EXPLOITING SPARSITY IN REMOTE SENSING AND EARTH OBSERVATION: THEORY, APPLICATIONS AND FUTURE TRENDS

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Tutorial for Invited Session "Sparse Reconstruction and Compressive Sensing in Remote Sensing"

ABSTRACT

Sparse signals are commonly expected in remote sensing and Earth observation. Along with the significant development of the compressive sensing theory, exploitation of sparsity in remote sensing became a very relevant and active field. Breakthroughs are brought in different remote sensing problems covering synthetic aperture radar, multispectral and hyperspectral image analysis, and LiDAR. Tailored to this special session, this tutorial gives a review, to the best knowledge of the session chair, on recent advances in sparsity exploitation in remote sensing and Earth observation, regarding the theory, applications and future trends.

***Index Terms*— sparsity exploitation, compressive sensing, remote sensing, synthetic aperture radar, hyperspectral imaging, optical remote sensing**

1. THEORY

Prominent problems in remote sensing for earth observation are:

- Notoriously ill-conditioned and undetermined inverse problems
  A typical example is super-resolution for radar, optical and hyperspectral imaging systems. In order to achieve good resolution and positioning accuracy the image to be reconstructed must be sampled much more densely than the resolution unit defined by the diffraction limit. This results in underdetermined systems.
- Non-Gaussian statistics and a large amount of outliers
  Many remote sensing techniques suffer from unmodeled noise contributions (e.g. turbulent atmospheric and ionospheric delay) and a large amount of outliers (e.g. by multi-path effects). Typical examples are Lidar or persistent scatterer interferometry.
- Expensive sensors and high data rate
  Advanced applications call for sensors with higher and higher resolution which leads to high requirements on the involved hardware and software. E.g. for radar systems, high pulse repetition frequency is required to sample higher resolution data which will lead to expensive sensors and renders the data rate high, although the information content does not grow accordingly.

The concept of sparsity offers a solution to many of these problems.

Let $\mathbf{x}$ be the signal to be reconstructed with a length of L and $\mathbf{y}$ be the measurement vector having N elements. The remote sensing measurement acquisition can be generally modeled as:

$$\mathbf{y} = \mathbf{F}(\mathbf{x}) + \boldsymbol{\varepsilon} \qquad (1)$$

Where $\mathbf{F}(\cdot)$ is the – possibly nonlinear – forward model and $\boldsymbol{\varepsilon}$ is the measurement noise. Linearizing the underlying measurement model yields:

$$\mathbf{y} = \mathbf{K}\mathbf{x} + \boldsymbol{\varepsilon} \qquad (2)$$

Where $\mathbf{K}$ is the sensing matrix (i.e. the Jacobian of $\mathbf{F}$). Often the system model of eq.2 is an underdetermined inverse problem, i.e. $N<L$, and appropriate regularization is required in order to obtain a robust

estimate of $\mathbf{x}$. If $\mathbf{x}$ is sparse, i.e. compared to its length L it has only few non-zero elements or its projection onto an orthogonal basis $\mathbf{\Phi}$ (e.g. Fourier, wavelet) has only few non-zero coefficients, this sparsity property can be used as a strong prior for regularizing the underdetermined inverse problem. Among the infinitely many solutions of the (noise-free) underdetermined system, the sparsest solution, i.e. the solution with $\mathbf{\Phi}\hat{\mathbf{x}}$ having the minimum L_0 norm, is assumed to be the most probable one. Since the measurements are contaminated with noise, the L_0 norm is jointly minimized with the classical residual term:

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \left\{ \left\| \mathbf{y} - \mathbf{K}\mathbf{x} \right\|_2^2 + \lambda_0 \left\| \mathbf{\Phi}\,\mathbf{x} \right\|_0 \right\} \quad (3)$$

where λ_0 is a regularization parameter balancing sparsity and residuals (noise). Eq.3 gives the theoretically most probable sparse solution. However, this optimization task is N-P hard, and hence is not applicable in practice. It can also give multiple and unrealistic high-energy solutions. A practical approach provided by compressive sensing (CS) is that under certain constraints [1], the L_0 norm prior used in eq.1 can be well approximated by the L_1 norm. This leads to an optimization task that mixes L_2 and L_1 expressions in the form:

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \left\{ \left\| \mathbf{y} - \mathbf{K}\mathbf{x} \right\|_2^2 + \lambda_1 \left\| \mathbf{\Phi}\,\mathbf{x} \right\|_1 \right\} \quad (4)$$

This approximation renders the problem convex and solvable by linear programming.

Besides this L_2 and L_1 norm minimization several other minimizers are proposed in sparse signal representation, e.g. for robust PCA computation [2], exploiting joint sparsity [3], etc.

2. APPLICATIONS

In the recent years, pioneer research has been carried out to apply this model for solving remote sensing problems that lead to exciting results. Selected remote sensing problems addressed by the community are as follows.

- SAR imaging [4]–[6]: Modern SAR sensors provide very high spatial resolution. This high resolution reduces the information content per pixel, and hence renders the signal medium sparse in azimuth and range. This is particularly true for sparse scenes, e.g. in coastal areas [7].
- Optimizing remote sensing systems [8]: Sparse signals can be well reconstructed from much fewer samples than the Shannon sampling theory requires. A straightforward application is to use the compressive sensing paradigm to design innovative imaging system aiming at acquiring much less data in an optimum way.
- SAR tomography (TomoSAR) [9]–[13] : TomoSAR uses stacks of repeat-pass SAR acquisitions to reconstruct the reflectivity of the scattering objects along elevation for every azimuth-range pixel. For certain imaging geometries, e.g. in urban environment, the signal is sparse in elevation and there are typically only 0~4 scatterers inside an azimuth-range pixel.
- Ground Moving Target Identification (GMTI) [14]: Signatures of moving targets in radar are in fact chirp signals with different Doppler and chirp rates depending on the velocities of the targets. Compared with the stationary background, they are sparse signals.
- Inverse SAR (ISAR) [15], [16]: An ISAR system illuminates a maneuvering target and collects a number of pulses coherently. The image of the interesting – mostly military – target is generally constructed by limited strong scattering centers, representing strong spatial sparsity.

Further applications in radars [17], [18] include, e.g. multiple-input/multiple-output (MIMO) radar [19], through-the-wall radar [20] and ground penetrating radar [21].

- Pan-sharpening and hyperspectral image enhancement [22]–[28]: The goal of both pan-sharpening and hyperspectral image enhancement is to fuse two images which have high spatial and high spectral resolution, respectively. Sufficiently small images patches normally have a sparse representation in overcomplete dictionaries trained from the data.
- Spectral unmixing for hyperspectral data [29]–[31]: The goal of spectral unmixing is to identify the materials inside a hyperspectral image pixel. Typically there are only few material classes

(endmembers) inside a pixel compared to the prodigious endmember spectral library.

- Dimension reduction of hyperspectral imagery: Hyperspectral data are characterized by very rich spectral information, which makes them apt to detecting targets of interest, but also introduce drawbacks caused by their high dimensionality. A high dimensional hyperspectral data cube can be decomposed into a low-rank matrix corrupted by a sparse error matrix [32].

Further applications in optical remote sensing include, e.g. classification [33], target detection [34]–[36], anomaly detection and hyperspectral compressive sensing [37].

- Lidar full waveform analysis [38]: Lidar returns are the convolution of the pulse shape and the reflectivity profile. High range resolution requires deconvolution, which can be regularized by the sparsity assumption.
- 3D water vapor tomography using GNSS and InSAR [39]: As the precipitable water vapor (PWV) deduced from GNSS wet delays and the estimated InSAR wet delays only yield integrated information in 2D, this calls for tomographic approaches to reconstruct 3D water vapor fields which can be sparsely represented in, e.g., a cosine transform basis.

In [40], highlight results from selected applications and overview on sparse reconstruction and compressive sensing in various remote sensing problem will be presented.

3. FUTURE TRENDS

After the first harvesting in sparsity exploitation in remote sensing community, further developments mainly lie in answering the following questions:

- Instead of deriving the limits of sparse remote sensing by giving SNR, N and mathematic conditions, can we change the perspective, i.e., starting from the practical scenarios and user specifications?
- How do intelligent compressive remote sensing systems look like that guarantee high probabilities of precise signal recovery?
- For practical problems, how to decide for conventional methods or CS based algorithms that bring the superior performance but relatively high computational cost?
- Where are further sparse signals or smart sparse signal representations to be exploited in remote sensing and Earth observation?

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