Wavelet Filter Banks

for Super-Resolution SAR Imaging

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This paper discusses innovative wavelet-based filter banks designed to enhance the analysis of super resolution Synthetic Aperture Radar (SAR) images using parametric spectral methods and signal classification algorithms. SAR finds applications in many of NASA's earth science fields such as deformation, ecosystem structure, and dynamics of ice, snow and cold land processes, and surface water and ocean topography. Traditionally, standard methods such as Fast-Fourier Transform (FFT) and Inverse Fast-Fourier Transform (IFFT) have been used to extract images from SAR radar data. Due to non-parametric features of these methods and their resolution limitations and observation time dependence, use of spectral estimation and signal pre- and post-processing techniques based on wavelets to process SAR radar data has been proposed. Multi-resolution wavelet transforms and advanced spectral estimation techniques have proven to offer efficient solutions to this problem.

I. Introduction

IN this study, one of two major approaches to SAR image processing for direction of arrival (DOA) of target has been considered. The approach considered here is based on the Fast Fourier Transforms (FFT), but the other is based on calculation of covariance matrix in an algorithm called MUSIC[1] (Multiple Signal Classification). In both cases, wavelet transforms will be integrated to evaluate the effect of raw data de-noising and compression on the overall efficiency of the algorithms. Wavelets have been applied extensively and successfully to many datasets in physical sciences, but there has not been a comprehensive study of their effects on SAR image processing. A few research efforts have reported[1,2,3] that de-noising based on wavelet filters has improved the performance of the FFT and MUSIC algorithms. Others[4,5] have reported on post-processing of SAR images (for de-noising and de-speckling) using wavelet analysis and how the image quality gets enhanced using sub-band coding. Effective algorithms for SAR image compression for either method have not been reported.

This research is intended to conduct a survey of the existing methods in SAR image processing using wavelet transforms. Additionally, it aims at designing and testing a new set of adaptive and non-stationary wavelet filter banks that are suitable for FFT-based and MUSIC algorithms in terms of compression and de-noising. The goal is to realize the effects of pre-processing on the outcome of these methods while looking for better approaches to SAR processing. One main advantage of wavelet transform is in that it preserves all the data acquired in the experimental process and filters out only the unwanted parts, as needed. Additionally, it is efficient enough to help speed up the overall process. The remainder of this paper is organized as follows: Section II gives the reader a little background on the requirements for this research and some of the challenges in SAR image processing; Section III discusses the methodology and the innovative techniques used in this research to overcome some of the challenges in SAR image processing; Section IV describes the results obtained from this research; and Section V is reserved for conclusive remarks for this research and the direction of the future work in this field. The main components of this research are described below and then the methodology, data, results, and conclusion follow.

II. Background

SAR is an improved version of the standard radar in which multiple images have been combined to create an image with higher resolution. This can be achieved by either a very large aperture antenna (impossible for most applications), small antenna on a moving object, or several small antennas spread out in the field of interest. SAR algorithms then measure the relative motion and distance between antenna and target to obtain a high resolution image of the target. Using this technique with high frequencies radio waves (micro through terahertz) has resulted in resolutions in the order of sub-millimeters. In addition to high resolution, SAR functions in all weather conditions. Dust, clouds, and other particles in air do not affect its performance. Furthermore, SAR can cover large areas of interest due to its nature. However, SAR has some deficiencies. The system bandwidth and illumination frequency of sweeping wave limits the resolution of the target image. Channel noise, speckles, and other artifacts degrade the image and affect its quality in tasks such as target reconstruction, restoration, detection, recognition, and classification. While many techniques have been developed to limit the adverse effects of these parameters on SAR data, many of these methods suffer from a range of issues such as computational involvement of algorithms to suppression of useful information. The emphasis in this paper is on the FFT-based approach to SAR image analysis[12]. In this algorithm, Fourier transform is first applied in one dimension along the *range* direction, the direction along which radar beams are sent, to each column of the image. Then, after applying a match filter to the result, the range compression is finished by applying the IFFT in 1-D in range direction in the same manner. Then, a similar process is applied in *azimuth* direction, the direction of the motion of the antenna. In both parts, one has to make sure that sampling in time and frequency domains are performed correctly and apply the necessary interpolations.

The solution to this problem, presented in this paper, takes advantage of the complex nature of SAR image data. The scaling of amplitude and shifting of phase in SAR data scattered reflections is very similar to the amplitude scaling and phase shifting in wavelet filter banks. Wavelet transforms, therefore, seem to be the perfect fit solution for analyzing SAR image data. This research requires several hardware and software components that set up the framework for SAR image processing and analysis. These include Matlab analysis and modeling software, a laptop equipped with at least 2GB of memory to run computationally intensive calculations, and programming (C/C++) environments to run programs and extract data. The digital signal processing algorithms serve to manipulate data so that they would be a good fit for SAR processing and analysis. In these algorithms a wavelet based approach has been considered for de-noising and compressing the datasets. A detailed description of the technique follows in the next section.

III. Methodology

A. Data

The dataset for this experiment was obtained from RADARSAT-1 raw signal data over Vancouver area extracted from data sets that was provided in a CD that came with a book by Ian G. Cumming and Frank H. Wong[12]. According to the authors, the CD data was provided by Radarsat International Inc. (http://www.rsi.ca). Data copyright belongs to Canadian Space Agency 2002. RADARSAT-1 is a satellite that was launched by Canadian Space Agency in November 1995 (http://www.artechhouse.com/Detail.aspx?strBookId=1059).

B. Algorithm

Traditionally, FFT and MUSIC algorithms have been applied to SAR images to analyze them for direction of arrival and image extraction. The shortcoming of these methods is in their dependence on time averaging over entire duration of the signal, susceptibility to noise, and lack of proper handling of large amounts of data. SAR image analysis requires resolution in particular time and frequency rather than frequency alone. Wavelets are the result of translation and scaling of a finite-length waveform known as mother wavelet. A wavelet divides a function into its frequency components such that its resolution matches the frequency scale and translation. To represent a signal in this fashion it would have to go through a wavelet transform. Application of the wavelet transform to a function results in a set of orthogonal basis functions which are the time-frequency components of the signal. Due to its resolution in both time and frequency wavelet transform is the best tool for detection and classification of signals that are non-stationary or have discontinuities and sharp peaks. Depending on whether a given function is analyzed in all scales and translations or a subset of them the continuous (CWT), discrete (DWT), or multi-resolution wavelet transform (MWT) can be applied[6-11].

An example of the generating function (mother wavelet) based on the Sinc function for the CWT is:

$$\psi(t) = 2Sinc(2t) - Sinc(t) = \frac{Sin(2\pi t) - Sin(\pi t)}{\pi t} \tag{1}$$

The subspaces of function (1) are generated by translation and scaling. For instance, the subspace of scale (dilation) a and translation (shift) b of the above function is:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a}) \tag{2}$$

When a function x is projected into subspace of function (2), an integral would have to be evaluated to calculate the wavelet coefficients in that scale:

$$WT_\psi\{x\}(a,b) = \langle x,\psi_{a,b}\rangle = \int_R x(t)\overline{\psi_{a,b}(t)}dt \tag{3}$$

And therefore, the function x can be shown in term of its components:

$$x_a(t) = \int_R WT_\psi\{x\}(a,b).\psi_{a,b}(t)db. \tag{4}$$

Due to computational and time constraints it is impossible to analyze a function using all of its components. Therefore, usually a subset of the discrete coefficients is used to reconstruct the best approximation of the signal. This subset is generated from the discrete version of the generating function:

$$\psi_{m,n}(t) = a^{-m/2}\psi(a^{-m}t - nb). \tag{5}$$

Where m and n represent the number of levels and number of coefficients used for scaling and shifting of wavelet basis, respectively. Applying a subset of (5) to a function x with finite energy will result in DWT coefficients from which one can closely approximate (reconstruct) x using the coarse coefficients of this sequence:

$$x(t) = \sum_{m\in Z}\sum_{n\in Z}\langle x,\psi_{m,n}\rangle.\psi_{m,n}(t). \tag{6}$$

The MWT is obtained by picking a finite number of wavelet coefficients from a set of DWT coefficients in (6). However, to avoid computational complexity, two generating functions are used to create the subspaces:

$$V_m \text{ Subspace: } \phi_{m,n}(t) = 2^{-m/2}\phi(2^{-m}t - n)$$

and

$$W_m \text{ Subspace: } \psi_{m,n}(t) = 2^{-m/2}\psi(2^{-m}t - n). \tag{7}$$

From (7), the two (fast) wavelet transform pairs (MWT) can be generated:

$$\phi(t) = \sqrt{2}\sum_{n\in Z}h_n\phi(2t - n)$$

and

$$\psi(t) = \sqrt{2}\sum_{n\in Z}g_n\phi(2t - n) \tag{8}$$

In this work the DWT has been used to compress and/or denoise raw SAR images before processing them through FFT algorithm. Due to its ability to extract information in both time and frequency domain, DWT is

considered a very powerful tool. The approach consists of decomposing the signal of interest into its detailed and smoothed components (high-and low-frequency). The detailed components of the signal at different levels of resolution localize the time and frequency of the event. Therefore, the DWT can extract the "short-time", "extreme value", and "high-frequency" features of the SAR images. In this report we present how DWT can improve the quality of DOA of target using FFT-based algorithm.

IV. Results

Data for this experiment was obtained from satellite imagery as described earlier. The aforementioned DWT algorithms were then applied (up to second order L2) to the raw "corrected" data to remove noise and/or compress data before they were carried out for analysis by FFT algorithm. Figures 1 through 6 shown below are processed SAR images before and after application of noise removal and compression filters in several different settings. As can be seen, the quality of the reconstructed image has not improved much due to denoising, but it shows some improvement in its visual quality due to compression. The quality of image at this stage is measured based on observation by several experts in the field. However, putting a quantitative value on this quality, is another issue the authors are trying to resolve; specially, when it comes to blind comparison of larger image databases. Another observation is that while the compressed data produces a fairly (visually) better reconstructed image, it also takes up less memory and computational power (due to its size). Therefore, the compressed image has the potential to benefit this effort in two folds. Another important remark is that the FFT algorithm due to its usage of Fourier transform and correlation analysis seems to suppress noise internally without a need for external denoising algorithms.

V. Conclusion

SAR image extraction and processing are of great interest to NASA's earth science fields such as deformation, ecosystem structure, and dynamics of ice, snow and cold land processes, and surface water and ocean topography. The long-term goal of this research is to enable increased autonomy and quality of NASA systems, with special emphasis on automated processing, validation, and reconfiguration. The overall theme of this work is automatic extraction and processing of high-resolution SAR images. Multi-resolution wavelet transforms and advanced spectral estimation techniques have been proposed to enable efficient solutions to this problem.

This research has led to 1) accelerate research in theories, principles, and computational techniques for SAR super-resolution image processing, 2) encourage the development of software and hardware platforms that promise more rapid, accessible, and effective SAR processing technologies, and 3) develop the tools that can be utilized to test and validate these technologies. As is evident from the attached experimental results/figures, application of wavelet based filters (in pre-processing stage) to compress data and remove noise (in some cases) has substantial effect on the accuracy and optimization of data (and therefore the computations in the next stages). The proposed filters in this case have proven to be efficient in removing noise and compressing data and establishing clean and efficient data for DOA computations. Another important aspect of these filters is its low cost computational requirements and high speed results. These filters can now be implemented in hardware where speeds in the order of nano-seconds can be obtained.

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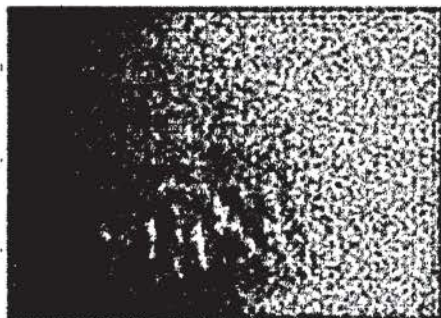
Figure 1. Original corrected raw data.

Figure 2. Compressed L2 corrected raw data.

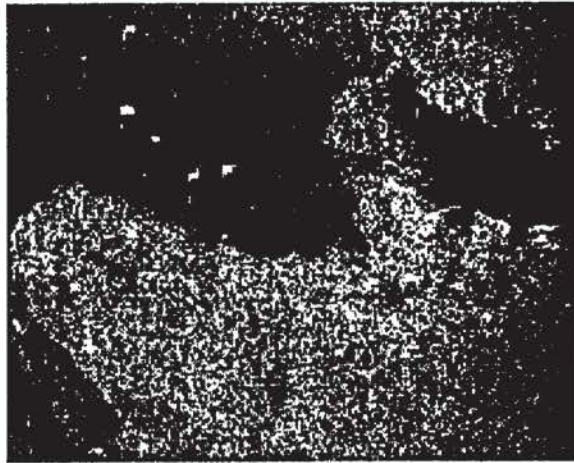Figure 3. Denoised L2 corrected raw data.

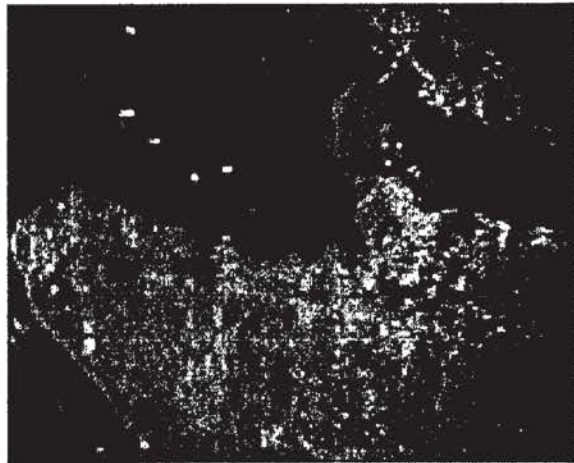Figure 4. Reconstructed image from original.

Figure 5. Reconstructed image from Compressed.

Figure 6. Reconstructed image from denoised.