# Enhancing Backscatter Localization Using Convex Total Variation Denoising in Ultrawideband Radar Systems

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February 2, 2025

***Abstract*—Effective soil moisture management is a critical step in sustainable agriculture, yet the expensive costs of soil moisture sensors hinder the widespread adoption of this technology. This work builds on improving ultrawideband radar low-cost soil moisture sensing by increasing the accuracy of soil moisture readings using convex preprocessing techniques. The project aims to refine this system by using convex total variation denoising on UWB radar data to achieve robust measurements. The refined system achieved an 8.5% improvement in soil moisture measurement accuracy. These findings contribute to developing accessible agricultural technologies that support more efficient water usage and sustainable farming practices.**

## I. Introduction

Effective soil moisture management is vital to modern agriculture. Although decades of research have shown that the use of soil moisture sensors can lead to substantial reductions in water usage while preserving crop yields, widespread adoption of this technology is often impeded by the high costs associated with the sensors [1]–[9]. Our work at Dr. Josephson's laboratory seeks to tackle this issue by utilizing ultra-wideband (UWB) technology in combination with backscatter tags [10], [11]. We utilized a UWB radar system from Sensor Logic, known as Chipotle. It is recognized for its 4mm range resolution and ability to penetrate obstacles, which are crucial for accurate backscatter localization.

Our WaDAR (Water raDAR) system measures soil moisture by utilizing radar time-of-flight (ToF) measurements between the UWB radar positioned above the soil and the backscatter tag beneath it to compute the apparent dielectric constant of soil. The tag oscillates at a frequency of 80 Hz, which we detect by applying a Fast Fourier Transform (FFT) to identify the peak at this frequency. Influenced by soil moisture, changes in the dielectric constant are mapped to volumetric water content (VWC) using established soil science models.

### A. Challenges in UWB-Based Soil Moisture Sensing

In laboratory tests, we recorded an average error of 2.7% [11]. Commercial-grade sensors generally achieve an average error of 1% to 3% [12]. By reducing our error rate, we would considerably improve the likelihood of adoption among farmers, which is vital for our objective of minimizing water usage.

One critical challenge is reliably detecting the backscatter tag's signal amidst clutter and noise. During field tests, environmental factors, such as vegetation, surface erosion, and elevated soil moisture levels, exacerbate multipath interference and reduce the accuracy of ToF measurements. Figure 2 illustrates a 3D range-Doppler plot obtained from radar capture, where the tag's signal peak must be precisely identified to calculate ToF. These challenges necessitate advanced signal preprocessing to improve the robustness of peak detection and minimize noise-induced errors.

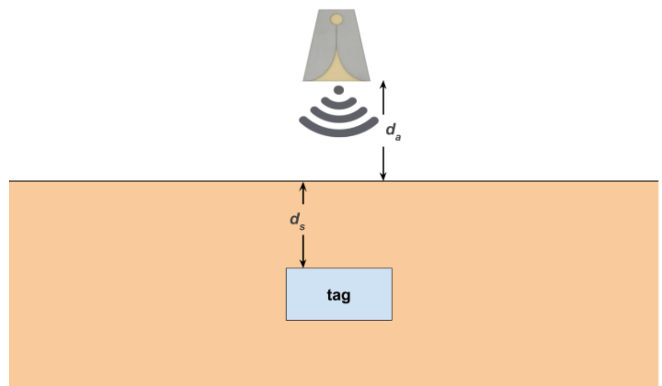


Fig. 1. The radar uses the Time of Flight (ToF) between the radar and tag to compute soil moisture.

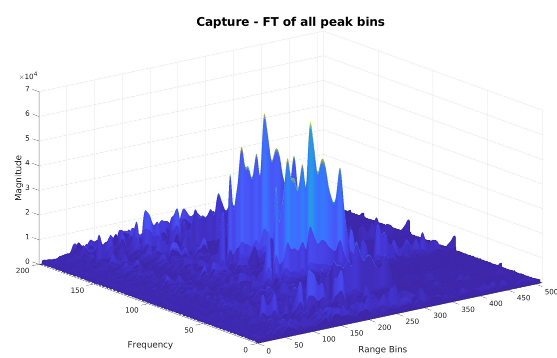


Fig. 2. 3D Range-Doppler plot of radar capture. The peak at 80 Hz is used as the tag's location to compute the ToF.

### B. TV Denoising

Total Variation (TV) denoising is a technique in image processing that aims to suppress noise while preserving key features like edges or sharp transitions. Introduced in [13], TV denoising works by minimizing the total variation of a signal, defined as the integral of the gradient magnitude. This approach favors piecewise-smooth signals, making it well-suited for applications with critical sharp transitions. Therefore, this project adopts it for peak detection in radar data.

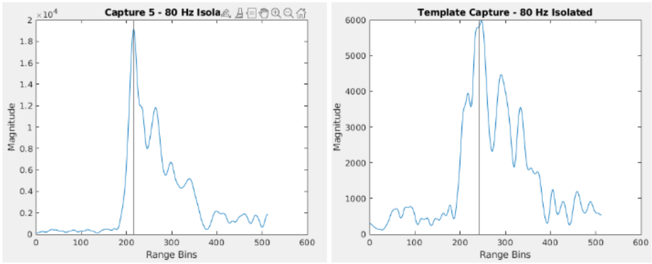


Fig. 3. Example of strong and noisy radar scans in the frequency domain. The difference in magnitudes and shapes of peaks can make tag localization difficult.

The TV denoising problem is typically framed as a convex optimization task. Given a noisy signal $f$, the denoised signal $u$ is obtained by solving:

$$\min_{u \in BV(\Omega)} ||u||_{TV(\Omega)} + \frac{\lambda}{2} \int_{\Omega} (f - u)^2 dx$$

where

| | |
|---|---|
| $\|\|u\|\|_{TV(\Omega)}$ | is the total variation of $u$ |
| $BV(\Omega)$ | is the set of functions with bounded variation |
| $\lambda$ | is a regularization parameter |

TV denoising has seen widespread application where noise can obscure critical features. A notable example is its use in producing the first image of a black hole [14]. In this project, TV denoising is applied to radar signal processing to address noise and clutter, which is common in outdoor soil moisture-sensing experiments. By enhancing the signal-to-noise ratio, this technique improves the accuracy of peak detection in range-Doppler plots, enabling more precise measurements of soil moisture.

## II. Method

### A. Problem Setup

The Total Variation (TV) regularization problem can be framed as the following convex optimization problem:

$$\min_{s} \lambda V(s) + \frac{1}{2} ||s - s_{\text{observed}}||_2^2$$

where:

- $s \in \mathbb{R}^{512 \times 1801}$: is the 2D FFT of the radar data matrix that represents the noise-reduced radar data. The columns corresponding to frequencies less than 10 Hz and greater than 190 Hz are omitted.
- $s_{\text{observed}} \in \mathbb{R}^{512 \times 1801}$: is the FFT of the noisy radar data matrix (input) that the optimization process seeks to denoise. The columns corresponding to frequencies less than 10 Hz and greater than 190 Hz are omitted.
- $V(s)$: represents the total variation of the 2D signal $s$, defined as:

$$V(s) = \sum_{i,j} \sqrt{|s_{i+1,j} - s_{i,j}|^2 + |s_{i,j+1} - s_{i,j}|^2} \in \mathbb{R}$$

  This term penalizes significant differences between neighboring values in the distance and frame ($i$ and $j$), encouraging smoothness while preserving peaks in the radar data.
- $\lambda \in \mathbb{R}$: is the regularization parameter that controls the strength of the smoothness penalty, balancing the trade-off between noise reduction and signal fidelity.

Due to the drastically varying magnitudes, the convex minimization cannot be applied directly to the FFT. The magnitude at frequencies under 10 Hz are 5 to 6 orders of magnitude higher than the backscatter tag's peak. The radar captures the entire environment, including all the stationary objects oscillating at 0 frequency. Since normalization would not suffice due to the significant differences in magnitudes, the problem is framed to only apply the algorithm to frequencies greater than 10 Hz and less than 190 Hz. Frequencies higher than 190 Hz are also constrained due to the radar's Nyquist frequency of 200 Hz.

### B. Approach

The optimization problem is solved in Python using the CVXPY library. The Splitting Cone Solver (SCS) solver is used because of the large scale of the problem. The optimization problem is solved for a range of regularization parameters, and the optimal parameter is selected based on the minimization of the objective function. All other plotting and data manipulation are done in MATLAB because all radar-specific functions are already written in MATLAB. All pertaining code and data can be found in the appendix.

## III. Results

The TV denoising algorithm was applied to the radar data using ten radar captures from lab experiments. A regularization parameter of $\lambda = 1000$ was used based on observations. The algorithm achieves a 1.7 dB improvement in the signal-to-noise ratio (SNR) of the 80 Hz peak. The peak's magnitude is preserved while the noise is reduced, as shown in Figure 5. The 3D range-Doppler plot in Figure 4 demonstrates the peak's preservation in the radar data. The standard deviation of the peak was improved by ten range bins, translating to a 40 mm improvement in the localization of the backscatter tag. According to our current range bin to soil moisture calibrations for the UCSC farm, this improvement would lead to a 0.23% improvement in VWC measurements. This improvement changes our sensing system's accuracy from 2.7% to 2.47%, which is an 8.5% improvement in sensing accuracy.

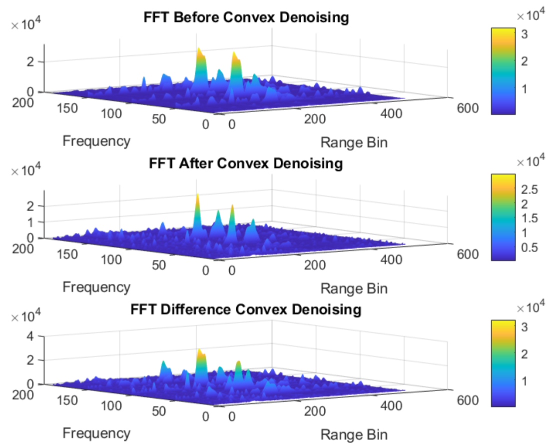


Fig. 4. 3D Range-Doppler plot of radar capture. The peaks seen correspond to the backscatter tag's oscillation and location.

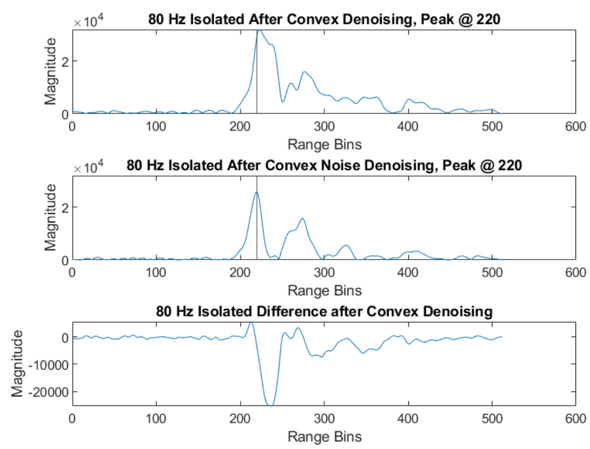


Fig. 5. Isolated plot of the 80 Hz peak in the frequency domain. The peak is preserved while the noise is reduced. The vertical line corresponds to the peak used to compute soil moisture.

## IV. Discussion

The results of this project demonstrate that convex total variation denoising can effectively reduce noise in radar captures, improving the signal-to-noise ratio and peak detection accuracy. By applying the denoising process in the frequency domain, our processing was able to preserve the backscatter tag's peak while reducing noise. This enhancement led to a 1.7 dB improvement in peak SNR and an 8.5% improvement in soil moisture sensing accuracy. The results suggest that this preprocessing step significantly enhances the accuracy of our soil moisture sensing system and could allow us to measure soil moisture at higher soil moisture levels than previously possible. The future of this convex total variation denoising algorithm lies in further testing on field captures in untested soil conditions and higher moisture levels.

| Metric | Original | Denoised | Improvement |
|---|---|---|---|
| Peak SNR (dB) | 20.4 | 22.1 | 1.7 |
| Standard Deviation (Range Bins) | 18 | 8 | 10 |
| Localization Accuracy (mm) | 72 | 32 | 40 |
| Soil Moisture Accuracy (%) | 2.8 | 2.47 | 0.23 (8.5%) |

TABLE I
Results of the peak detection algorithm on the denoised signals. The relative soil moisture accuracy is calculated based on the difference a 40 mm improvement in localization accuracy would make.

## V. References


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