Sediment Volume Search Sonar: Automated Detection and Classification Algorithms

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Sediment Volume Search Sonar (SVSS)

• Detect proud and buried unexploded ordnance (UXO) in shallow water



Data Cube Visualization



ATR Approach

- Two-stage ATR approach
 - Fast, simple, general-purpose MondrianB detector
 - Generate set of alarms to classify
 - Reduces amount of data to process
 - Follow-on, more sophisticated convolutional neural network (CNN) classifiers
 - Ensemble of tiny CNNs using different architectures and also different input representations
 - Leverage all available information in robust manner

Normalization Algorithm

- 1. Determine dominant interface
- 2. Determine multipath region
- 3. For each cross-track position *x*, compute median of depth slice
- 4. For each along-track position *y*, compute median of depth slice
- 5. Convert to logarithmic scale



Impact of Normalization



Detection Algorithm: MondrianB

- Compute summed intensity in three concentric volumes
 - Target
 - Guard
 - Background



• Target-to-background ratio test

$$\left(\frac{n_B - n_G}{n_T}\right) \left(\frac{T(x, y, z)}{B(x, y, z) - G(x, y, z)}\right) \geq \tau_s$$



Integral Images

- A: Image (data)
- W: Integral image
- U: Summed intensity in a block

$$W(x, y, z) = \sum_{x' \le x} \sum_{y' \le y} \sum_{z' \le z} A(x, y, z) \qquad \mathbf{V}$$

$$U = \sum_{j \in \{0,1\}^3} (-1)^{3-||j||_1} W(\alpha^j)$$

Example Target Alarms



Classification

- Take alarms generated by MondrianB detector and make predictions with classifier(s)
- CNN-based approach
 - 8 new basic CNN architectures designed
 - Different architectures uncover/exploit different clues
 - "Vanilla" architecture: alternating convolutional blocks and pooling layers
 - Ensemble approach in terms of architectures and also in terms of input data representations
 - Tiny CNNs to balance network complexity with amount of labeled data available
 - Avoid overfitting

Era of Deep Learning





















UXO Classification with Sonar Data





Deep Learning



• Key Ratio: Model Complexity / Training Data

Convolutional Neural Networks (CNNs)



CNNs for SAS Data

- Simpler task
 - Number of classes, image complexity
- Resource constraints
 - Data, computing power
- Solution: Tiny networks





3-d CNNs



3-d inputs

-0.9 Along-Track (m)

-0.2 0.8

3-d CNN Architectures







CNN	CNN	Conv.	Conv. Layers	Filters Per	Filter Sizes (Voxels)	Pooling Factors	Number of
Label	Depth	Blocks	Per Conv. Block	Conv. Layer	$[x \times y \times z]$	$[x \times y \times z]$	Parameters
Α	2	2	1	4	$[6 \times 6 \times 6] [4 \times 4 \times 5]$	$[8 \times 8 \times 12] [4 \times 4 \times 4]$	2157
В	2	2	1	4	$[8 \times 8 \times 12] [6 \times 6 \times 7]$	$[6 \times 6 \times 9] [4 \times 4 \times 4]$	7117
С	3	3	1	4	$[6 \times 6 \times 6] [5 \times 5 \times 5] [4 \times 4 \times 5]$	$[4 \times 4 \times 6] [2 \times 2 \times 2] [2 \times 2 \times 2]$	4161
D	3	3	1	4	$[11 \times 11 \times 12] [8 \times 8 \times 7] [4 \times 4 \times 5]$	$[3 \times 3 \times 5] [2 \times 2 \times 2] [2 \times 2 \times 2]$	14273
Е	6	3	2	4	$\begin{bmatrix} 5 \times 5 \times 6 \\ 4 \times 4 \times 5 \end{bmatrix} \begin{bmatrix} 5 \times 5 \times 6 \\ 4 \times 4 \times 5 \end{bmatrix} \begin{bmatrix} 5 \times 5 \times 3 \\ 4 \times 4 \times 3 \end{bmatrix}$	$[2 \times 2 \times 4] [2 \times 2 \times 2] [3 \times 3 \times 3]$	7557
F	6	3	2	4	$\begin{bmatrix} 7 \times 7 \times 12 \\ 5 \times 5 \times 7 \end{bmatrix} \begin{bmatrix} 5 \times 5 \times 8 \\ 4 \times 4 \times 5 \end{bmatrix} \begin{bmatrix} 3 \times 3 \times 3 \\ 3 \times 3 \times 3 \end{bmatrix}$	$[3\times3\times4][2\times2\times2][1\times1\times1]$	10525
G	9	3	3	4	$\begin{bmatrix} 4 \times 4 \times 5 \\ 3 \times 3 \times 5 \\ 3 \times 3 \times 4 \end{bmatrix} \begin{bmatrix} 4 \times 4 \times 4 \\ 3 \times 3 \times 4 \\ 3 \times 3 \times 3 \end{bmatrix} \begin{bmatrix} 4 \times 4 \times 4 \\ 4 \times 4 \times 4 \\ 3 \times 3 \times 4 \end{bmatrix}$	$[2 \times 2 \times 3] [2 \times 2 \times 2] [2 \times 2 \times 2]$	6313
Н	12	3	4	4	$\begin{bmatrix} 4 \times 4 \times 3 \\ 3 \times 3 \times 3 \\ 3 \times 3 \times 3 \\ 3 \times 3 \times 3$	$[2 \times 2 \times 3] [2 \times 2 \times 2] [1 \times 1 \times 3]$	5141

Data Collections











Human Assessment

Large / Strong

Α





В



Small / Weak





Performance: Proud Targets



Data Collection

Performance: Buried Targets



Data Collection

Classification

- 3-d CNNs with SVSS data
 - Train: Sayers "Deep" site
 - Test: Sayers "Shallow" site
 - "Target" = man-made object

	Data Set	Seafloor Area	Sediment Volume	Number of	
Location	Usage	(m^2)	(m^3)	Clutter	Targets
Site B	Training	15390	23392.8	11029	550
Site A	Test	15630	23757.6	6074	671

- Assessment
 - Asymmetric costs of misclassification
 - False alarm rates at key PdPc values



Classification Performance





Inside CNN A



CNN E

() Convolutional layer 2	(c) Convolutional laver 3	(d) Convolutional layer 4



CNN Intermediate Responses



Conclusions

- Automated detection and classification algorithms show promise for proud and buried targets in volumetric sonar data
 - Require more extensive field tests (and data!), especially in different environments
- Future/ongoing work: Develop CNNs for alternative data products (e.g., acoustic color)





* Image courtesy of Tim Marston (APL/UW)