR Signal

Pulse radar systems using stop-go approach [16] where the radar antenna transmits chirp signal at time t and the position of the antenna x repeatedly on repetition interval. When the transmitted signal hits an object, it will induce currents hence the object emits the scattered field which is the same signal, but weaker and time delayed. The scattered field $\mathcal{E}^{sc}(t, x)$ is formed from the interaction between the target and the incident field. Thus its value is the response target which depends on the geometry and material properties of the target and the shape. The equation of baseband modulated scattered field signal can be written as follows:

$$\mathcal{E}_B^{sc}(t,x) = -\int \frac{{\omega_o}^2}{16\pi^2 R^2} V(z).\, G_a.\, a(t).\, e^{(-i\omega_o\tau + i\pi\alpha(t-\tau)^2)} dz \qquad (2\text{-}1)$$

where G_a is the amplitude of the transmitter signal and $a(t) = \mathrm{rect}\left(\left(t - T_p/2\right)/T_p\right)$ is a rectangular gate function with T_p as the pulse duration time (Cheney and Borden 2009). Furthermore, the $\omega_o = 2\pi f_c$ is the carrief frequency and LFM pulse chirp rate. Meanwhile, $R(z) = |x - z|$ is the distance between the antenna and the target and $\tau = 2R(z)/c$ is the time delay, which is the travel time of chirp signal from the antenna to the target and back to the antenna.

In continuum model, radar antenna is usually pointed toward the earth on the moving platform and simultaneously emits radar signals. The antenna path is denoted by index η_i, which represents antenna position movement path with $\eta_i = 1, \dots, N$. The time scale on this model is defined into 2 scales, which the time scale on the antenna movement is much slower (slow time) than the time scale on the EM wave of a radar signal (fast time). The received radar signal can be defined as follows:

$$\mathcal{E}_B^{sc}(t,\eta_i) = -\int \frac{{\omega_0}^2}{16\pi^2 {R_{\eta_i k}}^2} V(z).G_a.\, a(t).e^{\left(-i\omega_0\tau_{\eta_i k} + i\pi\alpha\left(t-\tau_{\eta_i k}\right)^2\right)}\, dz \tag{2-2}$$

where $\tau_{\eta_i k} = 2.R_{\eta_i k}/c$ is the delay time of SAR echo at index η_i dan $R_{\eta_i k}$ is the distance (range) between the radar antenna at the position η_i and each target at the position z (x_k, y_k).

For radar imaging, the scattered field can be measured at the antenna and the reflectivity V(z) is a function that must be resolved. We assume the value of the coefficient $V_k \in \mathbb{C}^{Nx1} (N = N_a \, x \, N_r)$ is the coefficient value of the backscattered signal from sparse targets, where k is an index of sparse targets and N_a and N_r are the sampling number of slow time and fast time signal. The linear equation of the SAR signal is formed by separating the components reflectivity V_k and acquisition matrix Ψ SAR signal in the form of discrete (Arief *et al.* 2016) written as follows:

$$s_{RT}(t_n,\eta_i) = \sum_{k=1}^{N} \psi_k(t_n,\eta_i) \,.\, V_k \quad \text{or} \quad S = \Psi \,.\, V_k \tag{2-3}$$

A measured SAR echo S is obtained by using high rate ADC as required by the Nyquist theorem. The goal of reconstruction is to determine the target reflectivity $V_k = [v_1, v_2, \cdots, v_N]^T$ from the measured SAR echo S and the model of SAR signal acquisitionΨ.

From eq. (2-2) the SAR signal acquisisiton model $\psi_k(t_n,\eta_i)$ is derived as follows:

$$\psi_k(t_n,\eta_i) = A_k \,.\, e^{-j\varphi(t_n,\eta_i)} \tag{2-4}$$

$$\psi_k(t_n,\eta_i) = [A_k e^{-j\varphi_1(1,1)}, \dots, A_k e^{-j\varphi_1(1,N_r)}, A_k\, e^{-j\varphi_1(2,1)}, \dots, A_k e^{-j\varphi_1(N_a,N_r)}]^T$$

where

$$A_k = \frac{{\omega_0}^2}{16\pi^2 {R_{\eta_i k}}^2} \left| a\left(t_n - \frac{2R_{\eta_i k}}{c}\right) \right|^2 .\, G_a$$

$$\varphi(t_n,\eta_i) = 4\pi f_c \frac{R_{\eta_i k}}{c} - \pi K_r \left(t_n - \frac{2R_{\eta_i k}}{c}\right)^2$$

The new mathematical model of general Ψ is interpreted as basis vector at the fast-time t_n and slow-time η_i and can be written as:

$$\Psi = [\psi_1(t_n,\eta_i), \psi_2(t_n,\eta_i), \dots, \psi_N(t_n,\eta_i)] \tag{2-5}$$

Where the time scale of fast time and slow time signal is indexed by $t_n = 1, \dots, N_r$ and $\eta_i = 1, \dots, N_a$. N_r and N_a are the amount of sampling number of fast time and slow time signal.

2.2 Partial Acquisition Model of SAR Signal

In this section a new method is proposed to reduce the dimension of the matrix Ψ in formula (2-5) by dividing the matrix per block in order to reduce computational load. The matrix Ψ as shown in Figure 1(a) has a large size of $(N_a N_r \times N_{target})$, where N_a and N_r are the maximum number of sampling of slow time and fast time signal. This causes the inverse solution of target reflectivity $V_k = \text{inverse}\big(f(S, \Psi)\big)$ becomes complex. One important step in the algorithm CS is randomly low sampling on recieved radar signal s_{RT} (3) is required. A low sampling model in form of fewer random measurement is needed to reduce the SAR raw data. It represents as incomplete matrix. The number of measurements m must be at least smaller than the signal/image dimension $M \ll N$. The new incomplete radar signal is formulated as follows:

$y = \Phi S_{RT} = \Phi\Psi V_k + n$ (2=6)

where Φ is a randomly low sampling measurement matrix with size of M × N, and n is noise matrix. The noise can be stochastic or deterministic. The number of measurements M must have at least greater than the number of K non-zero value but can be significantly smaller than the dimensions of the scene N ($K < M \ll N$). The fewer the number of M measurements are taken, then the lower sampling rate. The matrix y contains here only M of the total entries N are known, which means undersampling ratio $r = M/N$.

The sampling technique on the raw data SAR can be conducted by low sampling of both slow time and fast time signal simultaneously (Arief *et al.* 2015, 2016). The low sampling of slow time (azimuth) signal is obtained by random arrangements of transmitted radar pulses (Liu and Boufounos 2011; Yang *et al.* 2014) and the low sampling of fast time (range) signal is obtained by using lower rate ADC than received signal (Arief *et al.* 2013; Sun *et al.* 2014).

To find the sparse target reflectivity V_k in general required a number of equations as much V_k. Especially in the case of a sparse target that the target number N_{target} less then dimensions of the matrix Ψ. So Ψ can be reduced. With this assumption, the computational load in solving inverse problems can be reduced as well.

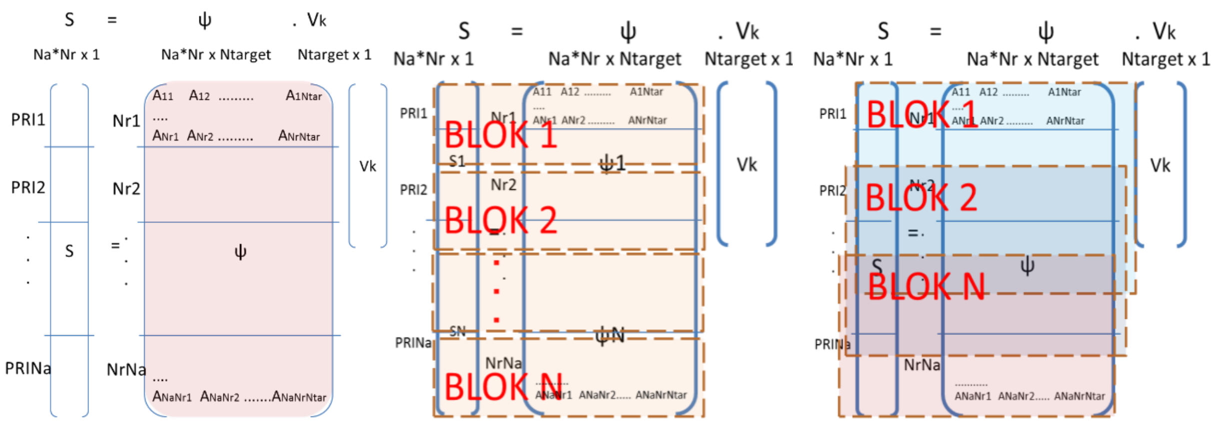
The new matrix $\boldsymbol{\Psi_B}$ is formed by dividing the original $\boldsymbol{\Psi}$ into several blocks as shown in Figure 2.1b and 2.1c, so the dimension $\boldsymbol{\Psi}$ could be smaller.

The proposed scheme of the partial acquisition technique is devided in 2 models i.e.: (a) a partially matrix $\boldsymbol{\Psi_{B1}}$ is obtained by deviding the acquitition matrix (2-5) in several N blocks in the same size. E (see Figure 1b) (Arief *et al.* 2017) and (b) the proposed partial overlapped matrix $\boldsymbol{\Psi_{B2}}$ is obtained by deviding the acquitition matrix (2-5) in larger block size and the block are overlapped with other blocks.

Each block produces a new matrix $\boldsymbol{\Psi_{Bi}}$, which has different size and value compared to other blocks. Thus, the linear equation of each block can be formulated as follows:

$S_i = \Psi_{Bi} . V_{ki}$ for $i = 1,2,\dots,N$ (2-7)

where i is an index of each block. The reflectivity target $V_{k1}, V_{k2}, \dots, V_{kN}$ should ideally have the same value. But because the value S_i and Ψ_{Bi} of every blocks are different, the results of V_{ki} are solved using L1 algorithm (Candes and Romberg 2005) and obtained different magnitudes.



(a) (b) (c)

Figure 2-1: (a) Fully acquisition matrix $\boldsymbol{\Psi}$ (b) partially $\boldsymbol{\Psi_{B1}}$ by deviding in the same block size (Arief et al. 2017) (c) proposed partial acquisition matrix $\boldsymbol{\Psi_{B2}}$

Algorithm

Input : SAR raw data s, fully acquisition matrix Ψ_{Full}, number of blocks N
to be find : reconstructed target vk'
Procedure :
for i=1 to N
create partially acquisition matrix Ψ_{Bi}
create low sampling matrix Φ
calculate $y_i = \Phi\Psi_B V_{Ki}$
calculate V_{Ki} using L1 algorithm
calculate PSNR value o $V'_{K1}, V'_{K2}, \ldots, V'_{KN}$
end
compare $V'_{K1}, V'_{K2}, \ldots, V'_{KN}$
choose the best PSNR value of V_{Ki}
end

Figure 2-2: Reconstruction algorithm for partially SAR acquisition

The best reconstructed value from V_{ki} is obtained by comparing the PSNR value of each blocks and the highest PSNR is choosen as the final reconstructed reflectifity target. Figure 2-2 showed the proposed algorithm.

2.3 Experiment Step

Experiments were performed on the input data SAR of ship target from Radarsat-1 as shown in Figure 2-3. The target has different pixel intensities and illustrated in one area with a size of 31x31 pixels. SAR parameters used to generate image are as follows: stripmap mode, the frequency of 5.3 GHz, azimuth and range resolution 1.00 m respectively. The total number of samples is $N_S = Na \times Nr$, where $N_a = 96$ are $N_r = 126$ ($N_S = 12096$). Randomly low sampling of the radar signal is performed on each block with the number of measurements as M = 1000 samples, with details of 20 samples in azimuth and 50 samples in the range direction.

Two experiments were carried out by evaluating the performance of the partially SAR acquisition of model Ψ_{B1} and Ψ_{B2} in Figure 2-1. The difference between experiments of Ψ_{B1} and Ψ_{B2} model is in the Ψ_{B1} model where the reconstruction result is the average result of the PSNR or RMSE value of a number of blocks from the selected SAR acquisition matrix of 1/2,1/3,1/4 of the matrix full. Mean while the experiments of model Ψ_{B2} aims to obtain the best reconstruction results from any of the 9 blocks having the best PSNR or RMSE values of 3/4, 2/3, 1/2, 1/3, 1/4 of full size of matrix Ψ.

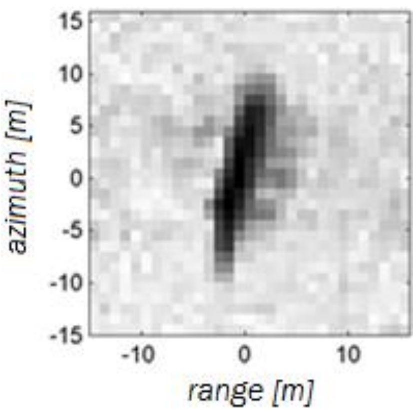


Figure 2-3: Input raw data of a ship target of Radarsat-1

The objective of Ψ_{B2} model experiment is to know the performance of reconstruction results on each block and look for the smallest number of sampling ratios but still have a good performance which above the accepted PSNR threshold.

Reconstruction results of both model were calculated by comparing the values of PSNR and RMSE. The greater PSNR values or the smaller RMSE values show good reconstruction results. The results were also compared with the limit values of the quality of an image PSNR. According to (Welstead 1999; Zain *et al.* 2011), the threshold value of acceptable PSNR to the quality of an image is 29-34 dB.

3 RESULTS AND DISCUSSION

3.1 Experiment of model Ψ_{B1}

Experiment was conducted by comparing between partially acquisition and fully acquisition model. The result of the reconstruction is to distinguish between the fully and partially SAR acquisition. The block dividing scheme as described in Figure 2-1 (b) states that the full acquisition matrix is divided into several blocks equally of 1/2, 1/3 1/4 of the full block. The experiment of model Ψ_{B1} is performed on the ship target as sparse target. This target represents the real target that has a lower level of sparsity compared with the target point.

Which means that the number of sampling must be more than a target point on the same block size to get good reconstruction results.

Figure 3-1 shows the reconstruction results with partial acquisition matrix of model $\boldsymbol{\Psi_{B1}}$ compared to full acquisition matrix. In the experiment, the reconstruction result was obtained by using CS method in evaluating the linear model of full SAR acquisition Ψ_{Full}.

The performance of the reconstruction is influenced by the low number of M samples at random. The more sampling numbers are used, the more accurate the reconstruction results of the target reflectivity are seen from the values of PSNR and RMSE. The number of M divided by the total number of sampling in the azimuth direction and range signifies the data compression ratio ($r = M/N_a \times N_r$). The number of under sampling of M is chosen according to the RIP requirements to ensure good reconstruction and it depends on the sparsity of an object (Candes and Recht 2009).

The PSNR value of full block decreased from 65.047 dB to 34.104 dB and 32.075 dB at partial acquisition matrix with size 1/2 and 1/3 of full block. This PSNR value is above the threshold value of PSNR received. The PSNR value decreases or RMSE value increases with the division of the smaller blocks. The reconstruction result of 1/4 of full block indicates PSNR value of 24.847 dB. It shows a lower quality than conventional methods RDA.

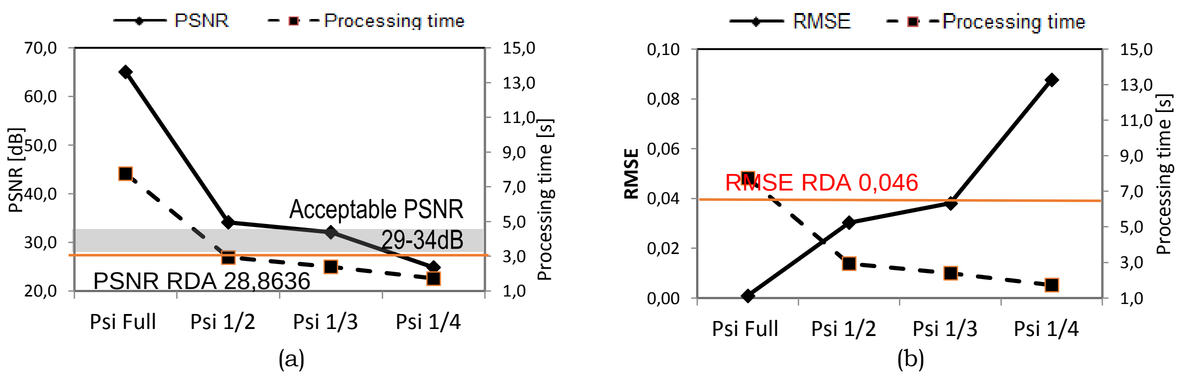


Figure 3-1: (a) The PSNR values and (b) RMSE values and processing time of target ship using CS with Ψ_{Full} and Ψ_{B1}=1/2,1/3,1/4 of full block

The error rate of SAR image reconstruction increases, if the dimension of the partial acquisition matrix gets smaller. The other advantage of the partial acquisition model is that the image of the target vessel can be reconsructed using a partial matrix with 1/2, 1/3, 1/4 of full blok faster than the full matrix by a factor of 2.64 to 4.49 times.

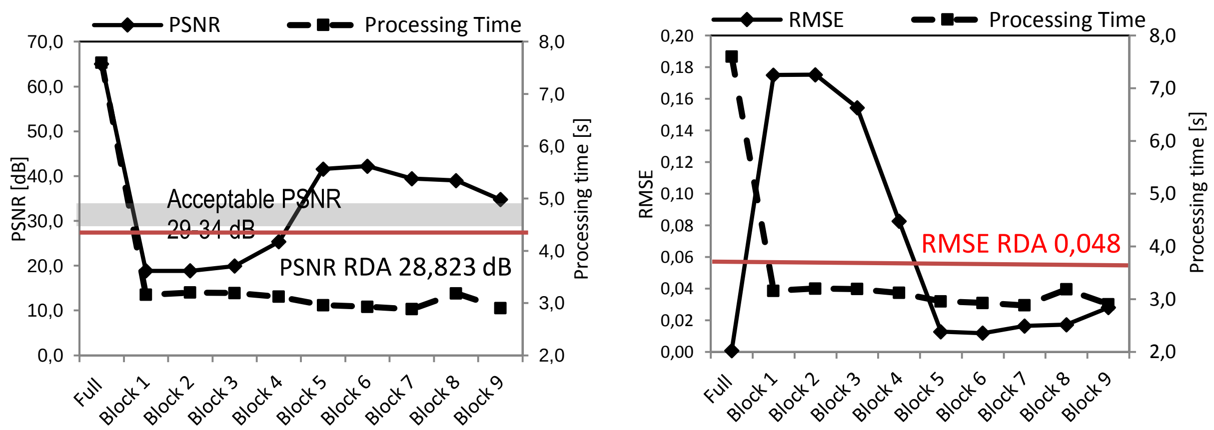
3.2 Experiment of model Ψ_{B2}

The experiment using model Ψ_{B1} states that the larger dimension of the matrix partial acquisition Ψ_{B1} produce better reconstruction results. Then the next experiment carried out to evaluate the performance of the model Ψ_{B2} with maintaining large dimension according Figure 2-1c.

In the first experiment of this section established 9 blocks with 1/2 part of matirks full. So from this procedure was obtained each partial block Ψ_{B2i}, where $i = 1 \dots 9$. It aims to find a partial block Ψ_{B2i}, which produces the best reconstruction result. The performance of model Ψ_{B2} shows the calculated results of reconstruction targets in Figure 3-2, which is looking for a partial block with best reconstruction result by comparing the values of PSNR and RMSE among all blocks. The result is below the quality of RDA in blocks 1-4, while blocks 5-9 show better results.

From the reconstruction results of the partial acquisition matrix of each block obtained that the best quality of the reconstruction result is on the block to 6th with PSNR 42.235 dB and RMSE 0.0123, which is better than PSNR of conventional method (RDA) and the threshold value of acceptable PSNR. The calculation time of the reconstruction results with 1/2 part of a full matrix can accelerate the reconstruction process with an average factor of 2.5 times compared to the full matrix.

The next following experiment was performed to evaluate the reconstruction results of the partial matrix Ψ_{B2}. The size of new partial matrix Ψ_{B2} is set to be respectively 3/4, 2/3, 1/2, 1/3, 1/4 of the matrix of full $\boldsymbol{\Psi}$ and the partial blocks are sorted from the start line of the raw data until the end. The best results of each block are compared and displayed in Table 3.1 and Figure 3.3. The reconstruction result showed the best PSNR value of 61.93 dB within 4.66 s on block 3/4 of full matrix. The PSNR values decreases with decreasing block size. But the calculation time of the required reconstruction is faster.



(a) (b)

Figure 3-2: (a) PSNR Value and (b) RMSE value and processing time of the reconstruction results using overlapped block matrix method with size 1/2 dari Ψ_{Full} compared to RDA

Blocks with size above 1/3 of full matrix produce very good reconstruction with PSNR value above acceptable PSNR threshold. Reconstruction on blocks of 1/4 size of full matrix results in a PSNR value of 25.85 dB, which has a quality below the acceptable PSNR threshold.
With this method, the dimensions of the SAR acquisition matrix can be reduced, so the SAR raw data volume is also reduced. This has the consequence of degrading the quality of the reconstruction outcome, but on the other hand gains an excess of time acceleration in the calculation of the reconstruction process. This experiment shows the smallest limit of the dimensions of the SAR acquisition matrix, but shows the quality of the reconstruction results above the threshold value of accepted PSNR.

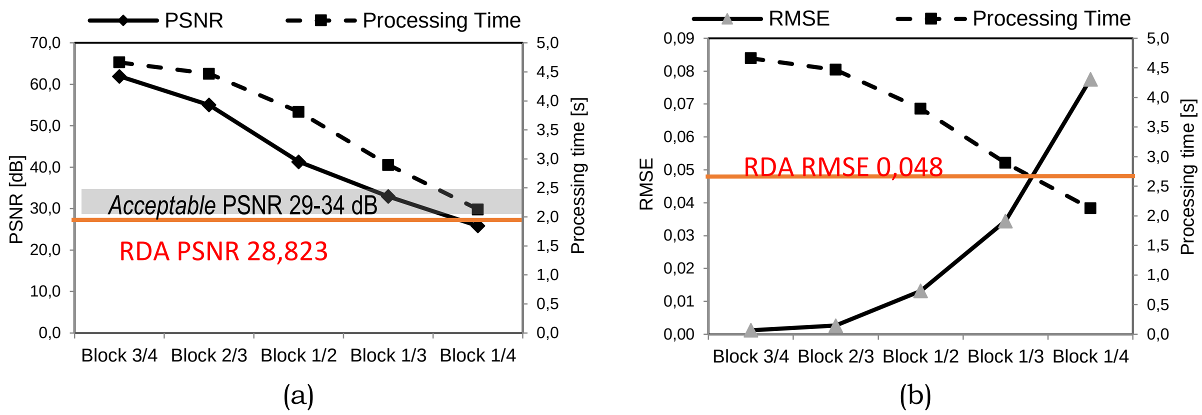


Figure 3-3: (a) PSNR Value and (b) RMSE value and processing time of the reconstruction results using overlapped block matrix method with size 3/4,2/3, 1/2,1/3,1/4 of Ψ_{Full} compared to RDA

Table 3-1 Quantitave results of the experiment of model Ψ_{B2}

Measurement unit	**Block 3/4**	**Block 2/3**	**Block 1/2**	**Block 1/3**	**Block 1/4**
PSNR (dB)	61,923	55,012	41,298	32,930	25,846
RMSE	0,001	0,003	0,013	0,034	0,077
Processing Time (s)	4,662	4,468	3,812	2,896	2,128

4 CONCLUSION

The new method of partial acquisition techniques have been proposed and analyzed. The proposed partial acquisition technique of SAR system using compressive sampling method consist of 2 reduction steps of raw data including to reduce the sampling rate of ADC of received radar signals and to reduce the dimension of the measurement.

This study concludes that the performance of the proposed technique could suppress the side lobe and improve the quality of SAR images better than those obtained using conventional method (RDA). The proposed technique provides with acceptable PSNR with fewer numbers of measurement of SAR signals and could speed up the computation time by a factor of 2.64 to 4.49 times, faster than using a full acquisition matrix.

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