A study of the partial acquisition technique to reduce the amount of SAR data

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Abstract. Synthetic Aperture Radar (SAR) technology is capable to provide high resolution image data of earth surfaces from a moving vehicle. This causes large volumes of raw data. Many researchs were proposed about compressed radar imaging, which can reduce the sampling rate of the analog digital converter (ADC) on the receiver and eliminate the need of match filter on the radar receiver. Besides the advantages, there is a major problem that produces a large measurement matrix, which causes a very intensive matrix calculation. In this paper is studied a new approach to partial acquisition technique to reduce the amount of raw data using compressed sampling in both the azimuth and range and to reduce the computational load. The results showed that the reconstruction of SAR image using partial acquisition model has good resolution comparable to the conventional method (Range Doppler Algorithm). 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 method can speed up the computation time by a factor of 2.64 to 4.49 times faster than with a full acquisition matrix.

1. Intoduction

One of main challenges to obtain high resolution synthetic aperture radar (SAR) images is the acquisition mechanism of a backscatter signal using a high rate of analog digital converter (ADC) according Shannon / Nyquist theorem [1]. This causes the volume of SAR raw data larger. The conventional approach is not only complicated and expensive, but also led to work onboard components becomes heavy. But on the other hand, the capacity of onboard memory and downlink transmission is limited. To solve this problem, many techniques have been proposed to compress SAR data. Scalar compression technique was first used is block adaptive quantization (BAQ). BAQ technique 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 [2], FFT-BAQ [3], ALOS PALSAR 2 [4], Flexible Dinamic BAQ (FDBAQ) on Sentinel-1 [5].

Unlike conventional compression methods above, the theory of compressive sensing (CS) [6–8] 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 [9,10] and which states that the radar system with CS can eliminate the need of match filter on the radar receiver and reduce the sampling rate of the ADC on the receiver. Liu [11] proposed the use random sampling for SAR signal transmission 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 [12] proposed a sparse representation model in the form of a linear equation with Alltop sequence. Wei [13] 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 [14–16]. This paper proposes a model of partial SAR data acquisition to reduce the dimension of the acquisition matrix of SAR signal based on the linear model of the SAR raw data, so that the processing load can be reduced.

2. Method

2.1 Linear model of recieved 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. The chirp signal has a pulsed LFM radar transmitted waveform and can be written as follows:

$$\mathcal{E}^{in}(t,x) = \mathrm{G_a}.\,\mathrm{a(t)}.\,\mathrm{e}^{\mathrm{i}(\omega_\mathrm{o}(\mathrm{t})+\pi\alpha(\mathrm{t})^2)} \tag{1}$$

where $\mathrm{G_a}$ is the amplitude of the transmitter signal and $\mathrm{a(t)} = \mathrm{rect}\big((t - T_p/2)/T_p\big)$ is a rectangular gate function with T_p as the pulse duration time. The $\omega_\mathrm{o} = 2\pi f_c$ is the carrief frequency and LFM pulse chirp rate. When the 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 $\mathcal{E}^{\mathrm{sc}}(\mathrm{t,x})$ is formed from the interaction between the target and the incident field $\mathcal{E}^{\mathrm{in}}(\mathrm{t,x})$. Thus its value is the response target depends on the geometry and material properties of the target and of the shape. The equation of scattered signal according [14] can be written as follows:

$$\mathcal{E}^{\mathrm{sc}}(\mathrm{t,x}) = -\int \frac{{\omega_0}^2}{16\pi^2\mathrm{R}^2}\mathrm{V(z)}.\,\mathrm{G_a}\,.\,\mathrm{a(t)}.\,\mathrm{e}^{\mathrm{i}(\omega_\mathrm{o}(\mathrm{t}-\tau)+\pi\alpha(\mathrm{t}-\tau)^2)}\mathrm{dz} \tag{2}$$

where $\mathrm{R(z)} = |\mathrm{x} - \mathrm{z}|$ is the distance between the antenna and the target and $\tau = 2\mathrm{R(z)}/\mathrm{c}$ is the time delay, which is the travel time of chirp signal from the antenna to the target and back to the antenna.

For radar imaging, the scattered field can be measured at the antenna and the reflectivity $\mathrm{V(z)}$ is a function that must be resolved. We assume the value of the coefficient $V_k \in \mathbb{C}^{\mathrm{Nx1}}(\mathrm{N} = \mathrm{N_a}\,\mathrm{x}\,\mathrm{N_r})$ is the coefficient value of the backscattered signal from sparse targets, where k is an index of sparse targets and $\mathrm{N_a}$ and $\mathrm{N_r}$ are the sampling number of slow time and fast time signal. The linear equation of the SAR signal (2) is formed by separating the components reflectivity V_k and acquisition matrix Ψ SAR signal in the form of discrete [16] written as follows:

$$\mathrm{s_{RT}}(\mathrm{t_n},\eta_\mathrm{i}) = \sum_{\mathrm{k=1}}^{\mathrm{N}} \psi_\mathrm{k}(\mathrm{t_n},\eta_\mathrm{i})\,.\,\mathrm{V_k} \quad \text{or} \quad \mathrm{S} = \Psi\,.\,\mathrm{V_k} \tag{3}$$

where $\psi_\mathrm{k}(\mathrm{t_n},\eta_\mathrm{i}) = \mathrm{A_k}\,.\,\mathrm{e}^{-\mathrm{j}\varphi(\mathrm{t_n},\eta_\mathrm{i})}$

$\psi_\mathrm{k}(\mathrm{t_n},\eta_\mathrm{i}) = [\mathrm{A_k}\mathrm{e}^{-\mathrm{j}\varphi_1(1,1)},\ldots,\mathrm{A_k}\mathrm{e}^{-\mathrm{j}\varphi_1(1,\mathrm{N_r})},\mathrm{A_k}\,\mathrm{e}^{-\mathrm{j}\varphi_1(2,1)},\ldots,\mathrm{A_k}\mathrm{e}^{-\mathrm{j}\varphi_1(\mathrm{N_a},\mathrm{N_r})}]^\mathrm{T}$

$\mathrm{A_k} = \frac{{\omega_0}^2}{16\pi^2{\mathrm{R}_{\eta_\mathrm{i}\mathrm{k}}}^2}\left|\mathrm{a}\left(\mathrm{t_n} - \frac{2\mathrm{R}_{\eta_\mathrm{i}\mathrm{k}}}{\mathrm{c}}\right)\right|^2.\,\mathrm{G_a}$ and $\varphi(\mathrm{t_n},\eta_\mathrm{i}) = 4\pi\mathrm{f_c}\frac{\mathrm{R}_{\eta_\mathrm{i}\mathrm{k}}}{\mathrm{c}} - \pi\mathrm{K_r}\left(\mathrm{t_n} - \frac{2\mathrm{R}_{\eta_\mathrm{i}\mathrm{k}}}{\mathrm{c}}\right)^2$

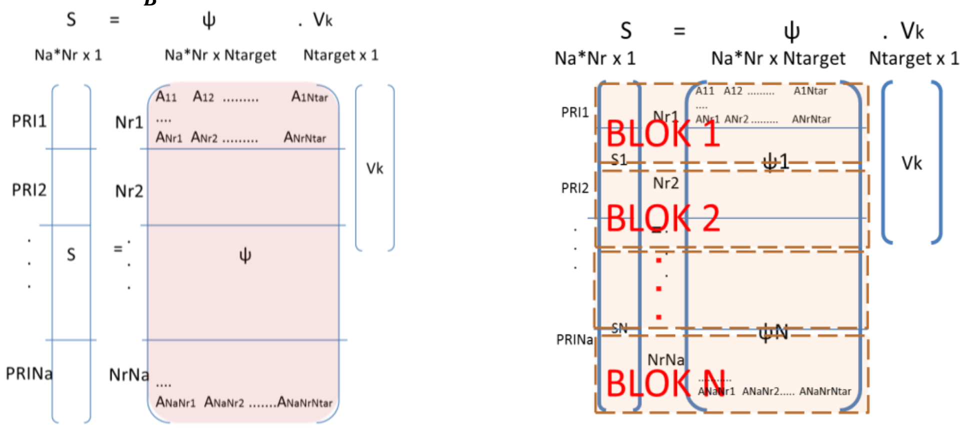
The time scale of fast time and slow time signal are indexed by $\mathrm{t_n} = 1,\ldots,\mathrm{N_r}$ and $\eta_\mathrm{i} = 1,\ldots,\mathrm{N_a}$. where $\mathrm{N_r}$ and $\mathrm{N_a}$ are the amount of sampling number of fast time and slow time signal. Suppose the scatter coefficient vector $\mathrm{V_k} = [\mathrm{v_1},\mathrm{v_2},\cdots,\mathrm{v_N}]^\mathrm{T}$, the new mathematical model of general SAR signal acquisition Ψ is interpreted as basis vector at the fast-time $\mathrm{t_n}$ and slow-time η_i and can be written as:

$$\Psi = [\psi_1(\mathrm{t_n},\eta_\mathrm{i});\psi_2(\mathrm{t_n},\eta_\mathrm{i});\ \ldots;\psi_\mathrm{N}(\mathrm{t_n},\eta_\mathrm{i})] \tag{4}$$

A measured SAR echo S is obtained by using high rate analog digital converter (ADC) as required by the Nyquist theorem. The goal of SAR image reconstruction is to determine the target reflectivity V_k from the measured SAR echo S.

2.2 Partial acquisition model of SAR signal

In this section proposed a new method to reduce the dimension of the matrix Ψ in formula (7) 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 $V_k = \text{inverse}(f(S, \Psi))$ becomes complex. To find the target reflectivity V_k, the number of equations is not required the number of rows $(N_a \times N_r)$ of the matrix Ψ. For this reason, the dimension of the matrix Ψ can be reduced. So the computational load to resolve inverse problems can be reduced as well. The new matrix $\boldsymbol{\Psi_B}$ is formed by dividing the original Ψ into several blocks as shown in Figure 1(b), so that the dimension $\boldsymbol{\Psi_B}$ becomes smaller.



(a) (b)

Figure 1 (a) Fully acquisition matrix Ψ (b) partially $\boldsymbol{\Psi_B}$ by deviding in several blocks

2.3 Low sampling method

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 represent incomplete matrix. The new incomplete radar signal is formulated as follows:

$$y = \Phi S_{RT} = \Phi \Psi V_k + n \tag{5}$$

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 be at least greater than the number of K non-zero value, but significantly smaller than the total entries $(K < M \ll N)$. The undersampling ratio become $r = M/N$. The low sampling of slow time (azimuth) signal is obtained by random arrangements of transmitted radar pulses [11,17] and the low sampling of fast time (range) signal is obtained by using lower rate ADC than received signal [15,18].

2.4 Reconstruction algorithm

The scheme of the proposed partially SAR acquisition method states that a new partially matrix $\boldsymbol{\Psi_B}$ is obtained by deviding the acquitition matrix (7) in several N blocks in the same size. Each block produce a new matrix $\boldsymbol{\Psi_{Bi}}$, which has diffrent value compared to other blocks. Thus, the linear equation of each block can be formulated as follows:

$$Blok\ i \rightarrow S_i = \Psi_{Bi} . V_{ki} \qquad \text{for } i = 1,2,\dots,N \tag{6}$$

where i is an index of each block. The reflectivity target $V_{k1}, V_{k2}, \ldots, V_{kN}$ 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 [19] and obtained different magnitudes. 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 showed the proposed algorithm.

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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 = ΦΨ_B V_Ki
    calculate V_Ki using L1 algorithm
    calculate PSNR value of V'_K1, V'_K2, …, V'_KN
  end
  compare V'_K1, V'_K2, …, V'_KN
  choose the best PSNR value of  V_Ki
end
```

Figure 2 Reconstruction algorithm for partially SAR acquisition

3. Result and discussion

This section describes the performance evaluation of the new model of partially SAR acquisition which are the basis for reconstructing the sparse target on CS-based SAR imaging. Experiments were conducted by evaluating the performance of the partially SAR acquisition and compared to fully SAR acquisition. Experiments were performed on the two input data SAR: an ideal target in the form of point target and ship target from Radarsat-1 as shown in Figure 3.

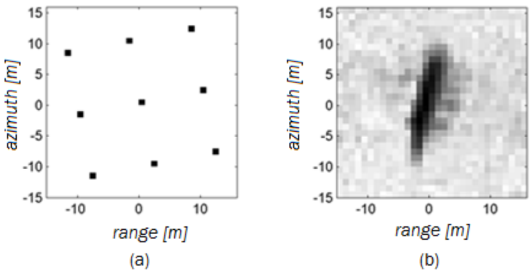

Figure 3 Input raw data (a) point target and (b) a ship target of Radarsat-1 as a complex scene

Both these targets have 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 numbers of samples are $N_S = Na \times Nr$, where $N_a = 96$ are $N_r = 126$ ($N_S = 12096$). Low sampling were carried out for all blocks by randomly sampling with M = 50-90 samples at the point target and M = 720-1020 samples at ship.

3.1 Experiment on point targets

Scheme as described in Figure 1(a) divides the acquisition matrix $\boldsymbol{\Psi_{Full}}$ into several blocks each be 1/2, 1/3 1/4, 1/5 1/6 section. The low random sampling is performed on each block a number of measurements M = 90, with 10 samples in azimuth and 9 samples in the range direction. The result of the reconstruction of the experiment is to distinguish between the fully and partially SAR acquisition.

In the first simulation, the full acquisition matrix is divided into 2 blocks of the same size. Reconstructed results were calculated using algorithm as shown in figure 2 for each block and the best reconstruction result is obtained by comparing the value of its PSNR. The PSNR values of block 1 and block 2 are 49.030 dB and 58.595 dB, RMSE values are 0.036 and 0.011, and the calculation times are

3.719 seconds and 3.519 seconds. From the both calculation is obtained best reconstruction result of block 2 with PSNR 58.595 dB, RMSE 0,011 and a calculation time of 3.519 seconds. The next simulation were performed also at 1/3, 1/4, 1/5 and 1/6 of the full block. The PSNR and RMSE values of the reconstructed target point using the proposed method can be seen in Figure 4 and Table 1.

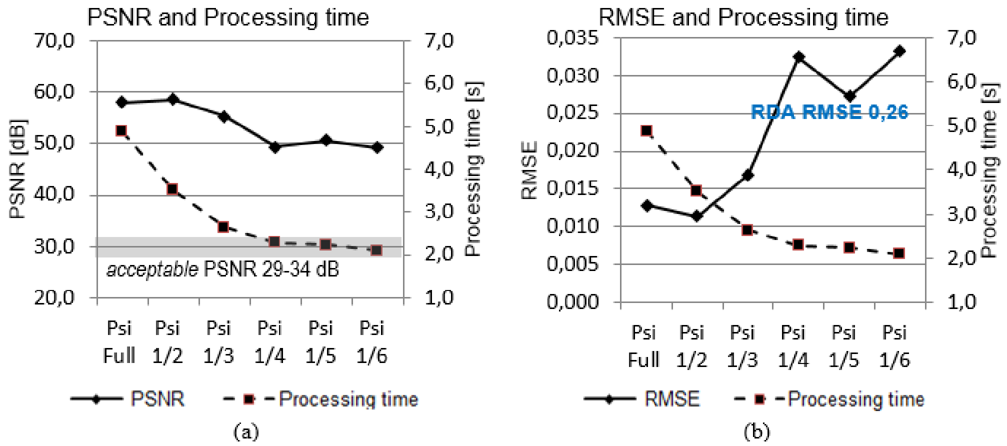

Figure 4 The PSNR, RMSE values and processing time of target point using CS with Ψ_{Full} and Ψ_{B1}=1/2,1/3,1/4,1/5,1/6 of full block

Table 1 Reconstruction result of target point using CS with with Ψ_{Full} and Ψ_{B1}=1/2,1/3,1/4,1/5,1/6 of full block

Parameter	Size of block	CS full	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6	Best	Mean
PSNR [dB]	1/2	58,066	49,030	58,595					58,595	53,812
RMSE		0,013	0,036	0,011					0,011	0,024
Rec. time [s]		4,877	3,719	3,519					3,519	3,619
PSNR [dB]	1/3	58,066	49,062	52,948	55,322				55,322	52,444
RMSE		0,013	0,035	0,021	0,017				0,017	0,024
Rec. time [s]		4,877	2,844	2,657	2,639				2,639	2,714
PSNR [dB]	1/4	58,066	47,863	49,274	42,616	45,684			49,274	46,359
RMSE		0,013	0,040	0,032	0,066	0,047			0,032	0,046
Rec. time [s]		4,877	2,540	2,283	2,316	2,414			2,283	2,388
PSNR [dB]	1/5	58,066	48,494	50,006	37,229	37,323	50,576		50,576	44,726
RMSE		0,013	0,036	0,030	0,132	0,129	0,027		0,027	0,071
Rec. time [s]		4,877	2,412	2,284	2,138	2,074	2,231		2,231	2,228
PSNR [dB]	1/6	58,066	49,226	48,686	33,364	36,773	39,535	49,230	49,230	42,802
RMSE		0,013	0,033	0,034	0,208	0,140	0,104	0,033	0,033	0,092
Rec. time [s]		4,877	2,263	2,082	1,900	1,951	1,943	2,096	2,096	2,039

In this experiment, the reconstruction results on partial SAR acquisition model with blocks 1/2 and 1/3 showed equivalent quality with full matrix acquisition. The reconstruction of the target point with 1/6 partial matrix acquisition of the full block (smallest building blocks of the simulation) have good image quality of best PSNR 49.230 dB, RMSE 0.033 or average (mean) PSNR 42.802 dB, RMSE 0.092.

The image quality of the experimental results of the proposed method are still better than those from the conventional method RDA and has a PSNR value of 23.206 dB and RMSE 0.26. PSNR value is still above the threshold of acceptable PSNR is between 29-34 dB according to [20].

There are some facts that PSNR decreased or RMSE value increases with the division of the smaller blocks. The proposed method resulted in the target point reconstruction with a 1/6 block is still very good, well above the required PSNR and can reduce the computational load. The calculation time of point target using the partial acquisition matrix is faster, because the size of the partial acquisition matrix $\boldsymbol{\Psi_B}$ is getting smaller. The complexity of matrix multiplication becomes smaller. Compared with the calculation of the full block, a calculation of 1/6 block is accelerated 2.32 times (see table 1).

3.2 Experiment on ship target

The next experiment is performed on the ship target. This target represents the real target that has a lower level of sparsity and more complex scene compared with the target point. As the previous section, the block dividing scheme as described in Figure 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. Randomly low sampling of the radar signal is performed on each block with more number of measurements than point target as M = 1000 samples, with details of 20 samples in azimuth and 50 samples in the range direction.

Results reconstruction targets calculated using an algorithm in Figure 2, which is looking for the best reconstruction results by comparing the value of PSNR. Figure 5 shows the results of reconstruction with partial acquisition matrix.

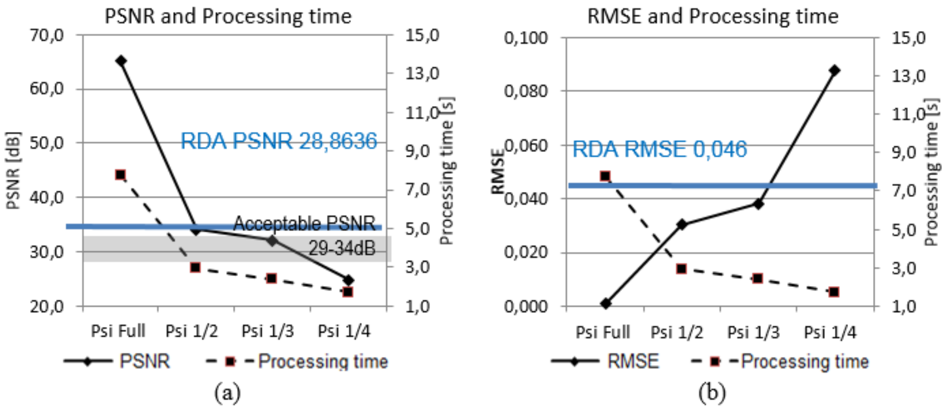

Figure 5 The PSNR, RMSE values and processing time of target ship using CS with Ψ_{Full} and Ψ_{B1}=1/2,1/3,1/4 of full block

The 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. 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. SAR image reconstruction error rate increases, if the dimension of the partial acquisition matrix gets smaller. The 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.

4. Conclusion

The new method of partial acquisition techniques have been proposed, performed experiments and analyzed. The experimental results show the performance of the method is better than the conventional method of RDA. It can suppress the side lobe and improve the quality of SAR images from fewer numbers of measurement of SAR signals and can speed up the computation time by a factor of 2.64 to 4.49 times faster than with a full acquisition matrix. The fewer measurement numbers of received radar signals is conducted by low sampling of slow time signals (azimuth) by setting the transmitted radar pulses at random and by low sampling of fast time signals (range) below the Nyquist frequency. Partial acquisition model generates good quality SAR image almost equal with to the full acquisition model at few numbers of measurement to a target point. While on the target ship, this method provides good image quality above acceptable PSNR value.

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