A comparison of classifiers for oil spill detection

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30th October 2014

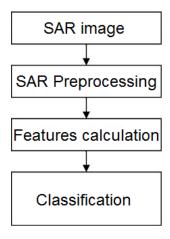
Overview

- What are Oil Spills
- Oil Spill Detection
- SAR Images
- SAR Preprocessing
- Features & Selection
- Typical Problems
- Summary of Classifiers
- Research
- Recommendations & Conclusion

What are Oil Spills?

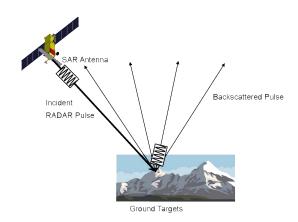


General oil spill detection approach

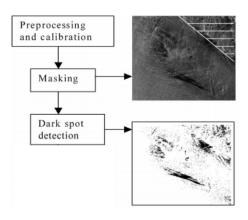


Synthetic Aperture Radar Image

- Radar?
- Synthetic Aperture?
- Advantages
- Problems



SAR Preprocessing

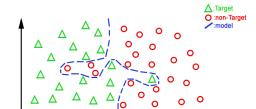


Features

- What are features?
- Types of features
 - Geometrical
 - Physical
 - Texture
 - Contextual

Feature Selection

- Choosing features
- Over fitting
- Curse of dimensionality



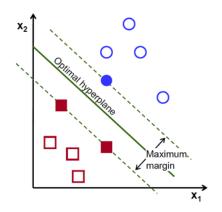
Typical problems

- Lookalikes
- Imbalanced dataset
- Data is scarce
- Gathering contextual features

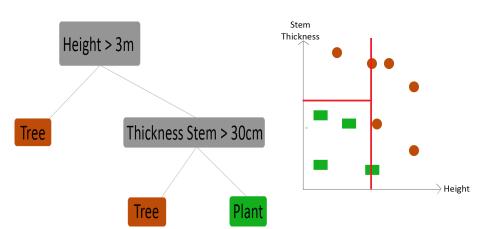
Supervised learning



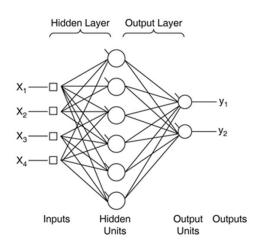
Support vector machines



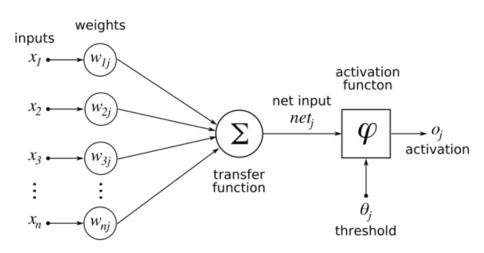
Decision Tree



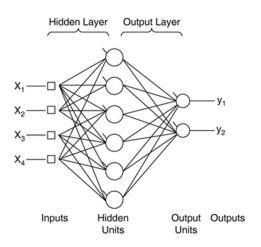
Multilayer perceptrons



Perceptron



Multilayer perceptrons



Research goals

- Accuracy comparison
- Classifier characteristics vs field specific problems

Difficulties researching

- SVM was hardly used
- Not all details were specified
- Use of different datasets (unverified samples)
- Use of different features
- Free lunch theorem

Fail

We did not manage to compare our three classifiers

The best classifier?

- Different accuracy in different situations
- SVM and MLP for large datasets
- SVM and MLP for non-linear cases
- DT for small datasets
- DT easiest to interpret

Recommendations

- More research on SVM
- More research on Random Forest
- Shared database
- Bagging
- Image fusion

Summary

- Oil spill detection
- Classifiers
- Research
- Difficulties
- Recommendations

Study	Data Type	Preprocessing	# Features	Formations(lookalike & oilspills)	Results
Oil spills 99	ERS-2 SAR, 24 high-res images 8-bit	transformation, Filtering, data normalization	10	90 & 69	MLP(10:51:2) accuracy: 86.67% lookalike acc. 91.18% oil spills acc.
Oil spills [7]	ERS SAR, 600 low-res images	Resampling, Radiometric range correction, georeference	11	68 & 71	MLP(11-8-4-1) accuracy: 90% lookalike acc. 82% oil spills acc.
Oil spills 62	ERS-2 SAR, 24 high-res images	-	10	90 & 69	MLP(10-51-2) accuracy: 84.4% lookalike acc. 85.3% oil spills acc.
Oil spills 60	ERS SAR, 12 high-res images	8-bit transformation, filtering	-		MLP(4-2-1) accuracy: 96.46% overall acc.
Oil spills [18]	ERS SAR, 70 images	-	12	78 & 111	MLP(12-8-8-1) 0.227 root mean square error(rmse)
Oil spills 66	RADARSAT-1, 93 images	log-transformation, standardization	15	94 & 98	MLP 75.93% overall acc. SVM 79.63% overall acc. DT(Bundling) 90.74% overall acc.
Oil spills 37	Envisat, 47 images		9	155 & 80	MLP(9:11:2) 96.3% lookalike acc. 92.9% oil spill acc.
					DT 92.6% lookalike acc. 92.9% oil spill acc.
Oil spills 56	ERS-1 SAR, 59 low-res images		9	2471 & 42	DT 96% lookalike acc. 86% oil spill acc
Oil spills 61	ERS-2 SAR, 24 high-res images		9	90 & 69	DT forest 84.4%
Hydro-acoustics [50]	Sonar	Echoview	15	-	SVM accuracy: 89.5%, DT accuracy: 86.8%
Land coverage 1986 [2]	LandSat SAR	'Using data miner'	11	-	SVM max accuracy: 90.53%, DT accuracy: 93.48%
Land coverage 2001 [2]	LandSat SAR	'Using data miner'	10	-	SVM max accuracy: 93.67%, DT accuracy: 94.07%
ECG arrhythmias 40	MIT-BIH arrhythmia database	-	10	-	accuracy SVM 99%, MLP 98.22%
Remote Sensing[68]	Satimage	feature extraction	26	-	accuracy for SVM 93.16% ,and for MLP 96.98%
signature recognition 19	user signature data	feature extraction	2	· .	Recognition rate SVM 66.5 , MLP 71.2
wind speed prediction[41]	daily wind speed data		high dimensional feature		MSE on testing data for the MLP is 0.0090 while it is 0.0078 for the SVM
Hashimoto's disease 44	66 Thyroid ultrasound images	normalization	59	54 healthy and 85 sick	MLP(6-8-1): 89.4% sick class 61.1% healthy class. DT: 89.4% sick class 94.4% healthy class.

In case you need our credentials

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