URSI GASS 2020, Rome, Italy, 29 August - 5 September 2020

Raw GNSS Data Compression using Compressive Sensing for Reflectometry Applications

Bushra Ansari*, Vishal Kaushik, Sanat K. Biswas
Department of Electronics and Communication Engineering, IIIT Delhi, New Delhi, India

Abstract

Global Navigation Satellite System (GNSS) is a passive and in-expensive technique for remote sensing applications. GNSS reflectometry (GNSS-R) aims at analyzing the multi-path signal reflected from the surface surrounding the receiving antenna. One of the challenge is the size of the raw GNSS-R I/Q data. The data size is very large even for a short duration of time. To address this issue an algorithm is proposed using the Compressive Sensing (CS) theory, to compress and reduce the size of data that is to be transmitted for further processing. The data is first compressed using the CS theory and then reconstructed using convex l_1 minimization algorithm. In addition, the performance of different sparsifying and measurement matrices that are used in the compression are compared and reconstruction of the original signal is performed. The algorithm proposed is verified for the raw Global Positioning System (GPS) and Navigation with Indian Constellation (NavIC) data set.

1 Introduction

GNSS-Reflectometry (GNSS-R) has gained attention due to its unique and inexpensive characteristics. In GNSS-R method, the GNSS signals are acquired in bi-static or multi-static radar configuration. The main objective of GNSS-R is to receive GNSS multi-path signals and derive useful information about the reflecting surface. The signal properties (signal-to-noise ratio (SNR), signal power etc.) of the multi-path signal deviates from that of the directly received GNSS signal. The change in signal properties depends on the surface properties of the ground and hence provides a wide range of opportunities. Some of its applications include soil moisture and vegetation height measurement [1], snow height retrieval [2], and altimetry estimation [3].

In the GNSS-R technique, the direct and the reflected signal is received using a GNSS antenna. After that, raw I/Q GNSS data is to be sent to the remote server through wireless channel for further processing as shown in Fig.1. The data used in GNSS-R has a size of around 100 thousand samples for a very short duration, which take long transmission time while sending it through the wireless channel for GNSS-R analysis. Hence it is necessary to develop an algorithm to reduce the amount of data to be stored on board and transmitted, for GNSS-R applications.

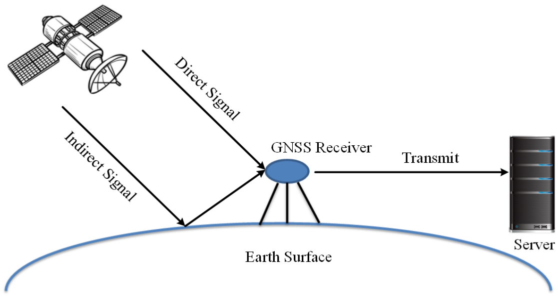


Figure 1. GNSS-R Geometry

The above-mentioned problem can be solved by compressing the GNSS data first and then reconstructing it at the receiver end. The problem is segmented into three steps, the first step is the sparse representation of the GNSS data in a sparse domain. The second step is the formation of the measurement vector of lower dimensions than the original signal. The last step is the reconstruction of the original signal from a reduced number of measurement. According to previous work done in this area, [4] a two-stage deterministic CS algorithm has been proposed. The deterministic CS matrix is not robust to noisy signal. A study is performed in [5], which uses multiple measurement vector as the reconstruction algorithm, this algorithm is complex as it uses multiple measurement CS theory. To solve these problems a compression and reconstruction algorithm based on compressive sensing is used in this paper which is applicable to the noisy input signal as well. The proposed method has low algorithmic complexity than the previously proposed algorithms [4, 5]. Finally, the proposed algorithm is applied on both direct and multipath GPS data collected by TechDemo satellite (TDS)-1 and simulated NavIC signal collected using bladeRF SDR. Additionally, the Normalised Mean Square Error (NMSE) performance of different sparsifying and measurement matrix is compared. The algorithm is further validated by generating the Delay Doppler Maps (DDMs) for both the original and the reconstructed signal.

The rest of the paper is organised as follows: In section II, the mathematical formulation for the compression and reconstruction of the GNSS signal is explained. Section III provides the details of the simulation setup. Results and discussions are included in section IV and section V concludes the paper outlining the future work.

2 Mathematical Formulation

Compressive sensing is an emerging signal processing technique. It is a sampling method which provides efficient signal compression and reconstruction by using the fact that a sparse signal can be reconstructed from a lesser number of samples. In the compression process, a certain number of samples in the sparse domain are discarded, assuming that the majority of samples are non-significant. Hence less number of measurements are acquired and can be used to reconstruct the complete signal. The missing information can be reconstructed using the CS sparse recovery algorithms [6]. The CS theory can be applied to GNSS signals as well, as it has a sparse representation in both Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) domain, as shown in Fig. 2.

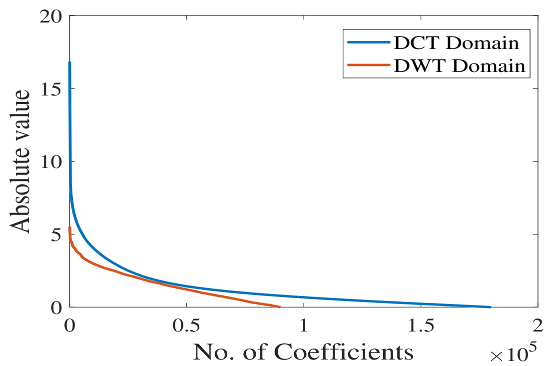


Figure 2. Sparase Representation of signal in DCT and DWT Domain

Consider a signal $x \in R^m$, of size $m \times 1$ that has a sparse representation in a transform domain. The signal can be represented sparsely in a particular transform domain, by multiplying the signal with the sparsifying matrix i.e. DCT or DWT matrix. The signal with a reduced number of samples, constructed using the sparse signal, is called the measurement vector. The measurement vector $y \in R^n$ of size $n \times 1$ where $n < m$ will be used for original signal recovery. The vector $y \in R^n$ is a linear measurement of the signal x given by $y = Ax$, where A is the measurement or sensing matrix of size $n \times m$. This system is under-determined, so the reconstruction of the signal x is an ill-posed problem. Therefore, an optimization algorithms can be used to obtain an optimal solution for this system. The sparse signal recovery algorithms are based on the convex-optimization technique. One of the method that is based on convex l_1 minimization which gives near optimal solution can be defined as:

$$min \|x\|_1 \, subject \ to \ y = Ax \tag{1}$$

This convex minimization approach is called as Basis Pursuit (BP). However, in case of noisy measurements, the linear measurement vector is represented as $y = Ax + N$, where N is the noise and $\|N\|_2 \leq \varepsilon$, where ε is sufficiently small value. This optimization approach is called Basis Pursuit Denoising (BPDN) and is defined as [6]:

$$min \|x\|_1 \, subject \ to \ \|y - Ax\|_2 \leq \varepsilon \tag{2}$$

The BPDN algorithm can be solved using SPGL-Toolbox which is a Matlab solver for large-scale sparse reconstruction. The procedure followed in compression and reconstruction of GNSS I/Q data set is summarized in the Algorithm 1 given below:

Algorithm 1: CS based reconstuction algorithm

INPUT: x (GNSS Signal)

STEP1: Compression of GNSS signal i.e. sparse representation and generation of mesurement vector .

$$Dx = \psi$$

where D is the sparsifying marix and ψ is the sparse representation of GNSS signal.

$$y = Ax \ \ i.e. \ \ y = AD^{-1}\psi$$

where y is the measurement vector and ϕ is the measurement matrix.

STEP2: Wireless transmission of measurement vector.

STEP3: Obtain the sparse signal using convex l_1 minimization algorithm.

$$min \|Dx\|_1 \, subject \ to \ \|y - Ax\|_2^2 \leq \varepsilon$$
$$min \|\psi\|_1 \, subject \ to \ \left\|y - AD^{-1}\psi\right\|_2^2 \leq \varepsilon$$

STEP4: Reconstruction of original signal from the sparse vector.

$$\widehat{x} = D^{-1}\psi.$$

OUTPUT: $\widehat{x}$ (Reconstructed Signal)

The performance of the algorithm for GNSS signal compression and reconstruction is further verified by generating the Delay Doppler Maps (DDMs) for both the original and the reconstructed data set. DDM is defined as the amplitude/power distribution of the reflected signal in a 2-D array of delay offsets and doppler shifts around the specular point.

3 Simulation Setup

The study presented in this paper is conducted on the real-time raw GPS and the NavIC data-set. The GPS IF data is from TDS-1 satellite which is available at FTP server ftp://ftp.merrbys.co.uk. The data file is first processed using the softGNSS [7] algorithm to obtain the data vector. The data is collected for a duration of 2 minutes 20 second, with the sampling rate of 16.367 MHz and the intermediate frequency of 4.188 MHz. For experimentation using NavIC data-set, a simulation testbed is developed as shown in Fig.3. The NavIC data for Reflected (multipath) scenario is simulated using the GNSS Simulator SIMAC2. The Multipath data is simulated for two different surface properties (i.e. dielectric constant) using physics based model.

After that, the bladeRF SDR is used to receive the NavIC data sets. The NavIC data sets are collected for a duration of 10ms, with the sampling rate of 5 MHz. Finally, two data sets are collected for two different surface properties (i.e.dielectric constant). The Dielectric constant for Data set-1 is 5 and Data set-2 is 20. These data sets are further processed for reflectometry application in MATLAB environment.

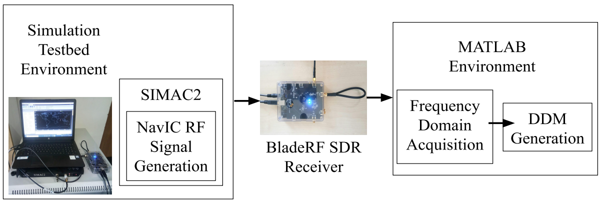


Figure 3. Simulation setup for NavIC signal Processing

4 Results and Discussion

The TDS-1 I/Q data and simulated and sampled NavIC I/Q data are compressed and then reconstructed using the algorithm mentioned in section-II. The normalised mean square error (NMSE) in signal reconstruction is calculated at different sampling ratio to show the comparison between different matrices. The NMSE is defined as:

$$NMSE = \frac{\|\hat{x} - x\|_2^2}{\|x\|_2^2} \tag{3}$$

where $\hat{x}$ is the recovered signal and x is the original signal. The performance of DCT and DWT sparsifying matrix is compared in terms of NMSE at different sampling ratio for the Toeplitz, Bernoulli and Gaussian measurement matrix. One of the case with toeplitz matrix is presented in Fig. 4. It is observed that the NMSE of the DCT sparsifying matrix is less than that of the DWT matrix, which states that the DCT matrix is performing better than the DWT matrix. Similarly, the performance of Toeplitz, Bernoulli and Gaussian measurement matrix is evaluated as shown in Fig. 5.

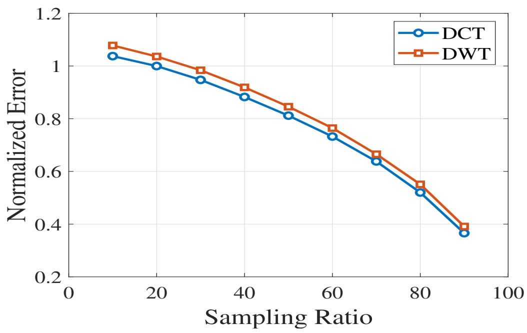


Figure 4. Comparison between DCT and DWT sparsifying matrix for different sampling ratio.

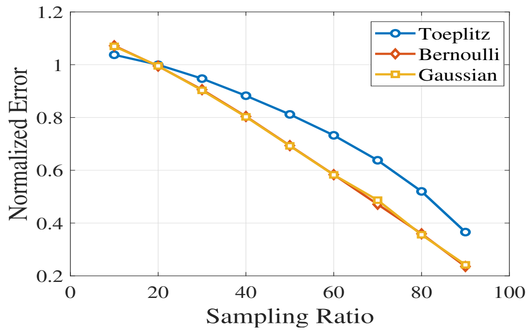


Figure 5. Comparison between Toeplitz, Bernoulli and Gaussian measurement matrix for different sampling ratio.

The performance of Toeplitz measurement matrix is better as compared to Bernoulli and Gaussian matrix in terms of signal reconstruction. Now the GNSS data compression and reconstruction is performed using the DCT sparsifying matrix and toeplitz measurement matrix. The GNSS data is reconstructed from 40% of original data samples. Additionally, after performing the frequency-domain correlation of the reconstructed data with the locally generated GPS/NavIC code (depending on the data used), the same satellite PRN i.e. PRN 24 and code delay is found as detected for the original data. The frequency domain acquisition for the original and reconstructed GPS data for satellite PRN 24 is presented in Fig.6 and Fig.7 respectively.

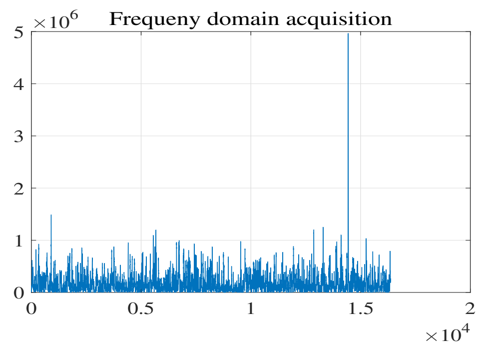


Figure 6. Frequency domain acquisition for the Original GPS data.

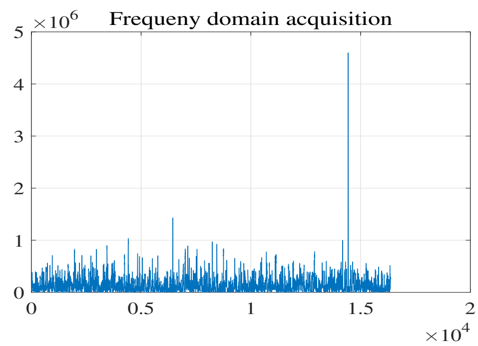
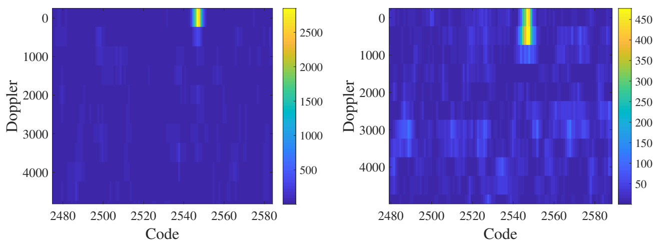


Figure 7. Frequency domain acquisition for the Reconstructed GPS data.

For reflectometry application, the DDMs of two NavIC data sets for different surface properties (i.e. dielectric constant 5 and 20) are generated. Now according to bi-static radar equation [8], the coherent power levels for two different surfaces will vary depending on the surface properties. The DDMs for two different NavIC data sets are presented in Fig.8 and Fig.9. The correlation power levels of the DDM shows variation depending on the surface properties. Moreover, the DDMs of the data which is reconstructed using the proposed algorithm also shows the variation in the correlation power. The experimental results of DDMs obtained from the original and reconstructed data set are sumamrized in the Table.1

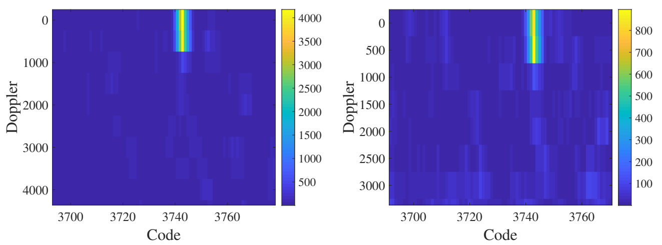
Table 1. Change in correlation peak with different surface dielectric constant

Dielectric Constant	Correlation peak (Original Data set)	Correlation Peak (Reconstructed Data set)
5	2848	476.8
20	4176	849.9



(a) Original Data **(b)** Reconstructed Data

Figure 8. DDM for the multi-path NavIC signal for Dielectric Constant 5



(a) Original Data **(b)** Reconstructed Data

Figure 9. DDM for the multi-path NavIC signal for Dielectric Constant 20

The results presented in Fig.8 and Fig.9 implies that the similar variations in correlation power can be achieved with the reconstructed GNSS signal as shown by the original GNSS signal DDMs. Hence, only few significant GNSS data samples can be transmitted and then reconstructed at receiver's end for further processing. It will reduce the amount of data to be stored on board and transmitted for further processing.

5 Conclusion

In this paper, Compressive Sensing based reconstruction algorithm is proposed that is reducing the data size for reflectometry application. The BPDN convex optimisation algorithm of compressive sensing theory is applied to the GNSS signal. From the experimental results, it has been concluded that for compression of the signal, DCT sparsifying matrix with Toeplitz as the measurement matrix has better performance. The satellite acquisition is also performed for both the original and reconstructed data sets and the same satellite PRN and code delay is detected for both data. Additionally, it is feasible to differentiate between two surface properties (i.e. dielectric constant) from the DDMs generated from the reconstructed data. However, further research is required to validate and generalize this algorithm for more variations in surface properties.

References

[1] K. M. Larson, J. J. Braun, E. E. Small, V. U. Zavorotny, E. D. Gutmann, and A. L. Bilich, "GPS Multipath and Its Relation to Near-Surface Soil Moisture Content," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2010.

[2] E. D. Gutmann, K. M. Larson, M. W. Williams, F. G. Nievinski, and V. Zavorotny, "Snow measurement by GPS interferometric reflectometry: An evaluation at Niwot Ridge, Colorado," *Hydrological Processes*, 2012.

[3] R. N. Treuhaft, S. T. Lowe, C. Zuffada, and Y. Chao, "2-cm GPS altimetry over Crater lake," *Geophysical Research Letters*, 2001.

[4] S. H. Kong, "A deterministic compressed GNSS acquisition technique," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 2, pp. 511–521, 2013.

[5] X. Li, A. Rueetschi, Y. C. Eldar, and A. Scaglione, "GPS signal acquisition via compressive multichannel sampling," *Physical Communication*, vol. 5, no. 2, pp. 173–184, 6 2012.

[6] A. Draganic, I. Orovic, and S. Stankovic, "On some common compressive sensing recovery algorithms and applications," *Facta universitatis - series: Electronics and Energetics*, vol. 30, no. 4, pp. 477–510, 7 2017.

[7] K. Borre, D. M. Akos, N. Bertelsen, P. Rinder, and S. H. Jensen, *A software-defined GPS and Galileo receiver: a single-frequency approach*. Springer Science & Business Media, 2007.

[8] C. Zuffada, C. Chew, and S. V. Nghiem, "Global Navigation Satellite System Reflectometry (GNSS-R) algorithms for wetland observations," in *International Geoscience and Remote Sensing Symposium (IGARSS)*, 2017.