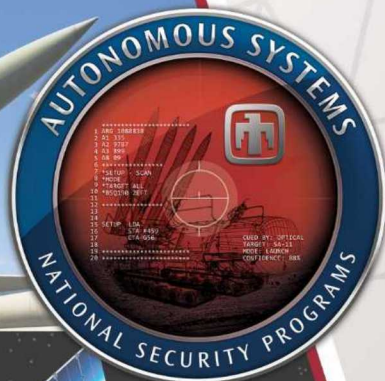


Multinomial Pattern Matching

John A. Richards, Ph.D.
Pathfinder Technologies
Sandia National Laboratories

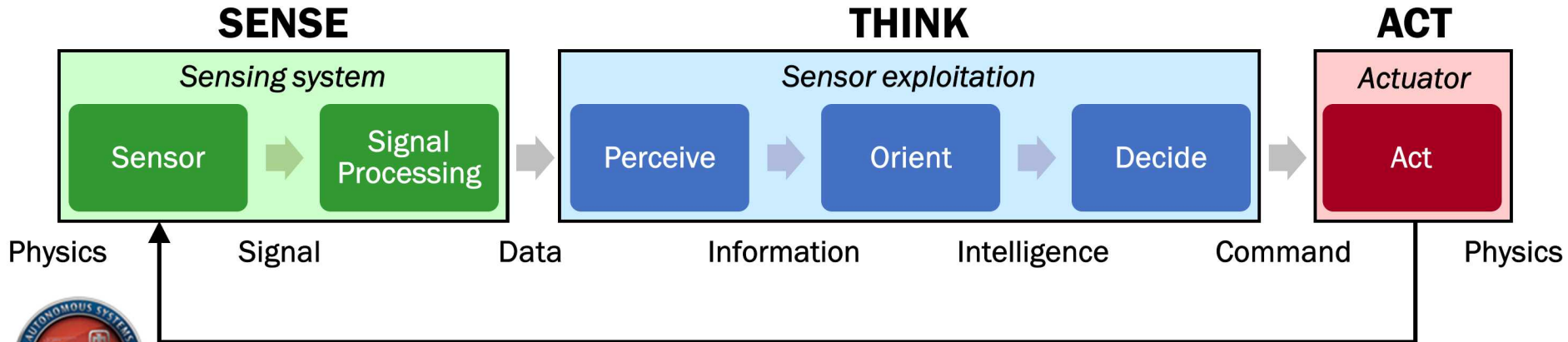


Overview



Multinomial pattern matching (MPM) is an object recognition algorithm designed for use with synthetic aperture radar (SAR) imagery

- Context: autonomous sensing systems
- Provide the “think” in the Sense-Think-Act loop
- Automate tasks and workflows for collaboration between users and machines



Commercial vs. defense applications

Commercial applications

- Structured environments
- Larger tolerance for error
- Large, well-labeled data sets
- Closed-set recognition often viable
- Common imaging modalities
- Usually involves class-level ID
- Will accept high Pfa to get high Pd
- Black-box systems are acceptable
- Good network connectivity
- Can compute in the cloud

Defense applications

- Adversarial environments
- Very low tolerance for error
- Limited, poorly-labeled data sets
- Open-set recognition usually essential
- Esoteric imaging modalities
- Usually requires type-level ID
- Will accept low Pd to get low Pfa
- Results must be fully explainable
- Little or no network connectivity
- All computation must be on-board

Defense applications generally must operate in different contexts and under different constraints than commercial applications

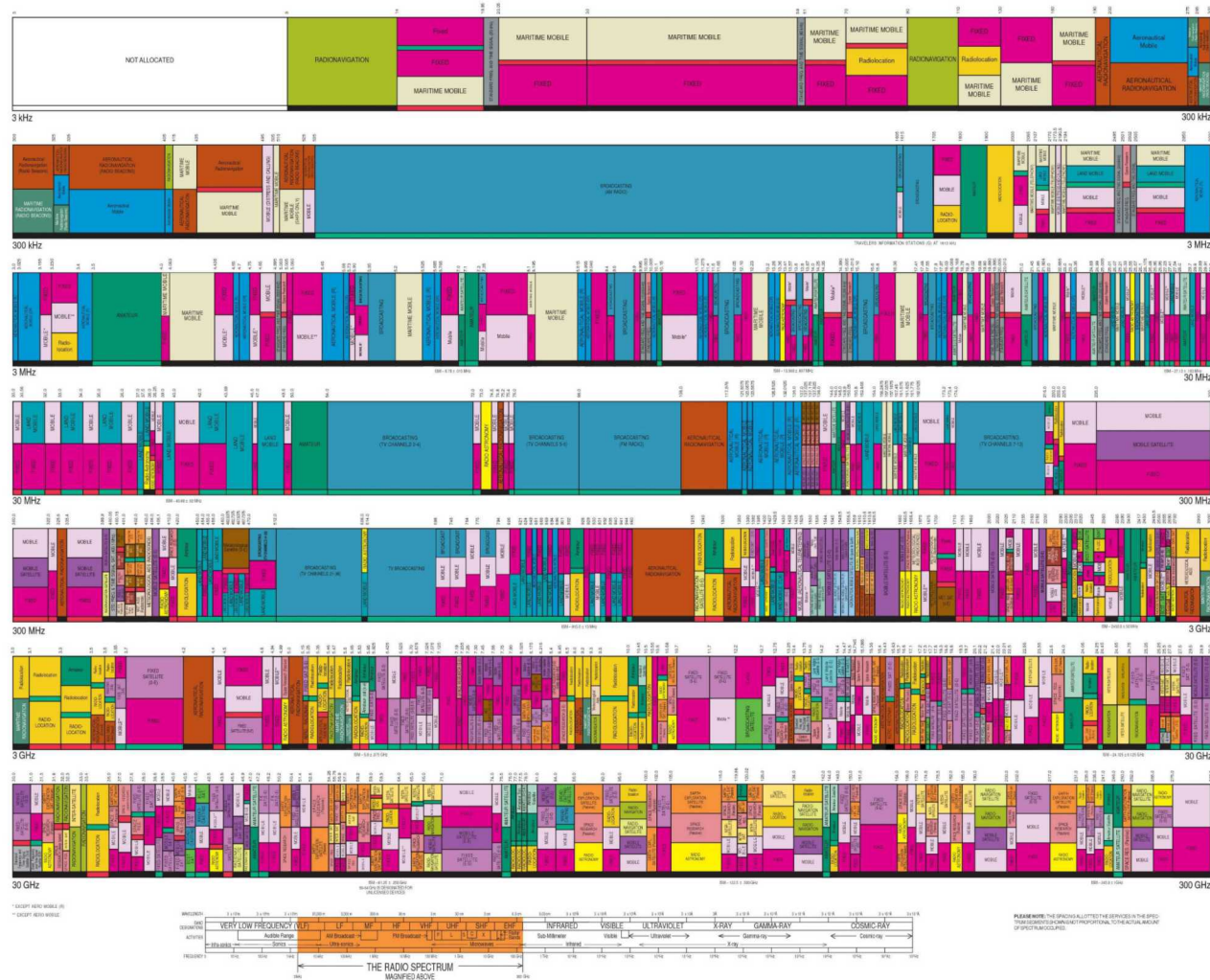


Radar sensing



- Long standoff
- All-weather
- Day/night
- Wide-area
- Fine resolution
- Operational use

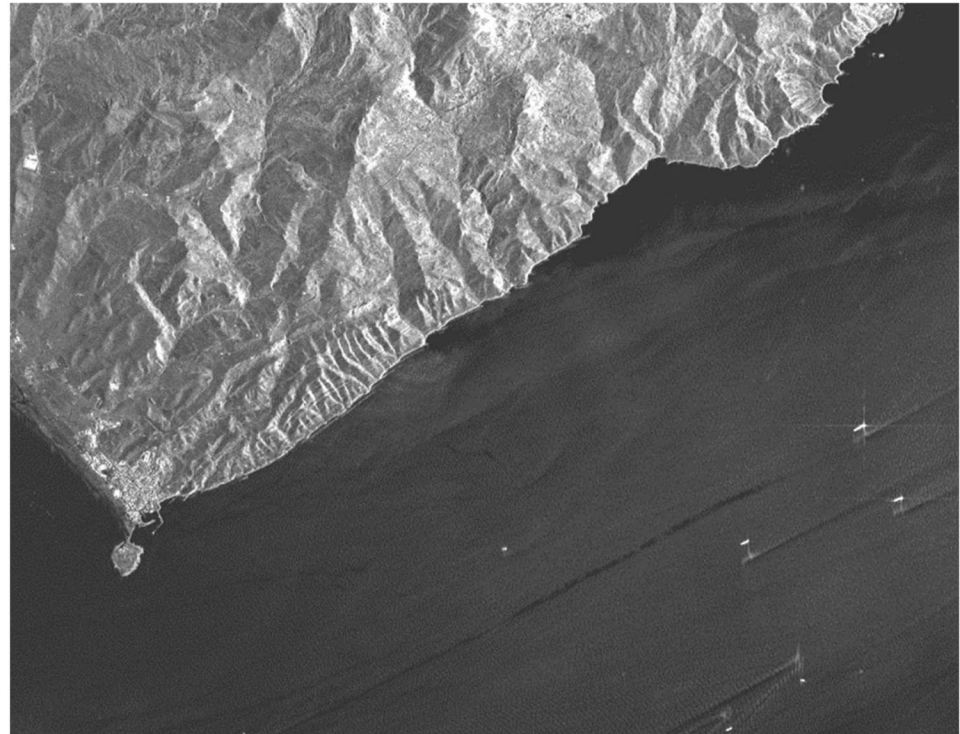
US radio frequency allocations



Synthetic aperture radar (SAR)



Synthetic aperture radar (SAR)



Optical imagery vs. SAR imagery



Optical imagery

- Signatures dominated by diffuse returns
- Signatures stable across wide changes in geometry
- Resolution varies with range
- Angle/angle axes
- Magnitude-valued imaging
- Often abundant
- Simulation often fast and high-fidelity

SAR imagery

- Signatures dominated by specular returns
- Signatures vary strongly with small changes in geometry
- Resolution fixed with range
- Range/angle axes
- Complex-valued imaging
- Usually limited
- Simulation usually slow and low-fidelity

Object recognition approaches designed for optical imagery
usually do not work well with SAR imagery

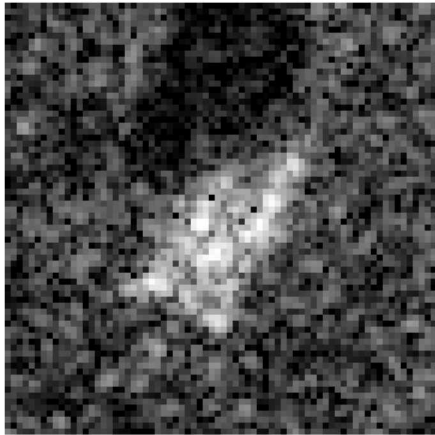


SAR target signatures

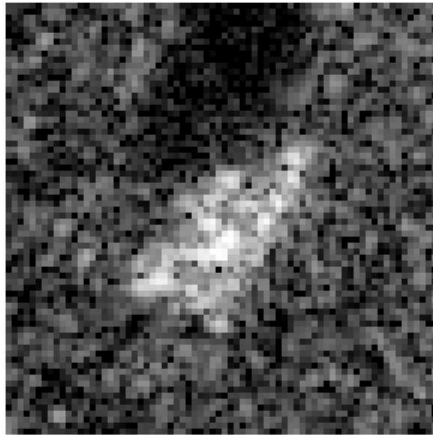


T72 SAR chips (25°–28°)

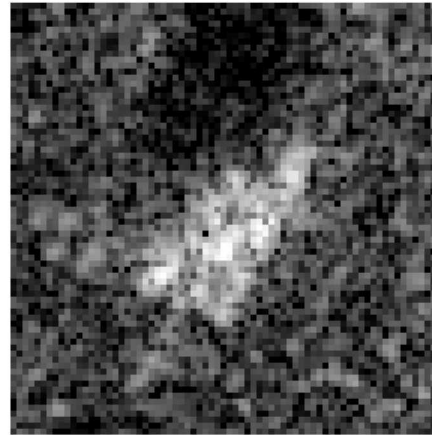
25°



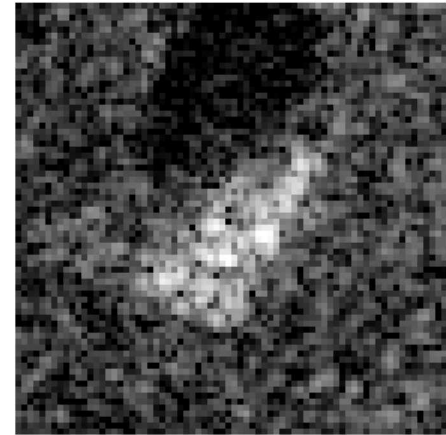
26°



27°



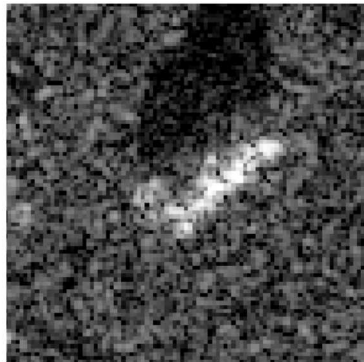
28°



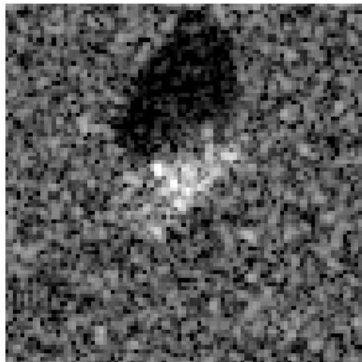
SAR target signatures



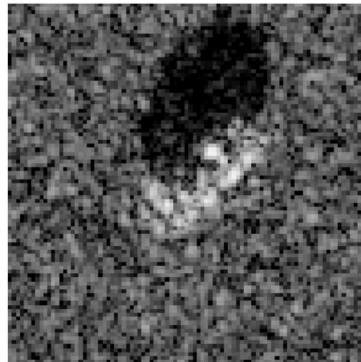
2S1



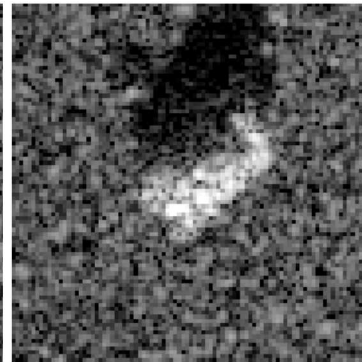
BMP2



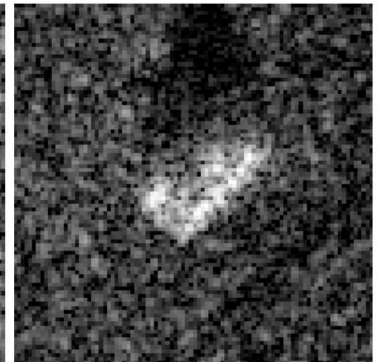
BTR70



T72

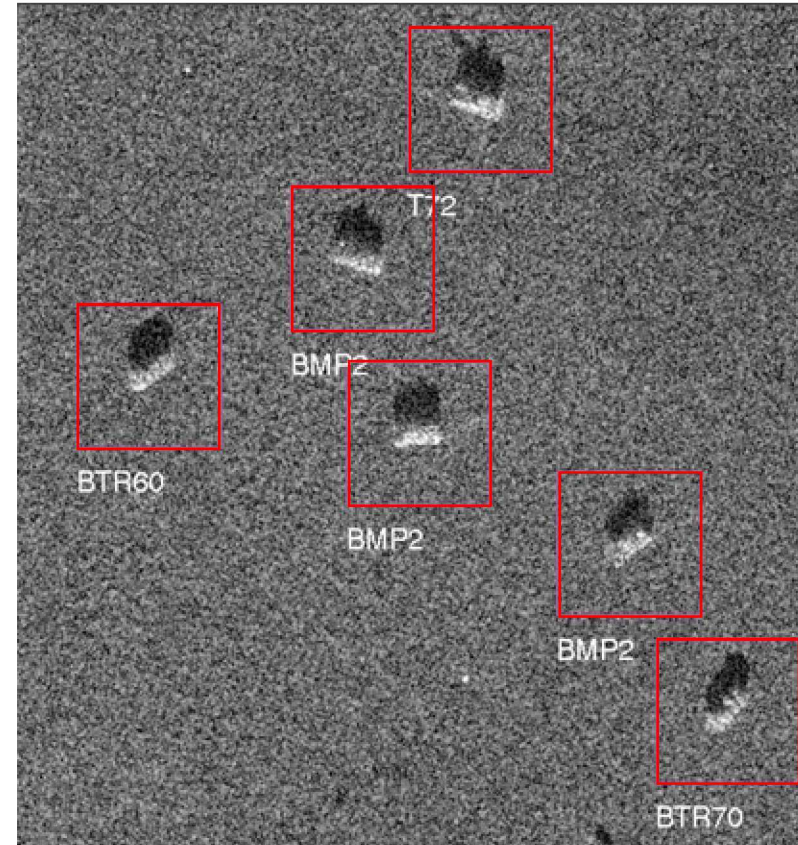


ZSU23

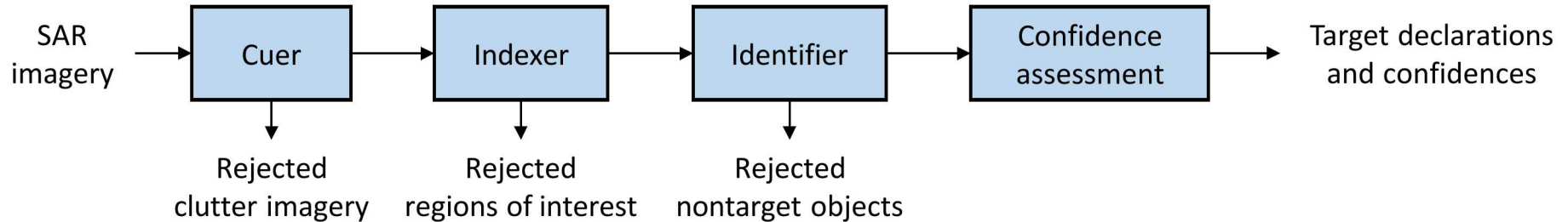


Automatic target recognition (ATR)

- Operational goals
 - Detect and identify targets of interest
 - Direct human or machine attention to relevant portions of imagery or signal data streams
 - Provide target-identity results for analyst or machine interpretation
- Link to synthetic aperture radar
 - In wide operational use
 - Operational SAR spurred the need for ATR in national security applications
- Implementation requirements
 - Must operate in real time
 - Must reject unknown target types
 - Must be trainable with almost no real data



A typical SAR ATR



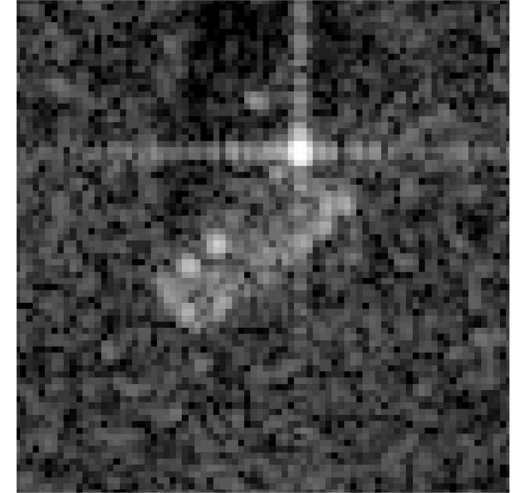
- Cuer
 - Strips potential target regions from background clutter
 - Processes large amounts of imagery very quickly
- Indexer
 - Rejects obvious nontarget regions falsely passed by cuer
 - Passes likely targets to identifier with type and pose hypotheses
- Identifier
 - Tests signatures against type and pose hypotheses
 - Calculates match scores indicating similarity of signature to each hypothesis
- Confidence assessment
 - Assigns probabilities to each target type possibility
 - Quantifies uncertainty for machine processing and human interpretation



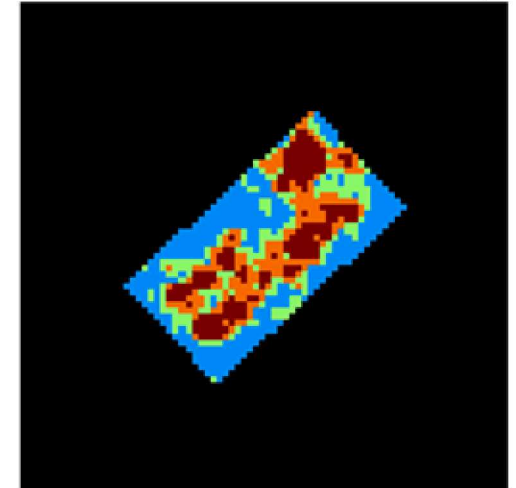
Multinomial pattern matching (MPM)

- Identifier algorithm
 - Produces match scores representing similarity between observed signatures and target models
 - Tests ROIs and hypotheses provided by cuer and indexer
- Employs multinomial transform
 - Maps amplitudes to quantiles
 - Discards absolute pixel amplitudes in favor of relative pixel amplitudes
- Represents targets with statistical models of multinomial distributions at each pixel
 - Accommodates real-world signature variation
 - Models attributes of each target type, not differences between types
- Match scores separate targets, nontargets
 - Can be thresholded to yield declarations
 - Can be fused with other identifiers
 - Can be used to calculate confidences
 - Open-set classification

Raw SAR chip



Multinomial-transformed chip

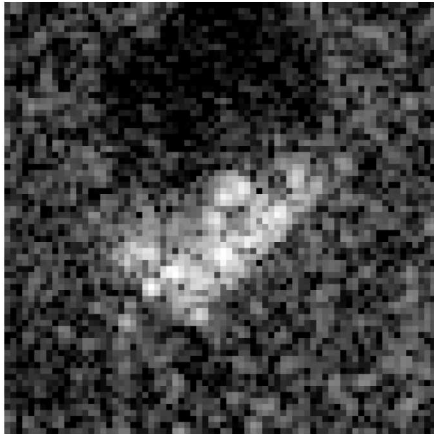


MPM examples

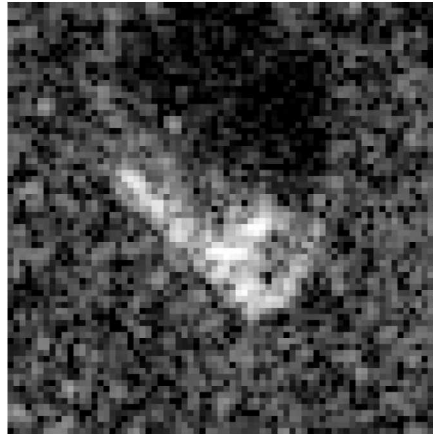


Four-quantile MPM transform applied to T72 SAR chips (45°–315°)

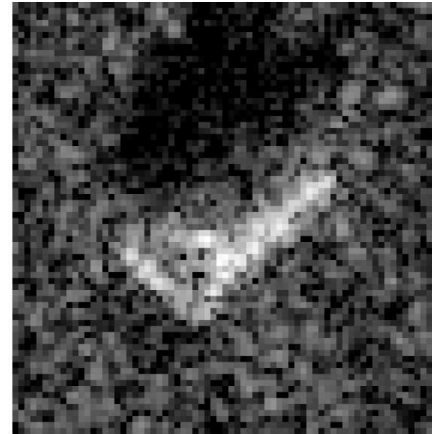
45°



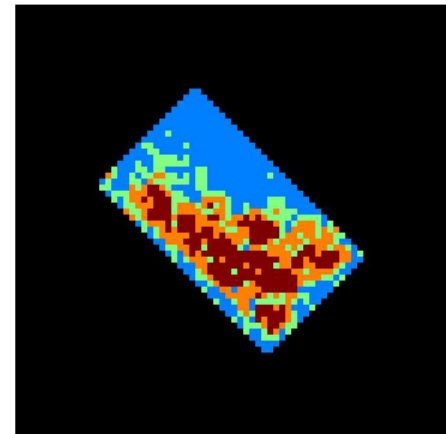
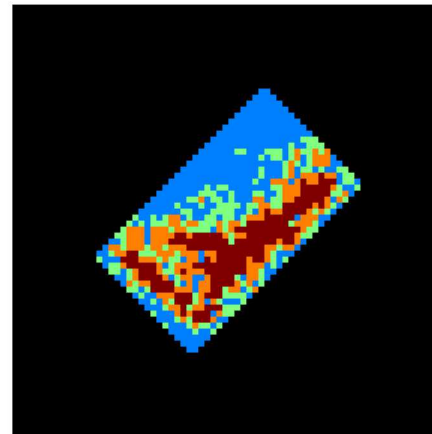
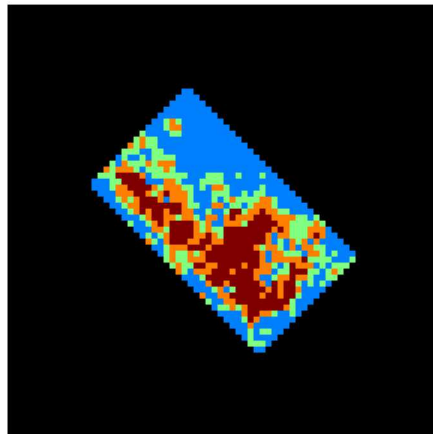
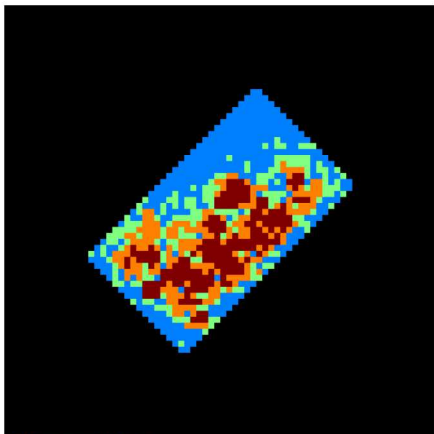
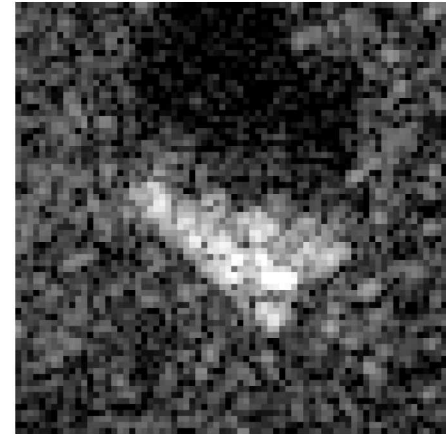
135°



225°



315°

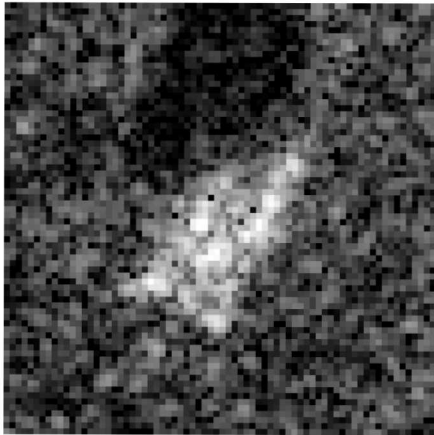


MPM for SAR

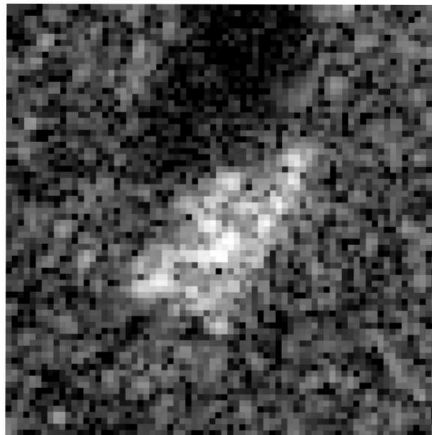


Four-quantile MPM transform applied to T72 SAR chips (25°–28°)

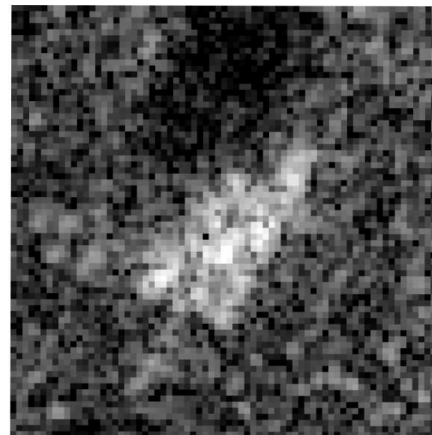
25°



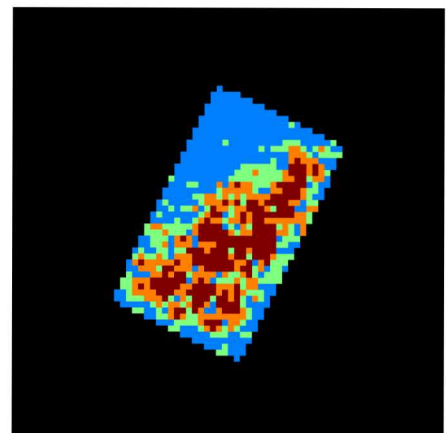
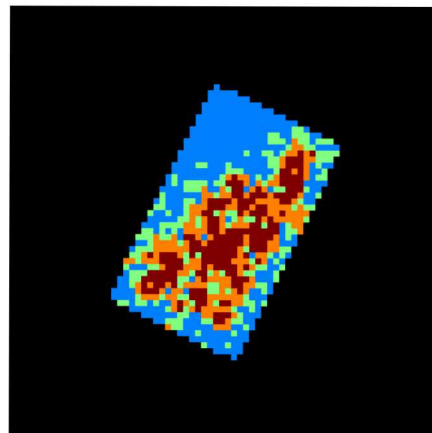
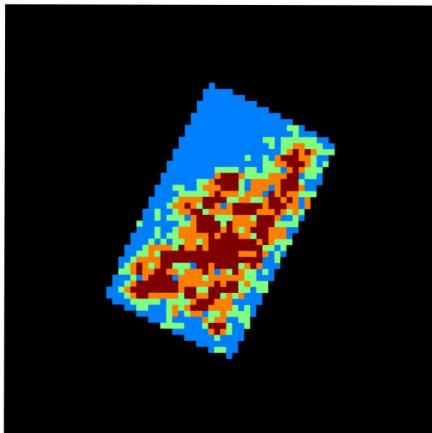
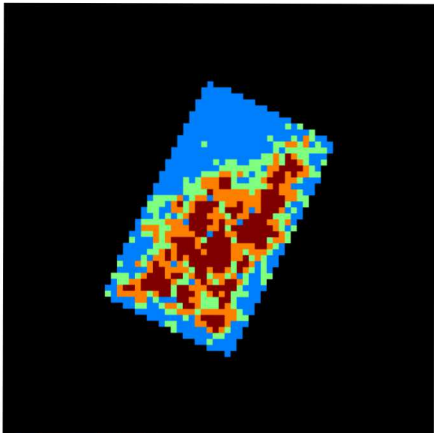
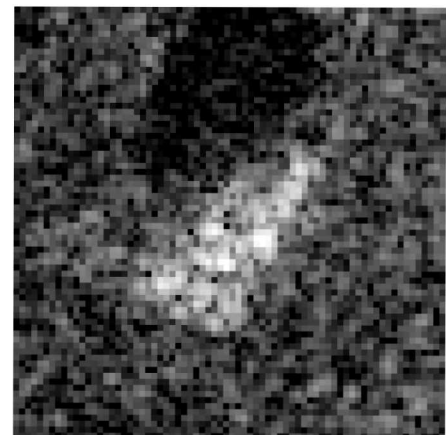
26°



27°



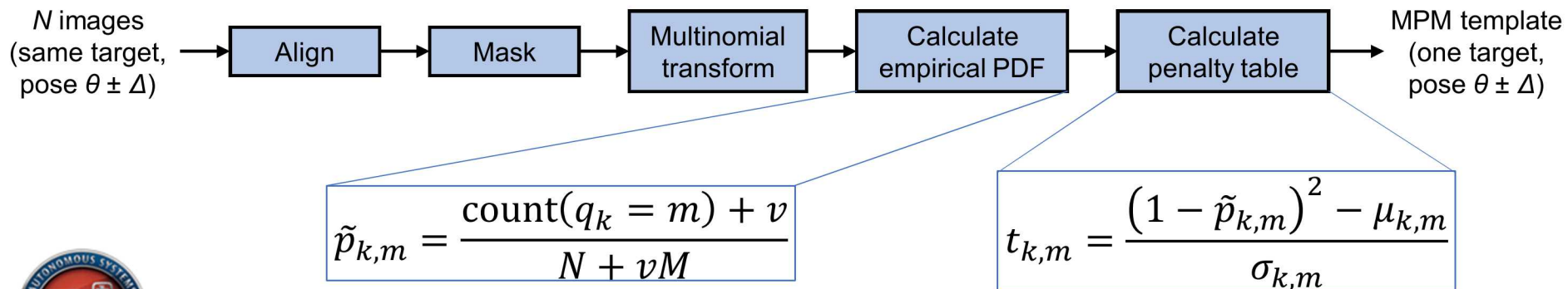
28°



MPM training



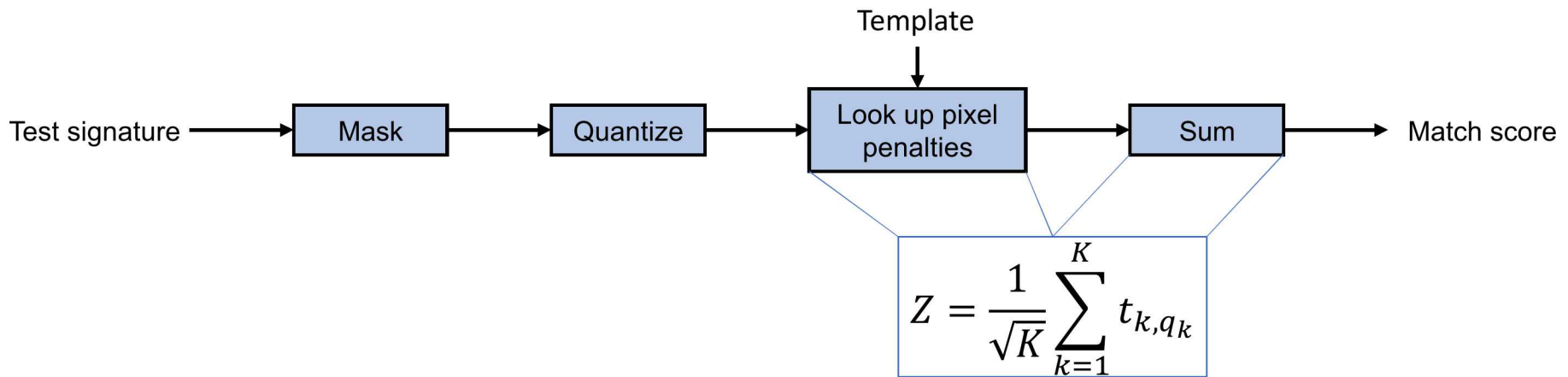
- Offline process for statistical characterization
 - Each statistical representation is called a template
 - A template is a pixelwise lookup table of quantile penalties
 - Distinct templates for each target at each geometry
- Templates are usually trained from simulated data
- Rule of thumb: ≥ 10 signatures per template



MPM testing



- Online process for match-score calculation
- Compare collected signature (cuer ROI) to template (indexer hypo)
- Process signature match scores to yield identification

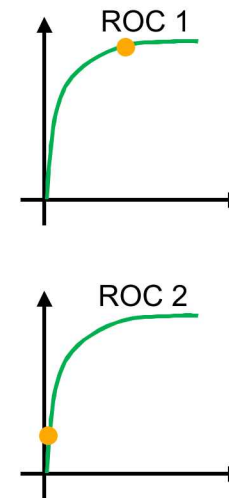
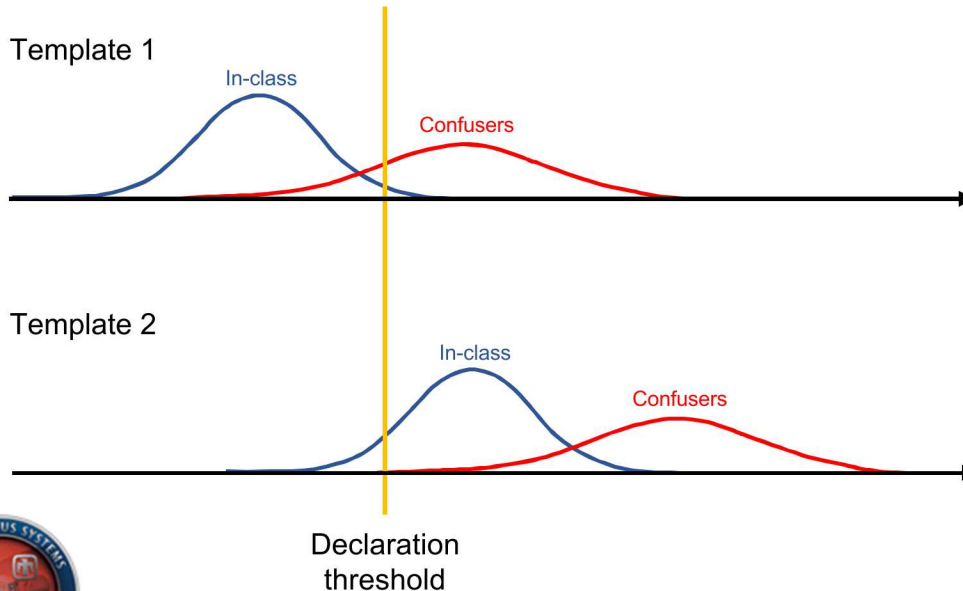


- For signatures drawn from training distribution, $Z \sim N(0,1)$
- For signatures drawn from another distribution, $Z \gg 0$
- Simple thresholding operation provides open-set recognition



MPM validation

- Offline process performed after training
- Bias and scale empirical template match-score distributions
- Accommodate unmodeled variability and simulation effects
- Equalize response between templates
- Allows approximate dialing-in of P_d (given in-class validation data) or P_{fa} (given out-of-class validation data)



$P_d = 0.95$
 $P_{fa} = 0.40$

$P_d = 0.10$
 $P_{fa} = 0.01$



SAMPLE dataset



- Public SAR dataset from AFRL
- Multiple targets
- Multiple geometries
- Simulated and collected data



SAMPLE dataset



2S1

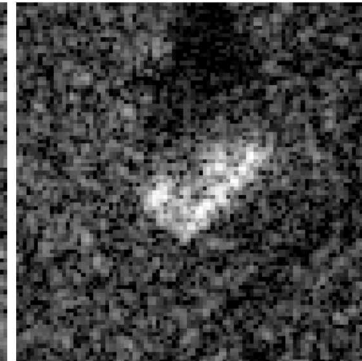
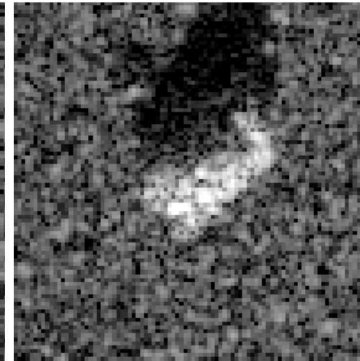
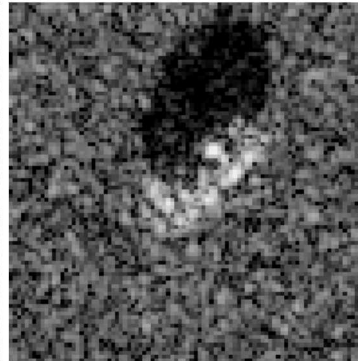
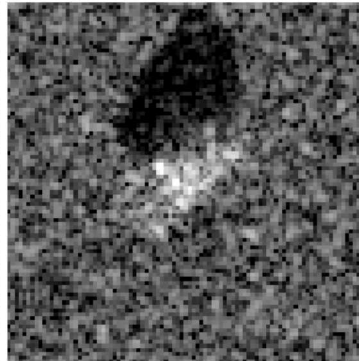
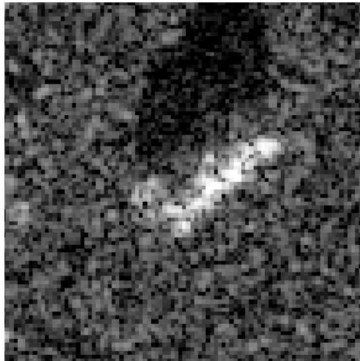
BMP2

BTR70

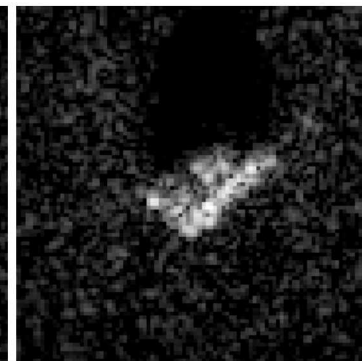
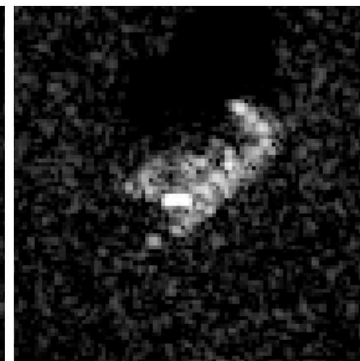
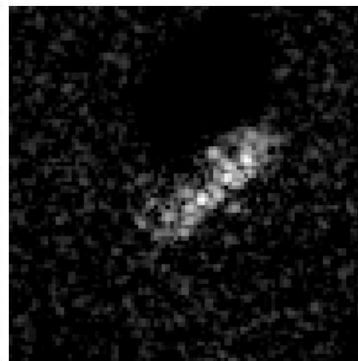
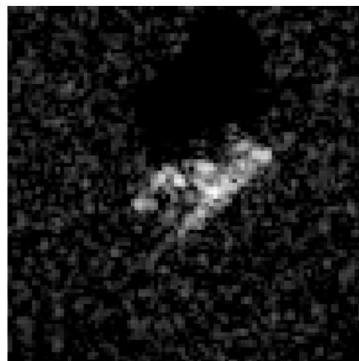
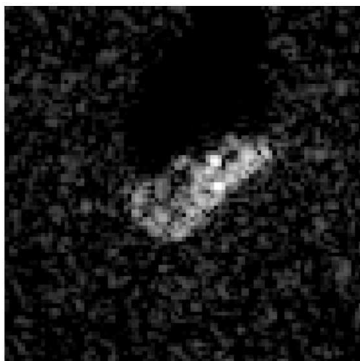
T72

ZSU23

collected



simulated



MPM SAMPLE experiment



- Train templates from simulated data
 - Four targets: 2S1, BMP2, BTR70, T72
 - Five-degree azimuth pose bins from 10° – 80°
- Validate/bias templates with 10 random collected signatures per target
- Test all collected data for five vehicles
 - Four trained targets: 2S1, BMP2, BTR70, T72 (correct ATR response: ID as trained type)
 - One untrained confuser: ZSU23 (correct ATR response: reject)
- Assume naïve indexer
 - Each signature is tested against all four templates
 - Each signature is tested at all poses within 20° of truth

2S1



BMP2



BTR70



T72



ZSU23



MPM SAMPLE experiment results



Confusion matrix

	2S1	BMP2	BTR70	T72	Reject
2S1	0.397	0.006	0.086	-	0.512
BMP2	0.065	0.411	-	-	0.523
BTR70	0.022	-	0.500	-	0.478
T72	-	-	0.019	0.574	0.407
ZSU23	0.006	-	0.086	-	0.908

- $P_{dec} = 0.516$
- $P_{id|dec} = 0.891$
- $P_{cc} = 0.837$
- $P_{fa} = 0.092$
- $CRR = 0.908$

“When given a target, how often does the ATR speak?”

“When the ATR speaks about a target, how often is it correct?”

“When the ATR speaks, how often is it correct?”

“When given a nontarget, how often does the ATR speak?”

“When given a nontarget, how often is the ATR remain silent?”



Summary



Multinomial pattern matching (MPM) is an object recognition algorithm designed for use with synthetic aperture radar (SAR) imagery

- Statistically grounded
- Template-based
- Fully explainable
- Computationally efficient
- Trainable from simulated data
- Robust to SAR variation
- Type-level recognition
- Open-set recognition

