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Multinomial Pattern Matching for High Range Resolution Radar Profiles

Melissa L. Koudelka, Ph.D.
John A. Richards, Ph.D.
Mark W. Koch, Ph.D.

Sensor Exploitation Applications
Sandia National Laboratories
Albuquerque, New Mexico

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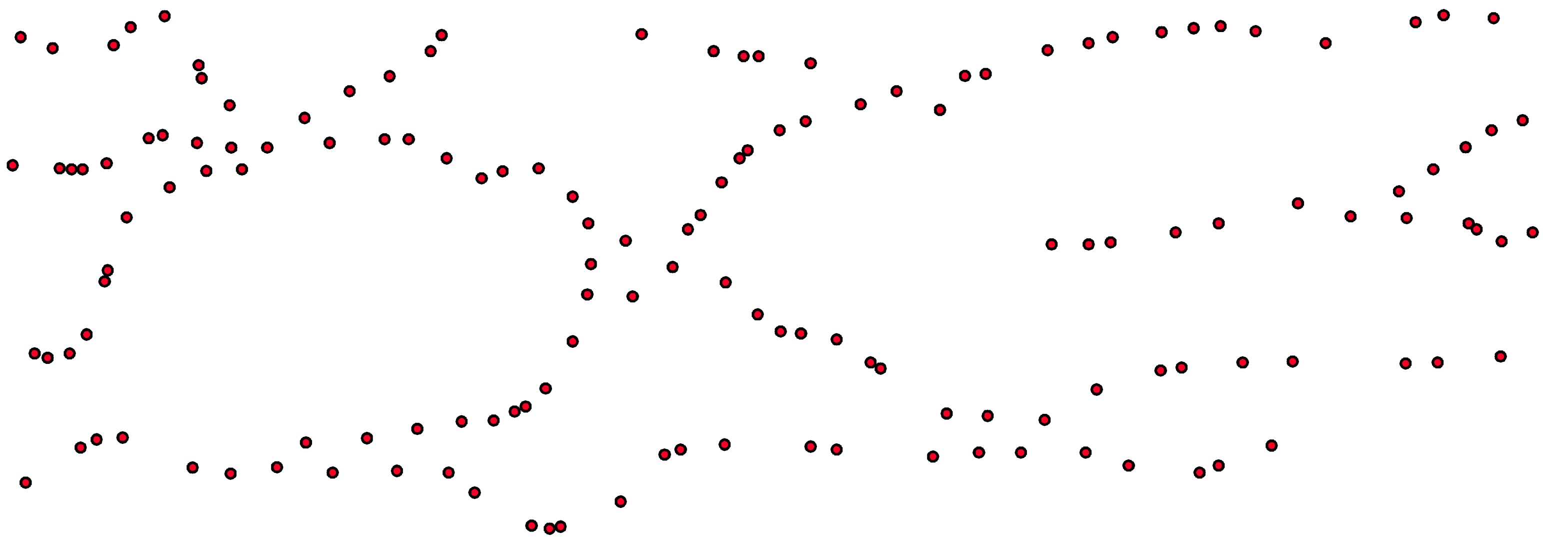
Agenda

- Context
- Fingerprinter overview
- MPM algorithm details
- Tracklet-association scoring
- Discussion

Target fingerprinting context

- Sensor resource manager (SRM):
  - Tells radar where to point and what collection mode to use (HRR/MTI/SAR)



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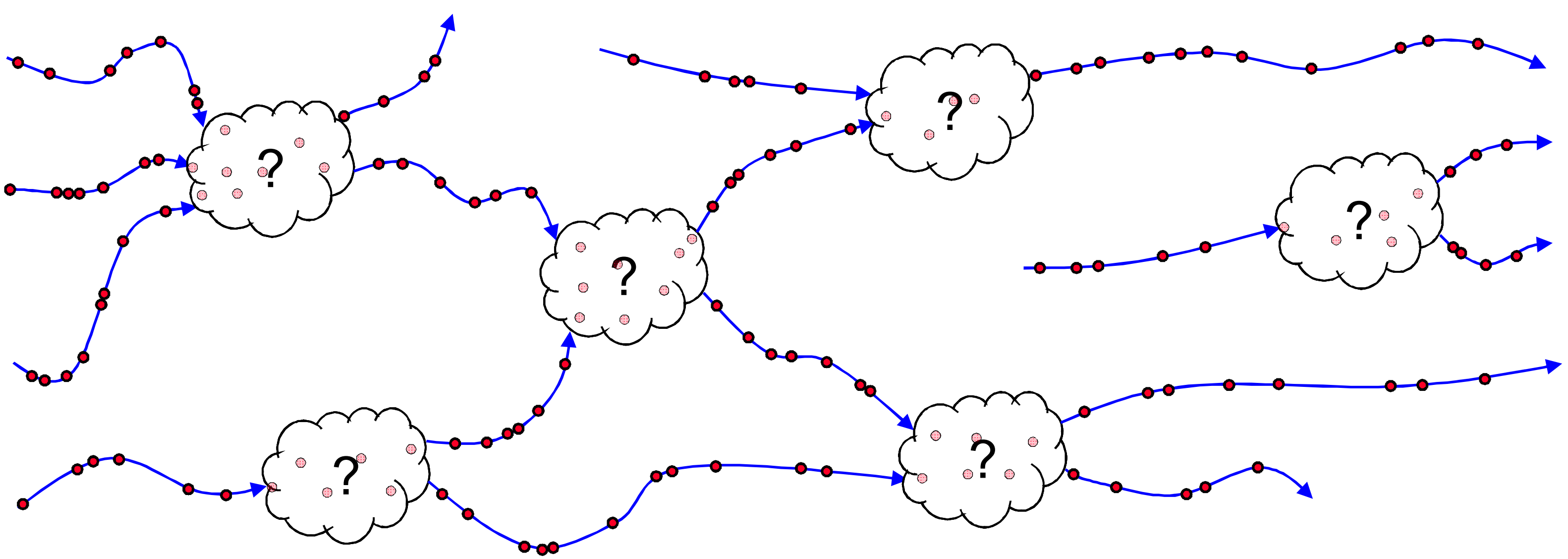
- Sensor resource manager (SRM):
  - Tells radar where to point and what collection mode to use (HRR/MTI/SAR)
- Feature-aided tracker (FAT):
  - Collects kinematically unambiguous measurements into tracklets



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  - Tells radar where to point and what collection mode to use (HRR/MTI/SAR)
- Feature-aided tracker (FAT):
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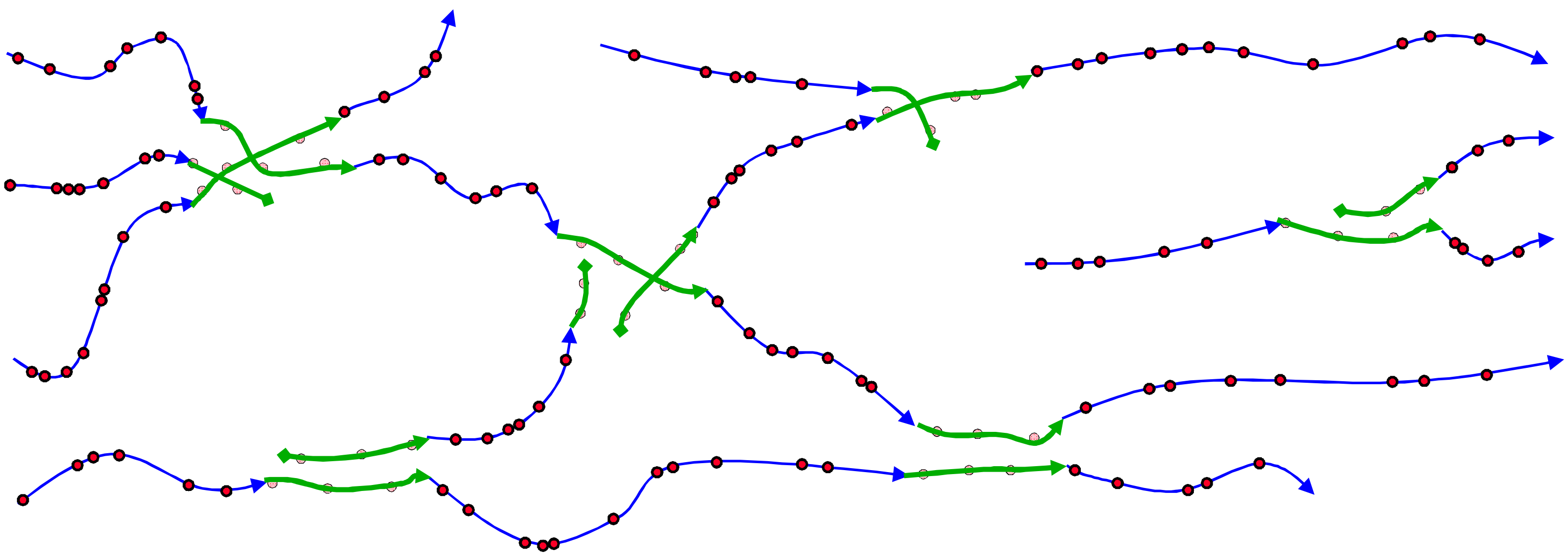
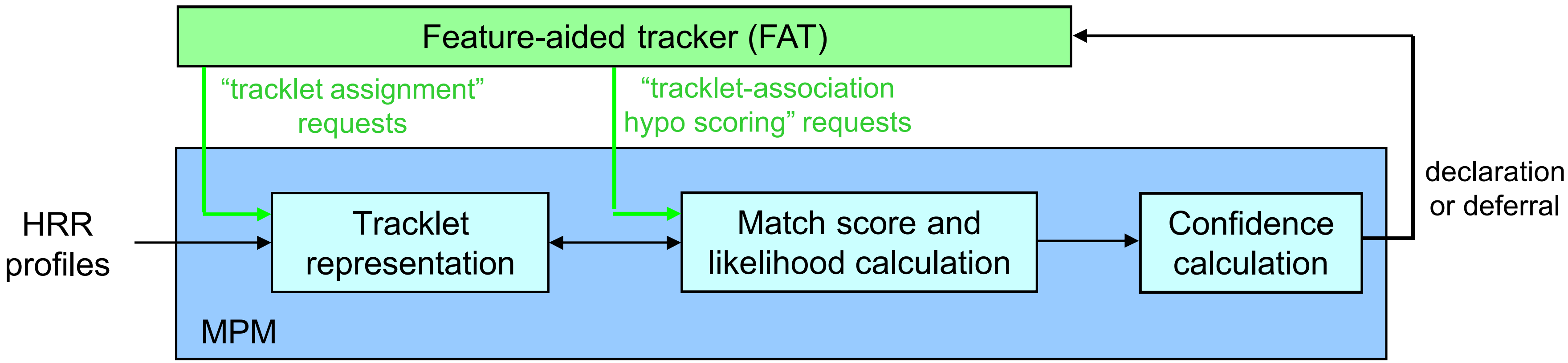
- Fingerprinter:
  - Uses tracklets' HRR profiles to resolve kinematic ambiguities, enable tracklet stitching



Fingerprinter overview



- Tracklet representations:
  - Compact, fixed-size representations of FAT-specified measurements
  - Incrementally updated whenever new data is available
- Match score and likelihood calculations:
  - Calculated on the fly for specific tracklet-association hypotheses when requested by FAT
  - Use most-recent incremental tracklet representations
- Confidence calculation:
  - Fusion of likelihoods to yield overall tracklet-association confidences and declaration/deferral

MPM signature stabilization: quantile transform

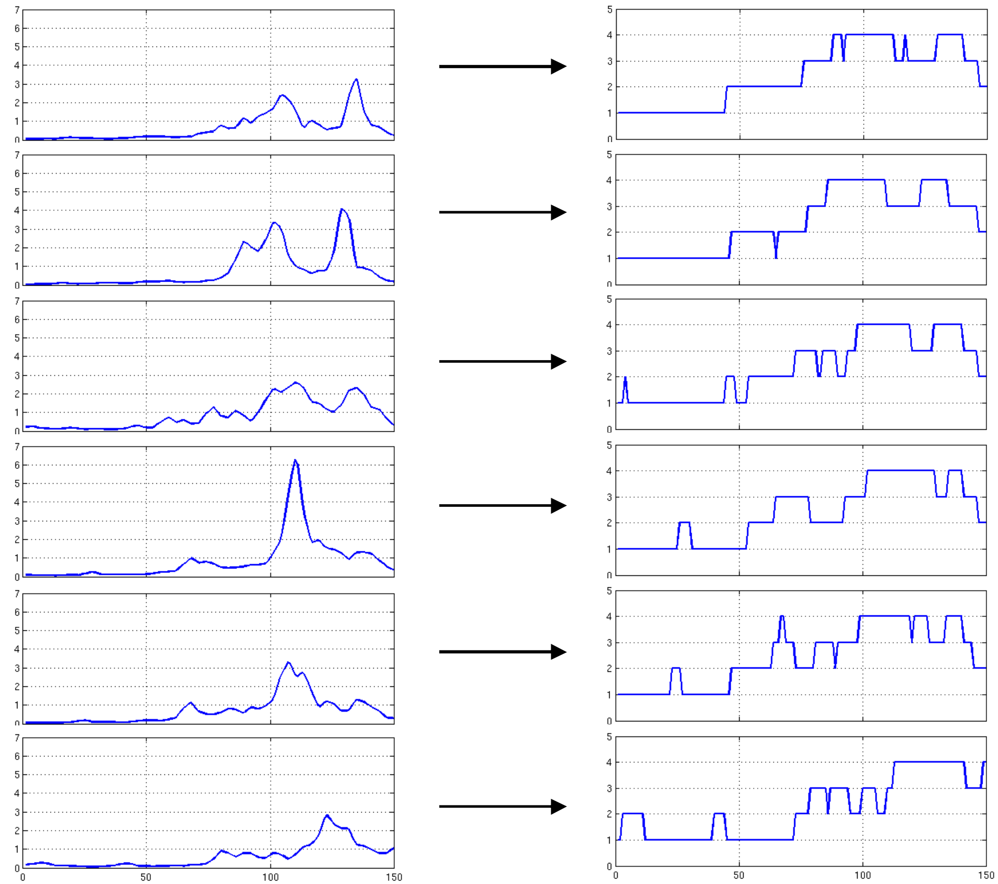
- Motivation:
  - Absolute amplitudes are fickle
  - Relative amplitudes are stable
  - Why waste effort trying to model absolute amplitude variation?

- Implementation of M-quantile transform:
  - Rank-order all N samples in profile in increasing order of amplitude
  - Samples 1 to N/M $\rightarrow$ $q = 1$
  - Samples $(N/M + 1)$ to $2N/M$ $\rightarrow$ $q = 2$

    $\vdots$ $\vdots$
  - Samples $((N - 1)/M + 1)$ to N $\rightarrow$ $q = M$

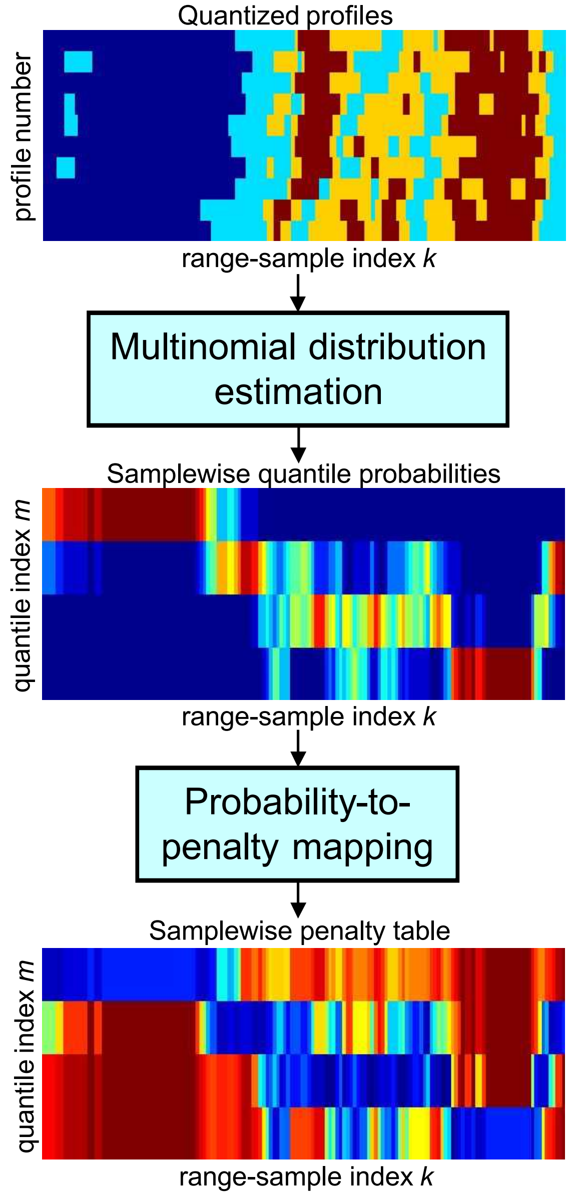
- Effects:
  - Discards unreliable information
  - Preserves relevant information
  - Invariant to unknown/incorrect calibration
  - Enhances in-class stability
  - Facilitates statistical characterization

Example: 4-quantile transform (T72, 146°–154°)



MPM template generation

- Model samplewise quantile distribution
  - Assume a multinomial distribution
  - Incrementally update as data becomes available
  - Maintain MPM template for each aspect bin
  - Hedge bets to avoid assigning probability values of 0 or 1
- Map samplewise probabilities to penalties
  - Used to score templates against each other
  - Smaller probabilities ↔ larger penalties
  - Normalized to zero mean, fixed variance
- Match score is sum of samplewise penalties
- In-class and out-of-class match-score distributions are separable
  - $s_{\text{in-class}} \sim N(0,1)$
  - In general, $s_{\text{out-of-class}} > s_{\text{in-class}}$



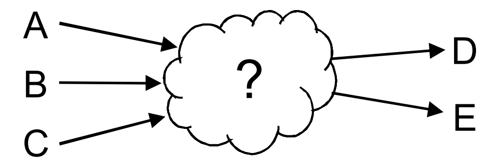
Tracklet association scoring

MPM templates → Hypothesis enumeration → Match score calculation → Distribution estimation → Likelihood calculation → Confidence calculation → declaration or deferral

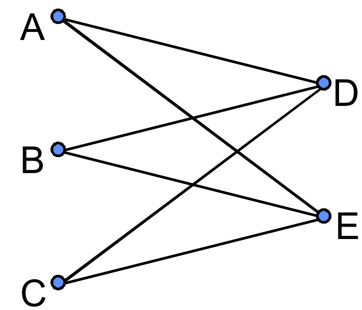
- Hypothesis enumeration
  - List all pre-ambiguity-to-post-ambiguity joint tracklet associations (including those with “hiding” vehicles)
- Match score calculation
  - Calculate match scores for each pairwise tracklet association
- Distribution estimation
  - Estimate in-class match-score distributions
  - Set out-of-class match-score distributions to generic null-class priors with user-specified offsets
- Likelihood calculation
  - Compare match scores to estimated match-score distributions to yield likelihoods
- Confidence calculation
  - Combine likelihoods to yield confidences for each hypothesis for each template type
  - Do things robustly to prevent arbitrarily bad matches from driving confidences
  - Combine hypothesis likelihoods from multiple sources to get tracklet-association confidences
  - Sort and threshold confidences to yield declaration or deferral

Tracklet association scoring: hypothesis enumeration

- Example:
  - Five tracklets
  - Three are pre-ambiguity; call them A, B, C
  - Two are post-ambiguity; call them D, E



- Six pairwise pre-to-post tracklet associations
  - A-D, A-E, B-D, B-E, C-D, C-E

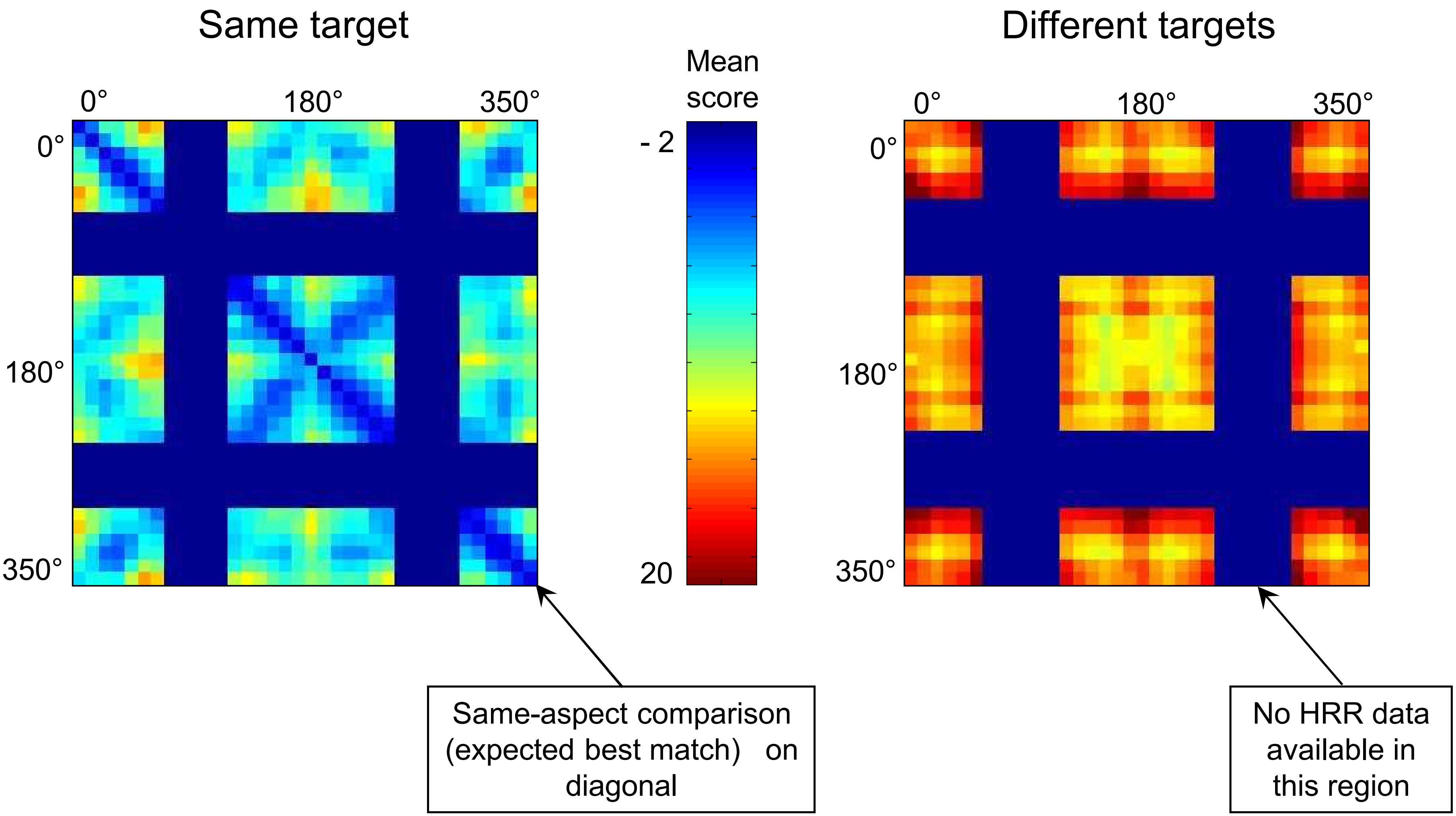


- Five pairwise "hiding-target" pairings
  - A-X, B-X, C-X, D-X, E-X

- Thirteen joint association hypotheses
  - Six with 2 pre-to-post, 1 hiding
  - Six with 1 pre-to-post, 3 hiding
  - One with 0 pre-to-post, 5 hiding

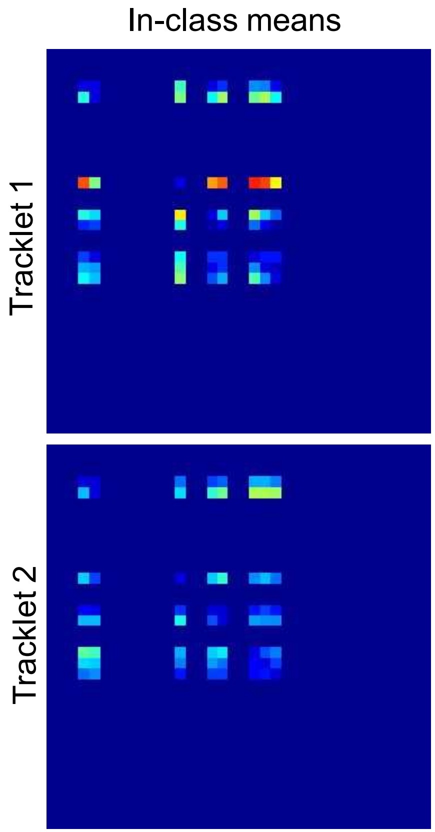
2 pre-to-post 1 hiding	H_1: {A-D, B-E, C-X} ↔ {D-A, E-B}
	H_2: {A-D, B-X, C-E} ↔ {D-A, E-C}
	H_3: {A-E, B-D, C-X} ↔ {D-B, E-A}
	H_4: {A-E, B-X, C-D} ↔ {D-C, E-A}
	H_5: {A-X, B-D, C-E} ↔ {D-B, E-C}
	H_6: {A-X, B-E, C-D} ↔ {D-C, E-B}
1 pre-to-post 3 hiding	H_7: {A-D, B-X, C-X} ↔ {D-A, E-X}
	H_8: {A-E, B-X, C-X} ↔ {D-X, E-A}
	H_9: {A-X, B-D, C-X} ↔ {D-B, E-X}
	H_{10}: {A-X, B-E, C-X} ↔ {D-X, E-B}
	H_{11}: {A-X, B-X, C-D} ↔ {D-C, E-X}
	H_{12}: {A-X, B-X, C-E} ↔ {D-X, E-C}
0 pre-to-post 5 hiding	H_{13}: {A-X, B-X, C-X} ↔ {D-X, E-X}

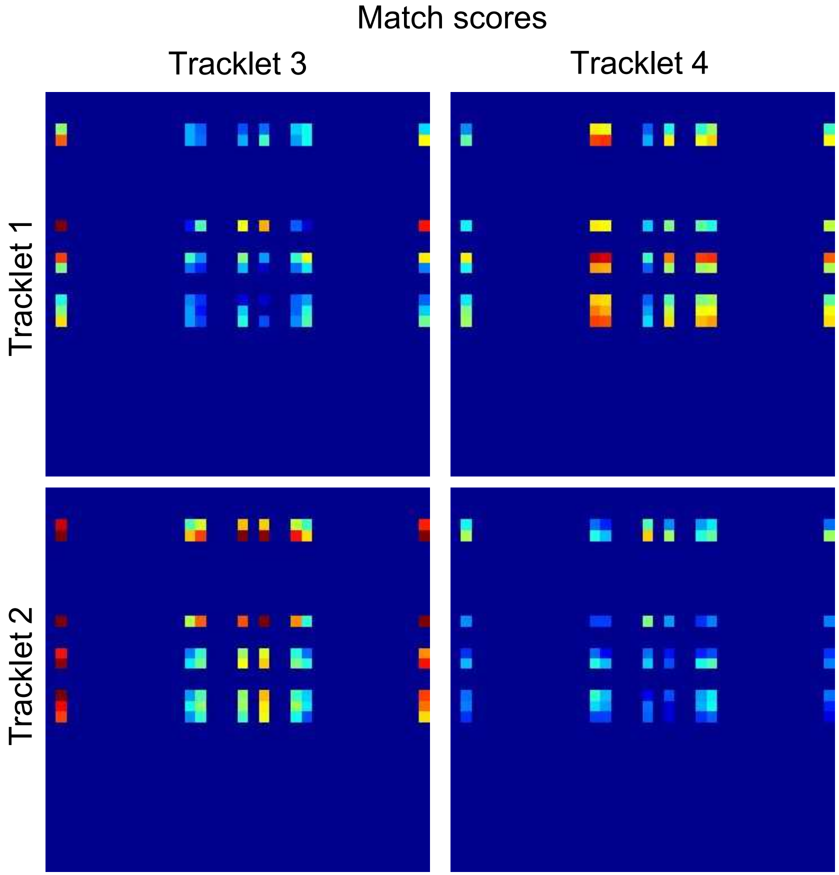
Example: MPM match scores by aspect



Example: in-class MPM means and match scores

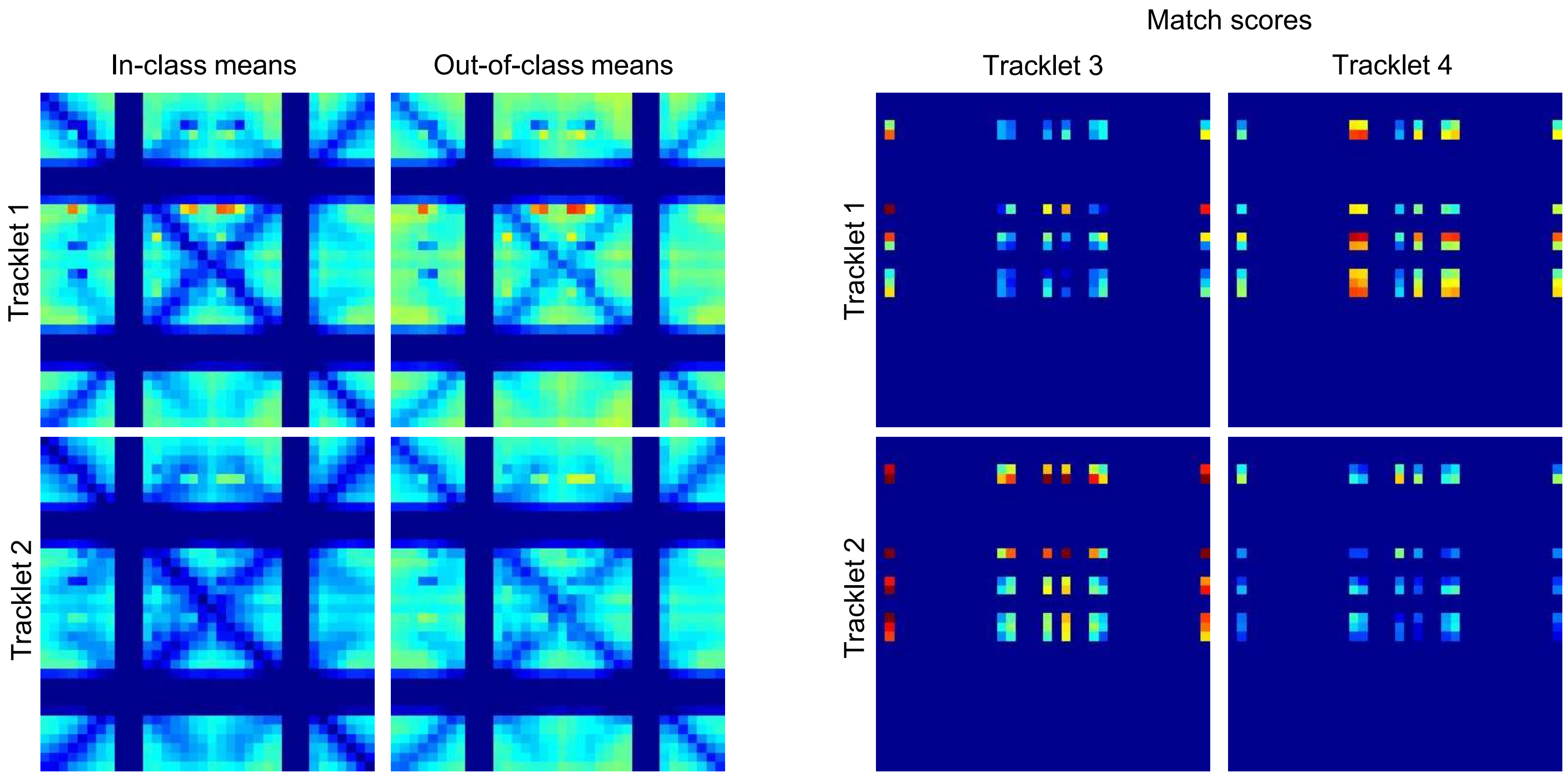
- Simple example: two-in, two-out problem
  - Tracklets 1, 2 enter ambiguity
  - Tracklets 3, 4 exit ambiguity
  - Make pre-to-post-ambiguity assignment
- Calculate template-to-template MPM match scores for all pre-to-post tracklet pairs





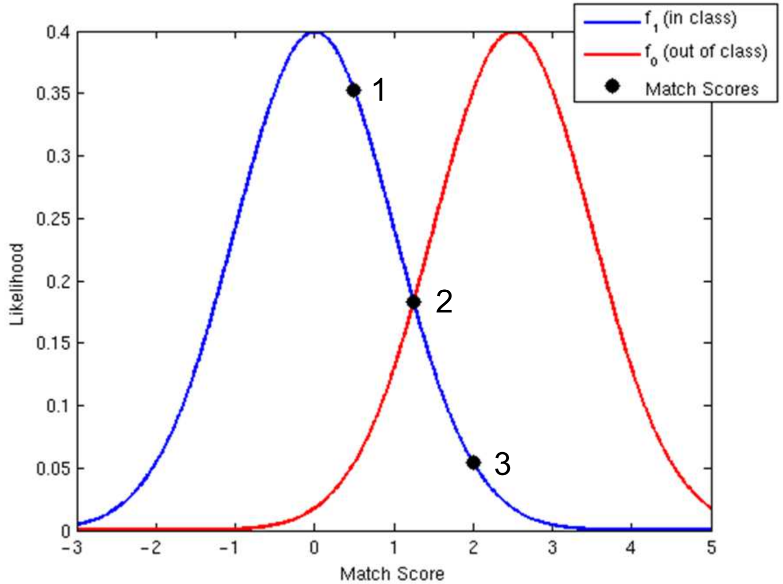
Example: in-class and out-of-class MPM means and match scores

- Incorporate generic in-class prior to interpolate full in-class grids
- Float generic out-of-class prior relative to in-class grid to yield out-of-class grids



Tracklet association scoring: likelihood calculation

- Get tracklet-association likelihoods by cross-comparing match scores with statistics
  - Model nominal in-class and out-of-class distributions as Gaussians
  - Add robustness and clip likelihoods by contaminating nominal Gaussian distributions
  - Average across aspect bins to get overall likelihood for MPM templates
- Get hypothesis likelihoods by combining pairwise tracklet-association likelihoods for all enumerated hypotheses



$$LLR = \log\left(\frac{f_1(x)}{f_0(x)}\right)$$

Point	Score	LLR
1	0.50	1.875
2	1.25	0
3	2.00	-1.875

Tracklet association scoring: confidence calculation

- Compare hypothesis likelihoods to yield hypothesis confidences for each stream

$$C_{\text{stream}}(H_i) = \frac{L_{\text{stream}}(H_i)}{\sum_{j=1}^{N_H} L_{\text{stream}}(H_j)}$$

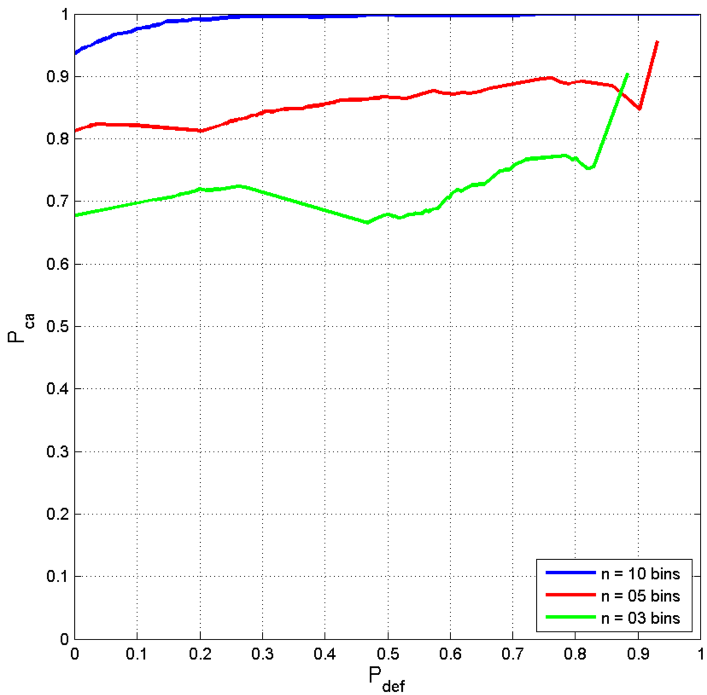
- Compute pre-to-post confidence matrix from fused hypothesis confidences
  - C_{ij} is the confidence in assigning pre-tracklet *i* to post-tracklet *j*
  - C_{i0} is the confidence in assigning pre-tracklet *i* to "hiding target"

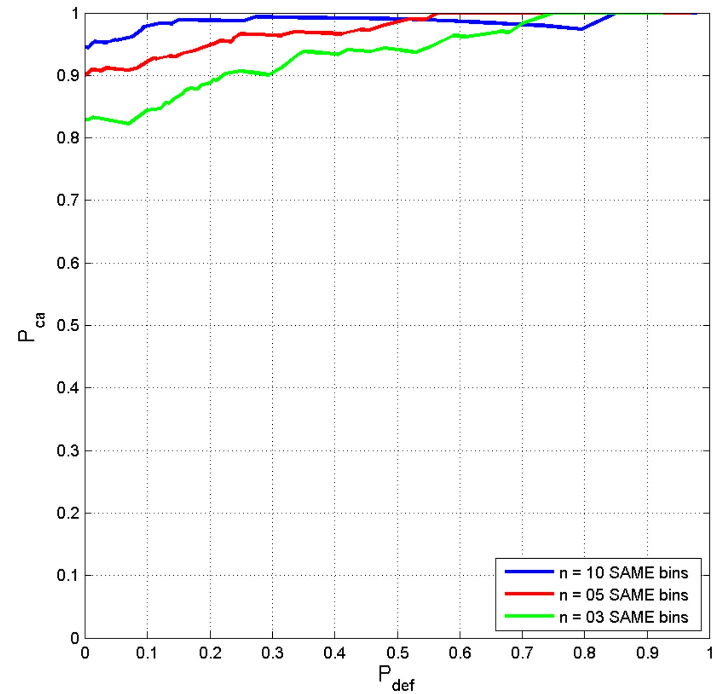
Pre \ Post	3	4	null
1	C_{13}	C_{14}	C_{10}
2	C_{23}	C_{24}	C_{20}

$$\sum_j C_{ij} = 1$$

- Decision rule:
  - Make declaration if maximum confidence exceeds pre-selected threshold
  - Declaration can be "pre-ambiguity target is not present in post-ambiguity target set"
  - Defer if no confidence exceeds pre-selected threshold

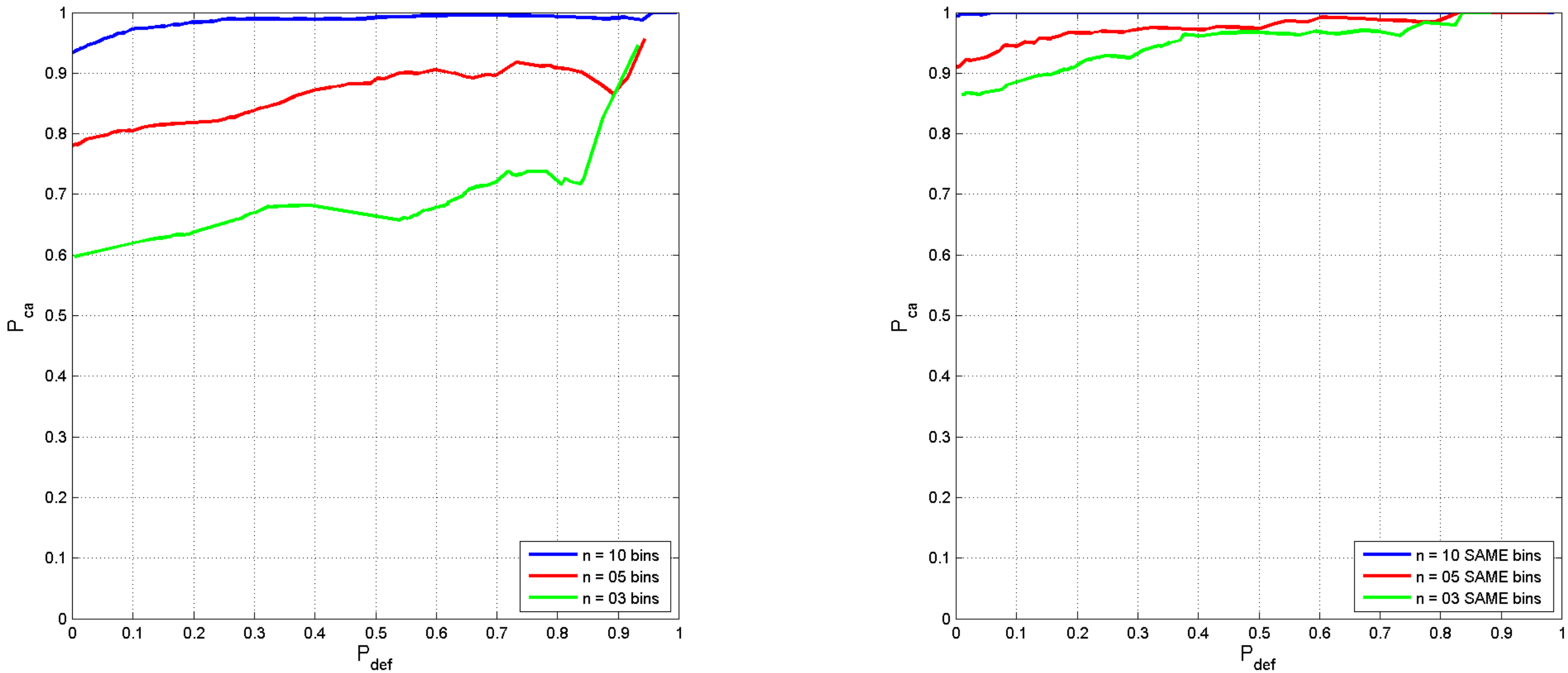
MPM performance: baseline scenario





- Simple baseline scenario
  - 2-in, 2-out, no replacement, randomized targets
  - Profiles formed from publicly available MSTAR data for 10 targets
  - Data available in 3, 5, or 10 randomized aspect bins (6 profiles per bin)
  - Left plot: pre- and post-bins chosen independently; Right plot: pre- and post-bins identical
- Performance improves significantly with additional data or aspect consistency
- Bottom line: strong assignment capability even with only seconds of target observation

MPM performance: additional targets



- Same experiment with additional targets
  - 3-in, 3-out, no replacement, randomized targets
  - Profiles formed from publicly available MSTAR data for 10 targets
  - Data available in 3, 5, or 10 randomized aspect bins (6 profiles per bin)
  - Left plot: pre- and post-bins chosen independently; Right plot: pre- and post-bins identical

- Bottom line: performance does not degrade significantly in more complex scenarios

Summary

- Build in robustness to limited signature/feature variability
  – Limit impact of any individual observation on the overall match score
  – Limit in-class/out-of-class likelihood ratios by using contaminated distributions
- Model similarities within classes, not differences between classes
  – Learn specific in-class distributions
  – Use generic out-of-class distributions
  – Enable rejection of arbitrary out-of-class targets (e.g., “hiding vehicles”)
  – Essentially, ask “A or not A?”, “B or not B?” instead of “A or B?”

Sandia contacts

Sensor Exploitation Applications
Sandia National Laboratories
Albuquerque, New Mexico

Melissa L. Koudelka
mlkoude@sandia.gov
(505) 284-8843

John A. Richards
jaricha@sandia.gov
(505) 845-8229