Inversion via Bayesian Multi-modal Iterative Adaptive Processing (MIAP)

Leslie Collins, Yongli Yu, Peter Torrione, and Mark Kolba
Electrical and Computer Engineering
Duke University

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Outline

• RDOF Feature Selection
• Adaptive Uncertainty Processing
• Tracking/Classification
• Sensor Management
• Processing Georgia Tech Data
Adaptive Feature Selection
Subsurface Sensing (Landmines, UXO, Subsurface Structures)

- Simulate seismic, EMI, and MAG data
- Large number of features available
- Pre-screener needed based on RDOF feature set
- Issue: best features function of sensor implementation, test site, etc.
- In some scenarios, need to adaptively select features
- Ultimately: AMMP applied to results of pre-screener
RDOF Feature Selection

• Guide initial selection of features
• Adaptively prune features based on input from multiple sensors
• Carin et al. proposed RDOF for induction sensing
  – Induction, mag, seismic still produce many features
  – JCFO verified by Carin on acoustic data – not previously applied to EMI/MAG/Seismic data
• Evaluated JCFO/adaptive feature selection on:
  – EMI and MAG for UXO
  – EMI and GPR for landmines
JCFO

• Classification of a feature vector, $\mathbf{x}$, performed using kernel-based technique

$$c(\mathbf{x}) = \sum_{n=1}^{N} w_n K(\mathbf{x}, \mathbf{x}_n) + w_0$$

• For a binary classifier with labels, $l$, of $+1$ and $-1$, training data $\mathbf{T}$ and weights $\mathbf{w}$

$$p(l = 1 / \mathbf{x}, \mathbf{T}, \mathbf{w}) = \frac{1}{1 + e^{-c(\mathbf{x})}}$$

$$p(l = -1 / \mathbf{x}, \mathbf{T}, \mathbf{w}) = 1 - p(l = 1 / \mathbf{x}, \mathbf{T}, \mathbf{w})$$

• A Laplacian sparseness prior is placed on the weights of the training samples $\mathbf{x}_n$
Associate each training sample with parameter \textit{Beta}, and each feature with parameter \textit{Theta}.

Example: training data of 128 samples, 17 features for each sample

\begin{itemize}
  \item \textbf{Theta}[1]
  \item \textbf{Theta}[2]
  \item \textbf{Theta}[3]
  \item \textbf{Theta}[4]……
  \item \textbf{Theta}[17]
\end{itemize}

\begin{itemize}
  \item \textbf{Beta}[1]
  \item \textbf{Beta}[2]
  \item \textbf{Beta}[3]
  \item \textbf{Beta}[4]
  \item \textbf{Beta}[128]
\end{itemize}

\textbf{Training Objective}: Estimating parameters of \textbf{Theta} and \textbf{Beta}

Feature Selection: Sparsity in \textbf{Theta} implies that it finds only a few features highly relevant for classification. (making some Theta[i]=0)

Kernel function selection: Sparsity in \textbf{Beta} implies that it finds a small subset of data highly representative of the different classes (making some Beta[i]=0)

Find the maximum a posterior (MAP) estimate of \textbf{Theta} and \textbf{Beta} using \textit{EM algorithm}.
EMI Results – FPDS System

![Graph showing EMI results for different systems](image)
MIAP
Traditional Versus Collaborative/MIAP Approach

**Traditional:**
- Sensor → Algorithm → Threshold
- Data or Feature Fusion
- Algorithm Fusion
- Decision Fusion

**Collaborative/MIAP:**
- Sensor → Algorithm → Adaptive Control
- Sensor → Algorithm
MIAP Bayesian Processing

\[ \Lambda(r) = \frac{\int f(r / \Theta, H_1) f(\Theta / H_1) d\Theta}{\int f(r / \Omega, H_0) f(\Omega / H_0) d\Omega} \]

- Two modes of adaptation
  - Statistical parameters tracked and updated (e.g. covariance matrix)
  - Priors on uncertain parameters modified based on context (e.g. size, depth of radar response indicates an anti-tank mine, EMI library modified accordingly)
MIAP for Landmine Detection

- Prior work suggests adaptively pruning EMI/MD library using signature magnitude improved processor performance: LM vs HM
- Multi-modality processing
  - suggests adaptively pruning EMI/MD library using GPR magnitude: AP vs AT
  - suggests adaptively pruning GPR library using EMI/MD discrimination algorithms: mine type
  - New work: incorporate uncertainty in pruning algorithm into processing algorithm
- Sensor fusion at data level or decision level
The document contains a diagram and text related to a MD Signature Library. The diagram shows a matrix with rows labeled as LM, Sig 1, Sig 2, Sig 3, Sig M-1, and Sig M, and columns labeled as AP, AT, LM, and HM. The text includes a mathematical expression:

**Sources of uncertainty**

\[ f(r_x / H_1) = \frac{1}{N_{t(\theta_i)}} \sum_{i=1}^{2} p(\theta_i^1) \left[ \sum_{j=1}^{N_{t(\theta_i)}} f(r_x / t_{\theta_i,j}, H_1) p(t_{\theta_i,j}) \right] \]

\[ \theta_1^1 = \text{AP}, \quad \theta_2^1 = \text{AT} \]
Simulations: Proof of Concept

MIAP can reduce $P_f$ by

$$\Phi(\Phi^{-1}(P_d) + d) - \Phi(\Phi^{-1}(P_d) + d_0)$$

$$d^2 = \frac{(\Delta \mu)^2}{\delta_0^2 + \frac{(\Delta \mu)^2}{4}} < d_0^2 = \frac{(\Delta \mu)^2}{\delta_0^2}$$

Experimental gains mimic these (2 test cases)
Follow-on Developments

- Theoretical treatment of imperfect class decision algorithms (assuming perfect performance hurts performance!)
- Theoretical proof of performance gain (previous page)
- Derivation of weight parameters for the multi-Gaussian case
- Determination of the optimal threshold (operating point) of individual classifiers
- Consider uncertainty in imperfect class decision algorithms
Substantial differences in pdfs of sensor outputs between testing and training sets (data from old JUXOCO grid)
Resulting ROCs are quite different, and threshold settings do not translate.

Need to consider uncertainty in threshold settings and performance metrics of individual sensors across testing and training sets.
classifier performance sensitivity test, algorithm assume $d=9$

Full uncertainty case
Even when not considering testing/training feature uncertainty, MIAP is more robust than full uncertainty case.
Uncertainty in Feature Distributions

• Assume the mean of the test data is a variable which has a uniform distribution centered at the training value.

• To incorporate this uncertainty into the MIAP algorithm use

\[
\lambda(\tilde{c}) = \frac{\sum_c \int P(x | \mu_c, c, \text{mine}) P(\mu_c) d\mu_c w_c}{\sum_c \int P(x | \mu_c, c, \text{clutter}) P(\mu_c) d\mu_c w_c}
\]
incorporate uncertainty in variance
Tracking
Adaptive Prescreening

- Previously used adaptive prescreener in depth bins (LMS)
- Extended subsurface anomalies across depth bins cause false alarms
- First approach: SSAD
- Second approach: target tracking
Segmented Shifting And Differencing

- Multiple Anomalies may move in opposite time/depth directions simultaneously
- Need to cancel all anomalies using nearby shifted versions of them if available
Consider a $M \times 1$ time-domain vector of interest $X$. Let $x_i$ represent the $i^{th}$ length $N$ sub-vector of $X$:

$$x_i = X((i - 1) \ast N + 1 : i \ast N)$$ (1)

$$i \in \{1, 2, ..., M/N\}$$

Now consider a set of vectors $\{C^1, C^2, ..., C^k\}$ drawn some guard-band distance away from the location of $X$. Let

$$C^j_{i,m} = C^j((i - 1) \ast N + 1 + m : i \ast N + m)$$ (2)

$$m \in \{-N, -N + 1, ..., N - 1, N\}$$

For each sub-vector $x_i$ we search for sub vectors from the corresponding $C^j_{i,m}$ over $i$ and $j$ to minimize the energy of the difference of the vectors.

$$v^j_{i,m} = x_i - C^j_{i,m}$$ (3)

$$J, M = arg\min_{j,m} \{v^j_{i,m} \ast v^j_{i,m}\}$$ (4)

For each $x_i$, the resulting difference vector $v^j_{i,M}$ becomes the energy measure which yields our decision statistic after post-processing.
Results of SSAD Processing
Model 1 and Mode 2 Data

Pre-SSAD Processing

Post-SSAD Processing

Second Ground Bounce, Extended Subsurface Clutter, and Target in Mode 1 and Mode 2 Data
Tracking/Discrimination

- Based on JMPD formulation developed by Kastella and colleagues and others using information-based metrics
- Can track unknown # of targets using Bayesian precepts
- Targets can be born and can die
- Well suited to GPR subsurface structure tracking
- Will evaluate extensions using particle filtering and alternative information metrics
- Must extend to consider coincident targets
Off-road NIITEK GPR processing
Sensor Management
Discrimination-Based Sensor Management

• Initial algorithm based on Kastella et al.

\[ D(P, Q) = \sum_{s=1}^{S} P(s) \ln(P(s)/Q(s)) \]

• Select a cell which maximizes \( \Delta D \)

• Can be calculated recursively

• Initial simulations manage sensor threshold, cell sampling
Preliminary Results

Error probability vs. number of measurements for 1 sensor and 1 target

Measurements

Pe
disc: 0 dB
direct: 0 dB
direct: 3 dB
direct: 6 dB
Work in Progress

- Extend to multiple sensors
- Consider unknown Pd, Pf for each sensor
- Constrained search (for ground based sensing as opposed to airborne)
- Overlapping targets
- Alternative measures of D (may not allow recursive formulation)
Application to Lab Data: Georgia Tech’s EMI, GPR and Seismic Sensors
19 Rocks

Burial Scenario #3
This photograph shows the locations and orientations of the rocks, the aluminum can, and the VS-50 AP mine buried in the boxed region shown on the layout (previous slide). The corners of the region are indicated by the red and green markers.
EMI Energy

![EMI Imag NRG With Targets (black) and Clutter (red)](image1)

![EMI Real NRG With Targets (black) and Clutter (red)](image2)

nz = 33
EMI Q-MSD (Train 3, Test 4)
Seismic Pre-processed Energy

Seismic Energy With Targets (black) and Clutter (red)

nz = 33
GPR Pre-screener and Matched
(Train 3, Test 4)
EMI Train & Test

EMI MSD and NRG ROC Curves (Train & Test Collections 3 & 4)

EMI MSD and NRG ROC Curves (Train & Test Collections 2 & 4)
GPR LMS & Energy

GPR LMS & Energy ROC Curves (train 4 test 4)
Seismic Results
Simple Fusion Results (Train 3, Test 4)
MIAP Processing

- Split data according to AP/AT classification
- Can utilize GPR pre-screener decision statistics to accomplish this
- Estimate Gaussian PDFs for other features for both AP and AT targets
- Utilize a-priori information from GPR (AP or AT) before calculating likelihood ratio based on Gaussian PDFs
Decision Statistics By Target Type

AT Confidence Values (Aggregate over all Training/Testing)

AP Confidence Values (Aggregate over all Training/Testing)
MIAP Results with Perfect AP/AT Classification
MIAP Results with Gaussian AP/AT Classification

⇒ Only Change
MIAP and Fusion (Train 3, Test 4)
ICA Results (VS50 & Metal Clutter)
Accomplishments

- Adaptive Feature Selection (JCFO) successfully applied to landmine problem
- Uncertainties incorporated into MIAP processor improve robustness
- Adaptive tracking technique improves GPR detection performance
- Encouraging sensor management results
- Multi-sensor data from Georgia Tech processed – using adaptive fusion