AATR Technical Review: March 22, 2018

• Institution: Boston University

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Executive Summary

• Requirements: adapt EDS ATR system to changes in:
  • Desired $P_D$, $P_{FA}$
  • Definition of threats: mass, density, thickness, type, ...
  • Differential $P_D$, $P_{FA}$ per threat class
  • New threats from specifications without training data

• Approach:
  • Modify ATR performance by retraining with reweighing
  • Cross-validate predicted performance with training data before deploying
  • For objects with no training data, use hierarchical classifier approach trained based on false alarm performance
Technical Description: Baseline ATR

• Standard processing sequence: Segment Objects, Extract features, Classify Objects

• Segmentation
  • Restrict images to densities in window of interest
  • Precondition images with bilateral filtering to enhance contrast, reduce effect of metal artifacts
    • No other metal artifact correction techniques used
  • Connected component labeling for initial segmentation – result in merged and split objects
  • Merged objects initially split along histograms
  • Secondary object splitting technique based on histogram of widths to detect merging of sheet/bulk objects, followed by sheet segmentation
    • Extensions of skeletonization and distance transforms

CT Images ➔ Segment Objects ➔ Extract Features ➔ Classify Objects ➔ Threat Detections

CT slice

Width Histogram

Spit of merged object into sheet, two bulks
• Feature extraction
  • Ground-truth labeled data (TO-4): Segmented volumes with object labels for potential threats
  • For each volume, focus on interior region to extract features
  • Main features: average density, overall density variance, local texture (average variance of density over local textures)
  • Secondary features: volume, mass, thickness, shape (discrete: sheet vs bulk)
  • Note: Secondary features known for many training data objects, must be estimated from data for test objects

Texture measure:
Standard deviation of density values, averaged across patches in object
Baseline ATR - 3

- **Classification**
  - Two-stage classification: Identify potential threats with primary features, then prune with selected secondary features (mass, thickness)
  - Training data selected based on ORS specification to have balanced threats, confusers in desired region of interest

- **Primary Classifier family: Random Forests**
  - Ensemble classifier with multiple decision trees (60)
  - Each tree trained with random subset of data, random selection of feature orders
  - Best performer (but not by much) in recent JMLR article (Fernández ’14)
  - Believed as more robust to generalization

- **Secondary classifier family**
  - Minimum size thresholds (mass, thickness)
Adaptive ATR

• Philosophy of approach:
  • Develop general adaptation approaches that are applicable across ATR systems (e.g. SVMs, decision trees, random forests, AdaBoost)
  • Exploit theory for adaptation of parametric classifiers in decision theory

• Adaptation with respect to desired PD/PFA tradeoff (AM1)
  • Parametric approach: modify costs of PD vs PFA errors
  • Our approach: Zadrozny, Langford, Abe ‘03 – Transparent Box approach: reweight data
  • Select weights using cross validation on training data with bagging: train on 80%, test on 20%

• Results in predicted ROC curve
Adaptive ATR - 2

• Adaptation with respect to change of threat material (AM2)
  • Retraining classifier trees

• Adaptation with differential PD/PFA for different materials (AM3)
  • Limited parametric theory: Differential weights on errors for different materials
  • Select differential weights using cross validation on training data

• Adaptation with respect to minimum mass (AM4)
  • Secondary classification: potential threats identified reduced using mass-based threshold
  • Threshold tuned to preserve PD on training data, compensate for segmentation errors

• Adaptation with respect to minimum thickness (AM5)
  • Secondary classification: potential threats reduced using minimum thickness
  • Threshold tuned to preserve PD on training data, allow for errors in thickness estimates
Adaptation with respect to new threats with no training data (TO7-AM2)

- Main issue: no training data (labeled or otherwise)
- Limits ability to extract same features, use similar classifiers
- Only information provided: density range, minimum mass and thickness

Approach: Hierarchical classifier

- Parallel classifiers: baseline as previous plus added classifier using only features as in ORS
- New features: average density, mass, thickness

Cannot use cross-validation to estimate PD for added classifier: hard to predict performance

- No training samples of threats
- Select parameters based on training data PFA
- Alternative: simulate samples (ideally with full tomography model), not used
Evaluation Metrics

• Output of ATR: Volumetric image with location of detected threat volumes in bag

• Ground truth used in scoring: Volumetric image of true threat volumes in bag, hand developed using videos of packing container plus manual recognition

• Fundamental metrics:
  • Detection: Significant overlap between detected threat volume and ground truth threat volume
  • False alarm: Reported threat volume that does not have corresponding ground truth threat volume
Results & Comments

- Some segmentation leakage limits upside in PD
  - Particularly with limited metal artifact correction
  - Best seen in AM4 where large mass objects are split
- Random forest shows significant variability in performance
  - Insufficient training data for technique?
- Hard to get second PD down in AM3 with reweighting approach

### Table 1: AROC

<table>
<thead>
<tr>
<th>OOI</th>
<th>Required PD (%)</th>
<th>Required PFA (%)</th>
<th>AATR PD (%)</th>
<th>AATR PFA (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>0.7</td>
<td>0.02</td>
<td>0.74</td>
<td>0.06</td>
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<tr>
<td>S</td>
<td>0.8</td>
<td>0.05</td>
<td>0.76</td>
<td>0.08</td>
</tr>
<tr>
<td>S</td>
<td>0.85</td>
<td>0.08</td>
<td>0.83</td>
<td>0.10</td>
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<tr>
<td>S</td>
<td>0.9</td>
<td>0.1</td>
<td>0.89</td>
<td>0.12</td>
</tr>
<tr>
<td>S</td>
<td>0.95</td>
<td>0.2</td>
<td>0.9</td>
<td>0.13</td>
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<tr>
<td>AROC</td>
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<td></td>
<td></td>
<td>0.91</td>
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### Table 2: PD/PFA for Varying OOs

<table>
<thead>
<tr>
<th>OOI</th>
<th>Required PD (%)</th>
<th>Required PFA (%)</th>
<th>AATR PD (%)</th>
<th>AATR PFA (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>90</td>
<td>10</td>
<td>90</td>
<td>20</td>
</tr>
<tr>
<td>S</td>
<td>90</td>
<td>10</td>
<td>93</td>
<td>20</td>
</tr>
<tr>
<td>R</td>
<td>90</td>
<td>10</td>
<td>92</td>
<td>20</td>
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</table>

### Table 3: Varying PD Weight

<table>
<thead>
<tr>
<th>OOI</th>
<th>Required PD (%)</th>
<th>Required PFA (%)</th>
<th>AATR PD (%)</th>
<th>AATR PFA (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C,S</td>
<td>C: 90, S: 90</td>
<td>10</td>
<td>C: 85, S: 89</td>
<td>15</td>
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<tr>
<td>C,S</td>
<td>C: 20, S: 90</td>
<td>10</td>
<td>C: 34, S: 89</td>
<td>14</td>
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<tr>
<td>C,S</td>
<td>C: 90, S: 20</td>
<td>10</td>
<td>C: 85, S: 43</td>
<td>11</td>
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</tbody>
</table>

### Table 4: PD/PFA for Varying Mass

<table>
<thead>
<tr>
<th>OOI</th>
<th>Min Mass [g]</th>
<th>Required PD [%]</th>
<th>Required PFA [%]</th>
<th>AATR PD [%]</th>
<th>AATR PFA [%]</th>
<th>Incremental Mass Range [g]</th>
<th>AATR Incremental PD [%]</th>
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</thead>
<tbody>
<tr>
<td>S</td>
<td>400</td>
<td>90</td>
<td>10</td>
<td>82</td>
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<tr>
<td>S</td>
<td>300</td>
<td>90</td>
<td>10</td>
<td>87</td>
<td>11</td>
<td>300 - 400</td>
<td>90</td>
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<tr>
<td>S</td>
<td>100</td>
<td>90</td>
<td>10</td>
<td>91</td>
<td>12</td>
<td>100 - 300</td>
<td>92</td>
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</tbody>
</table>

### Table 5: PD/PFA for Varying Thickness

<table>
<thead>
<tr>
<th>OOI</th>
<th>Min Thickness [mm]</th>
<th>Required PD [%]</th>
<th>Required PFA [%]</th>
<th>AATR PD [%]</th>
<th>AATR PFA [%]</th>
<th>Incremental Thickness Range [mm]</th>
<th>AATR Incremental PD [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
<td>10</td>
<td>90</td>
<td>10</td>
<td>80</td>
<td>9</td>
<td>N/A</td>
<td>N/A</td>
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<tr>
<td>R</td>
<td>6.5</td>
<td>90</td>
<td>10</td>
<td>74</td>
<td>10</td>
<td>6.5 - 10</td>
<td>71</td>
</tr>
<tr>
<td>R</td>
<td>0</td>
<td>90</td>
<td>10</td>
<td>70</td>
<td>10</td>
<td>0 - 6.5</td>
<td>62</td>
</tr>
</tbody>
</table>

### Table 6: ALERT Testing / TO7 Data

<table>
<thead>
<tr>
<th>OOI(s)</th>
<th>Density Range [MUH]</th>
<th>Minimum Mass [g]</th>
<th>Required PD [%]</th>
<th>Required PFA [%]</th>
<th>AATR PD [%]</th>
<th>AATR PFA [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>m1</td>
<td>330-525</td>
<td>42</td>
<td>90</td>
<td>10</td>
<td>89</td>
<td>1</td>
</tr>
<tr>
<td>m2</td>
<td>770-810</td>
<td>67</td>
<td>90</td>
<td>10</td>
<td>100</td>
<td>5</td>
</tr>
<tr>
<td>m3</td>
<td>1300-1375</td>
<td>174</td>
<td>90</td>
<td>10</td>
<td>92</td>
<td>11</td>
</tr>
<tr>
<td>m4</td>
<td>1350-1430</td>
<td>183</td>
<td>90</td>
<td>10</td>
<td>100</td>
<td>0</td>
</tr>
</tbody>
</table>
Discussion

• AATR approach with reweighting retraining adapts well to range of ORS specified
  • Performance can be improved with enhanced metal artifact reduction, segmentation
  • Extensible across classifier families

• Hierarchical classifier for new threats is practical, performs well
  • May be “interim” solution for fieldable system without perturbing baseline ATR
  • Need to solve performance verification gap – Perhaps through use of enhanced simulation

• Areas for improvement
  • Enhanced metal artifact correction/compensation – e.g. detect nearby metal as a feature and adapt classifier
  • Additional feature selection (without overtraining)
  • Classifier families with less randomness in behavior – using reweighting approach
  • Extension of reweighting approach to integrate both PD, PFA targets
  • Exploration of performance when many classes of threats are present – how to control PFA