Enhancing Ground Penetrating Radar Signals Through Frequency Compositing

Roger Tilley, Ph.D. Sandia National Laboratories, Livermore CA, USA <u>rtvax@sandia.gov</u>





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Outline



- Objectives and Motivation
- Real Data Testing Site & Equipment
- Modeling Basics (briefly)
- Real Data Analysis & Computer Model Verification
- Describe Optimization Problem Solver
- Describe EM Algorithm Capability with Trial Example with Known Outcome
- Describe Test Cases & Results
- Describe 3 state-of-the-art solutions & Compare with EM Algorithm Test Case Results
 - Dougherty Approach
 - Booth Approach
 - Bancroft Approach
- Applications
 - Explore scanning from heights above ground 5, 10, 20, 40 meters
 - Compare EM GMM to Chirp excitation function scans
- Conclusions



Objectives & Motivation

- Develop advanced GPR imaging technique for highresolution imaging of deeply buried objects
- Define Technique Developed
 - Test Technique on Example with Known Outcome
 - Evaluate Algorithm on Test Cases
- Determine how well Technique compares to state-of-theart solutions
- Determine how effective Technique is when scanning from various heights
- Compare Technique with Chirp excitation function
 - Explore geometric compensation methods on Chirp scans

Real experiments were performed to develop realistic simulations





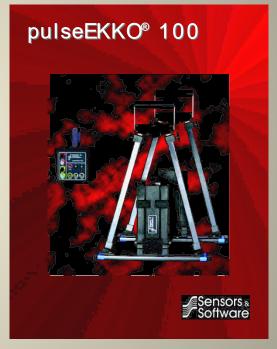
Target GPR imaging objects, tin roofing sheets, were buried at various depths. 8 sheets at 0.5,1.0,1.5,2.0,2.75,3.0,3.5 & 4.0meters in depth; roughly 2.0meters apart in a dry sand/clay soil mixture. These experiments provided ground truth GPR data for study.

Used a variety of COTS GPR hardware

pulseEKKO 100 Ground Penetrating Radar

Features:

- Multiple Frequency Antennas -
 - 12.5 MHz,25Mhz,50MHz,100MHz&200MHz
- **Bistatic Operation**
- **Intelligent Transmitter & Receiver**
- **Fiber Optic Cabling**
- **Battery powered**
- **Remote Trigger Electrical & Optical**
- **Programmable Sampling Interval**
- **Programmable Time Window**





Multistatic GPR sensors were used



Multistatic Sensor Platform Based on COTS Sensors

Features:

Antenna Array – 16 channels -- 9 Transmitters -- 8 Receivers

Center Frequency – 200Mhz

Dimension - 22.2 x 16.0 x 28.5 cm

Trace Scan width - 2 meters wide



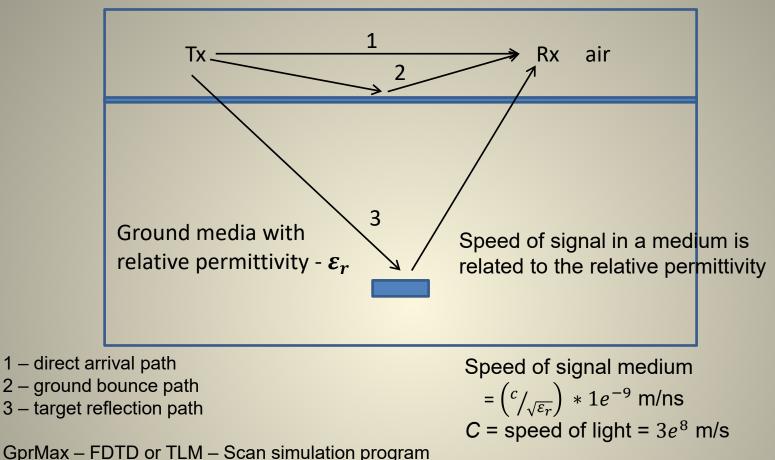
Developed a number of sensor platforms for low frequency sensors





<u>High Frequency</u> and <u>Low Frequency</u> radar on a wheeled platform in front of test lane containing buried tin sheets at Forest Lodge

Modeling Basics

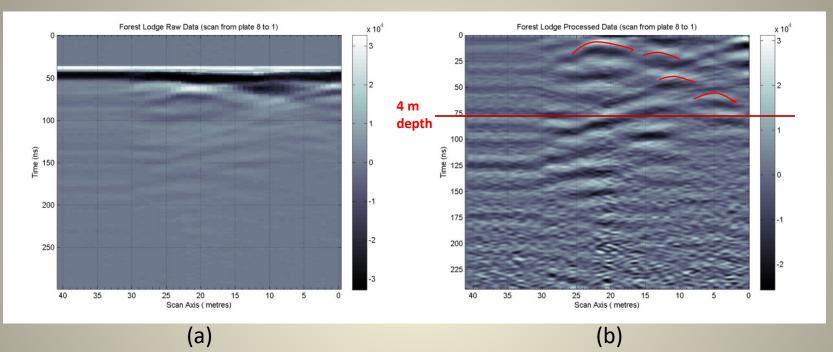


FDTD – Finite Difference Time Domain – solution of Maxwell's equations in differential form TLM – Transmission-Line Matrix – electrical network model solution to an electromagnetic field problem

MatGpr, ReflexW – Scan display & processing programs

Permittivity – measure of how an electric field is affected and affects a dielectric medium.

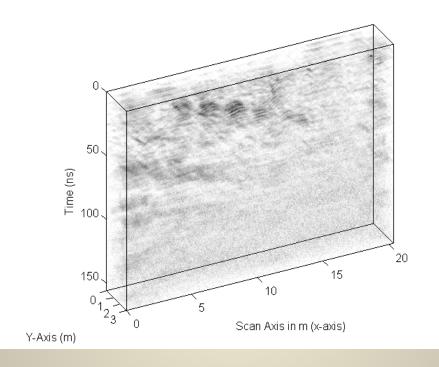
Real data experiments at low frequency in 2-D; raw and processed



"Ground truth" GPR scan results from the pulseEKKO 100 radar over the Forest Lodge test site at 25 MHz. Raw data is depicted in (a) while processed data is depicted in (b).

No clear Pattern emerges.

Real data experiments at a medium frequency in 3-D; processed data only



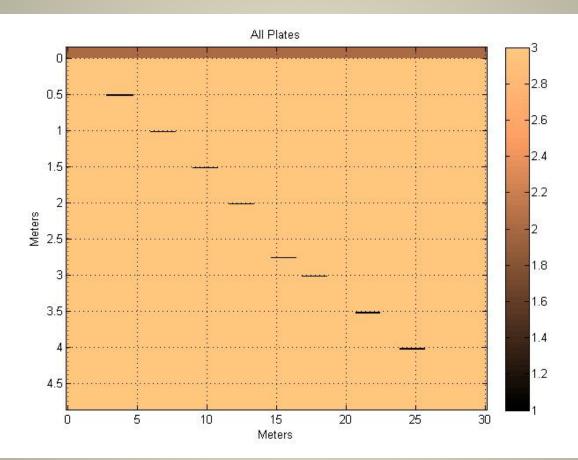


Processed 3-D data scanned by a multistatic radar over the Forest Lodge test site of buried tin sheets of known depth. 5 roofing sheets are visible in a stair step fashion.

Several methods were combined to process real data scans to enhance target viewing, available from MatGpr routine

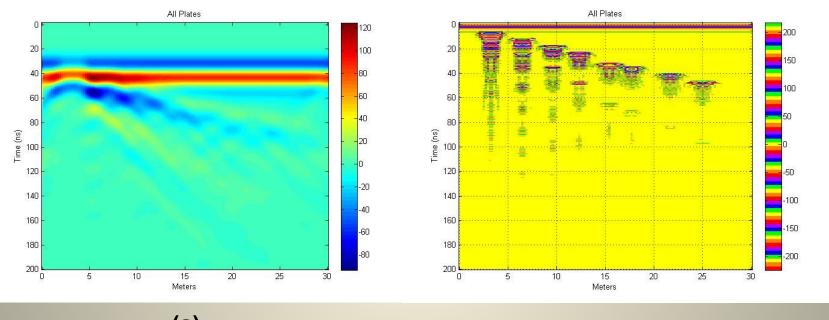
- Resample Scan axis increase number of traces
- Resample Depth (time) axis increase number of depth elements
- Relocated "time zero" remove ground bounce
- Remove global background trace information (average trace)
 - Add all traces, divide by the number of traces average trace
- Remove DC component from each trace (arithmetic mean)
 - Sum all data in a trace, divide by number of terms arithmetic mean
- Applied Dewow filter high pass filter; remove low frequency component
- Applied gain by inverse amplitude decay applies gain function to compensate for the mean or median attenuation

2-D models of simulated data were developed for FDTD analysis using GprMaxV2.0 Software



2-D GprMax model of buried tin roofing sheets, simulating the Forest Lodge test site

Analysis of simulated data at low & very high frequencies

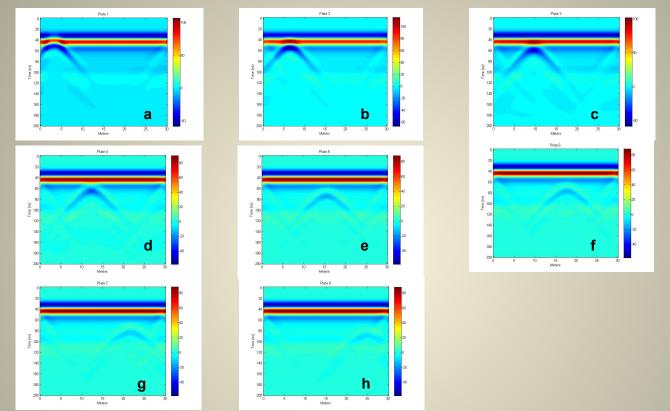


(a)

(b)

FDTD analysis results of the 2-D model using GprMax at 25 MHz (a), showing minimal detail and 900 MHz (b) showing distinct detail. Unexpected results in (b) are the reflections underneath each tin sheet reflection which has been found to occur in actual scans.

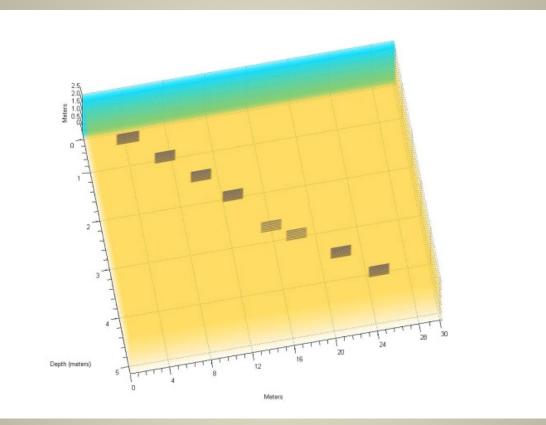
Analysis of simulated data for tin sheets modeled separately using GprMaxV2.0





FDTD analysis results from GprMax for 2-D model at 25 MHz, simulating buried roof sheets at Forest Lodge. Scans are of each tin sheet, 8 in all. Tin sheet (a) represents a buried sheet at 0.5 meters, (b) represents 1.0 meter buried sheet. It follows that (c), (d), (e), (f), (g), and (h) represent 1.5, 2.0, 2.75, 3.0, 3.5 and 4.0 meter buried sheets

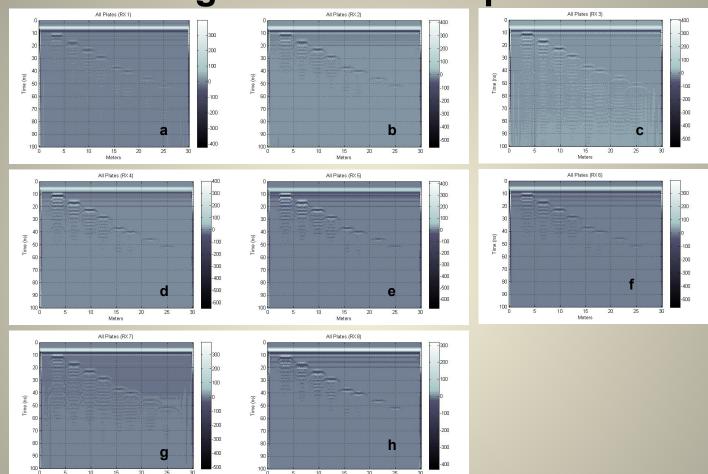
A 3-D FDTD model was developed of simulated data using GprMaxV2.0 Software





GprMax 3-D model of the Forest Lodge site of buried objects. This model was used to study FDTD response experiments conducted for this study

2-D slices depicting 3-D simulated data modeling results from GprMaxV2.0



3-D FDTD Analysis results at 200MHz. Plots (a) through (h) depict the software results along RXs representing slices of depth and scan length at points along the Z-axis. All 8 of the simulated buried tin sheets are shown.



Describe Optimization problem solver of choice

Expectation-Maximization algorithm (EM) using a Gaussian Mixture Model (GMM) feature is the optimization problem solver of choice to increase resolution of Ground Penetrating Radar (GPR) for deeply buried targets

- Assume GPR scans of the same target at differing frequencies form a cluster
- The EM algorithm is good at working with clusters
 - Determining which items belong and which do not.
 - Missing Data can be determined with increase probability
 - Provides an iterative computation of maximum likelihood estimation when the observed data is incomplete.
- Using a GMM to determine mixture weights for each scan through the use of mean and standard deviation of each scan in the cluster.
- Iterate until the log likelihood of the GMM objective function does not change much from iteration to iteration (choose the fixed value difference)
- Other distributions can be used but Gaussian is often used when the exact distribution of data is unknown.

EM Algorithm with GMM



Expectation step (expected value)

 Compute the conditional expectation of the group membership weights for data points including unobservable data given mean and covariance of data.

Maximization Step (Maximize parameters)

- Compute new parameter values for mixture weights, mean and covariance to maximize the finite mixture model
- Convergence is signaled by log likelihood of finite mixture model objective function, $f(x_i; \theta)$, not appearing to change substantially from one iteration to the next



Maximum Likelihood Estimation Vs Expectation-Maximization Gaussian Mixture Model

MLE estimation



Given a random sample $X_1, X_2, ..., X_n$ independent and identically distributed (i.i.d.) with a probability density function $f(x_i, \theta)$, where θ is the unknown parameter to be estimated; the joint probability density function (PDF) can be called $L(\theta)$:

$$L(\theta) = P(X_1 = x_1, X_2 = x_2, ..., X_n = x_n) = f(x_1; \theta) * f(x_2; \theta) ... f(x_n; \theta) = \prod_{i=1}^n f(x_i; \theta)$$

Assuming the PDF is Gaussian with variance, σ^2 , known and the mean, μ , unknown then the likelihood equation is:

$$L(\mu) = \prod_{i=1}^{n} f(x_i; \mu, \sigma^2) = \sigma^{-n} (2\pi)^{-n/2} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^{n} (x_i - \mu)^2\right)$$
$$\log\left(L(\mu)\right) = -n \log(\sigma) - \frac{n}{2} \log(2\pi) - \sum_{i=1}^{n} \frac{(x_i - \mu)^2}{2\sigma}$$

solve for the mean μ by taking the partial derivative with respect to μ and setting the result equal to 0, solving for μ ; the maximum likelihood estimate

$$\frac{\partial}{\partial \mu} \left(\log \left(L(u) \right) \right) = -2(-1) \sum_{i=1}^{n} \frac{(x_i - \mu)}{2\sigma^2} = 0$$
$$\mu = \frac{\sum_{i=1}^{n} x_i}{n} \quad \text{MLE estimate}$$



The MLE process becomes hard when there is more than one data set and only part of the combined data sets can be observed (hidden).

A mixture distribution has a PDF of the form $f(x) = \sum_{k=1}^{K} \alpha_k f(x; \theta_k)$. Where there are K number of components in the mixture model for each k. The joint PDF with n observed data for each k is defined as follows:

$$L(x|\alpha,\theta_k) = \prod_{i=1}^n \sum_{k=1}^K \alpha_k f(x_i; \theta_k)$$

with mixture weights α_k , complete observed data set x with constraints $\sum_k \alpha_k = 1$ and $\alpha_k \ge 0$ for all k.

$$\operatorname{Log}\left(\left(L(x|\alpha,\theta_k)\right) = \sum_{i=1}^n \log \sum_{k=1}^K \alpha_k f(x_i;\theta_k)\right)$$

The log of sums makes solving this equation using an MLE method challenging. There are many local maxima that are less than the global maximum. The weight values must be chosen. Choosing the weight value that arrives at a global maximum is not likely in short order; the choice is a chance guess for each calculation.

EM Simple



EM Simple –

- Computes probabilities of each possible completion of missing data; "expected value" – E-step
- Creates a weighted training set of all possible completions E-step
- A modified MLE processes with the weighted training set; providing new parameter estimates M-step

Reference:

C. B. Do, S. Batzoglou, "What is the Expectation Maximization Algortihm," Nature Biotechnology vol. 26, Issue 8, pp. 897-899, 2008, DOI 10.1038/NTBL1406.

http://www.nature.com/nbt/journal/v26/n8/pdf/nbt1406.pdf, 2019.1.15.



a finite mixture $f(\underline{x}; \theta)$ of K components as mixtures of Gaussian functions:

$$f(\underline{x};\theta) = \sum_{k=1}^{K} \alpha_k p_k(\underline{x}|\theta_k)$$

- $p_k(\underline{x}|\theta_k)$ are K mixture components with a distribution defined over $p(\underline{x}|\theta_k)$ with parameters $\theta_k = \{\underline{\mu}_k, C_k\}$ (mean, covariance)

$$p_k(\underline{x}|\theta_k) = \frac{1}{(2\pi)^{d/2}} e^{-\frac{1}{2}(\underline{x}-\underline{\mu}_k)^T C_k^{-1}(\underline{x}-\underline{\mu}_k)}$$

- α_k are the mixture weights, where $\sum_{k=1}^{K} \alpha_k = 1$.
- $\{\underline{x}_i, \dots, \underline{x}_n\}$ Data set for a mixture component in d dimensional space.



E-Step -

 $w_{ik} = \frac{p_k(\underline{x}_i | \theta_k) * \alpha_k}{\sum_{m=1}^{K} p_m(\underline{x}_i | \theta_m) * \alpha_m} \text{ membership weights}$ for $1 \le k \le K$, $1 \le i \le N$; with constraint $\sum_{k=1}^{K} w_{ik} = 1$ M-Step –

$$N_{k} = \sum_{i=1}^{N} w_{ik}$$

$$\alpha_{k}^{new} = \frac{N_{k}}{N}, \text{ for } 1 \leq k \leq K$$

$$\underline{\mu}_{k}^{new} = \left(\frac{1}{N_{k}}\right) \sum_{i=1}^{N} w_{ik} * \underline{x}_{i} \text{ for } 1 \leq k \leq K$$

$$C_{k}^{new} = \left(\frac{1}{N_{k}}\right) \sum_{i=1}^{N} w_{ik} * \left(\underline{x}_{i} - \underline{\mu}_{k}^{new}\right) \left(\underline{x}_{i} - \underline{\mu}_{k}^{new}\right)^{T}$$

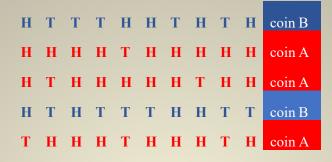
Convergence (log likelihood of $f(\underline{x}; \theta)$) –

$$\operatorname{Log} l(\vartheta) = \sum_{i=1}^{N} \log f(\underline{x}_{i}; \theta) = \sum_{i=1}^{N} \left(\log \sum_{k=1}^{K} \alpha_{k} p_{k}(\underline{x}_{i} | \theta_{k}) \right)$$

Repeat e-step, m-step & log-likelihood until log-likelihood no longer changes (or difference is small)

2 coin problem





Coin A and Coin B recorded tosses

2 coins are tossed creating 5 sets of 10 flip outcomes. All data is known; which coins, A or B produced which of the 5 sets.

MLE process is straight forward to determine the probability of coin A landing on a head (θ_A) and the probability of coin B landing on a head (θ_B).

$$\theta_{A} = \frac{Number \ of \ heads, coin \ A}{Total \ of \ heads \ and \ tails, coin \ A} = \frac{24}{24 + 6} = 0.80$$
$$\theta_{B} = \frac{Number \ of \ heads, coin \ B}{Total \ of \ heads \ and \ tails, coin \ B} = \frac{9}{9 + 11} = 0.45$$

The EM process is 2 steps, E-step and M-step. (which coin was flipped is unknown) The E-step for this case is defined as:

- assume coins A and B are equally likely; ($\lambda = 0.5$).
- start with some initial guess for probability of heads for coin A and coin B.
- compute the expected number of heads and tails for each coin.

Probability of observation coming from either coin A or coin B or both:

$$P(\mathbf{x} \mid \theta) = \lambda \,\theta_A^h \, (1 - \theta_A)^t + (1 - \lambda) \,\theta_B^h \, (1 - \theta_B)^t$$

Probability of observation coming from coin A:

 $P(y = \operatorname{coin} A \mid x, \theta) = P(A) = \frac{\lambda \,\theta_A^h \,(1 - \theta_A)^t}{\lambda \,\theta_A^h \,(1 - \theta_A)^t + (1 - \lambda) \,\theta_B^h \,(1 - \theta_B)^t}$

Probability of observation coming from coin B:

$$P(y = \operatorname{coin} B \mid x, \theta) = P(B) = \frac{(1-\lambda) \,\theta_B^h \,(1-\theta_B)^t}{\lambda \,\theta_A^h \,(1-\theta_A)^t + (1-\lambda) \,\theta_B^h \,(1-\theta_B)^t}$$

Expected number of heads for coin A: $P(A)^*$ (# of heads in observation set 1, 2, ... 5) Expected number of heads for coin B: $P(B)^*$ (# of heads in observation set 1, 2, ... 5)



E–Step con't



Expected number of tails for coin A: $P(A)^*$ (# of tails in observation set 1, 2, ... 5)

Expected number of tails for coin B: $P(B)^*$ (# of tails in observation set 1, 2, ... 5)

The M-step for this case is defined as:

• maximize the estimated parameters, computing new estimates. $\Sigma coin A$ number of heads

$$\partial_A = \frac{\sum coin A number of heads + \sum coin A number of tails}{\sum coin B number of tails}$$

 $\theta_B = \frac{1}{\sum \operatorname{coin} B \operatorname{number} of \operatorname{heads} + \sum \operatorname{coin} B \operatorname{number} of \operatorname{tails}}$

_	Initial guess: $\theta_A = 0.60$, $\theta_B = 0.50$				Coin A		Coin B	
Observations	Nh	Nt	P(A)	P(B)	Nh	Nt	Nh	Nt
x1: HTTTHHTHTH	5	5	0.45	0.55	2.2	2.2	2.8	2.8
x2: HHHHTHHHHH	9	1	0.81	0.20	7.2	0.8	1.8	0.2
х3: НТННННННТН	8	2	0.73	0.27	5.9	1.5	2.1	0.5
x4: HTHTTTHHTT	4	6	0.35	0.65	1.4	2.1	2.6	3.9
х5: ТНННТНННТН	8	2	0.64	0.35	4.5	1.9	2.5	1.1
				sum	21.2	8.5	11.8	8.5

New estimates after 1 iteration

$$\theta_A = \frac{21.2}{(21.2 + 8.5)} = 0.71$$
 $\theta_B = \frac{11.8}{(11.8 + 8.5)} = 0.58$

After 8 iterations $\theta_A = 0.8$, $\theta_B = 0.52$



Trial Example & Results

Some periodic signal characteristics

	Square Wave	Triangle Wave	Sawtooth
Freq. components	Odd # Harmonics	Odd # Harmonics	All harmonics
Relative Amplitude	1/Harmonic #	1/Harmonic # squared	1/Harmonic #
Phase	All Harmonics in phase	Every other Harmonic 180 deg. Out of phase	Even Harmonics 180 deg. Out of phase

Harmonic -- whole # multiples of fundamental frequency

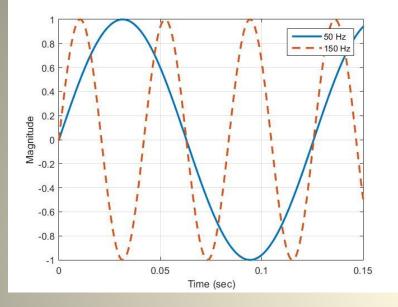


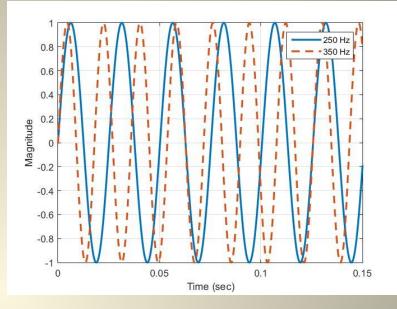
Trial Example Preparation & Processing

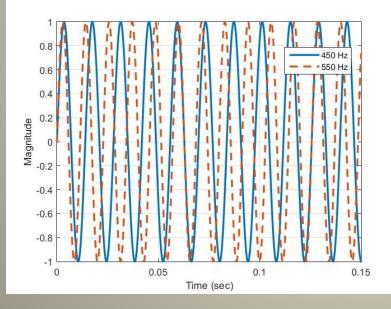
- For Square wave example create Odd harmonic sine waves
- Make magnitude of each sine wave equal to 1
- Process sine waves with EM GMM Algorithm
- Examine result

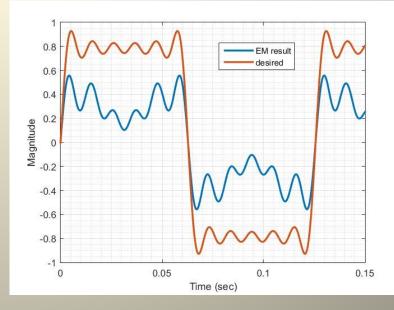
Trial Example & Results con't







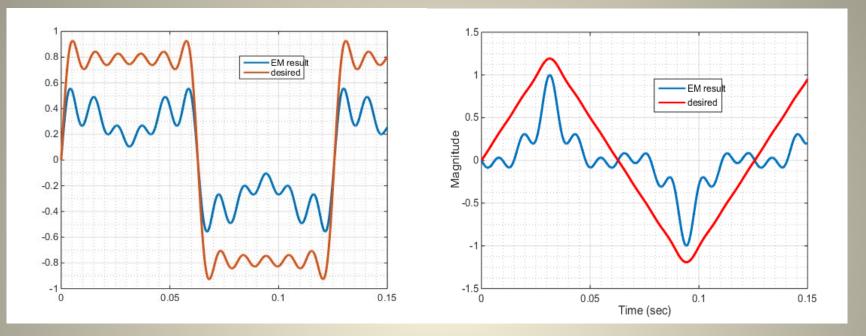






Square Wave attempt

Triangle Wave attempt



This implementation of the GMM only changes the Magnitude of the mixture signals.

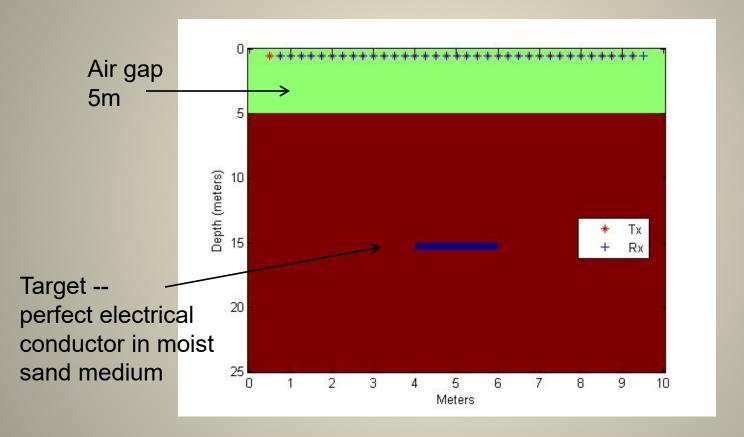
The convergence to Square or Triangle wave does not quite complete due to the constraint that the sum of membership weights $(\alpha_{ik}) = 1$; and the sum of the mixture weights $(W_k) = 1$. If one were to sum the weights of Square wave harmonics, one would find they are >1 (1 + 1/3 + 1/5 + 1/7 ...). A new constraint must be considered to make the EM algorithm work well.



Ground Penetrating Radar Example



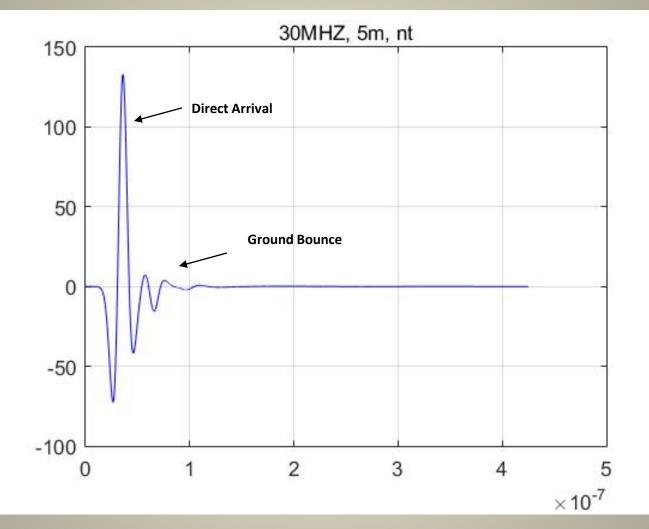
Test Case 1



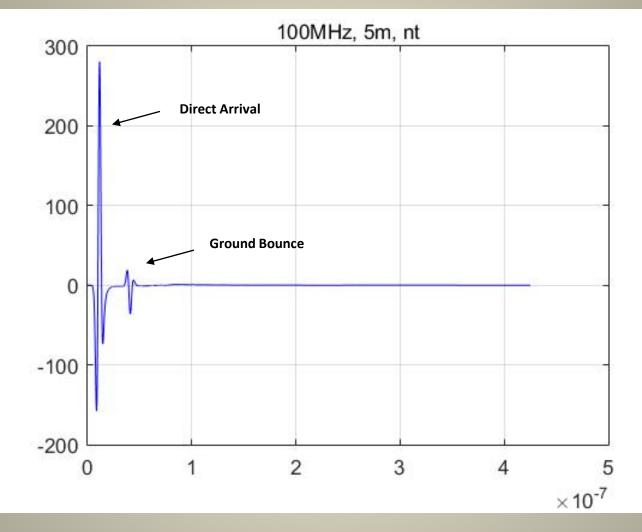
Dimensions -- height vs width (25 x 10) more like borehole. 1 Tx & 1 Rx (0.25 meter separation) stepped across width

Simulated GPR Scan using GprMax, no target, Tx/Rx 5 meters above ground



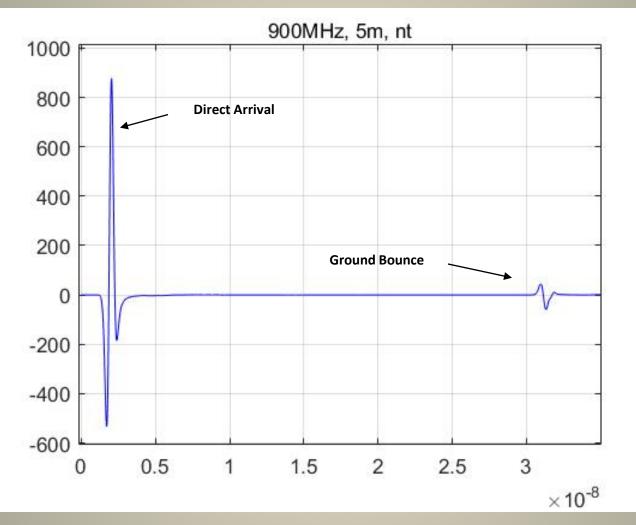


Simulated GPR Scan using GprMax, no target, Tx/Rx 5 meters above ground



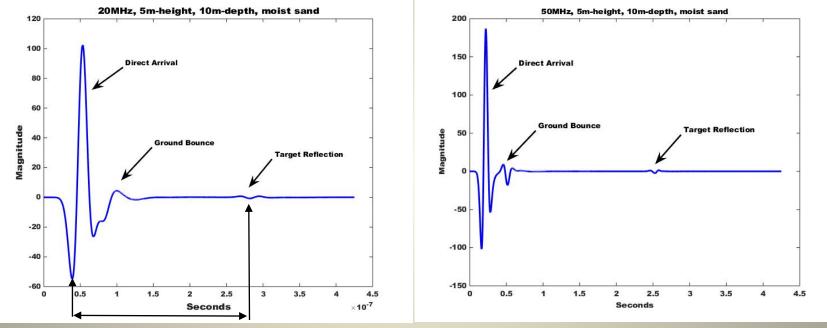
Simulated GPR Scan using GprMax, no target, Tx/Rx 5 meters above ground







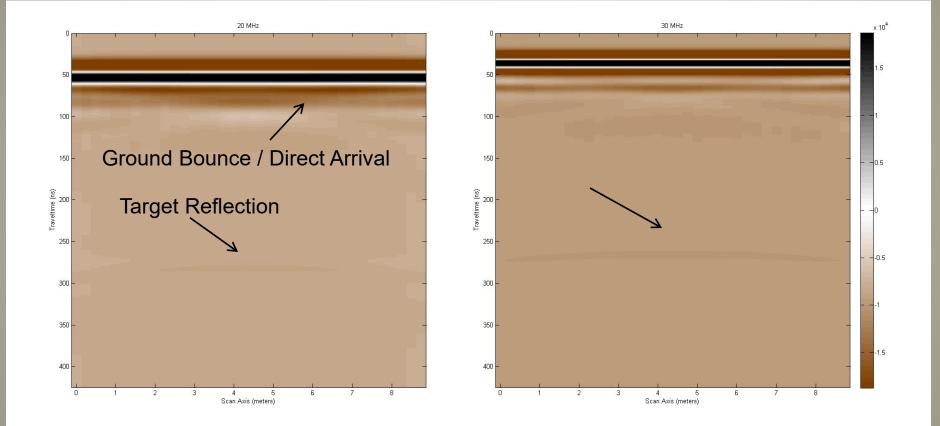
GPR trace depicting Two-way-transit-time for 2 frequencies of same target.



TWTT

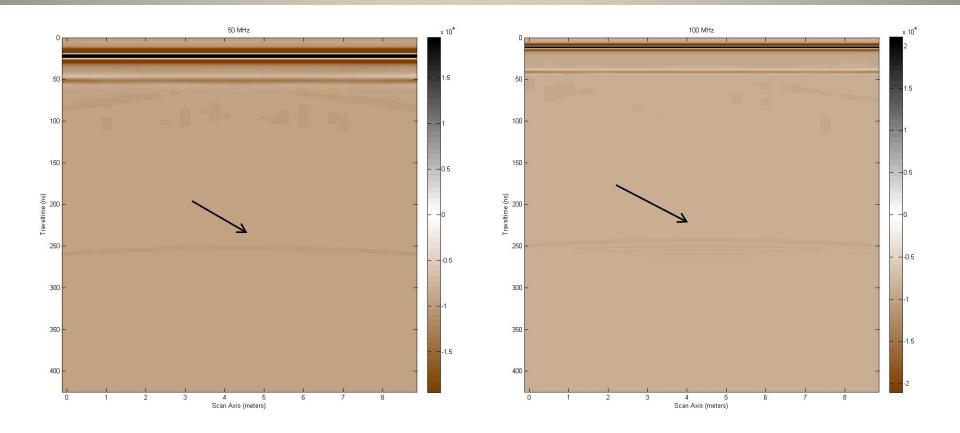
GPR Scans 20 & 30 MHz w/o processing





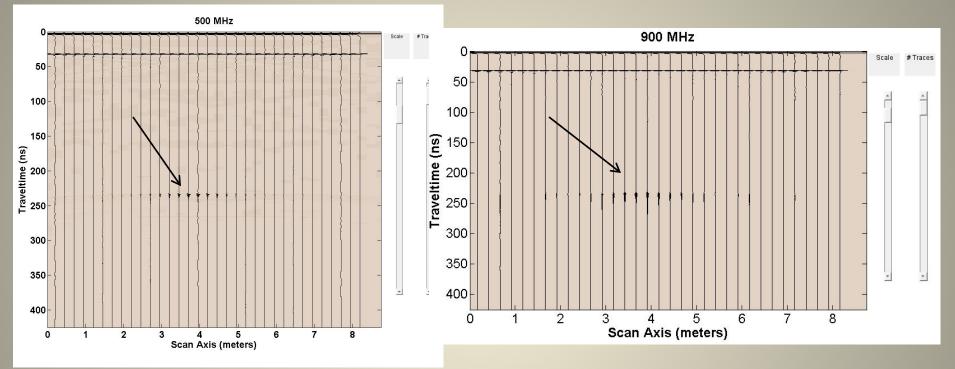






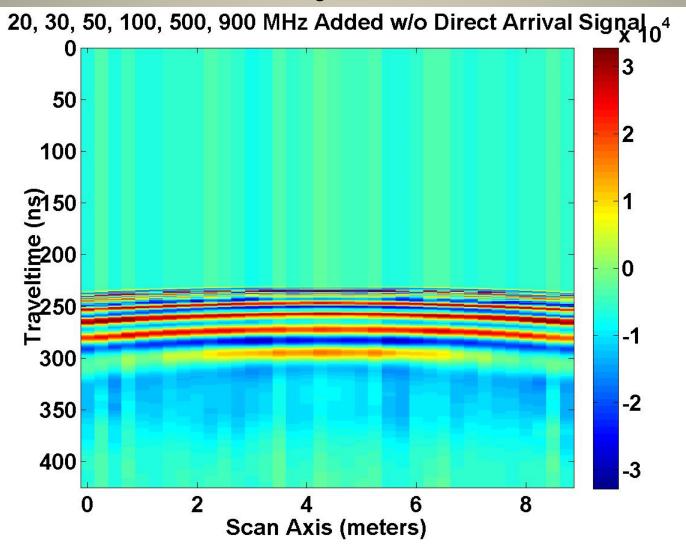


GPR Signal traces for 500 & 900 MHz w/o processing



Compositing GPR Scans of Test Case 1, Tx/Rx 5 meters above ground

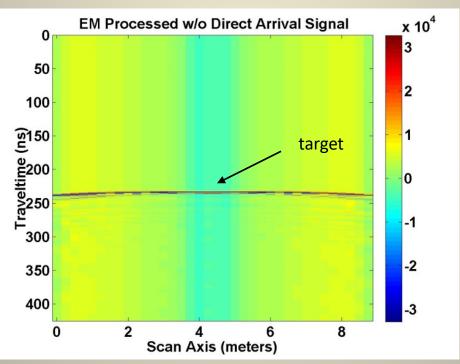




EM Approach



- Remove direct arrival/ground bounce by subtracting GPR scan with target from GPR trace w/o target
- Expectation Step
- Maximization step
- Iterate until convergence

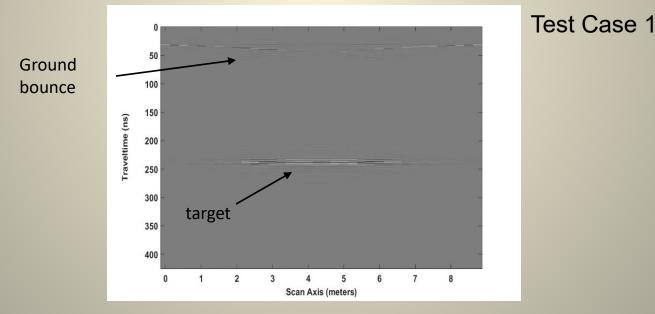


Target depth correct (~240ns two-way travel time); edge detection error due to borehole model & reflection dominated by lower Frequencies

Dougherty Approach

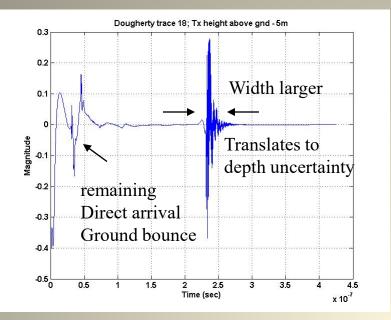
M. E. Dougherty, P. Michaels, J. R. Pelton, L. M. Liberty, "Enhancement of Ground Penetrating Radar Data Through Signal Processing", Symposium on the Application of Geophysics to Engineering and Environmental Problems 1994, pp. 1021-1028, Jan 1994, DOI 10.4133/1.2922053

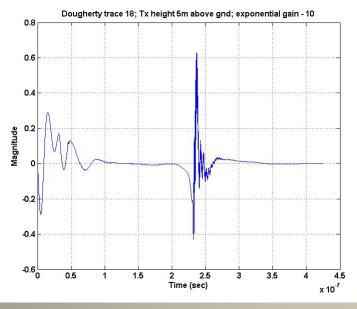
- Align each trace by the direct arrival pulse in each trace
- Remove DC shifts, Low frequency "wow" component
- Scale each trace by the L2 norm of the direct arrival pulse
- Sum traces → direct arrival estimate; Subtract estimate from each trace
- Gain recovery
- Equal weighting applied to each frequency trace while summed

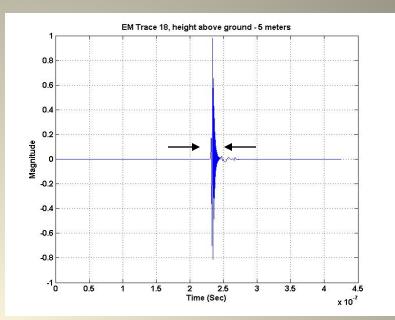


Depth indication less crisp than EM due to addition of low frequencies; ground bounce visible; limited edge detection problem. 43









Trace 18 of 36 traces total; roughly 5 m out of 10 m in total distance in the x direction of Test Case 1 model

- Dougherty
- EM process
- Dougherty exponential gain (gain constant (g) = 10) $b(i) = i * a(i) * e^{i * g * \frac{dt}{1000}}$ i - sample;a(i) - ith sample of original

amplitude trace.

Booth Approach



A. D. Booth, A. L. Endres, T. Murray, "Spectral Bandwidth Enhancement of GPR Profiling Data Using Multiple-Frequency Compositing", Journal of Applied Geophysics, vol 67, pp. 88-97, Jan 2009, DOI 10.1016/j.jappgeo.2008.09.015.

Method One – Simple summation attributed to Dougherty

Method Two – Scaled summation approach

- Determine the maximum value of each frequency spectra
- Equalize each spectra
- Value used to equalize each spectra provide the signal weighting prior to summation

Method Three -

- Determine frequency spectra of each trace
- Determine maximum value of each spectra; use these values to equalize spectra then use these values as weights for each trace when summing
- Shift traces to line up main peaks of the direct arrival signal for each frequency
- Sum all traces

Method Four – Dominant Frequency Amplitude Equalization (DFAE)

- Average spectra creating ensemble estimate for each frequency
- Equalize ensemble spectra for all frequencies (magnitude needed to equalize spectrum determines the weight for that frequency.)
- Sum all traces with appropriate weight.

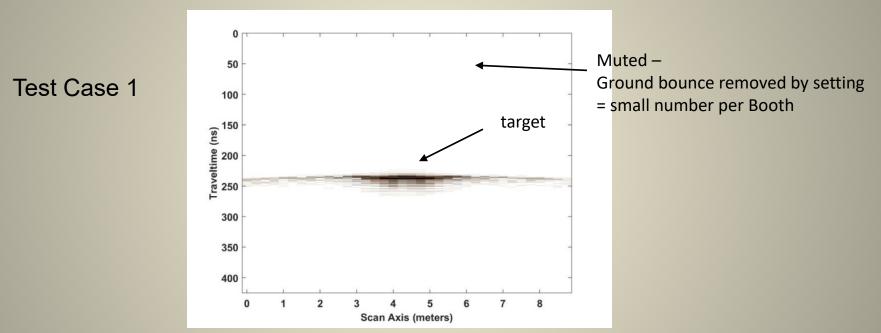


Optimal Spectral Whitening (OSW); alternative Booth weighting method

- Weighting factors are developed from a least-squares analysis (solve equation AW= S for W(weights)
 - Determine frequency spectra of each trace
 - Average trace spectra for each frequency
 - For one averaged frequency spectra, determine the magnitude for the value of each scan frequency. (in 20 Mhz spectra find magnitude for 30, 50, 100, etc. for example. Determines 1 row of matrix A.
 - Repeat for other averaged spectra (1 row for each spectra, 1 column for each magnitude)
 - S matrix is the desired spectral amplitude at a frequency.
 - Solve for W matrix $\rightarrow W = (A^T A)^{-1} A^T S$
 - Combine frequencies for a trace using weighting function; repeat for each trace
- Time Variant
 - Choose time window greater than longest wavelet period to be sampled (my case 20 MHz → 50 ns)
 - Each trace is comprised of several time windows
 - Repeat above steps (OSW) for all analysis time windows
 - Linearly interpolate the weighting function between time window centers
 - Combine traces using weighting function

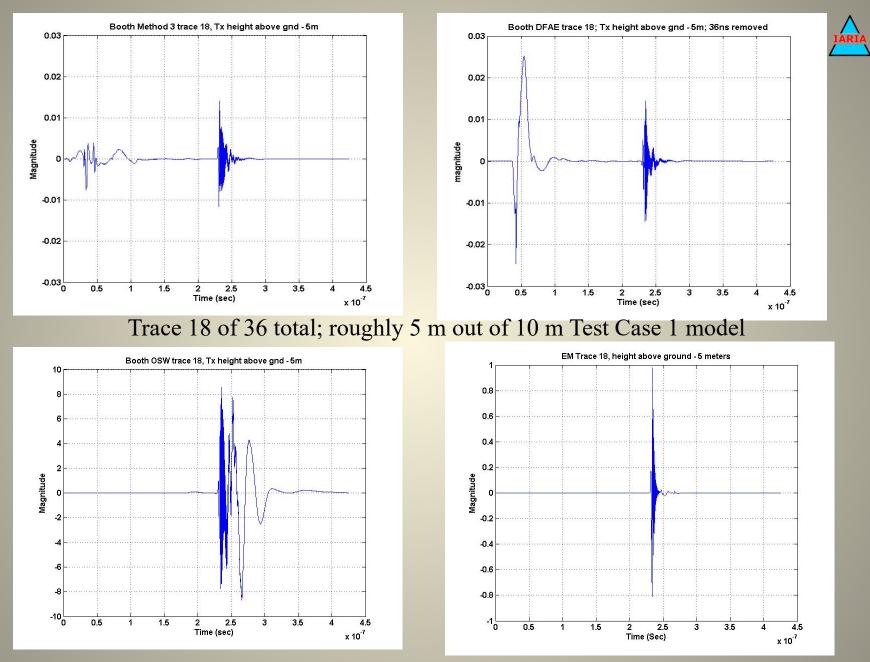
Booth Approach con't

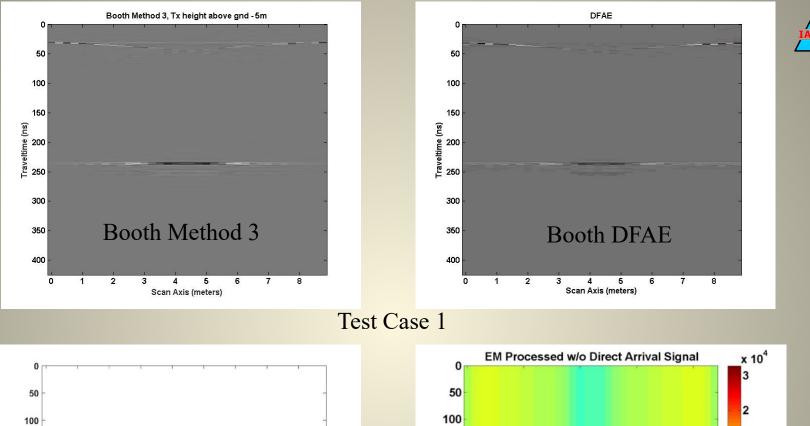


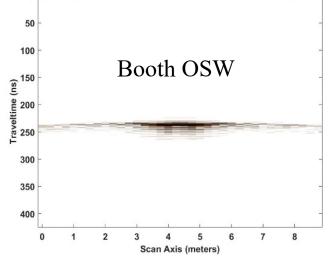


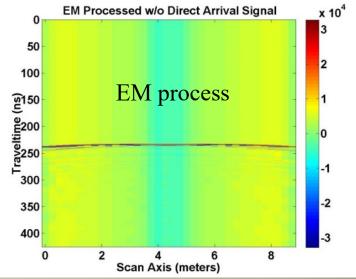
OSW method with 1 window

Target depth correctly identified but depth indication is broader than Dougherty and EM; edge detection problem.









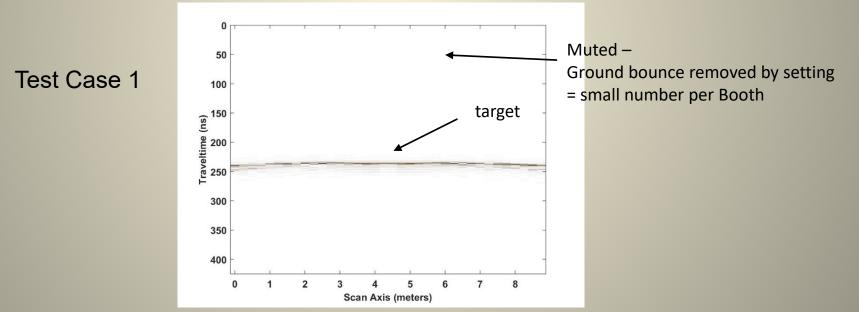
Bancroft Approach



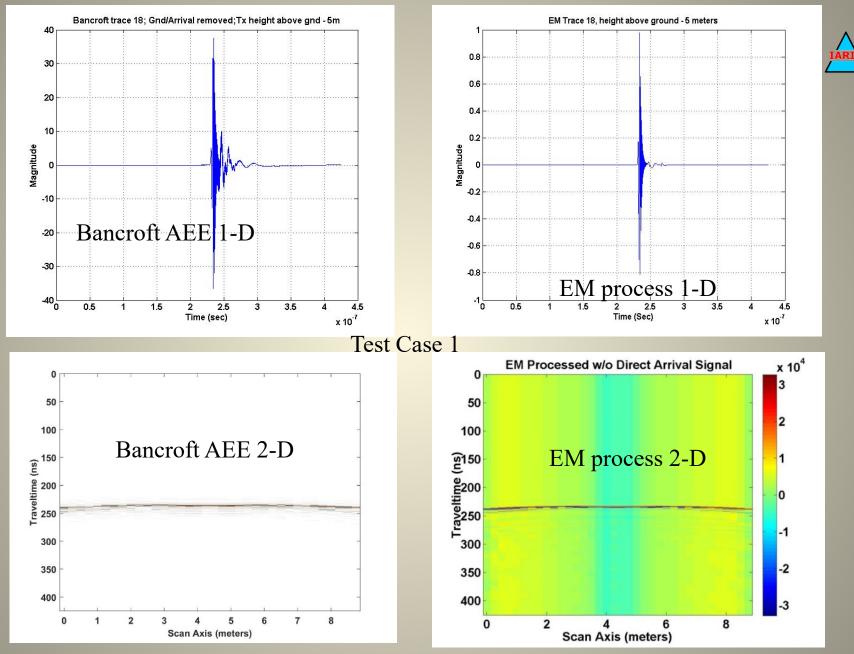
S. W. Bancroft, "Optimizing the Imaging of Multiple Frequency GPR Datasets using composite Radargrams: An Example from Santa Rosa island, Florida", PhD dissertation, University of South Florida, 2010.

Amplitude Envelope Equalization technique (AEE)

- Get absolute value of Hilbert transform of each trace (envelope)
- Average envelopes for all traces for one frequency
- Compute weights: average envelope of lowest frequency divided by average envelope of each frequency
- Combine traces using weights

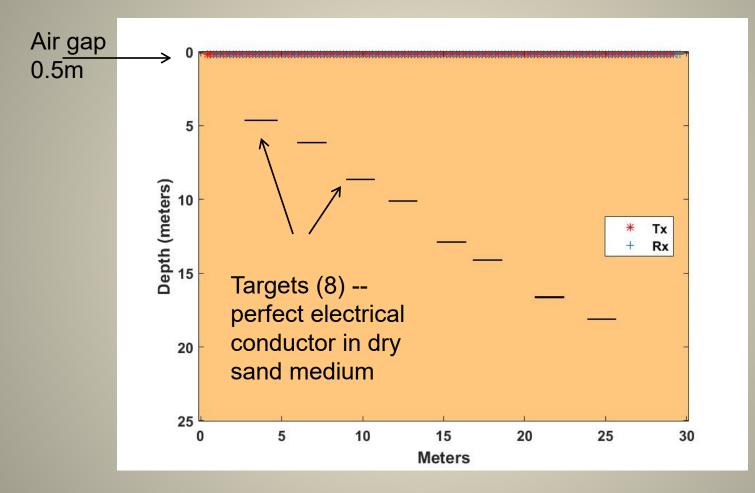


Depth indication sharp but broader than EM method; edge detection problem



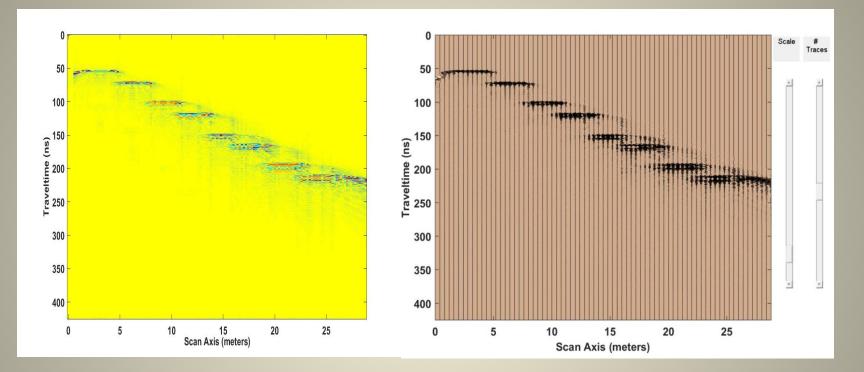
Test Case 2







EM GMM Results – test case 2



EM processed GPR Scan

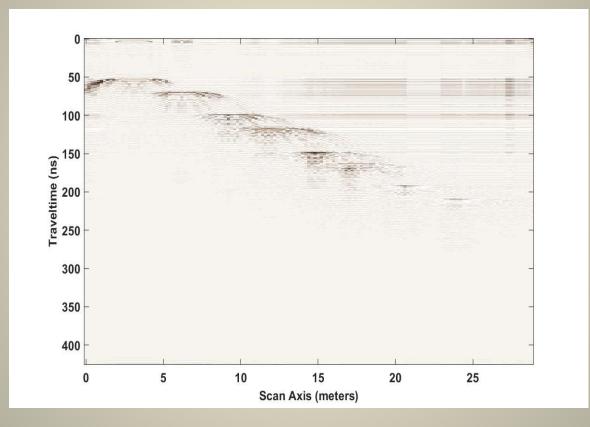
EM processed GPR Scan traces

All 8 plates are depicted; two-way travel time correct (approx. 50, 70, 100, 116, 148, 160, 190 & 208ns); edge detection less crisp as one descends in depth.



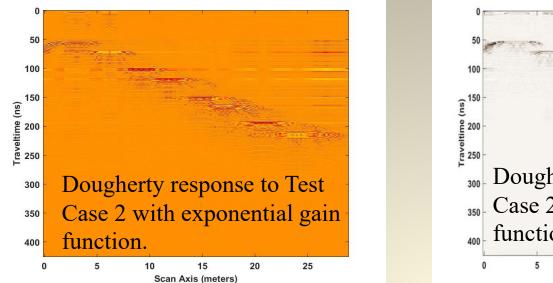
Dougherty Approach Result

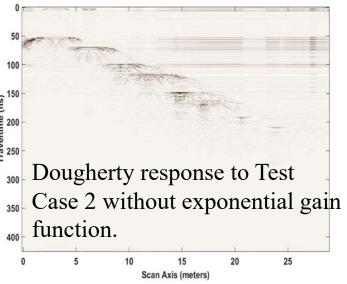
Test Case 2

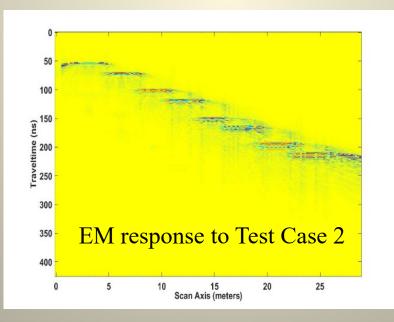


Only 5, barely 6 of 8 plates visible; edge detection a problem





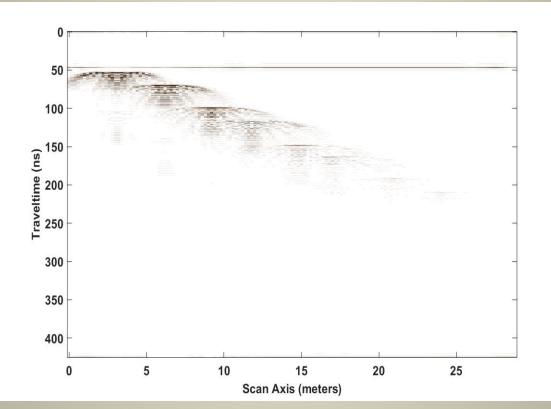






Booth Approach Result

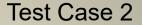
Test Case 2

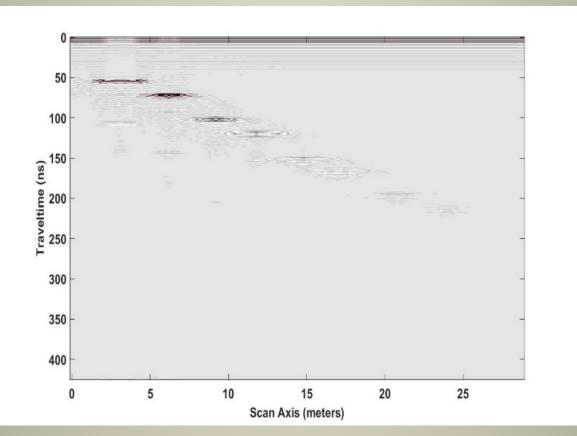


Ground bounce visible due to Booth mute process; only 4 and barely 5 and 6 of 8 plates visible; edge detection poorer than EM comparable to Dougherty.



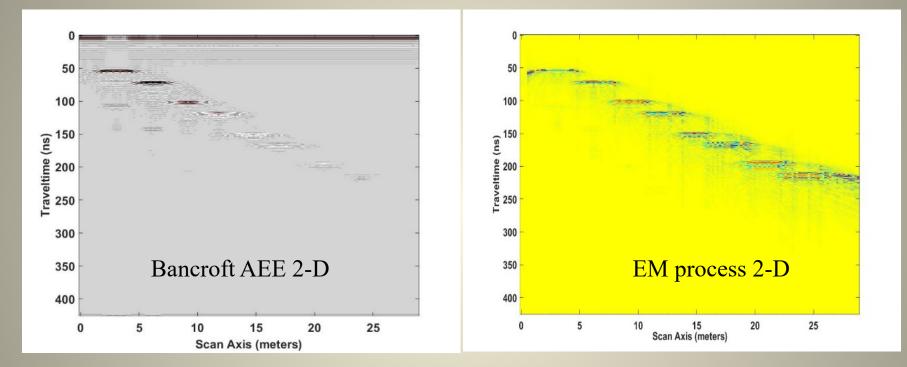
Bancroft Approach Result



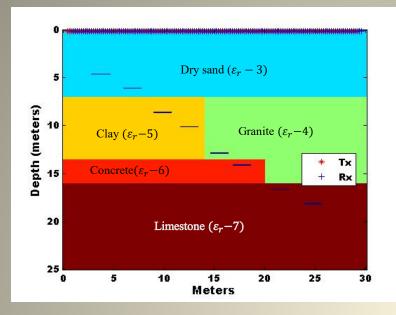


Only 4 of 8 plates visible with possibility of 3 more; ghost plates evident at 100ns & 150ns; edge detection better than Booth & Dougherty on par with EM.

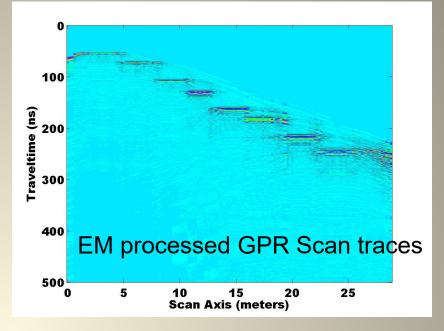


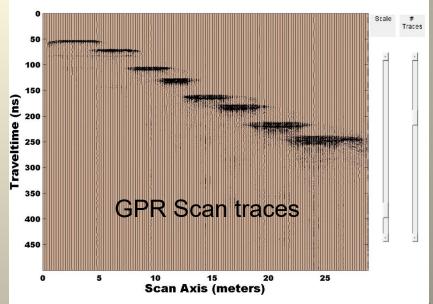


Test Case 2



GPR Test Case 3, (8) roofing sheets 2 meters long, 0.1 meters thick, buried at 8 different levels, in non-uniform media.

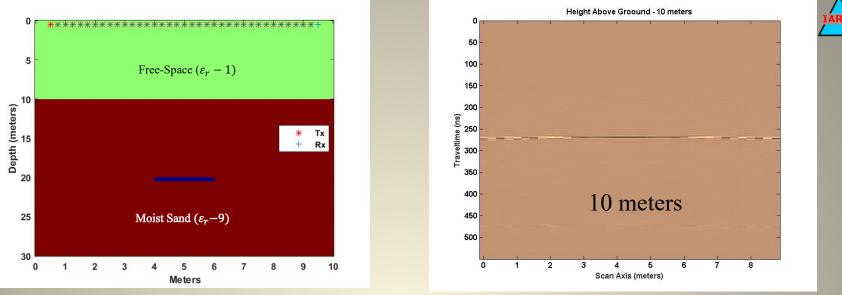




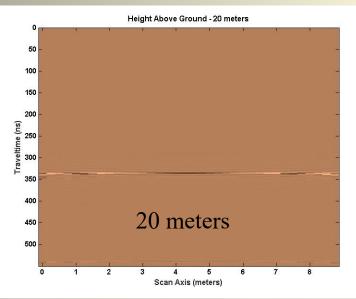
59

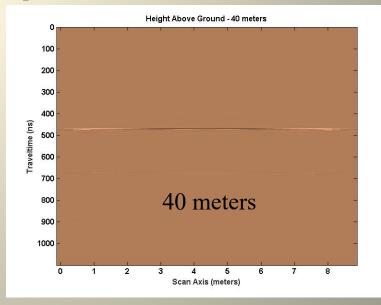


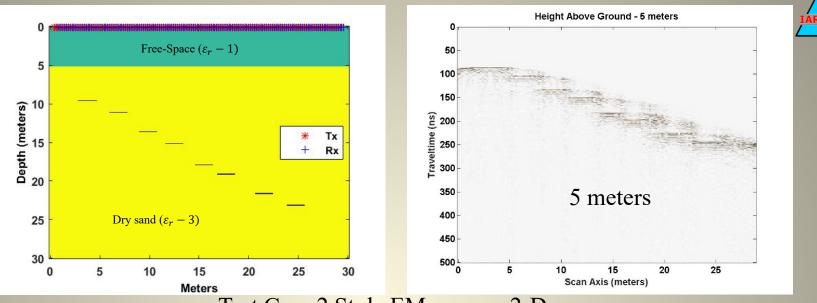
Standoff GPR



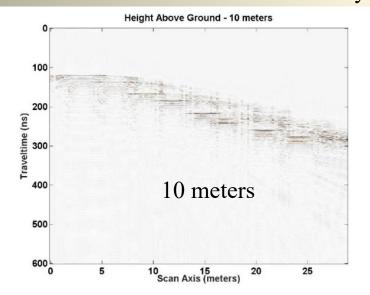
Test Case 1 Style EM process 2-D

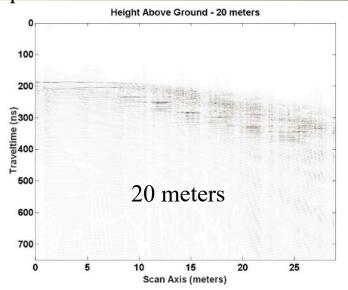




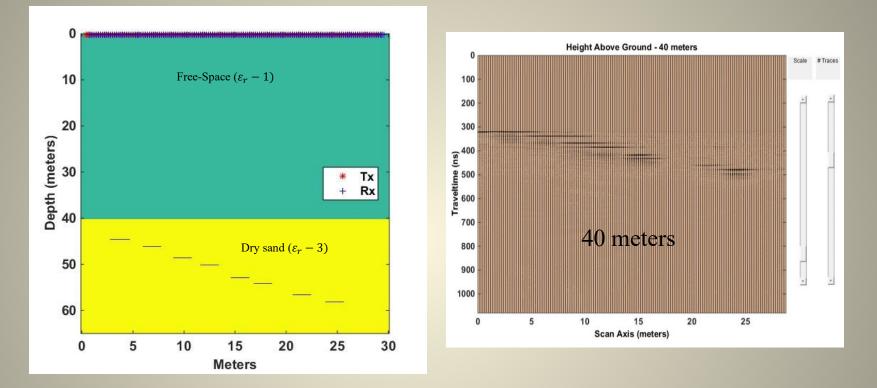


Test Case 2 Style EM process 2-D

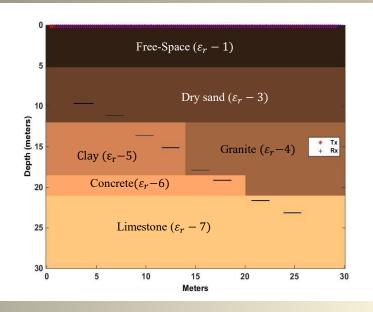


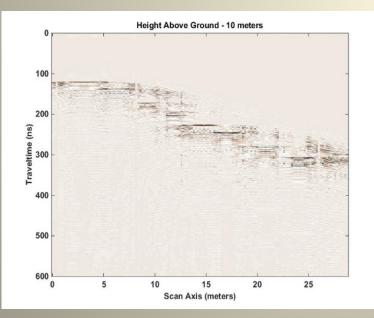


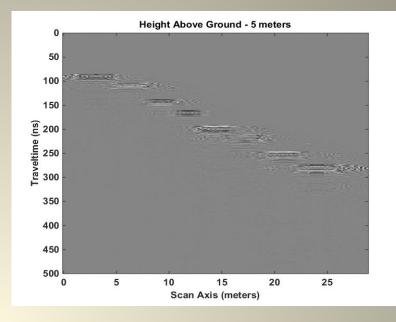


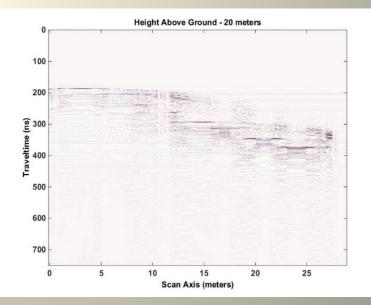


Test Case 2 Style EM process 2-D

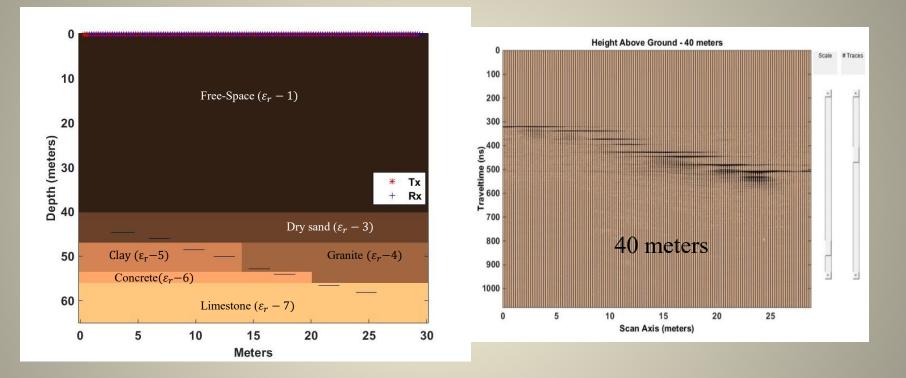










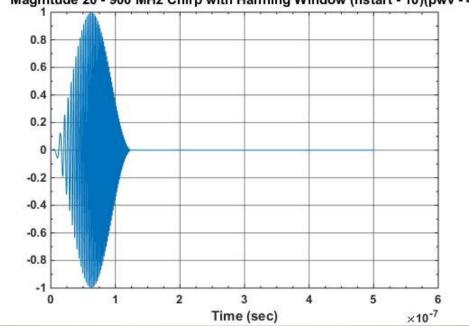


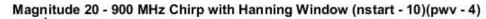
Test Case 3 Style EM process 2-D



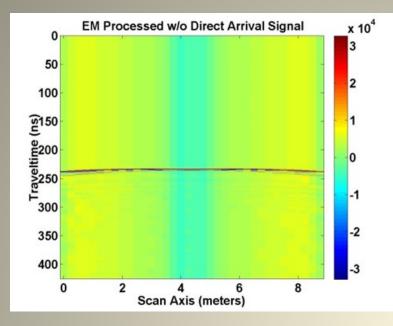
Chirp Excitation Function

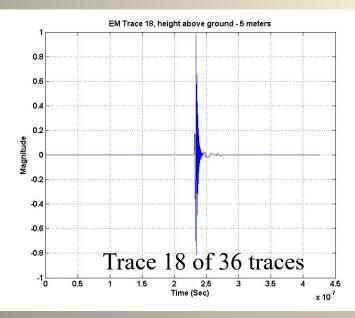


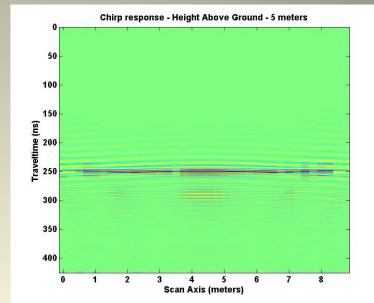




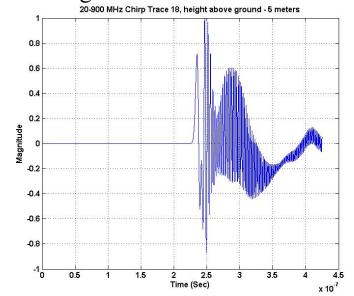
Computed Chirp Signal



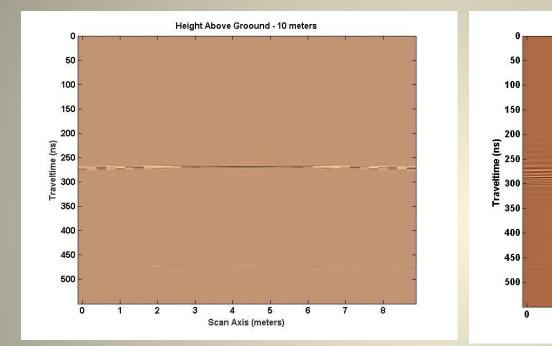




Chirp excitation signal response with direct arrival and ground bounce removed.







Test Case 1 Style EM process 2-D

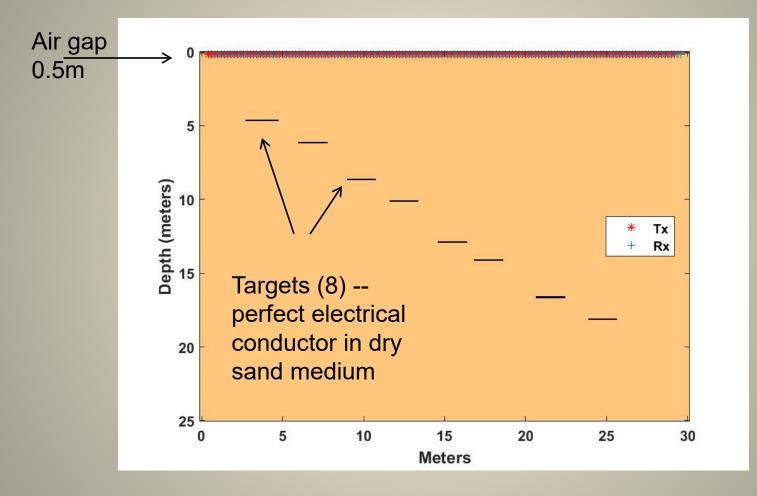
Chirp excitation signal response with direct arrival and ground bounce removed.

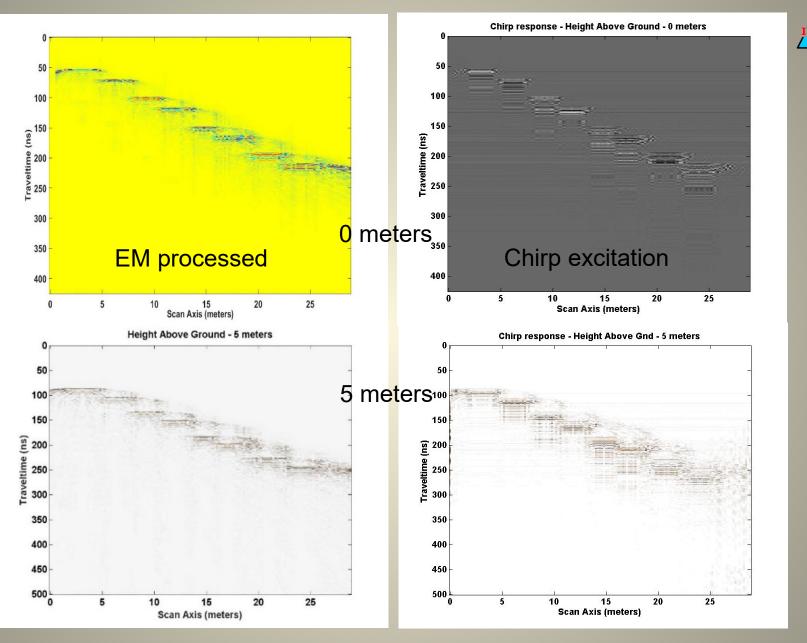
Scan Axis (meters)

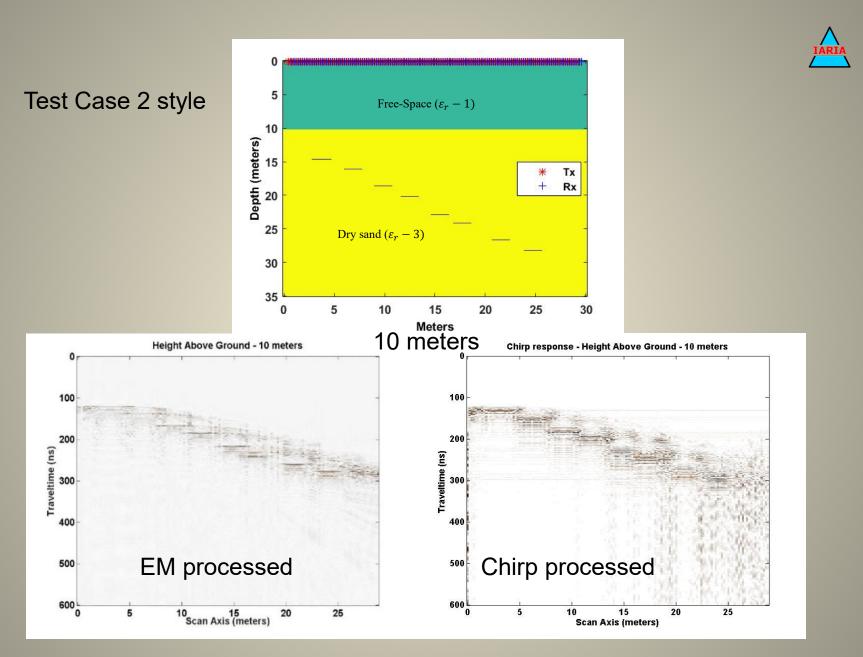
Chirp response - Height Above Ground - 10 meters

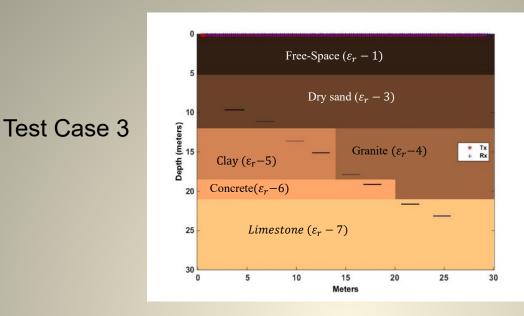


Test Case 2

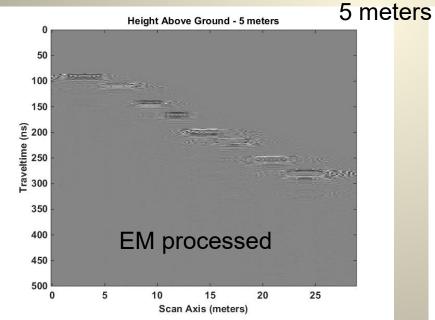




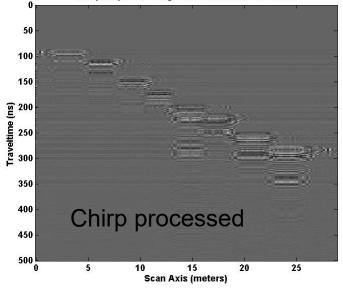


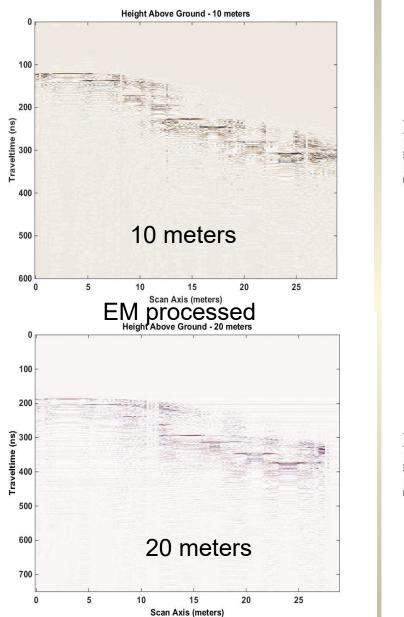


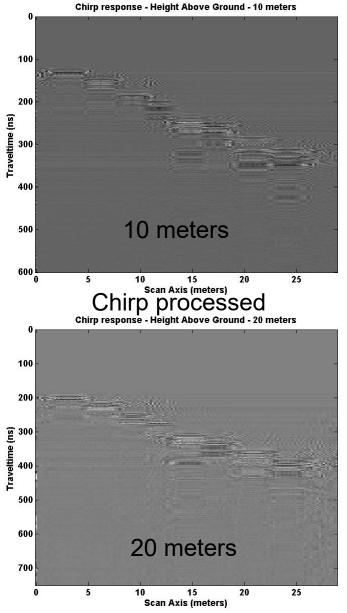




Chirp response - Height Above Ground - 5 meters







Observations



- In GPR imaging, there is a need to image <u>deeply buried</u> objects with <u>high-resolution</u>
 - <u>Problem</u>: High-resolution requires higher frequencies, but high frequencies have more attenuation
 - <u>Solution</u>: Need to use both low frequencies (for depth) and high frequencies (for resolution) for GPR imaging
- Without actual GPR equipment, I have shown that simulations match real experimental data quite accurately, and therefore can be useful for algorithm development inexpensively.
- The EM GMM algorithm works well for hidden data problems, unlike Maximum Likelihood Estimation.
 - MLE takes derivative of joint PDF with respect to unknown variable; solving for that variable (max value is determined).
 - EM GMM with observations hidden the joint PDF becomes a log of sums, the derivative of the log of sums is hard to calculate and solution variables must be guessed; max value convergence not guaranteed, using E-Step & M-Step creates MLE sub-problems guaranteed to converge to maximum value.
- The EM GMM algorithm works reasonably well for summing sine waves of a particular set of frequencies into a square or triangle wave.



Conclusions

- The Expectation-Maximization technique with the Gaussian Mixture model feature, performs reasonably well in producing a good image at the surface and at depth in various media (homogenous and nonhomogenous).
- With EM GMM, the target is illuminated at the defined depth in a more definitive manner than just adding frequency scans together.
- A test of a more complex structures produces a positive result also.
 - Several buried objects
 - Non-homogenous media
- When compared to 3 other methods (Dougherty, Booth, and Bancroft), the EM algorithm still performs well, out performing most.
- EM GMM algorithm performed well with Tx/Rx at various heights above ground.
- EM GMM performed better in depth detection than Chirp signals but required more passes over a target to generate the required number of frequencies to sum. Edge detection was worse for the EM GMM process.



Conclusions, cont.

- There are problem areas uncovered by this study which bear future study
 - Edge detection capability.
 - Reliably removing direct arrival/ground bounce without removing target data.
 - How to best align trace starting points across frequencies (lining up each trace by the direct arrival pulse then process, for example).
 - More complicated models should be used also.

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References



1 - R. Tilley, F. Dowla, F. Nekoogar, and H. Sadjadpour, "GPR Imaging for Deeply Buried Objects: A comparative Study based on FDTD models and Field Experiments, Selected Papers Presented at MODSIM World 2011 Conference and Expo; pp. 45-51, Mar. 2012; (NASA/CP-2012-217326); (SEE 20130008625).

2 - R. Tilley, H. Sadjadpour, and F. Dowla, "Compositing Ground Penetrating Radar Scans of Differing Frequencies for Better Depth Perception", International Journal on Advances in Software, vol. 10, no. 3 & 4, year 2017, pp 413-431, ISSN 1942-2628.

3 - R. Tilley, H. R. Sadjadpour and F. Dowla, "Compositing "Stand Off" Ground Penetrating Radar Scans of Differing Frequencies,", International Journal on Advances in Software, vol. 11, no.
3 & 4, year 2018, pp 379-389, ISSN 1942-2628

4 - R. Tilley, H. R. Sadjadpour and F. Dowla, "GPR Imaging for Deeply Buried Objects: A Comparative Study Based on Compositing of Scanning Frequencies and a Chirp Excitation Function," Geosciences Special Issue Journal on Advances in Ground Penetrating Radar Research, vol 9, no. 3, article no. 132, March 2019, ISSN 2076-3263.





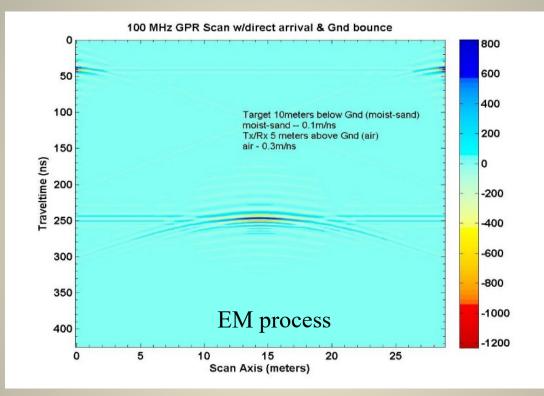




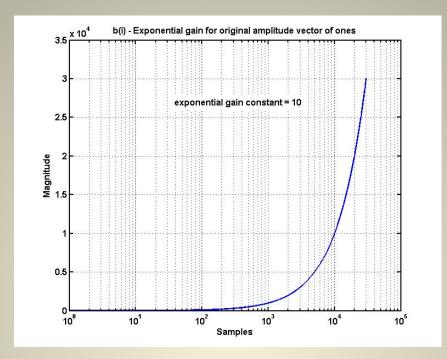
Extra Slides



Wider scan area to show the expected hyperbola and address the "bore hole" question on Test Case 1







Exponential Gain Recovery Function Example

i - sample

$$b(i) = i * a(i) * e^{i * g * \frac{dt}{1000}}$$

- a(i) ith sample of original amplitude trace.
- g exponential gain constant.
- *dt* sample rate.
- b(i) ith sample of gain recovered trace.

Material Properties



	λ = c / (fm *	sqrt(Er))		c -	c - speed of light (meters), fm - highest frequency of interest(Hz) [fm = 3 * f],					
					Er - relative permittivity of med	ium, λ - wavelength (m)				
	$\Delta L = \lambda/10$ rule of			thumb for spatial step (make $\Delta x = \Delta y = \Delta z = \Delta L$)			V = [c / Sqrt(Er)] * 1e-9 meters/nanosec		tw = 1.3* (2*depth)/vel	
λ	f	fm	c	٤r	Material	ΔL	Velocity in medium	Relative Permittivity	C	
m	Mhz	Hz	m/s	CI	Wateria	ΔL	m/ns	Er	m/s	
	IVITIZ	112	1173				11/113	Ci	11/3	
0.024845	9.00E+08	2.7E+09	3.00E+08	20	wet sand	0.002485	0.0671	20	3.00E+08	
0.012423	9.00E+08	2.7E+09	3.00E+08	80	fresh water	0.001242	0.0335	80	3.00E+08	
0.04969	9.00E+08	2.7E+09	3.00E+08	5	dry_sand_max	0.004969	0.1342	5	3.00E+08	
0.06415	9.00E+08	2.7E+09	3.00E+08	3	dry_sand_min	0.006415	0.1732	3	3.00E+08	
0.017568	9.00E+08	2.7E+09	3.00E+08	40	clay_max	0.001757	0.0474	40	3.00E+08	
0.04969	9.00E+08	2.7E+09	3.00E+08	5	clay_min	0.004969	0.1342	5	3.00E+08	
0.045361	9.00E+08	2.7E+09	3.00E+08	6	concrete	0.004536	0.1225	6	3.00E+08	
0.045361	9.00E+08	2.7E+09	3.00E+08	6	dry_salt_max	0.004536	0.1225	6	3.00E+08	
0.04969	9.00E+08	2.7E+09	3.00E+08	5	dry_salt_min	0.004969	0.1342	5	3.00E+08	
0.045361	9.00E+08	2.7E+09	3.00E+08	6	granite_max	0.004536	0.1225	6	3.00E+08	
0.055556	9.00E+08	2.7E+09	3.00E+08	4	granite_min	0.005556	0.1500	4	3.00E+08	
0.055556	9.00E+08	2.7E+09	3.00E+08	4	ice_max	0.005556	0.1500	4	3.00E+08	
0.06415	9.00E+08	2.7E+09	3.00E+08	3	ice_min	0.006415	0.1732	3	3.00E+08	
0.039284	9.00E+08	2.7E+09	3.00E+08	8	limestone_max	0.003928	0.1061	8	3.00E+08	
0.055556	9.00E+08	2.7E+09	3.00E+08	4	limestone_min	0.005556	0.1500	4	3.00E+08	
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0.111111	9.00E+08	2.7E+09	3.00E+08	1	free_space	0.011111	0.3000	1	3.00E+08	
0.037037	9.00E+08	2.7E+09	3.00E+08	9	moist_sand	0.003704	0.1000	9	3.00E+08	