



Leslie M. Novak Scientific Systems Company, Inc. 500 West Cummings Park, Suite 3000 Woburn, MA 01801 USA

E-mail <a href="mailto:lnovakl@ssci.com">lnovakl@ssci.com</a> <a href="mailto:novakl@charter.net">novakl@charter.net</a>

### ABSTRACT

Target recognition systems using Synthetic Aperture Radar (SAR) data require well-focused target imagery to achieve high probability of correct classification. Two techniques for improving the image quality of complex SAR imagery are investigated. The application of phase gradient re-focusing of target imagery having cross-range smearing is shown to significantly improve the target recognition performance of a model-based ATR system. The application of High Definition Imaging (HDI) is shown to enhance and improve the image quality and resolution of SAR target imagery -- the improvement in target recognition performance of a template-based ATR system using HDI-processed SAR imagery is quantified.

## **1 INTRODUCTION**

SAR image quality has a significant effect on the performance of SAR automatic target recognition systems. Template-based classifiers and model-based classifiers both require well-focused imagery in order to accurately match an observed target image to a database of stored templates or features such as peak-scatterer locations, etc. High-resolution SAR requires accurate motion compensation in order to form well-focused target images, and errors in motion compensation can yield images with poor image quality, such as excessive cross-range image smearing or blurring. Section 2 of this paper demonstrates the use of phase gradient processing to refocus target imagery degraded by cross-range smearing. ATR performance of a model-based classifier is investigated; the probability of correct classification (Pcc) is compared using target imagery having significant cross-range smearing versus target imagery that has been refocused using phase gradient algorithm (PGA) processing; it is demonstrated that model-based ATR performance is improved considerably by using PGA-processing prior to passing the target imagery to the ATR.

Section 3 of this paper applies to high-resolution SAR imagery already having good image quality, including imagery that has been well-focused using PGA-processing; the technique investigated improves image quality by enhancing the resolution of well-focused complex SAR imagery. A 10-target, template-based classifier is described and classifier performance is presented using SAR imagery having 0.3m x 0.3m, 0.5m x 0.5m, and 1.0m x 1.0m resolutions; classifier performance is presented in terms of confusion matrices and probability of correct classification (Pcc). Next, enhanced resolution imagery is formed from the original 0.3m x 0.3m and 1.0m x 1.0m data using Lincoln Laboratory's High Definition Imaging (HDI) algorithm -- this processing improves (approximately) the resolution of the data to 0.15m x 0.15m and 0.5m x 0.5m, respectively; and the image background speckle noise is reduced. The improvement in the performance of the template-based classifier due to using HDI-processed data is quantified.

Section 4 of the paper summarizes the results and conclusions of these studies. Section 5 provides the references used in this research study.



## 2 IMPROVING ATR PERFORMANCE VIA PGA IMAGE QUALITY ENHANCEMENT

This section presents an example of an ATR performance study using high-resolution SAR imagery gathered by the Lynx SAR. In this example the imagery was gathered at a nominal resolution of 0.15m by 0.15m in spotlight mode; a contiguous sequence of seven SAR images are used in this study. Figure 1 shows these seven images. Visually, these SAR images appear to have very good image quality (IQ), however, our target recognition studies show that SAR image #1 has the best image quality and SAR image #7 has the poorest image quality.

A side-by-side comparison of SAR Image#1 with SAR Image #7 is shown in Figure 2. Comparing the bright scatterer located on the uppermost target shows that Image #7 has significant cross-range blurring, most likely due to uncompensated platform motion. Our analyses will show that the average cross-range scatterer width = 17 pixels for the scatterers in Image #1, whereas the average cross-range scatterer width = 36 pixels for the scatterer in Image #7. These "image quality feature" values were calculated from the image data during our target recognition studies. As we will show, the importance of this observation is directly related to the performance of the ATR system. A model-based target recognition system was used to classify the individual targets in each image. The classifier was designed to recognize 20+ military targets. The target array in these studies, as shown in Figures 1and 2, contained twelve military targets, and seven of these targets were contained in the classifier's set of 20+ targets.





# Figure 1: Sequence of seven SAR images





A CFAR detector was used to detect the targets located in these seven SAR images. Each of the seven targets contained in the classifier's 20+ target set were presented to the model-based classifier; thus, a total of 49 target images were input to the classifier. Table 1 presents the target recognition results obtained for Image #1 (column 2) versus the results obtained for Image #7 (column 3). As the table shows, each of the targets contained in Image #1 were correctly classified (Pcc = 7/7). Four of the targets from Image #7 were incorrectly classified (highlighted in RED); thus, for this image, Pcc = 3/7.

Next, the targets from Image #7 were refocused using Phase-Gradient processing (see Reference [1]). Each target's brightest scatterers were CFAR detected and aligned as required by the PGA and averaged -- an average cross-range scatter width was calculated from the average of the brightest scatterers. Table 1 summarizes the cross-range scatter widths obtained for each target, and also an average width obtained for Image #1 and Image #7.

As stated previously, Image #1 has an average cross-range width = 17 pixels and Image #7 has an average cross-range width = 36 pixels. As shown in Table 1, column 4 tabulates the "classifier calls" and the average cross-range widths obtained after applying 3 iterations of phase gradient focusing to Image #7. After (PGA3) focusing, each of the targets in Image #7 were correctly classified (Pcc = 7/7) -- and the average cross-range width was reduced to 14 pixels.



TARGET	IMAGE #1	IMAGE #7	IMAGE #7
TRUTH	(ORIGINAL)	(ORIGINAL)	(AFTER PGA3)
T72	"T72"	" <mark>BRDM2</mark> "	"T72"
	WIDTH = 23	WIDTH = 45	WIDTH = 7
2S1	"2S1",	" <mark>BMP2"</mark> ,	"2S1"
	WIDTH = 19	WIDTH = 51	WIDTH = 19
M60	"M60"	" <mark>BRDM2</mark> "	"M60"
	WIDTH = 21	WIDTH = 47	WIDTH = 21
M2	"M2"	"M2"	"M2"
	WIDTH = 11	WIDTH = 21	WIDTH = 17
BMP2	"BMP2"	" <mark>M113</mark> "	"BMP2"
	WIDTH = 19	WIDTH = 37	WIDTH = 11
BRDM2	"BRDM2"	"BRDM2"	"BRDM2"
	WIDTH = 11	WIDTH = 21	WIDTH = 15
M113	"M113"	"M113"	"M113"
	WIDTH = 15	WIDTH = 27	WIDTH = 9
Table	PCC= 7/7,	PCC= 3/7	PCC= 7/7,
	WIDTH (AVG.) =	WIDTH (AVG.) =	WIDTH (AVG.) =
	17	36	14

A comparison of SAR target images from Image #7 is presented in Figure 3. The left target image shows significant cross-range image blurring; the right target image is the same target after reprocessing the complex image data using 3 iterations of the PGA algorithm. Table 2 summarizes the model-based classifier performance for each of the seven target images processed.





Figure 3: Target extracted from Image #7; original(left), after PGA3(right)

IMAGE	AVG. WIDTH	AVG. WIDTH	PCC	PCC
NUMBER	(ORIGINAL)	(AFTER PGA3)	(ORIGINAL)	(AFTER PGA3)
#1	17.0	11.5	7/7	7/7
#2	21.8	13.8	7/7	7/7
#3	23.2	16.1	6/7	7/7
#4	24.1	11.8	6/7	7/7
#5	26.4	16.0	5/7	5/7
#6	31.5	12.7	6/7	6/7
#7	35.5	14.1	3/7	7/7
Averages	25.6	13.7	40/49	46/49
Tab	le 2: Summary o	f Model-based Cl	assifier Performa	ince

An alternative image focusing algorithm based upon minimizing the image entropy is described in Reference [2]; however, results presented in Figure 4 indicate that minimum entropy focusing requires using at least 10 iterations of the entropy minimization algorithm in [2]. The entropy minimum is achieved using only 3 iterations of the PGA algorithm. Thus, PGA processing seems to be the preferred SAR image focusing technique.





## 3 IMPROVING ATR PERFORMANCE VIA HIGH-DEFINITION IMAGE PROCESSING

This section presents an approach that has been shown to improve the ATR performance of a templatebased classifier [3] using complex SAR imagery that has been resolution-enhanced using Lincoln Laboratory's High Definition Image (HDI) Processing [4]. The SAR imagery used in these studies was gathered in the fall of 1995 at the Redstone Arsenal in Huntsville, AL by the Sandia X-band (9.6 GHz) HH-polarization SAR. The data comprise a large set of military targets imaged over 360 deg of aspect. In these studies the recognition performance of a template-based mean-square-error (MSE) classifier was evaluated using imagery of 18 distinct targets contained in the data set. The target set shown in Figure 5 includes three versions of the BMP2 armored personnel carrier, the M2 armored personnel carrier, and the T72 main battle tank. The T72 tanks contain significant differences from tank to tank; T72#2 has barrels mounted on the rear of the target; T72#3 does not have skirts along the side of the target. The BMP2 and M2 armored personnel carriers have minor differences in target-to-target configuration. We trained a 10target classifier and then evaluated the ability of the classifier to recognize and classify all 18 targets shown in Figure 5. The initial evaluations used non-HDI-processed data to establish a baseline with which the performance using HDI-processed data could be compared. The improvement in classifier performance using HDI-processed data was then evaluated. Performance results are presented in terms of



classifier confusion matrices which show the number of correct and incorrect classifications achieved; the confusion matrices are summarized in terms of a probability of correct classification (Pcc) metric. We constructed 72 classifier templates per target, covering approximately 360 deg of aspect per target; the total number of classifier templates was 720. The classifier was initially tested using the training data images as test inputs, which provided a sanity check on the algorithm code.



Table 3 is the classifier confusion matrix for the 0.3 m x 0.3 m resolution data. When the classifier was tested using the training data, perfect classifier performance was achieved. When the classifier was tested using the independent test data, nearly perfect classifier performance was achieved (Pcc = 93.9 %). Note, however, that the performance for T72#2, which contained extra barrels on the rear of the tank, resulted in 39 images out of the 255 total declared unknown. The performance for T72#3 (which did not have skirts along the sides of the target) was nearly perfect; only 4 images out of the 251 total were declared unknown. At this resolution, the classifier rejected a large number of confuser vehicles (438 images out of the total of 499).



1	BMP2	BTR60	BTR70	M109	M110	M113	MI	M2	M548	T72	Unknown
BMP2#1	255										
BMP2#2	251				2		2 8	1			3
BMP2#3	251				2		8	1		2	2
BTR:60		256	· · · · · ·		-		()				
BTR70			256		S						
M109				256	5		-				
M110					256		1 - T				
M113						256					
M1							256				
M2#1							î î	256			
M2#2	0						ĩ i	251			4
M2#3							i. Ti	252			3
M548					1				256		1
T72#1							()			256	
T72#2					1		( )			216	39
T72#3					1		l I			247	4
4MMWV	12	6			[	37		2			187
M35									4		251
	inc Inc	lepender	t Test Da	ata		Co	onfuser	Vehicle	s (Not in	Training	) Set)

Table 4 shows the classifier confusion matrix for 0.5 m x 0.5 m resolution data. The probability of correct classification for these resolution data (calculated using only the independent test vehicles and the confuser vehicles) is 84.1%. At this resolution, the M35 truck was misclassified only 13 times out of the 255 total M35 test images. The HMMWV, however, was misclassified most of the time (only 61 HMMWV images were declared unknown).

Table 5 shows the classifier confusion matrix for the 1.0m x 1.0m m resolution data. For these specific targets at this resolution, we observe a very large degradation in classifier performance; the probability of correct classification degraded to 45.4%. Note, however, that nearly perfect classifier performance was achieved when the classifier was tested using the training data; this result shows the importance of testing classifiers using independent target test data.



			N	lumber	of Targ	jets Cla	ssified	as			
	BMP2	BTR60	BTR70	M109	M110	M113	M1	M2	M548	<b>T72</b>	Unknown
BMP2#1	256										
BMP2#2	235	1		0 13 K 34				8		7	3
BMP2#3	237	1				1		11		4	3
BTR60		255									1
BTR70			256								
M109				256							
M110		Ũ			256		i i				1
M113						255	[]				
M1							256				
M2#1								256			
M2#2				4	5			233		4	9
M2#3				2	5	1		239		4	5
M548									254		2
T72#1										256	
⊤72#2	i di V V	Û		) () ()	3		8	3		217	24
T72#3	_			1			2	1		241	6
HMMWV	29	8	1	9	3	115		14	3	1	61
M35	1			3	3	1			5		242
Та	able 4	<mark>lepender</mark> : Clas	nt Test D sifier l	<sup>ata</sup> Perfor	manc	e (0.51	n x 0.	Vehicle .5m);	s (Not in ' Pcc =	<b>Training</b> 84.19	6 [5]
	able 4	epender : Clas	nt Test D sifier l	<sup>ata</sup> Perfor Iumber	mance of Tar	e (0.51 gets Cla	n x 0. n ssifed	Vehicle .5m); l as	s (Not in ' Pcc =	Training 84.1%	set] [5]
Ta	able 4	Epender Clas BTR60	sifier ) N BTR70	ata Perfor Iumber M109	mance of Tar	e (0.5r gets Cla M113	n x 0. n x 0. nssifed M1	Vehicle: .5m);   as   M2	s (Not in Pcc = M548	Training 84.19 772	Set [5] Unknown
Ta BMP2±1	BMP2	epender : Clas BTR60	nt Test D sifier 1 N BTR70	ata Perfor Number M109	of Tar	e (0.51 gets Cla M113	n x 0. n x 0. nssifed M1	Vehicle: .5m); as M2 1	s (Not in ' Pcc = M548	Training 84.19 172	Set [5] Unknown
Ta BMP2#1 BMP2#2	BMP2 255 129	Epender : Clas BTR60	sifier D N BTR70 21	ata Perfor Number M109 8	of Tary M110	e (0.51 gets Cla M113 39	n x 0. nssifed M1	Vehicle (5m); as M2 1 15	s (Not in Pcc = M548	Training 84.19 T72 18	5et] [5] Unknown 6
Ta BMP2±1 BMP2±2 BMP2±3	EMP2 255 129 135	BTR60	NBTR70	ata Perfor Number M109 8 5	of Tary M110	e (0.51 gets Cla M113 39 43	n x O. nssifed M1 3	Vehicle (5m); as M2 1 15 25	s (Not in ' Pcc = M548	Training 84.19 T72 18 18	9 Set] 6 [5] Unknown 6 11
Ta BMP2±1 BMP2±2 BMP2±3 BTR60	EMP2 255 129 135	BTR60 15 7 255	N BTR70	ata Perfor Number M109 8 5	mance of Tary M110 1 2	e (0.51 gets Cla M113 39 43 1	n x (). assifed M1 3	Vehicle: .5m); as M2 1 15 25	s (Not in ' Pcc = M548	Training 84.19 172 18 18	9 Set 6 [5] Unknown 6 11
Ta BMP2±1 BMP2±2 BMP2±3 BTR60 BTR70 M400	BMP2 255 129 135	BTR60 15 7 255	nt Test D. sifier ] N BTR70 21 10 256	ata Perfor Aumber M109 8 5	manco of Tary M110 1 2	Cc e (0.51 gets Cla M113 39 43 1	n x (). n x (). assifed M1 3	Vehicle: .5m); as M2 1 15 25	s (Not in ' Pcc = M548	Training 84.19 172 18 18	9 Set] 6 [5] Unknown 6 11
Ta BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M1410	BMP2 255 129 135	BTR60 15 7 255	nt Test D sifier ] N BTR70 21 10 256	ata Perfor Number M109 8 5 256	manco of Tary M110 1 2	Cc e (0.51 gets Ck M113 39 43 1	m x 0. m x 0. mssifed M1 3	Vehicle: 5m); as M2 1 15 25	s (Not in ' Pcc =	Training 84.19 172 18 18	6 [5]
Ta BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113	EMP2 255 129 135	BTR60 15 7 255	nt Test D sifier 1 N BTR70 21 10 256	ata Perfor Mumber M109 8 5 256	manco of Tary M110 1 2 256	Cc e (0.51 gets Ck M113 39 43 1	m x O. m x O. mssifed M1 3	Vehicle: 5m); as M2 1 15 25	s (Not in ' Pcc =	Training 84.19 172 18 18	9 Set] 6 [5] Unknown 6 11
Ta BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1	EMP2 255 129 135	BTR60 15 7 255	nt Test D sifier ] N BTR70 21 10 256	ata Perfor Jumber M109 8 5 256	emance of Tary M110 1 2 256	253	n x 0. nssifed M1 3	Vehicle: 5m); as M2 1 15 25	M548	Training   84.19   172   18   18	2 Set 6 [5] Unknown 6 11 2
Ta BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1 M2#1	EMP2 255 129 135	BTR60 15 7 255	nt Test D sifier ] N BTR70 21 10 256	ata Perfor Jumber M109 8 5 256 256	entrance of Tary M110 1 2 256	253 1	n x 0. assifed M1 3 253	Vehicle: 5m); as M2 1 15 25	M548	Training   84.19   172   18   18	2 Set 6 [5] Unknown 6 11 2
Ta BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1 M113 M1 M2#1 M2#2	EMP2 255 129 135	BTR60	at Test D. sifier ] N BTR70 21 10 256	ata Perfor Jumber M109 8 5 256 1 1	manco of Tary M110 1 2 256	Cc e (0.51 gets Ck M113 39 43 1 253 1 1 1 36	n x 0. nssifed M1 3 253	Vehicle: 5m); as M2 1 15 25 255 2255	M548	16	2 Set 0 [5] Unknown 6 11 2 7
Ta BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1 M113 M1 M2#1 M2#2 M2#3	EMP2 255 129 135 1 1 1 1 4 21	BTR60 15 7 255 3 6	nt Test D. sifier ] N BTR70 21 10 256 2	ata Perfor Mumber M109 8 5 256 1 37 18	manco of Tary M110 1 2 256 14 6	Cc e (0.51 gets Ck M113 39 43 1 1 253 1 1 36 47	n x 0. nssifed M1 3 253 5 5	Vehicle: 5m); as M2 1 15 25 255 121 118	M548	Training 84.19 172 18 18 18 18	2 Set 0 [5] Unknown 6 11 2 7 4
Ta BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1 M2#1 M2#2 M2#3 M548	EMP2 255 129 135 1 1 1 14 21	BTR60 15 7 255 3 6	at Test D. sifier ] N BTR70 21 10 256 2 2	ata Perfor Jumber M109 8 5 256 1 37 18	emance of Tary M110 1 2 256 256	253 1 36 47	n x 0. assifed M1 3 253 5 5	Vehicle: 5m); as M2 1 15 25 255 121 118	s (Hot in ' Pcc = M548	Training   84.19   172   18   18   18   18   18   18   27	2 Set 0 [5] Unknown 6 11 2 7 4
Ta BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1 M2#1 M2#1 M2#3 M548 T72#1	EMP2 255 129 135 1 1 1 1 4 21	BTR60 15 7 255 3 6	at Test D. sifier ] N BTR70 21 10 256 2	ata Perfor Jumber M109 8 5 256 1 37 18	manco of Tary M110 1 2 256 14 6	Cc e (0.51 gets Ck M113 39 43 1 1 253 1 1 36 47 1	n x 0. assifed M1 3 253 5 9	Vehicle: 5m); as M2 1 15 25 255 121 118	s (Not in ' Pcc = M548	Training 84.19 172 18 18 18 18 18 18 255	2 Set 0 [5] Unknown 6 11 2 7 4
Ta BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1 M2#1 M2#1 M2#2 M2#3 M548 T72#1 T72#2	EMP2 255 129 135 1 1 1 1 1 21	BTR60 15 7 255 3 6 12	at Test D. sifier 1 N BTR70 21 10 256 2 2 2	ata Perfor M109 8 5 256 1 37 18	manco of Tary M110 1 2 256 14 6 9	Content (C)	n x 0. nssifed M1 3 253 5 5 9	Vehicle: 5m); as M2 1 15 25 255 121 118 32	s (Not in ' Pcc = M548	Training 84.19 172 18 18 18 18 18 18 18 18 18 21 255 94	2 Set 0 [5] Unknown 6 11 2 7 4 38
T2 BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1 M2#1 M2#1 M2#2 M2#3 M548 T72#1 T72#2 T72#3	Ind able 4 BMP2 255 129 135 135 1 1 1 1 1 4 21 7 19	BTR60 15 7 255 3 6 12 8	at Test D. sifier 1 N BTR70 21 10 256 2 2 2 3 6	ata Perfor M109 8 5 256 1 37 18 37 18 19 23	manco of Tary M110 1 2 256 256 14 6 9 5	Cc e (0.51 gets Cla M113 39 43 1 253 1 1 36 47 1 23 12	253 5 9 17	Vehicle: 5m); as M2 1 15 25 255 121 118 32 19	s (Not in ' Pcc = M548	Training   84.19   172   18   18   18   18   18   127	2 Set Unknown 6 11 2 7 4 38 18
T2 BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1 M2#1 M2#1 M2#2 M2#3 M548 T72#1 T72#2 T72#3 HMMWV	Ind able 4 BMP2 255 129 135 135 1 1 1 14 21 7 19 48	BTR60 15 7 255 3 6 12 8 7	at Test D. sifier ] N BTR70 21 10 256 2 2 2 3 6 4	ata Perfor Jumber M109 8 5 256 1 37 18 37 18 19 23 4	emance of Tary M110 1 2 256 256 14 6 9 5	Construction of the constr	n x 0. assifed M1 3 253 5 9 17 14	Vehicle: 5m); as M2 1 15 255 121 118 225 121 118 32 19 13	s (Hot in ' Pcc = M548	Training   84.19   172   18   18   18   16   27   255   94   127	2 Set Unknown 6 [5] 2 7 4 38 18 22

Table 6 shows the classifier confusion matrix for HDI-processed  $0.3 \text{ m} \times 0.3 \text{ m}$  resolution data (after HDI processing, the resolution of the data is approximately  $0.15 \text{ m} \times 0.15 \text{ m}$ ). Comparing the results of Table 6 with the results of Table 3 shows somewhat-improved classifier performance; the probability of correct



classification using HDI-processed data has increased to 96.4%, an improvement of 2.5% over the conventionally processed data -- and with HDI-processed 0.3 m x 0.3 m data, the classifier rejected a larger number of confuser vehicles (471 images out of the total 499).

Table 7 shows the classifier confusion matrix for HDI-processed 1.0 m x 1.0 m resolution data (after HDI processing, the resolution of the data is approximately 0.5 m x 0.5 m). Comparing the results of Table 7 with the results of Table 5 shows a dramatic improvement in classifier performance. The probability of correct classification using HDI-processed data has increased by approximately 30% over that achieved with conventionally processed 1.0 m x 1.0 m resolution data; the probability of correct classification has increased from 45.4% to73.4%. With HDI-processed 1.0 m x 1.0 m data, the number of rejected confuser vehicles increased from 197 images to 321 out of a total of 499 images. Although HDI processing of 1.0 m x 1.0 m data has resulted in a significant increase in the probability of correct classification (Pcc = 73.4%), performance using conventionally processed 0.5 m x 0.5 m resolution data gave somewhat better probability of correct classification (Pcc = 84.1 %).

Figure 6 presents a side-by-side comparison of M35 Truck images; the right image was formed using conventional 2D FFT SAR processing; the left image is the corresponding HDI-processed image. This image comparison validates that HDI-processing does result in improved ATR performance. Visually, the left figure shows more clearly focused target scatterers, resulting in improved recognition of the target.



Figure 6:SAR Images of M35 Truck; Left Image, 1.0m x 1.0 m HDI-Processed; Right Image, 1.0m x 1.0 m 2D-FFT Processed



	10.000		SPECTRESS.	ING		i i ai gie			1000000000	1.0659250	1222020
	BMP2	BTR60	BTR70	M109	M110	M113	M1	M2	M548	T72	Unknown
BMP2#1	256			G.			9				
BMP2#2	252										3
BMP2#3	255							1		ļ.	
BTR60		256		2			9			2 - 5	
BTR70			256								
M109				256							
M110					256						
M113						256					
M1							255			2 - 2	
M2#1								256			
M2#2								251	2		2
M2#3								248	3		3
M548		2. 							256	12 (1	
T72#1				2	-					256	
T72#2										232	23
T72#3										245	6
HMMWV	4	1				13		3			223
				2	2			4	6		249
M35 Inde able 6:	ependen Class	t Test D Sifier	ata Perfo	orman Nu	Confuse ICE (O	er Vehick 0.3m > f Targe	es (Not i ( 0.3r ts Clas	in Traini n + F	ng Set) IDI); F as	Pcc =	96.4%
M35 Inde able 6:	ependen Class BMP2	t Test D Sifier BTR60	ata Perfo	orman Nui M109	Confuse ICE (O mber o M110	er Vehick 0.3m > f Targe M113	es (Not ( 0.3r ts Clas	n Traini n + F sified :	ng Set) IDI); F as M548	PCC =	96.4%
M35 Inde able 6:	ependen Class BMP2 256	t Test D Sifier BTR60	ata Perfo BTR70	orman Nui M109	Confuse ICE (O mber o M110	er Vehick 0.3m > f Targe M113	es (Not CO.3r ts Clas M1	in Traini m + F sified : M2	ng Set) IDI); F as M548	PCC =	96.4%
M35 able 6: BMP2#1 BMP2#2	ependen Class BMP2 256 202	t Test Di Sifier BTR60	ata Perfo BTR70	nman Nu M109	Confuse CCE (C mber o M110	f Targe M113	es (Not ( 0.3r ts Clas M1	in Traini m + F sified : M2	ng Set) IDI); F as M548	PCC = T72	96.4%
M35 able 6: BMP2#1 BMP2#2 BMP2#3	Ependen Class BMP2 256 202 195	t Test Da Sifier BTR60 4 2	ata Perfo BTR70 2 4	nrman Nui M109	Confuse ICE (O mber of M110	f Targer M113	es (Not ( 0.3r ts Clas M1	in Traini m + F sified : M2 17 22	ng Set) IDI); F as M548	PCC = 172 10 17	96.4%
M35 Inde able 6: BMP2#1 BMP2#2 BMP2#3 BTR60	Example 256 202 195	t Test D Sifier BTR60 4 2 254	ata Perfo BTR70 2 4	nrman Nur M109 2	Confuse ICCE (C mber of M110	f Targe M113	es (Not ( 0.3r ts Clas M1	in Traini m + F sified ; M2 17 22	ng Set) IDI); F as M548	<sup>D</sup> CC = 172 10 17	96.4%
M35 Inde able 6: BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70	BMP2 256 202 195	t Test D Sifier BTR60 4 2 254	ata Perfo BTR70 2 4 256	Prman Nui M109 2	Confuse ace (C mber o M110	er Vehick 0.3m > f Targe M113 1 4	es (Not ( 0.3r ts Clas M1	in Traini m + H sified a M2 17 22	ng Set) IDI); F as M548	PCC = 172 10 17	96.4%
M35 Inde able 6: BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109	BMP2 256 202 195	t Test Di Sifier BTR60 4 254	ata Perfo BTR70 2 4 256	2 256	Confuse ace (0 mber of M110	f Targe M113	es (Not ( 0.3r ts Clas M1	in Traini m + F sified : M2 17 22	ng Set) IDI); F as M548	PCC = 172 10 17	96.4% Unknown 19 10 2
M35 Inde able 6: BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110	BMP2 256 202 195	t Test Di Sifier BTR60 4 2 254	ata Perfo BTR70 2 4 256	2 256	Confuse CCE (C mber o M110 256	f Targe M113	es (Not ( 0.3r ts Clas M1	in Traini m + H sified a M2 17 22	ng Set) IDI); F as M548	PCC = 172 10 17	96.4% Unknown 19 10 2
M35 Inde able 6: BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 BTR70 M109 M110 M113	ependen Class BMP2 256 202 195	t Test Di Sifier BTR60 4 2 254	ata Perfo BTR70 2 4 256	2 256	Confuse Ce (C mber or M110 256	f Targe M113 1 4 255	es (Not ( 0.3r ts Clas M1	in Traini m + H sified a M2 17 22	ng Set) IDI); F as M548	DCC =	240 96.4% Unknown 19 10 2
M35 Inde able 6: BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1	Example 256 202 195	t Test Di Sifier BTR60 4 254	ata Perfo BTR70 2 4 256	2 256	Confuse CCE (C mber or M110 256	er Vehick 0.3m > f Targer M113 1 4 255	es (Not ( 0.3r ts Clas M1 255	in Traini m + H sified : M2 17 22	ng Set) IDI); F as M548	DCC =	96.4%
M35 Inde able 6: BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1 M113 M1	penden   Class   BMP2   256   202   195	t Test D. Sifier BTR60 4 254	ata Perfo 2 4 256	2 256	Confuse Ce (C mber o M110	f Targe M113 1 4 255	es (Not i ( 0.3r ts Clas M1 255	n Traini n + H sified : M2 17 22 256	ng Set) IDI); F as M548	DCC =	96.4% Unknown 19 10 2 1
M35 Inde able 6: BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1 M113 M1 M2#1 M2#1	ependen Class 256 202 195	t Test Di Sifier BTR60 4 2 254	ata Perfo 2 4 256	2 256	Confuse CCE (C mber or M110 256	r Vehick .3m > f Targe M113 1 4 255 2	es (Not i CO.3r ts Clas M1 255 1	n Traini n + H sified : M2 17 22 256 188	ng Set) IDI); F as M548	DCC =	96.4%
M35 Inde able 6: BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1 M113 M1 M2#1 M2#1 M2#2 M2#3	ependen Class 256 202 195	t Test Di Sifier BTR60 4 2 254	ata Perfo 2 4 256 2 2 2	2 256 13 16	Confuse CCE (C mber or M110 256 11 5	r Vehicle .3m > f Targer M113 1 4 255 2 3	es (Not i <u>( 0.3r</u> ts Clas <u>M1</u> 255 1 1	n Traini n + H sified : M2 17 22 256 188 180	ng Set) IDI); F as M548	PCC = 172 10 17 24 27	96.4% Unknown 19 10 2 1 1 10 13
M35 Inde able 6: BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1 M2#1 M2#1 M2#1 M2#2 M2#3 M548	ependen Class 256 202 195 4 8	t Test Di Sifier 4 2 254	ata Perfo 2 4 256 2 2 2	2 256 13 16	Confuse CCE (C mber o M110 256 11 5	er Vehick 2.3m > f Targe M113 1 4 255 2 3	es (Not ( 0.3r ts Clas M1 255 1 1	n Traini n + F sified 3 M2 17 22 256 188 180	ng Set) IDI); F as M548	PCC = 172 10 17 24 27	96.4% Unknown 19 10 2 1 1 10 13
M35 Inde able 6: BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1 M2#1 M2#1 M2#2 M2#3 M548 T72#1	256 202 195 4 8	t Test Di Sifier 4 2 254	ata Perfo 2 4 256 2 2 2	2 256 13 16	Confuse CCE (C mber o M110 256 11 5	er Vehick 2.3m > f Targe M113 1 4 255 2 3	es (Not CO.3r ts Clas M1 255 1 1	n Traini n + H sified 3 M2 17 22 256 188 180	ng Set) IDI); F as M548	PCC = 172 10 17 24 27 256	96.4% Unknown 19 10 2 1 1 10 13
M35 Inde able 6: BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1 M2#1 M2#1 M2#2 M2#3 M548 T72#1 T72#2	256 202 195 4 8	t Test Di Sifier BTR60 4 2 254	ata Perfo 2 4 256 2 2	2 256 13 16 5	Confuse Ce (C mber or M110 256	er Vehick 2.3m > f Targe M113 1 4 255 2 3 1	es (Not ( 0.3r ts Clas M1 255 1 1 7	n Traini n + H sified 3 M2 17 22 256 188 180 10	ng Set) IDI); F as M548 256	DCC = 172 10 17 24 27 256 190	240 96.4% 19 10 2 1 1 10 13 39
M35 Inde able 6: BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M113 M1 M2#1 M2#1 M2#3 M548 T72#1 T72#2 T72#3	256 202 195 4 8 3 5	t Test Di Sifier 4 2 254 1	ata Perfo 2 4 256 2 2	2 256 13 16 5 3	Confuse CCE (C mber or M110 256 256 11 5	er Vehick 2.3m > f Targer M113 1 4 255 2 3 1	es (Not i ( 0.3r ts Clas M1 255 1 1 7 3	n Traini n + H sified : M2 17 22 256 188 180 10 10	ng Set) IDI); F as M548 256	DCC = 172 10 17 24 27 256 190 211	240 96.4% 19 10 2 1 1 10 13 39 14
M35 Inde able 6: BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1 M2#1 M2#1 M2#1 M2#1 M2#3 M548 T72#1 T72#2 T72#3 HMMWV	256 202 195 4 8 3 5 25	t Test Di Sifier BTR60 4 254 254 1 1 8	ata Perfo 2 4 256 2 2 2 8	2 256 13 16 5 3 1	Confuse Ce (C mber o M110 256 11 5 4	er Vehick 2.3m > f Targer M113 1 4 255 2 3 1 101	es (Not i ( 0.3r ts Clas M1 255 1 1 7 3	n Traini n + H sified : M2 17 22 256 188 180 10 10 8	ng Set) IDI); F as M548 256	DCC = 172 10 17 24 27 256 190 211	96.4% Unknown 19 10 2 1 1 10 13 39 14 93
M35 Inde able 6: BMP2#1 BMP2#2 BMP2#3 BTR60 BTR70 M109 M110 M113 M1 M2#1 M2#1 M2#1 M2#1 M2#3 M548 T72#1 T72#2 T72#3 HMMWV M35	ependen Class 202 195 4 8 3 5 25 1	t Test D. Sifier BTR60 4 254 254 1 1 8	ata Perfo 2 4 256 2 2 2 8	2 256 13 16 5 3 1 3	Confuse Ce (C mber or M110 256 11 5 4	er Vehick .3m > f Targe M113 1 4 255 2 3 1 101 6	es (Not i ( 0.3r ts Clas M1 255 1 1 7 3	n Traini n + H sified : M2 17 22 256 188 180 10 10 8	ng Set) IDI); F as M548 256 14	PCC = 172 10 17 17 24 27 256 190 211	240 96.4% 19 10 2 1 10 13 39 14 93 230

Figure 7 presents a bar chart of the 10-target classifier probability of correct classification (Pcc) versus SAR image resolution. The corresponding classifier confusion matrices for the results presented in Figure 7 are presented above in Tables 3 through 7.





## 4 SUMMARY AND CONCLUSIONS

Phase gradient SAR image focusing was demonstrated to provide well-focused imagery; cross-range smearing of the imagery was significantly reduced, resulting in higher probability of correct classification as demonstrated by a 20+ target model-based classifier. High Definition Imaging was demonstrated to improve the image quality of complex SAR imagery; the effective resolution of SAR imagery was shown to be increased as demonstrated by the improved Pcc achieved by a 10-target template-based classifier.

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