Sea Ice Monitoring Using SAR Imagery and Deep Learning

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Outline

- Introduction project objectives
- Data Gathering and preparation
- Deep Learning model
- Classification results and examples Ice/Water and Ice Concentration
- Semantic segmentation using multiple spatial scales
- Conclusion

Introduction

- At the Canadian Ice Service (CIS), image analysts form ice charts (ice type, ice concentration) manually by examination of SAR images, contextual knowledge
- Time consuming, limited area coverage eg. Shipping lanes, communities
 - More coverage is better for assimilation into models
- Objective:
 - Make use of archive of RADARSAT-2 data and CIS ice charts to train a Deep Learning (DL) model
 - Investigate how DL could be used to automate and improve SARbased mapping of sea ice
- Project for the Canadian Space Agency, in collaboration with CIS



Image Data

Regions in Canadian Arctic

- Foxe Basin (FOXE) 2017 May to 2018 Mar
- Middle Arctic Waterways (MID) 2017 Jul to Oct
- Newfoundland (NFLD) 2016 Dec to 2017 Jun
- Western Arctic (WA) 2017 Jun to Nov
- Coronation Gulf 2017 Oct to Nov (testing only)
- CIS uses wide-swath dual-pol (HH-HV) ScanSAR data
 - Large spatial scale for ice features and context
 - 500 km swath, 50 m pixel
 - Images selected to overlap with ice chart data
- 239 RADARSAT-2 images and 489 SIGRID ice chart products





Label Data



- Sample weight for loss function and metric calculation
 - Zero-weight at pixels of Land and No-Data

- SIGRID ice charts
- polygons delineating:
 - Land
 - No-Data
 - Water
 - Ice concentration
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- Labels for ICE / WATER classification:
 - WATER: Water or Ice concentration <= 20%
 - ICE: Ice Shelf or Ice concentration > 20%

- Labels for Ice Concentration classification:
 - WATER: Water or Ice concentration <= 20%
 - ICE-20-40: Ice concentration 20 40%
 - ICE-40-60: Ice concentration 40 60%
 - ICE-60-80: Ice concentration 60 80%
 - ICE: Ice concentration 80-100% or Ice Shelf





Preprocessing

- Image data: gamma-zero conversion
 - labels of black-fill pixels to No-Data
- Label data: geometric transformation to radar geometry
 - rasterization
- Create 512 x 512 pixel chips for input to Deep Learning model
 - 25 km x 25 km
 - Overlap by 100 pixels (5 km)
 - Chips excluded if less than 50% of pixels labelled as Ice or Water
- Training, Validation and Test Data split
 - 75% training, 20% validation, 5% test
 - Split chips by image

Numbers of images and chips



	Mid-Arctic		Newfoundland		Western Arctic		Foxe Basin					
	Train	Val	Test	Train	Val	Test	Train	Val	Test	Train	Val	Test
Number of image frames	37	9	5	45	12	3	34	8	5	48	13	5
Number of chips	5965	1711	491	16434	4711	1350	9901	2838	814	12994	3725	1068

Deep Learning model: DeepLab

- DeepLab: used for semantic segmentation
- Preserves spatial resolution by using dilated convolutions instead of strides
- Dilated convolutions at multiple spatial scales provides context



Deep Learning model



Training Strategies

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- 1. Each region trained separately
- 2. Combination and region fine-tuning
 - Data from all regions combined to train a single combined model
 - · Separate models initialized with combined model, continued training for each region
 - Compared to separate training per region:
 - About 1% improvement in accuracy, 2% improvement in mean intersection-over-union

Results and examples below shown for separately trained regions

ICE / WATER classification – validation data									
NFLD MID WA FOXE									
Accuracy	Mean IOU	Accuracy	Mean IOU	Accuracy	Mean IOU	Accuracy	Mean IOU		
0.9582	0.9194	0.9175	0.8322	0.9675	0.8869	0.9286	0.8611		

ICE / WATER classification – test data									
NFLD MID			WA		FOXE		Coronation Gulf		
Accuracy	Mean IOU	Accuracy	Mean IOU	Accuracy	Mean IOU	Accuracy	Mean IOU	Accuracy	Mean IOU
0.9265	0.8460	0.9044	0.7900	0.9784	0.9554	0.9715	0.5945	0.9329	0.8533

Newfoundland 2017-Feb-09 accuracy 0.9659, mIOU 0.9158 510 km x 510 km

HH image, gamma0, -25 to 0 dB



HV image, gamma0, -30 to -10 dB



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Mid-Arctic 2017-Jul-20 accuracy 0.9323, mIOU 0.8721 450 km x 330 km

HH image, gamma0, -25 to 0 dB

HV image, gamma0, -30 to -10 dB



model labels





HV image, gamma0, -30 to -10 dB



HH image, gamma0, -25 to 0 dB



Western Arctic 2017-Sep-04 accuracy 0.9693, mIOU 0.9225 450 km x 535 km



HV image, gamma0, -30 to -10 dB





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Results and Examples – Ice Concentration Classification



- Relatively few pixels at intermediate concentrations
 - Less data available for training at these concentrations

Results and Examples – Ice Concentration Classification

IOU's of classes							
	WATER	ICE 20-40	ICE 40 - 60	ICE 60 – 80	ICE		
NFLD	0.92	0.34	0.16	0.28	0.76	0.8442	
MID	0.89	0.20	0.16	0.11	0.61	0.8192	
WA	0.96	0.14	0.19	0.23	0.78	0.9200	
FOXE	0.90	0.01	0.12	0.30	0.84	0.8845	

• Less data at intermediate concentrations \rightarrow poor intersection over union at these classes

Errors are often one class away

Newfoundland 2017-Apr-12 - 500 x 500 km Accuracy 0.8616

HH image, gamma0, -25 to 0 dB



HV image, gamma0, -30 to -10 dB



-10 $HV \gamma_0$

predictions



Mid-Arctic 2017-Jul-20 - 450 x 330 km Accuracy 0.8070



Semantic segmentation using multiple spatial scales

Problem:

- Model takes 512 x 512 pixel (25 x 25 km) chips
 - Model 'Field of View' (area around a pixel used to classify it) is about 250 pixels for the current model

- Difficult scenes tend to have large areas of uniform backscatter over a chip
 - No context for classification







Semantic segmentation using multiple spatial scales

- Create down-sampled image form 512 x 512 pixel chips
 - The same size chip at coarser resolution has context from larger area
 - Coarse resolution model
- Multi-scale model
 - Input original fine resolution chip and output of coarse resolution model
 - · Has more context than single scale model

	ICE / WATER classification – validation data						
	N	FLD	Μ	ID			
	Accuracy Mean IOU Accuracy		Mean IOU				
Single scale	0.9582	0.9194	0.9175	0.8322			
Multi-scale 4x down-sampled	0.9608	0. 9243	0.9320	0.8613			

Difficult NFLD Scene

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HV image, gamma0, -30 to -10 dB

Acc: 0.8950, mIOU: 0.7773



model labels



0.6386

• Noticeable improvement in difficult scene

Conclusion

- Ice-Water classification
 - Overall good performance and determination of ice / water boundary
 - Some difficult scenes
- Ice-concentration classification
 - Maintains ice / water boundary
 - Limited data at intermediate concentrations
- Multiple spatial scales
 - Improves overall performance
 - Noticeable benefit for difficult scenes with large areas of uniform backscatter
- Good example of how, given an extensive EO archive, such as RADARSAT-2, DL models can be trained to help automate operational exploitation

THANK YOU

