ATR from SAR Images using Target Region Outline Descriptors & Kernel-Based Classification.

Dr. Georgios C. Anagnostopoulos
Associate Professor of ECE @ FIT
georgio@fit.edu
http://my.fit.edu/~georgio

Computer Science Seminar @ FIT
Friday, February 27th 2009
Over the last decade, a sizeable sector of Automatic Target Recognition (ATR) research has focused on recognizing a variety of military ground targets based on Synthetic Aperture Radar (SAR) imagery data. While SAR technologies have become very efficient in providing good resolution radar maps of battlefields, identification of targets has been challenging due to variations in radar illumination over a scene and varying target poses.

To date, the bulk of successful ATR approaches can be grouped into two main categories: template-based and target geometry-based. Rather than using a single prototype for each class, template-based methods typically utilize reference collections in the spatial or frequency domain to account for intra-class variability, which are then used as prototypes for exemplar-based classifiers to make decisions. Template-based approaches have demonstrated high recognition quality, but directly utilize the raw radar magnitude returns and, therefore, are more prone to suffer in terms of generalization on unseen target signatures under extended operating conditions.

On the other hand, geometry-based approaches include methods that base their decision on the geometrical characteristics of the target and, therefore, significantly reduce the number of classification features employed in comparison to template-matching methods. Rather than considering the raw image intensity values as individual features, these methods preprocess the images and extract a relatively small amount of target geometry- and landmark-based features that are capable of capturing important information about a target class. While the reduced number of features of these methods promises more parsimonious recognizers, practice has unfortunately shown limited success. The probable cause is that these methods typically incorporate or assume invariances that often are of no use in SAR imaging.

The present talk presents preliminary work in attempting to develop an ATR approach that utilizes a limited amount of simple, yet robust geometry-based features in conjunction with a sparse, kernel-based classifier to obtain good generalization properties. In specific, approximate target outlines are first determined from SAR images via a simple mathematical morphology-based segmentation approach that discriminates target from radar shadow and ground clutter. Next, the obtained outlines are expressed as truncated Elliptical Fourier Series (EFS) expansions, whose coefficients are utilized as discriminatory features and processed by an ensemble of SVM classifiers.

In order to experimentally illustrate the merit of the proposed scheme, classification results on a 3-class target recognition problem are reported using SAR intensity imagery from the well-known Moving and Stationary Target Acquisition and Recognition (MSTAR) dataset. The novel approach was compared to a selected methods mentioned in the literature in terms of classification accuracy. The results illustrate that only a small amount of EFS coefficients is necessary to achieve recognition rates that rival other established methods and, thus, target outline information can be a powerful discriminatory feature for automatic target recognition applications relevant to SAR imagery.
Overview

- Synthetic Aperture Radar Imaging
  - Basic Concepts
- SAR-based ATR
  - Facts, Previous Approaches
- A Fresh Approach
  - Main Idea, Segmentation, Feature Extraction, Classification
- Elliptic Fourier Series
  - Basic Concepts, Coefficient Properties, Descriptors
- Experiments
  - Data Set, Outcomes
- Epilogue
  - Conclusions, Acknowledgments, Discussion
Synthetic Aperture Radar Imaging

Basic Concepts, Coefficient Properties, Descriptors
The Synthetic Aperture

- Aircraft emits a series of pulses while flying at constant speed & height
- Returning echoes are recorded, digitally processed and combined
- The obtained imaging result (radar reflectivity map) is almost equivalent to that of a very large antenna; thus, the term synthetic aperture.
- Image resolution is mainly proportional to the radio signal bandwidth (several feet to a few centimeters or lower)
Nature of the data
- Amplitude & phase for each location (pixel)
- Phase is usually discarded
- Pixel intensities correspond to amplitude of returns

Nature of images
- Targets have high reflectivity, so produce high intensity returns
- The ground reflects too but much less; this results in ground clutter (unwanted)
- Depending on the depression angle of the radar, there will be a shadow.
Nature of Targets in Images

- Different targets have **different configuration of reflective surfaces** and produce different images.
- The same target may generate a different reflective map depending on **target pose** (azimuth w.r.t. radar).

1.5º  61.5º  121.5º  181.5º  241.5º  301.5º
**Demonstration:** Reflective map as a function of pose.
SAR-based ATR

Basic Concepts, Coefficient Properties, Descriptors
A sizeable sector of Automatic Target Recognition (ATR) research has focused on recognizing a variety of military ground targets based on Synthetic Aperture Radar (SAR) imagery data.

SAR technologies have become very efficient in providing good resolution radar maps of battlefields.

Identification of targets has been challenging due to variations in radar illumination over a scene, varying target poses and, at least in the past, low resolution.

Current battlefield needs dictate unsupervised, ATR capabilities.

2S1 on the right, T62-C on the left. Can you tell a difference?
Template-Matching Methods

- Reference images (templates) in either the spatial or frequency domain that are generated from the training set
- Several templates are obtained to form an ensemble of templates for each target class to account for intra-class distortion due to variations in pose and illumination, as well as noise
- Each test image is compared to these templates in terms of a suitable distance metric, which is based on MSE, ML, correlation score, or other criteria.
Previously Studied Template Matching Methods

- **Correlation Score** criterion
  - Maximum Average Correlation Height (MACH) combined with Distance Correlation Classifier Filter (DCCF) [1]
  - Extended Maximum Average Correlation Height (EMACH) [2]
  - Polynomial Distance Correlation Classifier Filter (PDCCF) [2]
  - Minimum Noise and Correlation Energy (MINACE) [3]

- **Minimum Square Error** criterion
  - Quarter Power [4]
  - Log Magnitude [4]

- **Maximum Likelihood**
  - Conditionally Gaussian [4]

Disadvantages of Template Matching Methods

- Potentially **large demands in memory**: Large database of templates may have to be maintained in memory

- **Computationally intensive**:
  - Usually **high-dimensional feature space** involved
  - Example: 128x128 pixel image amounts to 16384 features

- Also, **large training set** involved as mentioned before

- Entire scene **including clutter** is incorporated into the templates. Clutter does not contain any discriminatory information.
High-level feature & geometry based approaches

- Features cannot always be computed accurately from raw sensor data, yet convey important information about the image
  - Examples: Length, width, pose, location of peaks, and other landmark- or geometry-related features of the target region [1]-[5]
- Radar Cross Section (RCS) [1]
  - Measure of how well a target reflects radar waves
- Log Standard Deviation (LSD) [1]
  - Measures the inter-pixel variation in intensity of pixels in the target region (textual roughness of region)
- Hu Moments, Principle Component Analysis (PCA), Independent Component Analysis (ICA) [7]

Disadvantages of Aforementioned Methods

- Certain geometric quantities cannot be estimated accurately enough (e.g. target width, length)
- Other landmark-based features are equally unreliable due to variations in illumination and pose; they have to explicitly treat different target poses like template based methods.
- Most of these methods implicitly assume certain invariances, including rotation invariance, which is not necessarily helpful.
- Dimensionality reduction methods like PCA and ICA could pose computational challenges and by nature may not be suitable for on-line learning. Also, they lack the ability to provide insight into the nature of the ATR problem.
A Fresh Approach

Features, Classification Method,
Investigate the potential of **target outline descriptors** as classification features.
- Outlines are usually more robustly estimated than other geometry- or landmark-based features.
- Outlines vary by target type and pose, not as much on radar illumination. Different poses are treated in a uniform way. Ultimately, pose information is not used in the model training process.

Aim to reduce the feature space dimensionality by using only a small subset of contour descriptors.
- Potentially **reducing computational complexity**, while trying to maintain interpretability and high-quality classification performance.
- Avoid unnecessary (and, potentially, harmful) invariance assumptions.

**Steps**
- Identify the target region via appropriate mathematical morphology-based **segmentation**
- Efficiently and compactly **describe the target outline**
  - We will use contour descriptors based on **Elliptic Fourier Series** (EFS) coefficients
- Propagate the target outline information to a robust classification system
  - We will use a sparse kernel machine, such as a **Support Vector Machine** as our model building block.
The magnitude SAR image of a candidate target is binarized twice via simple thresholding.

- Intensity threshold is selected as 0.4 of the peak intensity to yield a peak target region.
- Intensity threshold is selected as 0.15 of the peak intensity to yield an approximate target region.
- Morphologically close target region using a 3 by 3 structuring element
  - Close operation fills holes/small gaps in a binary image while preserving the boundary detail of an image
- Final Estimate of Target Region Characteristic Function is selected as any region of the closed target region that intersects any peak region
  - Approach preserves edge information of the target region while rejecting noise from the clutter region
Once the region has been identified, its boundary is extracted. EFS-based descriptors are calculated given this boundary.

- More on EFS in a little bit.
Support Vector Machines (SVM)
- Member of the Kernel methods in Machine Learning
- Allow for sparse representations, which may lead to superior generalization results.
- Via the “kernel trick” employ implicit mappings, which may facilitate these sparse representations

**Primal Problem**
\[
\text{minimize} \quad \frac{1}{2} \|w\|^2 + C \sum_i \xi_i \\
\text{s.t.} \quad y_i \left(\langle w, x_i \rangle + b \right) - 1 + \xi_i \geq 0
\]
Real data
- Using RBF Kernel

Legend
- **Green points**: class 1 patterns
- **Red points**: class 2 patterns
- **Yellow points**: support vectors
- **White lines**: maximum margin
- **Blue line**: decision boundary
We utilized the DAG-SVM [1] voting mechanism to cope with the multi-class nature of our problem.

Under this scheme only C-1 SVMs need to be evaluated to make a decision.

Each SVM need only be trained on two classes of the training data rather than the whole set of data.

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Elliptical Fourier Series

Basic Concepts, Coefficient Properties, Descriptors
Assume a parametric, closed curve $C$ on the plane. Since $C$ is closed, then we can assume that there is a parameterization based on a variable $\theta$, such that

$$C = \{(x, y) \in \mathbb{R}^2 \mid \mathbf{r}(\theta) = [x(\theta) \ y(\theta)]^T \quad \theta \in [0, 2\pi]\}$$

$$\mathbf{r}(\theta + 2\pi) = \mathbf{r}(\theta) \quad \forall \theta \in \mathbb{R}$$

Let $\mathbf{p}_k(\theta)$ be the phasor with integer angular frequency $k$ defined as

$$\mathbf{p}_k(\theta) \doteq \begin{bmatrix} \cos(k\theta) \\ \sin(k\theta) \end{bmatrix} \quad k = 0, 1, 2, \ldots$$
Under some mild constraints that typically apply to Fourier signal representations, the parametric description of can be expressed as an Elliptical Fourier Series (EFS), whose synthesis and analysis equations are

\[
\mathbf{r}(\theta) = \sum_{k=0}^{\infty} \mathbf{F}_k \mathbf{p}_k(\theta) \\
\mathbf{F}_k = \int_{2\pi} \mathbf{r}(\theta) \mathbf{p}_k^T(\theta) d\theta \quad k = 0, 1, 2, \ldots
\]

The matrix quantity \( \mathbf{F}_k \in \mathbb{R}^{2\times2} \) is called the \( k \)-th-order EFS coefficient of \( C \). In essence, this coefficient contains the ordinary \( k \)-th-order Fourier Series (FS) coefficients of the periodic function \( x(\theta) \) in its first row and of \( y(\theta) \) in its second row. The coefficient \( \mathbf{F}_0 \) is given as

\[
\mathbf{F}_0 = [\mathbf{r}_o \mid 0]
\]

where \( \mathbf{r}_o \) is the curve’s center of mass and \( 0 \) is the zero column vector.

Additionally, the synthesis equation reveals that \( \mathbf{r}(\theta) \) can be expressed as a superposition of phasors that are rotating at angular speeds that are proportional to their order \( k \).
Elliptical Fourier Series

Properties of EFS Coefficients

- **Spatial translation**

  \[ r'(\theta) \triangleq r(\theta) + \Delta r \quad \Rightarrow \quad \begin{cases} F'_o = F_o + [\Delta r \ \ | \ \ 0] \\ F'_k = F_k \quad k = 1,2,... \end{cases} \]

- **Generalized Scaling**

  \[ r'(\theta) \triangleq A_r(\theta) \quad \Rightarrow \quad F'_k = A F_k \quad k = 0,1,2,... \]

- **Shift (Starting Point)**

  \[ r'(\phi) \triangleq r(\phi - \psi) \quad \Rightarrow \quad \begin{cases} F'_o = F_o \\ F'_k = F_k H(k \psi) \quad k = 1,2,... \end{cases} \]

  where

  \[ H(\phi) \triangleq \begin{bmatrix} \cos(\phi) & -\sin(\phi) \\ \sin(\phi) & \cos(\phi) \end{bmatrix} \quad \phi \in (-\pi, \pi) \]

- is a rotation matrix that rotates a planar vector by an angle \( \phi \) in a counter-clockwise direction.
Elliptical Fourier Series

Properties of EFS Coefficients

- **Decomposition** \(^{[1]}\)

\[
F_k = \begin{cases} 
H(\phi_k) S_k \Lambda_k H(\psi_k) & \lambda_{1k} > \lambda_{2k} > 0 \\
\lambda_k S_k H(\psi_k) & \lambda_{1k} = \lambda_{2k} = \lambda_k > 0 
\end{cases} 
\quad k = 1, 2, ..., \\
\Lambda_k = \text{diag}\{\lambda_{1k}, \lambda_{2k}\} \\
S_k = \text{diag}\{1, s_k\} \\
\phi_k \in (-\pi/2, \pi/2] \\
\psi_k \in (-\pi, \pi] \\
s_k = \pm 1
\]

- For non-trivial, planar curves, each EFS coefficient can be associated to an **ellipse** (or, as a special case, to a circle) with major and minor axis lengths \(\lambda_{1k}\) and \(\lambda_{2k}\) respectively with \(\lambda_{1k} \geq \lambda_{2k} > 0\).

- The \(k\)\(^{th}\) phasor is moving on the coefficient’s associated ellipse, whose major axis is tilted by \(\phi_k\) radians with respect to the positive x semi-axis (we will refer to it as **rotation**).

- If the ellipse’s orientation is adjusted so that \(\phi_k = 0\) for \(\theta = 2\pi n\), phasor \(p_k(\theta)\) will form an angle of \(\psi_k\) radians with the major axis, which we will refer to as **shift**.

- The phasor’s motion will be counter-clockwise or clockwise, if \(s_k = 1\) or \(s_k = -1\) respectively.

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Elliptical Fourier Series

Geometric insight

- Geometric Interpretation of $F_k$
Elliptical Fourier Series
Geometric insight

Demonstration: Superposition of 3 components
Advantages

- Facilitates an appealing geometric interpretation
- Truncation of the EFS always reconstructs a closed shape boundary. This is an important quality for outline smoothing.
  - Not always true for other Fourier-based planar shape descriptors
- It can handle both convex and non-convex shape outlines.
- Can be used to derive shape descriptors that can be used to characterize, smoothen or approximate the outline of planar objects, which makes the EFS representation ideal for smoothing outlines in contrast to other Fourier representations [1].
- Easy calculation of EFS coefficients can be achieved via Fast Fourier Transforms for spatially-sampled curves as illustrated in [2]

Disadvantages

- EFS representation does not always yield a non-self-intersecting curve.
  - Not important, because it can be shown that the non-self-intersection quality is conserved after EFS truncation.

Elliptical Fourier Series
Planar Curve Descriptors based on EFS Coefficients

- Possible desiderata for EFS-based planar curve descriptors
  1. **Translation invariant**
     SAR Images: Important as the exact target location within a frame is not important.
  2. **Shift invariant**
     SAR Images: Important as the exact starting point for traversing a target outline may be arbitrary.
  3. **Scale invariant** (a possibility)
     SAR Images: Usually isn’t important, because of radar operational procedures
  4. **Rotation invariant** (another possibility)
     SAR Images: Undesirable, because target pose is relative to radar and SAR images of different azimuths do not correspond to rotations of a common image.

- Translation & Shift Invariant descriptors
  - Normalization with respect to first coefficient

\[
D_k = F_k \left( F_1^k \right)^T \quad k = 1, 2, \ldots
\]

\[
\tilde{D}_k = F_k H \left( -k \psi_1 \right) \quad k = 1, 2, \ldots
\]

- Potential Issue if \( F_1 \) is close to singular (very oblong 1st ellipse).
Experiments

Basic Concepts, Coefficient Properties, Descriptors
Experiments Data Set

- Various ground targets from the MSTAR Collection [1]

Some Experimental Results

Data Set

- Dataset Characteristics
  - 10 classes, 72 poses per target (every 5°), 48-by-48 pixels (lowest resolution)
  - In order to cope with the small dataset sizes involved, we used images that were recorded at a 17° compression angle for training, and the ones recorded at 15° compression angle for testing purposes. The legitimacy of this experimental setup stems from the fact that the differences between corresponding SAR images at 15° and 17° are assumed negligible, as has been done in prior works.

<table>
<thead>
<tr>
<th>Vehicle Class</th>
<th>Number Of Training Images</th>
<th>Number Of Testing Images</th>
</tr>
</thead>
<tbody>
<tr>
<td>2S1</td>
<td>299</td>
<td>274</td>
</tr>
<tr>
<td>BMP2</td>
<td>697</td>
<td>587</td>
</tr>
<tr>
<td>BRDM2</td>
<td>298</td>
<td>274</td>
</tr>
<tr>
<td>BTR60</td>
<td>256</td>
<td>195</td>
</tr>
<tr>
<td>BTR70</td>
<td>233</td>
<td>196</td>
</tr>
<tr>
<td>D7</td>
<td>299</td>
<td>274</td>
</tr>
<tr>
<td>T62</td>
<td>299</td>
<td>273</td>
</tr>
<tr>
<td>T72</td>
<td>691</td>
<td>582</td>
</tr>
<tr>
<td>ZIL131</td>
<td>299</td>
<td>274</td>
</tr>
<tr>
<td>ZSU23 A</td>
<td>299</td>
<td>274</td>
</tr>
<tr>
<td>Entire Set</td>
<td>3670</td>
<td>3203</td>
</tr>
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Results

<table>
<thead>
<tr>
<th>Feature Set</th>
<th>Number of Features</th>
<th>Classifier</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>QP Normalized Image</td>
<td>2304</td>
<td>Nearest Neighbor</td>
<td>94.10%</td>
</tr>
<tr>
<td>MINACE</td>
<td>4096</td>
<td>Nearest Neighbor</td>
<td>90.60%</td>
</tr>
<tr>
<td>Normalized Image</td>
<td>2304</td>
<td>Max Wins SVM</td>
<td>90.99%</td>
</tr>
<tr>
<td>PCA</td>
<td>28</td>
<td>Max-Wins SVM</td>
<td>89.56%</td>
</tr>
<tr>
<td>10 EFS-based descriptors</td>
<td>38</td>
<td>DAG-SVM</td>
<td>91.47%</td>
</tr>
<tr>
<td>7 EFS-based descriptors</td>
<td>26</td>
<td>DAG-SVM</td>
<td>97.31%</td>
</tr>
<tr>
<td>3 EFS-based descriptors</td>
<td>10</td>
<td>DAG-SVM</td>
<td>85.12%</td>
</tr>
</tbody>
</table>
### Results

- **Confusion Matrix for Quarter Power Method on the 10-class problem**

<table>
<thead>
<tr>
<th>Actual Class</th>
<th>2S1</th>
<th>BMP2</th>
<th>BRDM2</th>
<th>BTR60</th>
<th>BTR70</th>
<th>D7</th>
<th>T62</th>
<th>T72</th>
<th>ZIL131</th>
<th>ZSU234</th>
</tr>
</thead>
<tbody>
<tr>
<td>2S1</td>
<td>252</td>
<td>4</td>
<td>6</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>BMP2</td>
<td>1</td>
<td>559</td>
<td>7</td>
<td>2</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>9</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>BRDM2</td>
<td>0</td>
<td>2</td>
<td>246</td>
<td>8</td>
<td>9</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>9</td>
</tr>
<tr>
<td>BTR60</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>194</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>BTR70</td>
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<td>1</td>
<td>5</td>
<td>0</td>
<td>190</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>D7</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>271</td>
<td>1</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>T62</td>
<td>3</td>
<td>1</td>
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<td>2</td>
<td>2</td>
<td>0</td>
<td>227</td>
<td>24</td>
<td>9</td>
<td>5</td>
</tr>
<tr>
<td>T72</td>
<td>0</td>
<td>14</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>0</td>
<td>7</td>
<td>557</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>ZIL131</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>6</td>
<td>0</td>
<td>1</td>
<td>6</td>
<td>257</td>
<td>0</td>
</tr>
<tr>
<td>ZSU234</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>9</td>
<td>0</td>
<td>261</td>
</tr>
</tbody>
</table>

**Estimated Class Accuracy**

- 2S1: 98.05%
- BMP2: 95.88%
- BRDM2: 93.18%
- BTR60: 92.38%
- BTR70: 87%
- D7: 99.27%
- T62: 95%
- T72: 91.61%
- ZIL131: 91.46%
- ZSU234: 97.03%

**Total Classification Accuracy**: 94.10%
- **Results**
  - Confusion Matrix for EFS7 on the 10-class problem

<table>
<thead>
<tr>
<th>Actual Class</th>
<th>Estimated Class</th>
<th>Classificati on Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZSU23 4</td>
<td>2S1 255 BMP2 574 BRDM2 2 BTR60 3 BTR70 4 D7 0 T62 1 T72 2 ZIL131 0</td>
<td>97.32%</td>
</tr>
<tr>
<td>BMP2 1</td>
<td>574 3 BTR60 2 BTR70 4 D7 0 T62 1 T72 2 ZIL131 0</td>
<td>97.28%</td>
</tr>
<tr>
<td>BRDM2 0</td>
<td>2 BTR60 3 BTR70 4 D7 0 T62 1 T72 2 ZIL131 0</td>
<td>99.02%</td>
</tr>
<tr>
<td>T62 1</td>
<td>1 228 D7 1 271 T72 1 ZIL131 0</td>
<td>99.02%</td>
</tr>
<tr>
<td>T72 0</td>
<td>2 204 D7 1 203 T62 1 ZIL131 0</td>
<td>98.90%</td>
</tr>
<tr>
<td>ZIL131 1</td>
<td>1 1 7 275 D7 1 271 T72 1</td>
<td>98.32%</td>
</tr>
<tr>
<td>ZSU23 4</td>
<td>0 0 0 0 0 T62 1 Z72 1 228 D7 1</td>
<td>95.81%</td>
</tr>
<tr>
<td>Estimate Accuracy</td>
<td>98.8% 98.6% 97.7% 95.3% 93.5% 99.2% 95.3% 96.2% 98.2% 98.5%</td>
<td></td>
</tr>
<tr>
<td>Total Classification Accuracy</td>
<td>97.31%</td>
<td></td>
</tr>
</tbody>
</table>
Epilogue

Conclusions, Acknowledgments, Discussion
Conclusions
...and a brief summary.

- Pure target outline has not been investigated by others before. To the best of our knowledge, the contour description features just discussed are a first attempt along this direction.

- Target outline seems to be a robust feature for SAR target classification

- Only a few EFS-based contour descriptors are sufficient to satisfactorily describe target region outlines.

- The novel approach featured in this work, meaning the combination of EFD descriptors of the target region combined with SVM-based classification stage is computationally faster than popular competing approaches.
Many thanks to

**Louis P. Nicoli**
- Advisee, MS in EE at FIT, 2007; currently at Harris Corporation.
- Most of the experimental research on the present subject.

**Chris Sentelle**
- Co-advisee, Ph.D. Candidate in EE at UCF; currently at L3 CyTerra.
- SVM-related images.

**National Science Foundation**
- Grant No. 0647018 & 0647120
Theory of Neural Networks
Summer 2009

About the Course
Artificial Neural Networks (ANNs) refer to mathematical models that were invented to imitate the capabilities and qualities of real, biological neurons. In the research process of 3 decades they have proven themselves as powerful computational models and have found profound application in a variety of domains. The advertised introductory course focuses on ANNs and the theory behind them. It is offered at the graduate level as ECE 5268 in the Summer of 2009 by the ECE Dept. at Florida Tech and is instructed by Dr. Georgios C. Anagnostopoulos.

Course Objective
The goal of this course is to provide a basic introduction to elements of neural computation. After reviewing some basic material in Linear Algebra and Vector/Matrix Calculus, a variety of popular Artificial Neural Network (ANN) models along with their associated learning rules will be examined in depth. The utility of each model will be discussed and examined. In the process the student will also be exposed to a variety of Numerical Optimization techniques in the classic domain (like Gradient Descent, Newton-based and other methods) as well as in the combinatorial realm (like Genetic Algorithms, Particle Swarm Optimization, etc.). In addition, several applications based on ANN models will be discussed and demonstrated throughout the course.
Discussion

- Please feel free to ask any questions!
Many thanks for attending my presentation...