Possibilistic Context Identification for SAS Imagery

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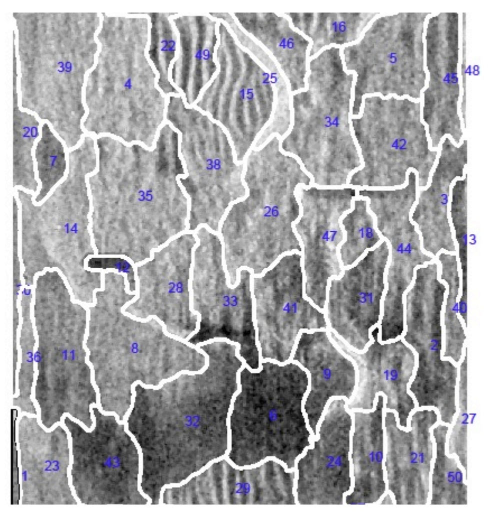
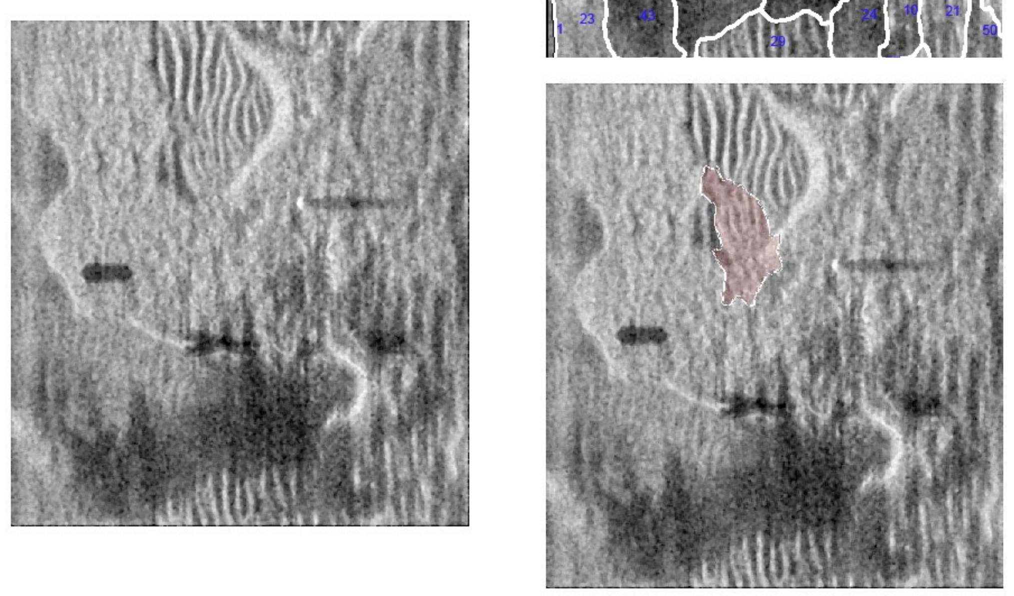
Motivation and Goal

Challenges:
- Gradual change between seabed types
- Multiple seabed types in one superpixel
- Difficulty in obtaining accurate training labels

Goal:
- Seabed context identification

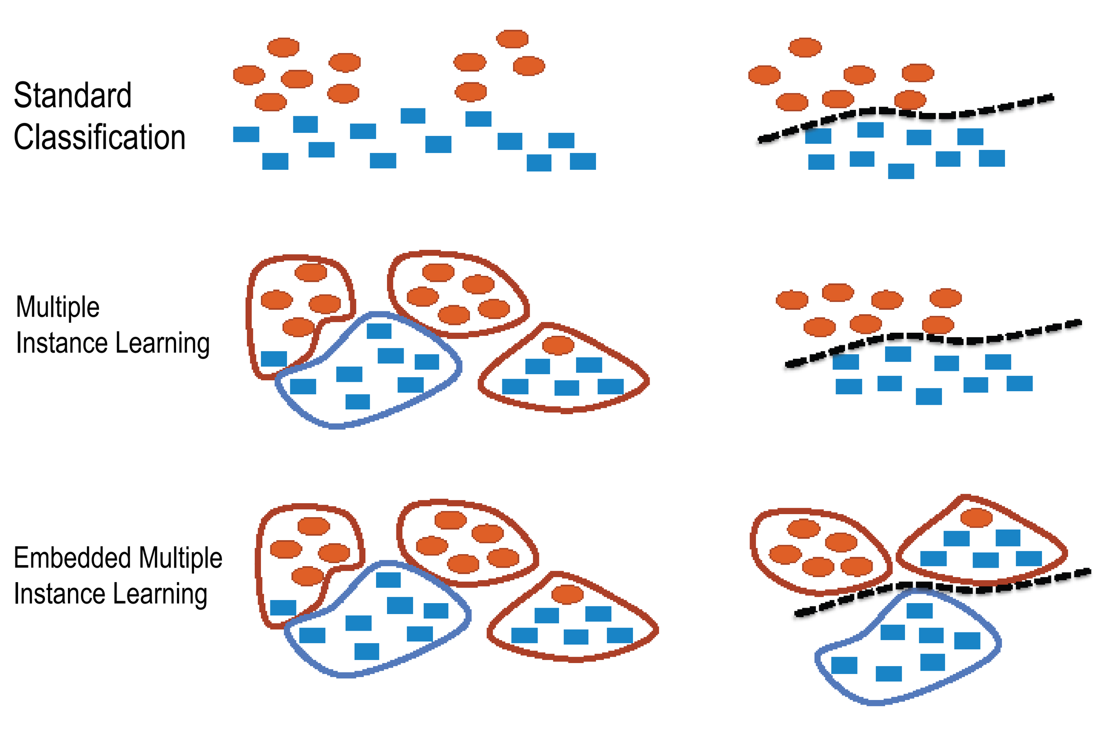
Method:
- Multiple Instance Learning
- Superpixel-level labeling
- Possibilistic



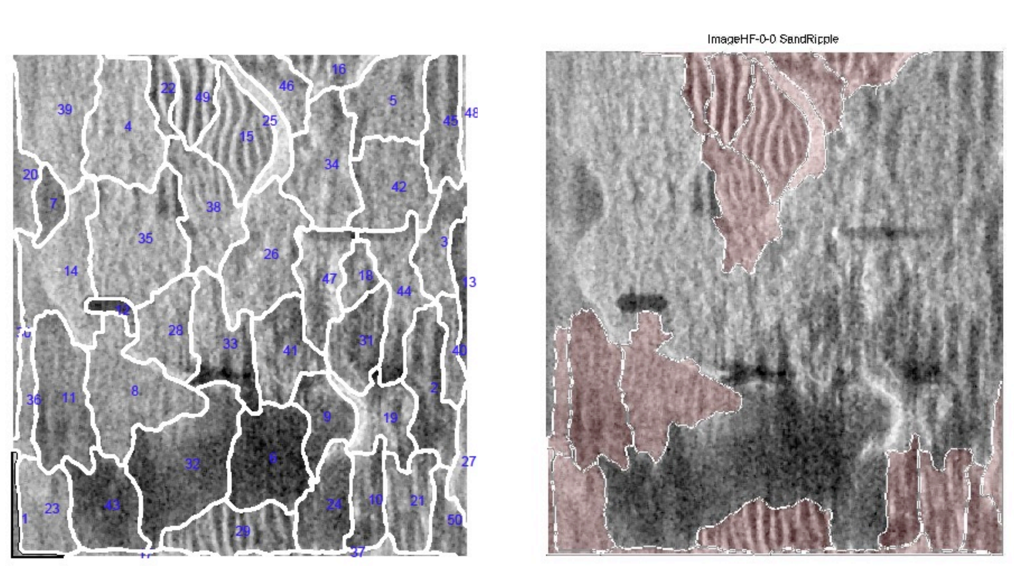


MILES Overview

Multiple **I**nstance **L**earning via **E**mbedded **I**nstance **S**election [2]



Bags ⇔ Superpixels
Instance ⇔ Pixel



MILES Feature Mapping

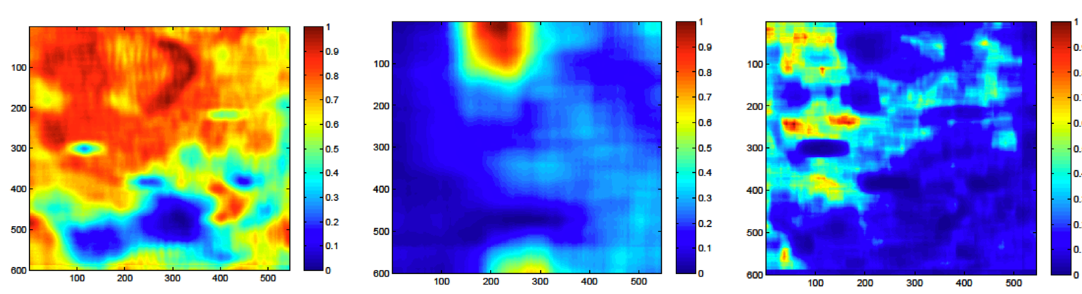
$$s(\boldsymbol{x}^k, \boldsymbol{B}_i) = \max_j \exp\left(-\frac{\|x_{ij} - \boldsymbol{x}^k\|^2}{\sigma^2}\right)$$

$s(\boldsymbol{x}^k, \boldsymbol{B}_i)$: similarity between instance k and Bag i

Similarity determined using distance between the instance and the most similar concept in the bag

Features for each data point

mean, LoG filter variance, Shape parameter computed from a neighborhood window



Mean | LoG filter variance | Shape parameter

MILES Classification

One-norm SVM classification

$$y = sign\left(\sum_{k=1}^{n} w_k s(\boldsymbol{x}^k, \boldsymbol{B}_i) + b\right)$$

Optimization Problem (objective function)

$$\min_{w,b,\eta,\xi} \lambda \sum_{k=1}^{n} |w_k| + c_1 \sum_{i=1}^{l^+} \xi_i + c_2 \sum_{j=1}^{l^-} \eta_j$$

such that $(\boldsymbol{w}^T \boldsymbol{m}_i{}^+ + b) + \xi_i \geq 1, i = 1, \ldots, l^+$

$(\boldsymbol{w}^T \boldsymbol{m}_j{}^- + b) + \eta_j \geq 1, j = 1, \ldots, l^-$

$\xi_i, \eta_j \geq 0$

where $\boldsymbol{m}(\boldsymbol{B}_i) = [s(\boldsymbol{x}^1, \boldsymbol{B}_i), s(\boldsymbol{x}^2, \boldsymbol{B}_i), \ldots, s(\boldsymbol{x}^k, \boldsymbol{B}_i)]^T$

Possibilistic Mapping

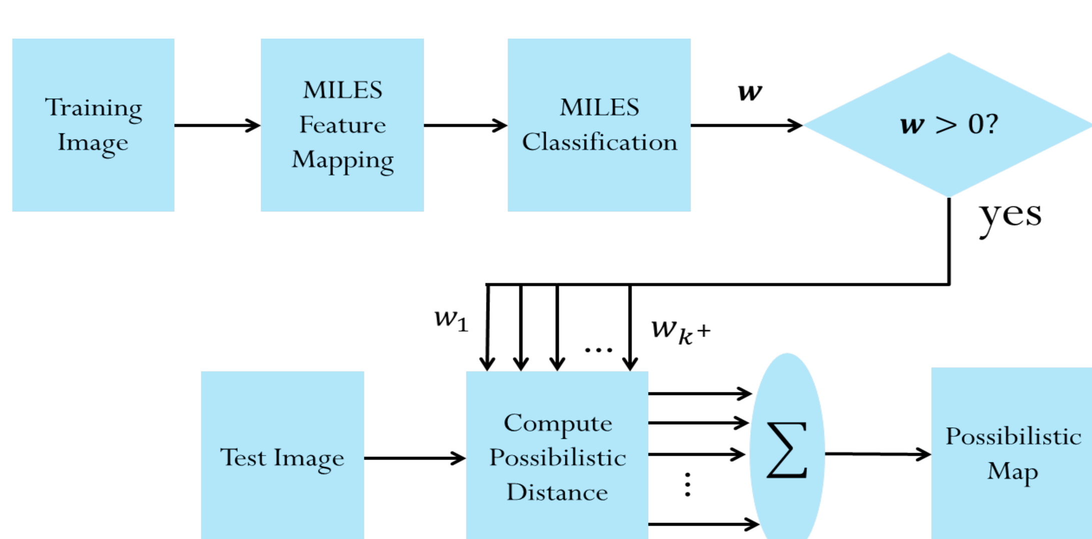
1: Obtain **w** from trained one-norm SVM

2: **for** $\forall k$: $w_k > 0$ **do**

3: $D^k(j) = [d^2(\boldsymbol{x}_j, \boldsymbol{x}^k)/\eta_k]^{\frac{1}{m-1}}$

4: **end for**

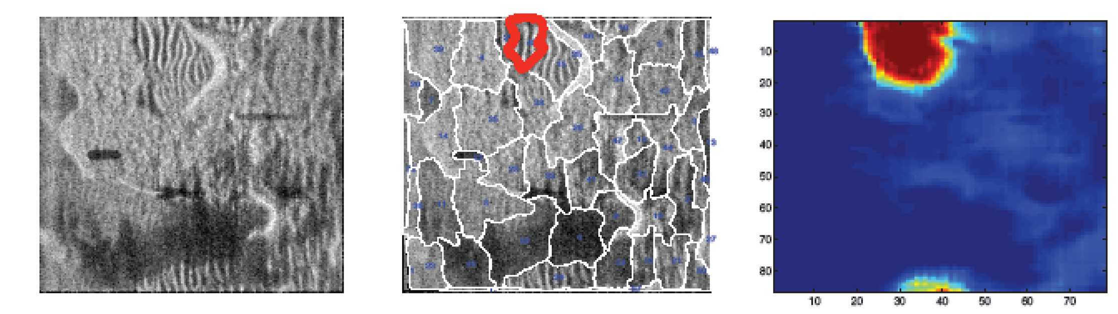
5: **return** $D_{Pos}(j) = \sum_{k: w_k > 0} w_k D^k(j)$



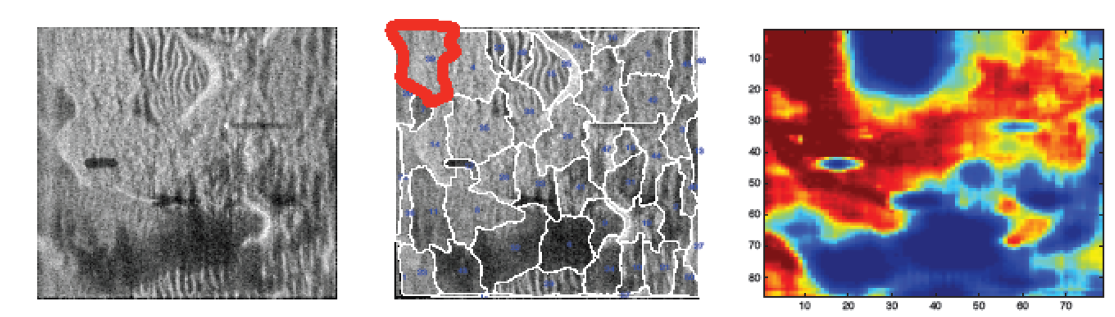
Results - Feature Mapping

It is demonstrated that the high-dimensional feature mapping is providing useful information for the one-norm SVM classification later.

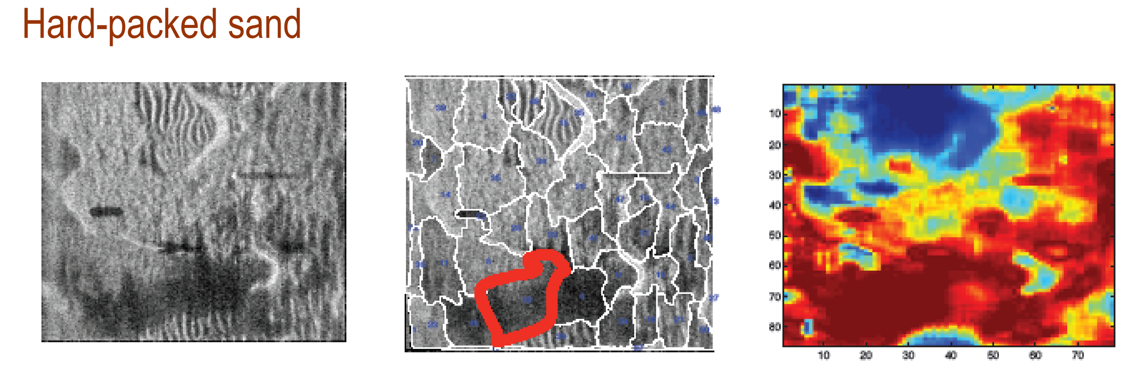
Sand ripple



Sea grass



Hard-packed sand



Results - One-vs-all Classification

MILES yields the lowest error and selects fewer features.

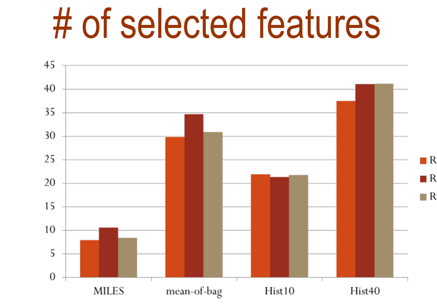
2-fold cross validation

Context Type	MILES	Mean-of-bag	Hist10	Hist40
Sand ripple	**0.1760±0.0109**	0.2713±0.0033	0.2944±0.0283	0.2923±0.0193
Hard-packed sand	**0.1219±0.0025**	0.1234±0.0000	0.1356±0.0050	0.1666±0.0099
Sea grass	**0.1147±0.0000**	**0.1147±0.0000**	0.1602±0.0044	0.1746±0.0066
Shadow	**0.0751±0.0013**	0.0758±0.0000	0.0830±0.0012	0.0815.±0.0033

462-fold cross validation

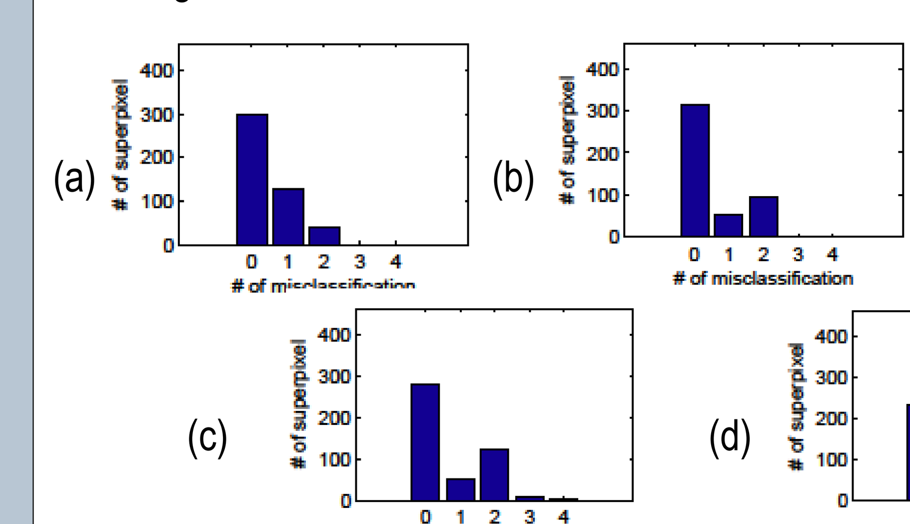
Context Type	MILES	Mean-of-bag	Hist10	Hist40
Sand ripple	**57**	96	135	153
Hard-packed sand	59	**57**	71	80
Sea grass	**53**	**53**	64	66
Shadow	**24**	27	55	57

\# of selected features



Results - Hamming Distance

Hamming distance measures multi-class error across all context labels.

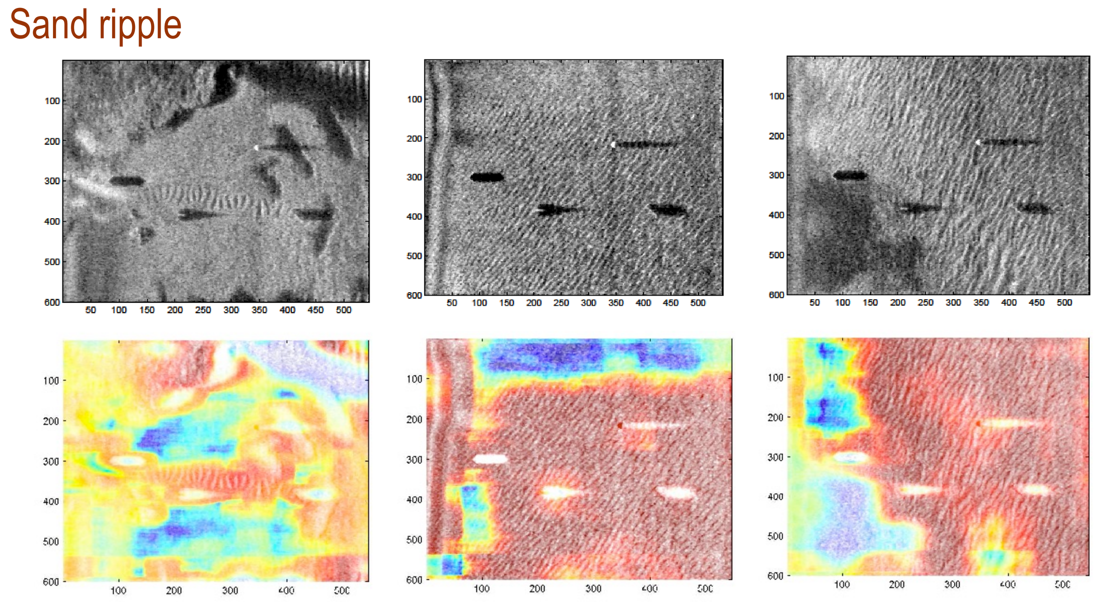


(a) MILES
(b) Mean-of-bag
(c) Hist10
(d) Hist40

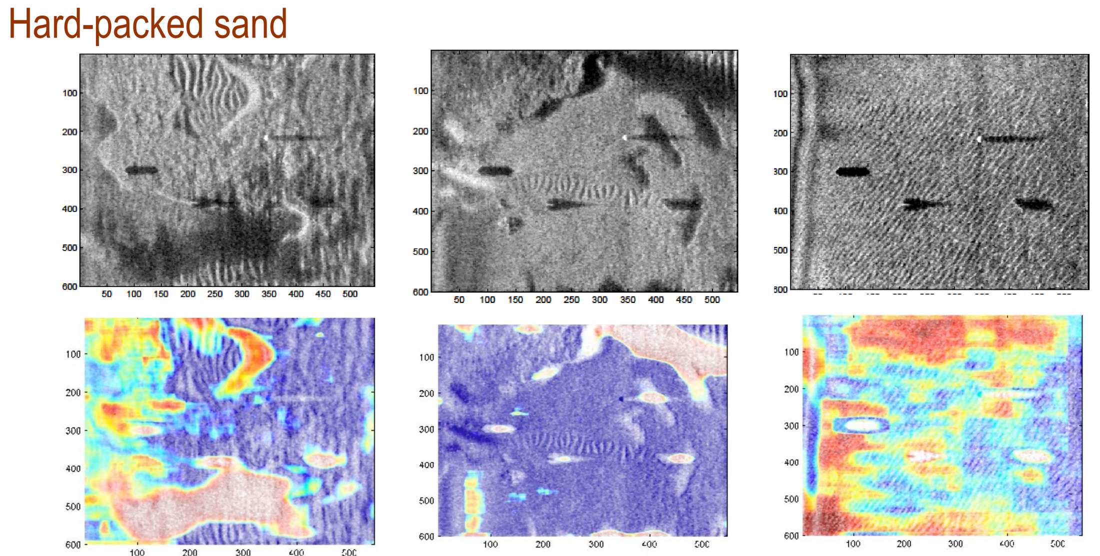
Results - Possibilistic Map

Possibilistic map highlights the desired regions.

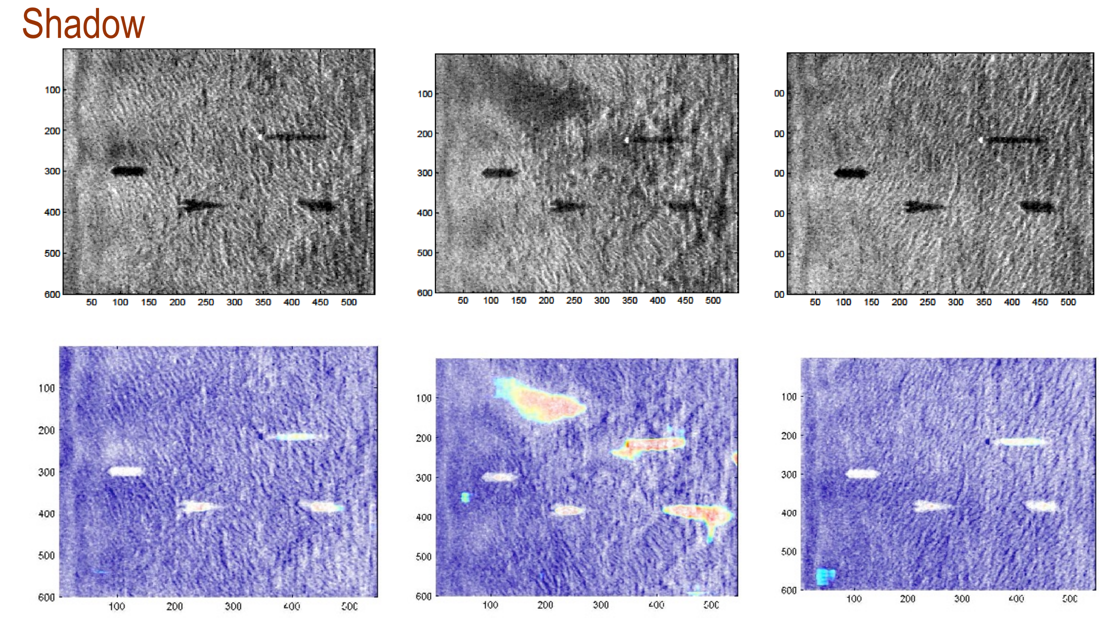
Sand ripple



Hard-packed sand



Shadow



Conclusion

This paper applies the MILES approach for SAS seabed context identification and presents an extension for possibilistic context identification.

Future work may include investigation into intelligent down sampling of SAS imagery and the investigation of the inclusion of other features (e.g., bathymetry-based features) during classification.

Selected References

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[5] R. W. Hamming, "Error detecting and error correcting codes," *Bell Syst. Tech. J.*, **29**(2), pp. 147-160, 1950.