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A Compressive SFCW-GPR System

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Introduction

- Radar Transmission modes
  - Impulse
  - Continuous wave
- SFCW-GPR
  - Advantages
    - Compensation of electronics imperfection by signal processing
    - Flexibility to adjust frequency range
    - (In some cases) electronics more available in market
  - Drawbacks
    - Slow scanning (data acquisition) speed, due to step-wise frequency scan
- **This paper**
  - Increase acquisition speed through compressive sensing/sampling (CS)

Compressive sensing

- Shannon-Whitaker Sampling Theorem

  a signal bandlimited to BW requires 2×BW sampling rate for exact reconstruction

- Compressive Sampling Theorem

  an *N*-length *K*-sparse signal can be exactly reconstructed from its *M*-subsamples

  $$M \geq C \cdot K \cdot \log(N)$$

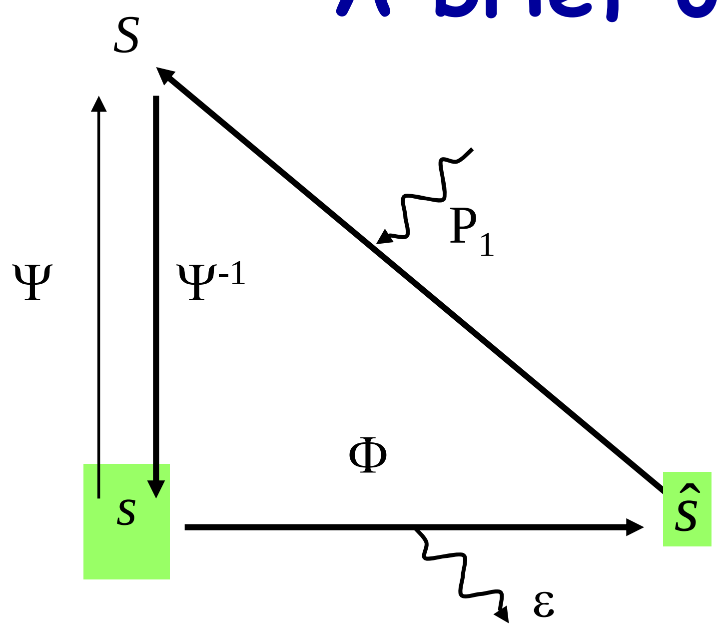
  where C is a small constant and $K<M<<N$.

- Bottom line
  - *classical sampling* assumes that signal's information is contained in its **frequency bandwidth**

    while

  - the *compressive sampling* assumes that the information of a signal is defined by its degree of freedom or **sparsity**.

A brief on CS theory



A generic multidomain diagram of compressive sampling/sensing

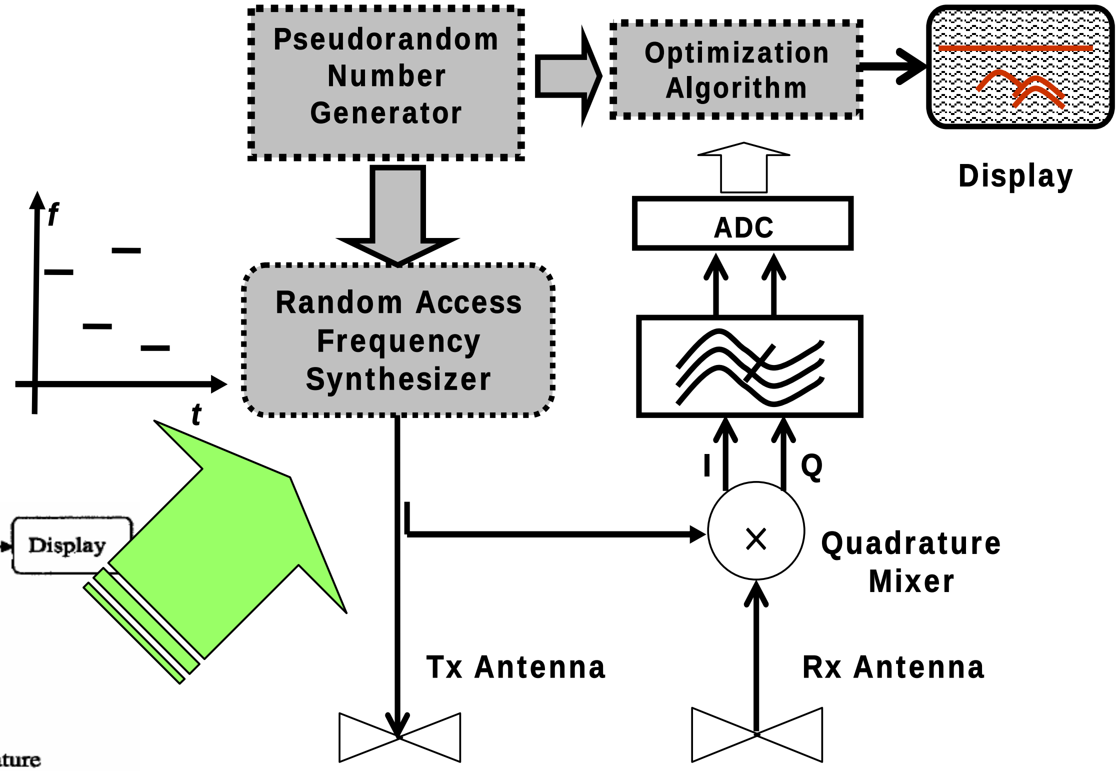
- Signal **s** is K-sparse on a sparsity basis Ψ (represented as an N×N matrix),
  - i.e., **s** = Ψ**S** with almost all of the **S** components are zero, except K-number of it.
- The measurement of **s**, i.e. <**s**, ϕ_k>, is performed on projection basis Φ that is represented as an M×N matrix. It yields an M length vectors that is much shorter than s (M<<N): subsampling.

- If $M \geq C \cdot K \cdot \log(N)$, s can be exactly reconstructed by the following P_1 minimization:

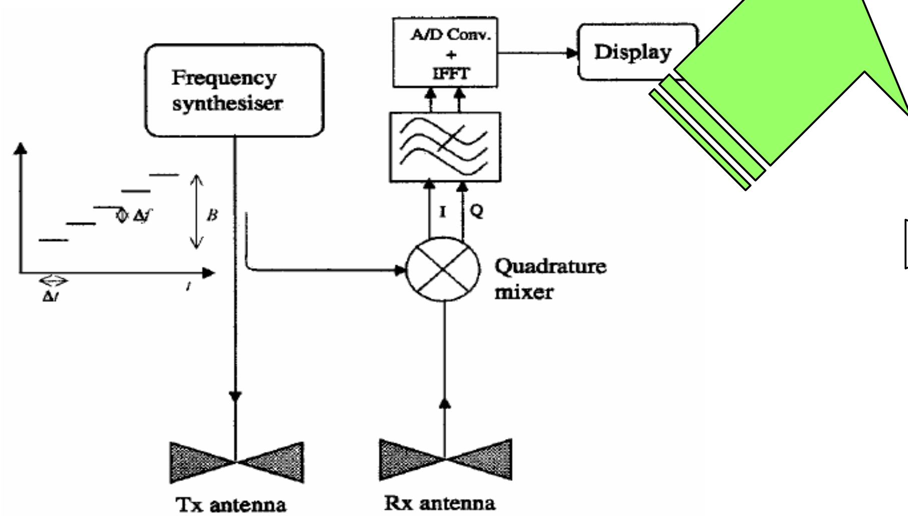
$$\min ||S||_1 \text{ s.t. } \quad \hat{s} = \Psi S$$

- The multidomain diagram says
  - Sparsity transform Ψ is *lossless*/invertible
  - Measurement/projection by Φ is *lossy*, but P_1 recovers the lost information

Construction of the Compressive GPR

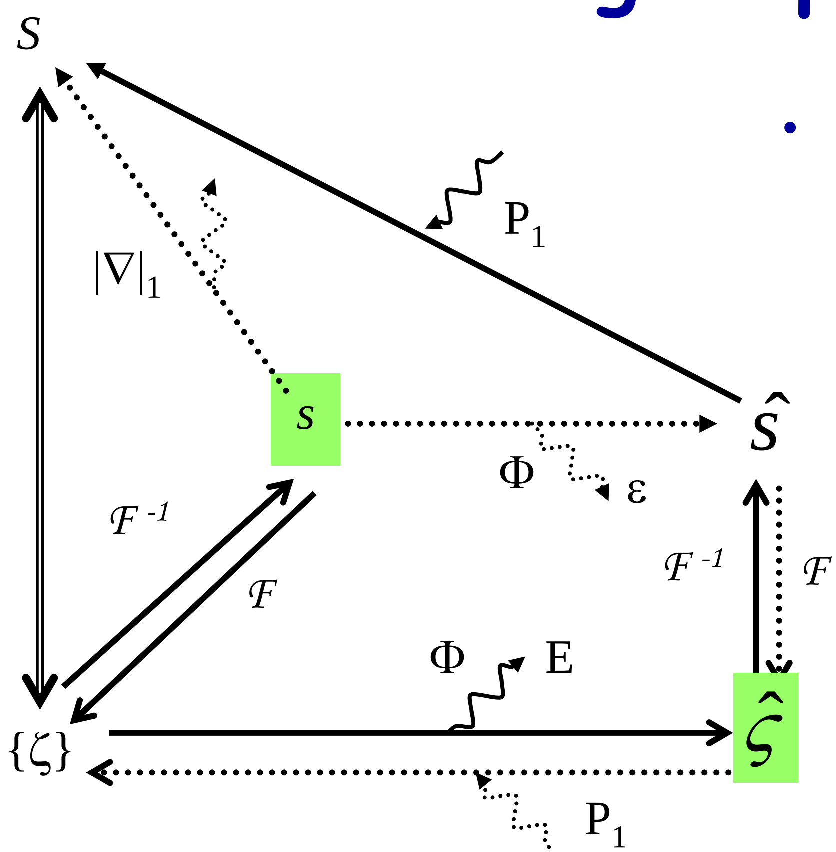


Compressive SFCW-GPR



“ordinary” SFCW-GPR

Signal processing



We do not use direct synthesis on sparsity basis as before, instead,

- The minimized sparsity is the TV (*Total Variance*)
- Signal **s** is synthesized in Fourier-domain

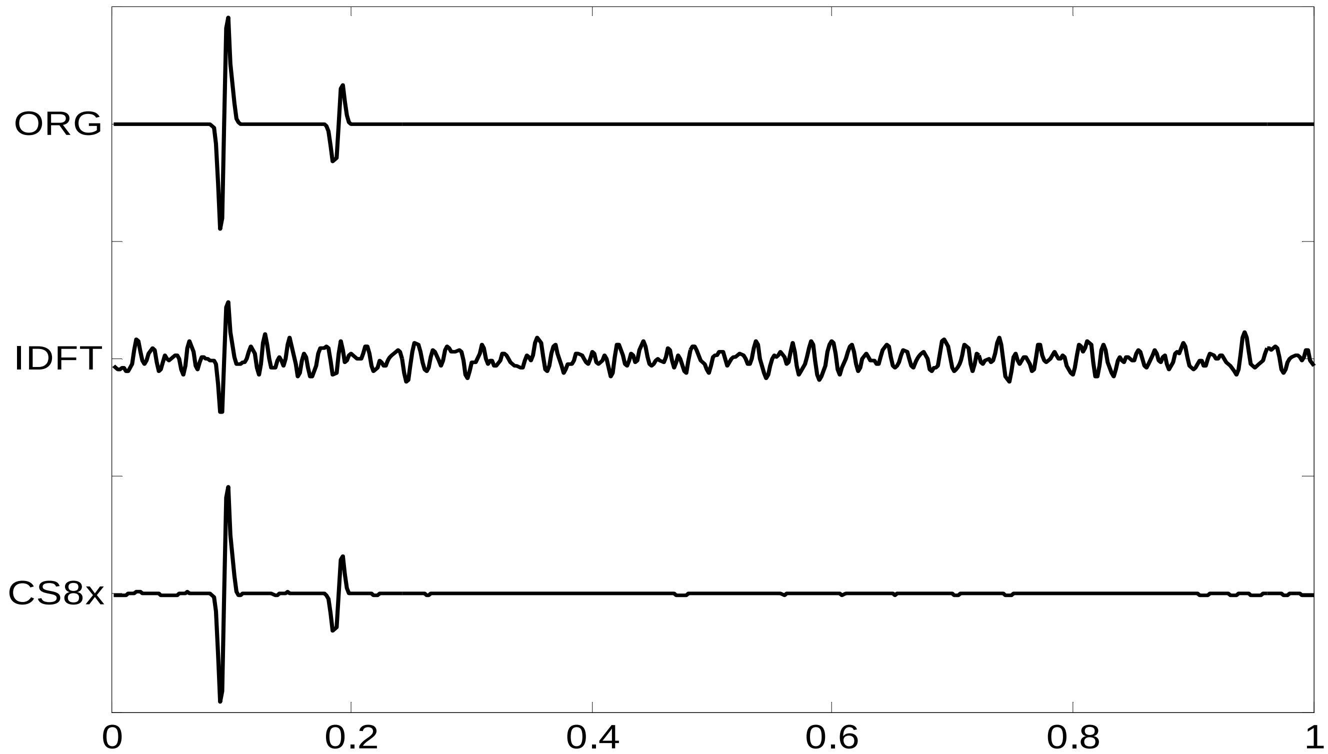
- **How it works?**
  - Normally, an SFCW-GPR measures Fourier coefficient ζ . The Compressive SFCW-GPR only select partial number of ζ **at random**, giving ζ_hat.
    - The *lossy* projection basis Φ is a random basis. All component of each basis vectors are zero, except one, whose position is random.
  - The signal **s**, or the A-scan, is smooth. Hence, the TV of the solution should be the smallest one.
  - In each cycle, the optimization algorithm select s_hat whose TV is the smallest one, which explain the observation ζ_hat:

$$\min_{\vec{x}\in R^N}\left\|\nabla(s)\right\|_1 \quad s.t.\ \hat{\varsigma}_k = \langle \phi_k, Fs\rangle,\ \forall k \in \{1,2,\ldots,M\}$$

  - **Solution: the A-scan is**

    s = $F^{-1}\zeta$

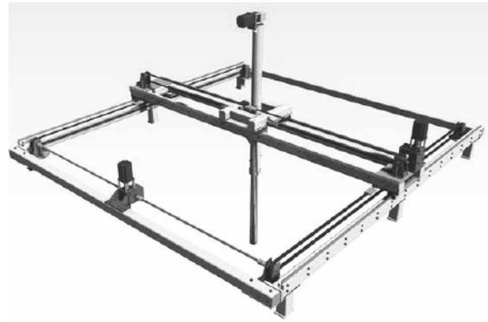
Experiments: (1) Simulation

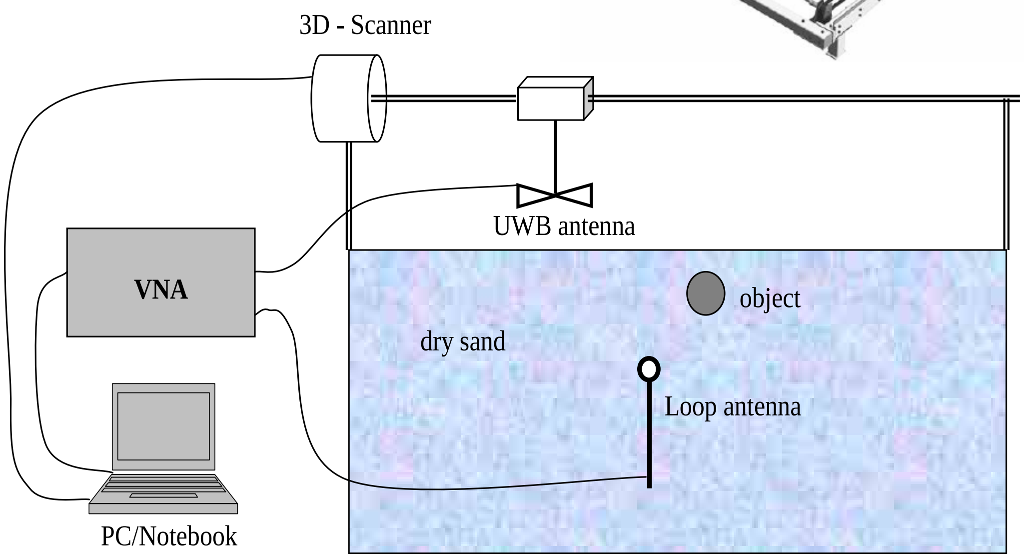


- Simulated monocycle undergoing double reflections
  - Scan frequency range (BW): 0 – 2048 MHz
  - Number of original samples (ORG): 529 points
- Subsampling eight times: pick 66 samples randomly
  - Direct IDFT inversion: 0.48 dB PSNR
  - Compressive sensing (CS8×): 197 dB PSNR (perfect reconstruction)

Experiments: (2) In GPR Test Range

GPR Test-Range in ITB, Bandung





- **GPR Test-range:**
  - Constructed by: IRCTR-TU Delft, IRCTR-IB, and ITB-Bandung
  - Sandbox: 3×3 m^2, compute-controlled 3D Scanner
  - Network Analyzer (VNA): 300 KHz – 3 GHz
- **Antennas:** Bowtie- (Tx) and Loop- antenna (Rx)
- **PC/Notebook:** collect data from VNA, perform signal processing

Experiments: (3) Performances

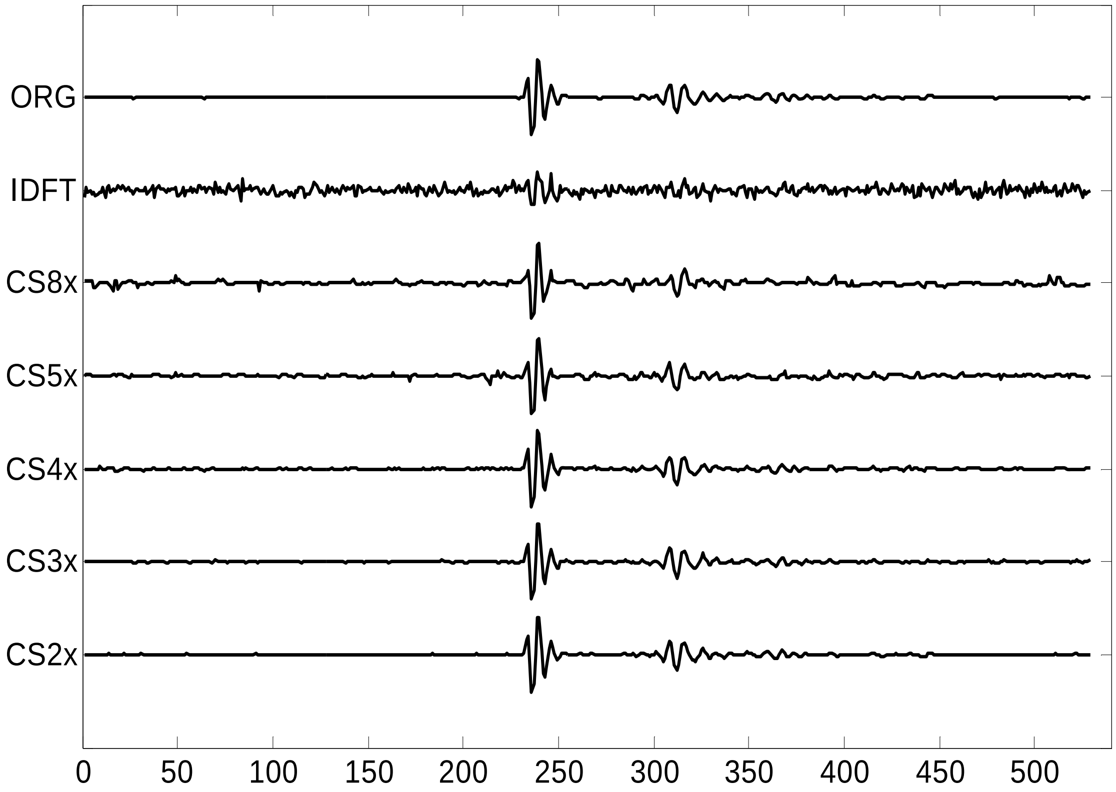
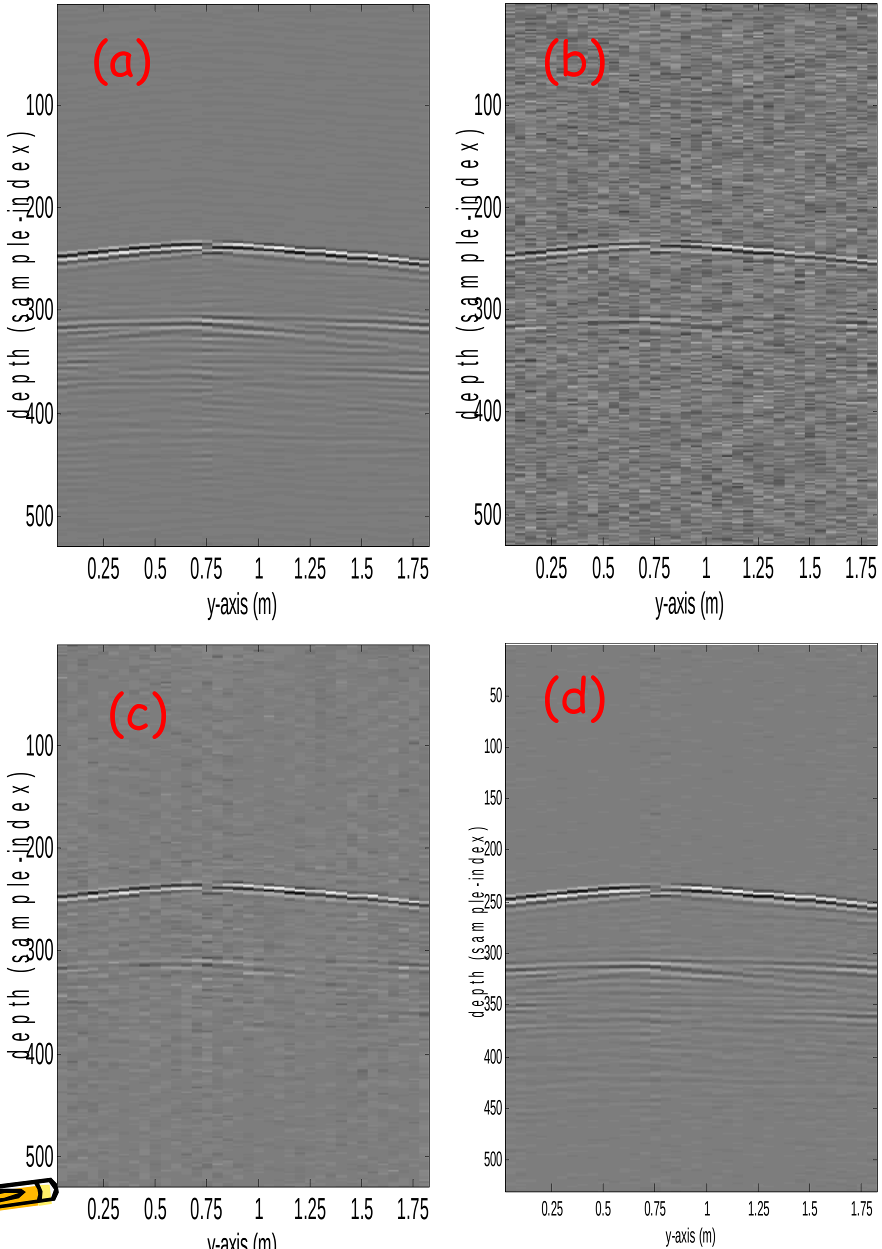


Table 1

No	No. of Samples	Compression Ratio	PSNR-IDFT (dB)	PSNR-CS (dB)
1	66	8.3	-0.4	12.4
2	96	5.5	4.2	38
3	160	3.3	8.6	43
4	192	2.8	12.2	50

- Synthesis of full data scan is plotted in the top (ORG).
- Second row displays 8.3× comporession, reconstructed by IDFT.
- Third row (CS8×), inversion result of 8.3× subsamples data.
- Next lines: inversion by CS method with corresponding compression ratio.
- Table 1 shows performance comparison of IDFT vs CS.

Experiments: (4) B-Scans



- <u>B-scan image:</u>
  - (a): full data reconstruction by IDFT
  - (b): 8.3× subsampled data reconstruction by IDFT
  - (c): 8.3× subsampled data reconstruction by CS
  - (d): 5.5× subsampled data reconstruction by CS
- B-scan image from CS reconstruction of subsampled data are much better !

Conclusions & Further Direction

Conclusions

- A novel SFCW-GPR system based on compressive sampling/compressed sensing has been presented.
- The system is capable to increase acquisition speed of the SFCW-GPR, while maintaining the results at a similar level.
  - solve fundamental problem of the stepped frequency radars
- The system has been demonstrated by simulation and actual measurement.

Further Direction

- A prototype of the compressive GPR is now under construction.

Acknowledgements

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Thank You