## **CHAPTER 5** RESULTS

#### 5.1 **SENTINEL-1A DATA:**

#### 5.1.1 SVM THRESHOLD IMAGE GENERATION:



Ship 0





Water 0 Figure 5.1: Training Images of Ship and Water Class for SVM

Water 1



## Sentinel 1A: IW Level 1 GRD: VH (Sigma nought)

Figure 5.2: Subset Test Image of Sentinel-1A

#### **CLUMP & SIEVE OPERATION:** 5.1.2



Figure 5.3: Clump & Sieve operation on Sentinel-1A

Clump 4 Sieve 5

#### 5.1.3 HISTOGRAM FREQUECY SLICING:



Figure 5.4: Histogram Frequency Sliced Images of Sentinel-1A

#### 5.1.4 DECISION TREE CLASSIFICATION:



Figure 5.5: ENVI Decision Tree Classifier for visualisation



Figure 5.6: ENVI Decision Tree Classified Image of Sentinel-1A

## 5.1.5 VALIDATION OF DETECTION:

<u>Test ship details:</u> MV Nand Panna (IMO-8219140) Length = 58.6m Breadth = 13m Gross Tonnage = 1313t

Weather:

Dir of Wind waves / swell: 320/235 Mean Period waves/ swell: 2s / 8s Temp / Water Temp: 26.5 / 27.1 Sign Height of combined wind / wind waves: 0.9m / 0.8m Atmospheric Pressure: 1010.5 Pa

AIS position (24-02-2016 AT 01:02:09 UTC) 18° 55.937' N 072° 52.121' E Source: www.bigoceandata.com



Figure 5.7: Test ship MV Nand Panna (Source: www.marinetraffic.com)



Figure 5.8: Test Ship Located in ENVI Decision Tree Classified Image of Sentinel-1A

#### 5.1.6 POSITIONAL ACCURACY OF DETECTION:

SOURCE /	LATITUDE	LONGITUDE	LENGTH	RMSE
TECHNIQUE				
SATELLITE AIS DATA	18° 55.937' N	072° 52.121′ E	58.6M	NA
(MV NAND PANNA)				
MANUAL C4S5 VH	18° 55.951′ N	072° 52.473′ E	59.7M	POSN=
(S1A IW GRDH)				0.0352
MANUAL C8S10 VH	18° 55.951′ N	072° 52.473′ E	59.7M	LEN = 0.786
(S1A IW GRDH)				
MANUAL C4S5 VV	18° 55.951′ N	072° 52.473′ E	68.16M	POSN =
(S1A IW GRDH)				0.261
MANUAL C8S10 VV	18° 55.946′ N	072° 52.473′ E	62.24M	LEN = 9.65
(S1A IW GRDH)				
SVM RBF C4S5 VH	18° 55.245′ N	072° 52.338′ E	35.6M	POSN =
(S1A IW GRDH)				0.4894
SVM LINEAR C4S5 VH	18° 55.951′ N	072° 52.473′ E	65.3M	LEN = 16.93
(S1A IW GRDH)				

Table 5.1: Positional Accuracy of detection of Sentinel-1A

#### 5.1.7 DETECTION PERFORMANCE (MANUAL):

Class No	No of pixels	Est Volume $(CM) = ros^3 x No$	Est Gross Tonnage	Ship class	AIS data No. Of	SAR data No.	Detec tion Accur	False alarm	Missed Detecti on
		of Pixelsx0.9			ship	ship found	acy		
0 (Black)	Min(5/10) & below	4500 & less	1228 & below	Dredgers & Misc	6 & more	76	6	70	0
1 (Red)	Min(5/10) -50	4500 - 45000 -	1228- 13187	Tugs & Supply ship	11	17	11	6	0
2 (Green)	50-100	45000 - 90000	13187- 26917	Bulk Carrier	1	4	1	3	0
3 (Blue)	100-150	90000 - 135000 -	26917- 40852	Cargo	1	2	1	1	0
4 (Yellow)	150-200	135000 - 180000	40852- 54919	Ocean Liner	0	2	0	2	0
5 (Cyan)	200-250	180000 - 225000 -	40852- 69085	Tanker	0	0	0	0	0
6 (Magenta)	250-300	225000 - 270000 -	69085- 83329	Cruise ship	1	1	1	0	0
7 (Brown)	300-350	270000 - 315000 -	83329- 97639	Oil tanker	1	1	1	0	0
8 (Dark Green)	350-400	315000 - 360000	97639- 112005	Super tanker	0	0	0	0	0
9 (Violet)	400-500	360000 - 450000 -	112005- 140809	Crane Vessel	0	0	0	0	0
10 (Sand Brown)	500 & Max	450000 to Max	above 140809	Water / land	0	0	0	0	0
11 (Torquise Blue)	Max to Inf	Max to Inf	above the limits	Water / land	0	0	0	0	0
				Total / Percentage	14	27	100	80	0

 Table 5.2: Detection Performance of Manual method on Sentinel-1A

#### 5.1.8 DETECTION PERFORMANCE (SVM BASED):

Class No	No of pixels	Est Volume $(CM) = res^3 No$	Est Gross Tonnage	Ship class	AIS data No. Of	SAR data No. Of	Detec tion Accur	False alarm	Missed Detecti on
		of Pixelsx0.9			ship	ship found	acy		
0 (Black)	Min(5/10) & below	4500 & less	1228 & below	Dredgers & Misc	6 and more	80	6	74	0
1 (Red)	Min(5/10) -50	4500 - 45000 -	1228- 13187	Tugs & Supply ship	11	35	11	24	0
2 (Green)	50-100	45000 - 90000	13187- 26917	Bulk Carrier	1	5	1	4	0
3 (Blue)	100-150	90000 - 135000 -	26917- 40852	Cargo	1	1	1	0	0
4 (Yellow)	150-200	135000 - 180000	40852- 54919	Ocean Liner	0	5	0	5	0
5 (Cyan)	200-250	180000 - 225000 -	40852- 69085	Tanker	0	0	0	0	0
6 (Magenta)	250-300	225000 - 270000 -	69085- 83329	Cruise ship	1	2	1	1	0
7 (Brown)	300-350	270000 - 315000 -	83329- 97639	Oil tanker	1	1	1	0	0
8 (Dark Green)	350-400	315000 - 360000	97639- 112005	Super tanker	0	3	0	3	0
9 (Violet)	400-500	360000 - 450000	112005- 140809	Crane Vessel	0	0	0	0	0
10 (Sand Brown)	500 & Max	450000 to Max	above 140809	Water / land	0	0	0	0	0
11 (Torquise Blue)	Max to Inf	Max to Inf	above the limits	Water / land	0	0	0	0	0
				Total / Percentage	15	52	100	246	0

#### Table 5.3: Detection Performance using SVM on Sentinel-1A

#### 5.1.9 DETECTION COMPARISON:



Figure 5.9: Detection Comparision of Manual vs SVM mtehods

#### 5.1.10 ACCURACY ASSESSMENT:

Table 5.4: Accuracy	Assesment	of various	methods of	on Sentinel-1A
rubic com riccuruc	1 100 content	or various	memous	m Sementer 111

SOURCE /	OVERALL	КАРРА	REMARKS
TECHNIQUE	ACCURACY	COEFFICIENT	
MANUAL C4S5 VH	NA	NA	REFERENCE
(S1A IW GRDH)			IMAGE
MANUAL C8S10 VH	98.7261%	0.9727	REC
(S1A IW GRDH)			
MANUAL C4S5 VV	22.7703%	-0.5360	NOT REC
(S1A IW GRDH)			
MANUAL C8S10 VV	22.7703%	-0.5360	NOT REC
(S1A IW GRDH)			
SVM RBF C4S5 VH	65.2505%	0.0155	REC UNDER
(S1A IW GRDH)			HIGH NOISE
SVM LINEAR C4S5 VH	81.6997%	0.6466	HIGHLY REC
(S1A IW GRDH)			

#### 5.1.11 ANALYSIS OF RESULTS:

(i) Choice between co-polar or cross-polar depends on the incidence angle.



Figure 5.10: Co-polar vs Cross polar data selection based on the Incidence angle (ENVI)

- (ii) Decision of Preprocessing should aim to reduce clutter & noise without reducing the probability of detection and effect of sieve 10 vs sieve 5.Sieve 10 does not detect the clumps less than the 10 adjacent pixels but the sieve 5 tends to increase the noise.
- (iii) SVMs of using linear, quadratic basis revealed more error-rate in classification when compared to the Guassian radial basis function and Multi layer perceptron models.
- (iv) RBF produces greater accuracy with higher time cost which can be reduced by cross validation while quadratic gives a robust accuracy in lesser.



Figure 5.11: Effect of Sieve operation and the minimum detectable ship (ENVI)

- (v) Linear function basis gives better visual appreciation of the finer details even smaller potential ship pixels
- (vi) MLP & Quadratic basis had tendency to overfit with limited training sets for S1A while for RISAT 1 Linear & Quadratic basis had similar behaviour.
- (vii) Finally, RBF gives higher accuracy with reduced probability of False alarm and hence modification of the constraint, sigma & with cross validation produce
- (viii) The semi emprical model for estimation of Gross tonnage was congruent with the validation data by detection of all the ship of corresponding class and the positional accuracy/measurement accuracy revealed that SVM based method increased the error while saved time for interpretation and automated the process.

(ix) Detection Performance of Sentinel-1A GRDH data revealed that the detection was high and also the false detection with SVM increased indicating precise detection capability of SVM detector.

#### 5.2 RISAT-1 DATA PROCESSING:

#### 5.2.1 DESIGN OF MANUAL DETECTOR:



Figure 5.12: Subset Image for processing of RISAT-1 MRS CEOS data (ERDAS IMAGINE)



Figure 5.13: Manual Selection of detection threshold (ENVI)



Figure 5.14: Threshold selection of RISAT-1 HH MRS data using Horizontal profile (ENVI)



Figure 5.15: Threshold selection of RISAT-1 HV MRS data using Horizontal profile (ENVI)



Figure 5.16: Histogram Frequency Slicing of RISAT-1 MRS data (ERDAS IMAGINE)

# 5.2.2 COMPARISON OF THE BEST SVM TECHNIQUES FOR THE ANALYSIS:



Figure 5.17: Comparison of SVM Techniques (ERDAS IMAGINE)

#### 5.2.3 SVM BASED APPROACHES:



Figure 5.18: Comparison of SVM linear and SVM polynomial degree-2 classification (ENVI)



Figure 5.19: Comparison of SVM sigma and SVM RBF (ENVI)

#### 5.2.4 TEST SHIP DETAILS:

The Oranje ship was taken as the test ship and the following are the

details:

- (i) IMO No. 9263904
- (ii) Total length = 156m
- (iii)Breadth = 28m
- (iv)Gross ton=18091T
- (v) AIS position (15-11-2016 AT 00:55 UTC) is 18° 53'22.55" N 072° 51'

27.51" E (Source: www.vtexplorer.com)



Figure 5.20: Ship Oranje (Source: www.marinetraffic.com)

#### 5.2.5 POSITIONAL ACCURACY:

SOURCE (RISAT-1 MRS)	LATITUDE (DMS N)	LONGITUDE (DMS E)	LENGTH (M)	BREADTH (M)
AIS DATA (ORANJE)	18° 53' 22.55"	072° 51' 27.51"	156	28
MANUAL HH	18° 53' 21.96"	072° 51′ 27.52"	170.12	41.48
MANUAL HV	NO DETECTION	NO DETECTION	NA	NA
SVM LINEAR HH	18° 53' 22.55"	072° 51' 26.9"	83.70	48.67
SVM POLY2 HH	18° 53' 22.54"	072° 51' 26.9"	80.12	45.99
SVM RBF HH	18° 53' 22.54"	072° 51' 26.9"	82.73	54.19
SVM SIGMOID HH	NO DETECTION	NO DETECTION	NA	NA
SVM LINEAR HV	18° 53' 22.55"	072° 51' 28.13"	217.22	67.5
SVM POLY2 HV	18° 53' 21.96"	072° 51' 27.52"	217.87	57.63
SVM RBF HV	18° 53' 22.55"	072° 51' 27.51"	229.9	51.31
SVM SIGMOID HV	18° 53' 22.55"	072° 51' 27.51"	219.76	63.96

Table 5.5: Validation of positional accuracy for RISAT-1 MRS data

The following of the derivatives after the analysis:

(i) Manual detection of the cross polar (HV) component was nearly impossible after repeated selection of the Thresholds because of the noise. However by the use of SVM detector near correct detection was obtained by using cross polar product. (ii) Length of the ship was under estimated and breadth was over estimated

by the co-polar products while both length and breadth was overestimated by the cross polar products.

(iii)RMSE of position indicated reliability of detection using SVM while RMSE of length and breadth indicated that it included the depth above waterline and hence estimated length and breadth has to be utilised with care.

SOURCE / TECHNIQUE	LENGTH (M)	BREADTH (M)	RMSE POSITION (S)	RMSE LENGTH (M)	RMSE BREADTH (M)
AIS DATA	156	28	0	NA	NA
MANUAL HH	170.12	41.48	0.59008474	14.12	13.48
MANUAL HV	NA	NA	NA		
SVM LINEAR HH	83.7	48.67	0.61	73.83	21.88
SVM POLY2 HH	80.12	45.99	0.610081962		
SVM RBF HH	82.73	54.19	0.610081962		
SVM SIGMOID HH	NA	NA	NA		
SVM LINEAR HV	217.22	67.5	0.62	65.39	32.69
SVM POLY2 HV	217.87	57.63	0.59008474		
SVM RBF HV	229.9	51.31	0.62	]	
SVM SIGMOID HV	219.76	63.96	0		

Table 5.6: RMSE calculation for RISAT-1 MRS data analysis

#### 5.2.6 DETECTION ACCURACY:

(i) SVM had a 100% detection and it could even detect much more details of those ship with or without AIS feed and also giving a potential of detection of even ships which are much smaller that the resolution of the data being analysed.

- (ii) False alarm was primarily due to lapse of data and not due to the increase in the noise or clutter due to weather elements and same could be seen by qualitative assessment by the image analyst.
- (iii)Missed detections also indicate that most of the class 3 ships (blue) has been misclassified as class 1 ships (Red). Hence the detection methods rule out the chance of any missed detection of such a big class.



Figure 5.21: Detection Performance of RISAT-1 MRS data analysis

Table 5.7:	Detection	Performance	of RISAT-1	MRS data
------------	-----------	-------------	------------	----------

Class No	No of	Est	Est	Ship	AIS	SAR	Detec	False	Missed
	pixels	Volume	Gross	classifi	data	Data	tion	alarm	Detecti
		$(CNI) = ros^3 V No$	Tonnage	cation	NO. Of	NO. Of	Accur		on
		of			shing	shing	acy		
		Pixelsx0.9			Sinps	found			
0 (Black)	below	below min	below	Dredge	13 &	0	0	0	0
	min (5)	(26244)	7568	rs &	more				
				Misc					
1 (Red)	05 to	26244 -	7568-	Tugs &	9	56	9	46	1
	10	52488	15453	Supply					
2 (Green)	10 to	52488 -	15453-	Bulk	16	19	16	3	0
	20	104976	31537	Carrier					
3 (Blue)	20 to	104976 -	31537-	Cargo	15	8	8	0	7
	30	157464	47860						
4 (Yellow)	30 to	157464 -	47860-	Ocean	2	8	2	6	0
	40	209952	64338	Liner					
5 (Cyan)	40 to	209952 -	64338-	Tanker	0	0	0	0	0
	50	262440	80931						
6	50 to	262440 -	80931-	Cruise	0	3	3	0	0
(Magenta)	100	524880	165023	ship					
7 (Brown)	100 to	524880 -	165023-	Oil	0	3	3	0	0
	200	1049760	336366	tanker					
8 (Dark	200 to	1049760 -	336366-	Super	0	1	1	0	0
Green)	300	1574640	510095	tanker					
9 (Violet)	300 to	1574640	above	Crane	0	0	0	0	0
	Max	to Max	510095	Vessel					
10 (Sand	Max	Max	510095	Water /	0	0	0	0	0
Brown)				land					
11	Max to	Max to Inf	above	Water /	0	0	0	0	0
(Torquise	Inf		the limits	land					
Blue)									
				Total /	42	98	42 /	55	8
				Percent			100		

#### 5.2.7 CLASSIFICATION ACCURACY:

- (i) Classification accuracy was computed using the best classified HV image and cross verified the other techniques as HV was more congruent with the ground truth.
- (ii) Cross polar analysis defined better performance while co-polar was giving about 55% congruence with the cross polar product.

SOURCE /	OVERALL	КАРРА	REMARKS
TECHNIQUE	ACCURACY	COEFFICIENT	
SVM RBF HV	NA	NA	REFERENCE IMAGE
MANUAL HH	56.2859	0.0374	NOT REC
MANUAL HV	-	-	NOT REC
SVM LIN/POLY2	100	1	REC
SVM LIN HH	57.3389	0.0554	NOT REC
SVM POLY2 HH	57.0954	0.0488	NOT REC
SVM RBF HH	57.0955	0.0488	NOT REC

Table 5.8: Accuracy Assessment of RISAT-1 MRS data analysis

#### 5.3 HYBRID POLARIMETRIC PROCESSING:

Polarimetric processing of the RISAT-1 SAR data was carried out to derive the polarimetric signatures of ships. Three cases were chosen namely oil tanker embarked at J4 (Jawahar dweep), near shore tug at J1 to J3 and container ship into seas. All the decompositions were carried out after preprocessing of product using PolSARPro (documentation of PolSARPro ver 5.0). Target decomposition using both hybrid and Psuedo-quad polarimetric data (Tarang) was used to identify the ship and recoganise them. However these polarimetric parameter retrieval has been limited to the ship detection problem rather than a complete autonomous ship classification. Nevertheless this can easily be extended to capture various ship signatures and can be retrieved to identify the ship uniquely and its draught, contents, type and other information.

#### 5.3.1 RANEY DECOMPOSITION:

Raney (2007) decomposition based on m-delta has been found to be more efficient in handling the CTLR rather than the Psuedo-quad converted decomposition methods. Intentionally the choice of the decomposition methods both coherent and incoherent was done to have ease of similarity with Raney decomposition and the conformity index based decomposition. We can deduce based on the experiments that Raney decomposition gives better clarity in the objective area of oceans for ship detection and better both computationally as it does directly based on the corrected C2 (covariance matrix) while the other methods are based on the derived T3 matrix (coherency matrix) based on the mono-static and reflection symmetry.



Figure 5.22: Raney Decomposition - Container ship (C2 Matrix of RISAT-1 CTLR data)



Figure 5.23: Raney Decomposition - Oil tanker (C2 Matrix of RISAT-1 CTLR data)



Figure 5.24: Raney Decomposition - offshore tug (C2 Matrix of RISAT CTLR data)

#### 5.3.2 KROGER COHERENT DECOMPOSITION:



Figure 5.25: Kroger Coherent decomposition - Oil tanker (T3 Matrix of Psuedo-quad derived from C2)



Figure 5.26:Kroger Coherent decomposition - Offshore tug (T3 Matrix of Psuedo-quad derived from C2)



Figure 5.27: Kroger Coherent decomposition - Container Ship (T3 Matrix of Psuedo-quad derived from C2)

#### 5.3.3 INCOHERENT DECOMPOSITION:

#### 5.3.3.1 Freeman Decomposition:



Figure 5.28: Freeman incoherent decomposition - Oil tanker (T3 Matrix of Psuedo-quad derived from C2)



Figure 5.29: Freeman incoherent decomposition - Container ship (T3 Matrix of Psuedo-quad derived from C2)



Figure 5.30: Freeman incoherent decomposition - Off shore (T3 Matrix of Psuedo-quad derived from C2)

#### 5.3.3.2 Yamaguchi Decomposition:



Figure 5.31: Yamaguchi Decomposition - Oil tanker (T3 Matrix of Psuedo-quad derived from C2)



Figure 5.32: Yamaguchi Decomposition - Container ship (T3 Matrix of Psuedo-quad derived from C2)



Figure 5.33: Yamaguchi Decomposition - Offshore tug (T3 Matrix of Psuedo-quad derived from C2)