ALERT AATR TO-7
Program Review

A Cascaded Classification Approach to CT-Based Adaptive Target Recognition

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Introduction

Background

Robot Vision Lab, Purdue University

The Robot Vision Laboratory at Purdue performs state-of-the-art research in sensory intelligence for the machines of the future. This laboratory has made pioneering contributions in 3D object recognition, vision-guided navigation for indoor mobile robots, task and assembly planning, among others.

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Executive Summary

Major Accomplishments:

- An implementation of the ***<u>Cascaded Classifier Architecture</u>*** for Adaptive Automatic Target Recognition.
- Testing of the algorithm for different Adaptability Metrics including **Mass, Thickness** and **PD/PFA** on the TO-4 dataset.
- Testing of the algorithm for modularity – system operation as an extension to an existing ATR segmenter.
- Testing of the algorithm for new OOIs.

Results:

- The implemented AATR system was able to achieve PD/PFA values close to the target values on the TO-4 dataset for three different Materials-of-Interest (MOIs).
- The cascaded structure was also tested for three different ATR systems to demonstrate the system's ability to extend existing ATR systems to AATR systems.

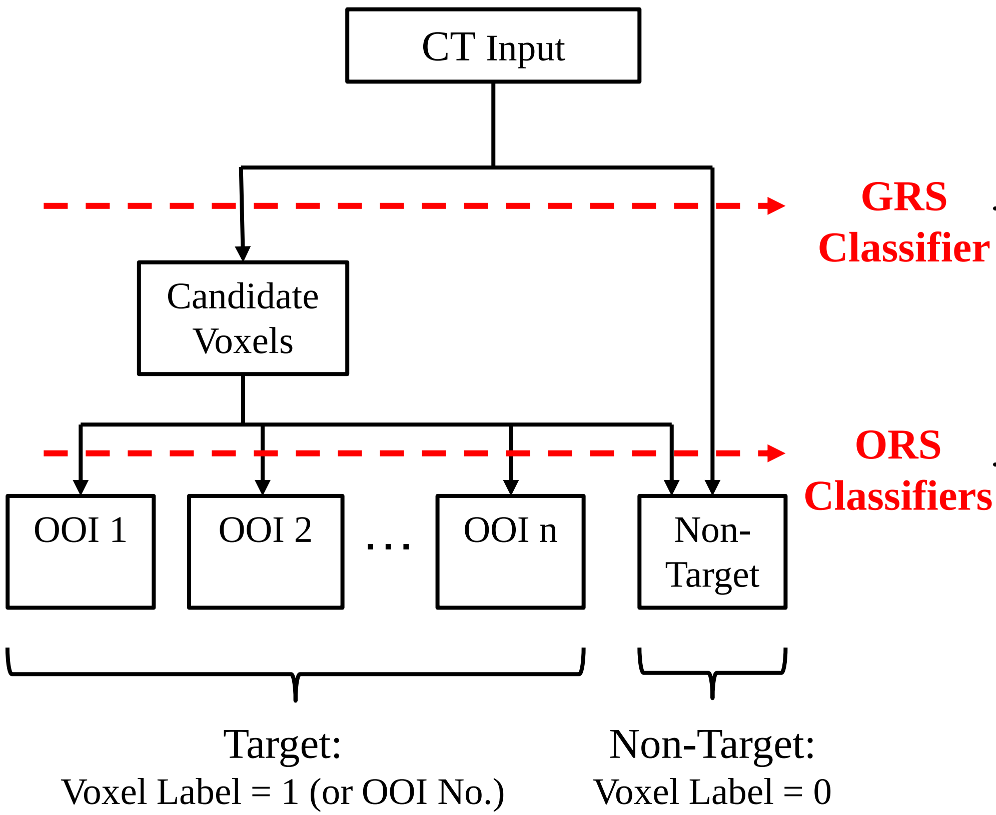
Future Goals:

- Development of the algorithm to better handle unknown OOIs for Phase III testing.

Proposed Solution -
Cascaded Classification Approach

How to de-sensitize an existing ATR classifier to variable OOI specifications without exhaustive re-training?

Solution: Bifurcation of the AATR Classifier into two classifiers



GRS Classifier:

- Akin to an ATR Segmenter.
- Performs Supervoxel segmentation.
- Generates Candidate Blobs for OOI Classification.
- Trained only once for a given GRS file.

ORS Classifiers:

- Classifies the Candidate Blobs.
- Uses only contextual (ORS) features for classification.
- Retrained for every new ORS.
- Fast retraining using Dynamic Sample Weighting.

Technical Description

Implementation - GRS Classifier/Segmenter

Input CT Image

Pre-processing

Mumford-Shah Energy Minimization

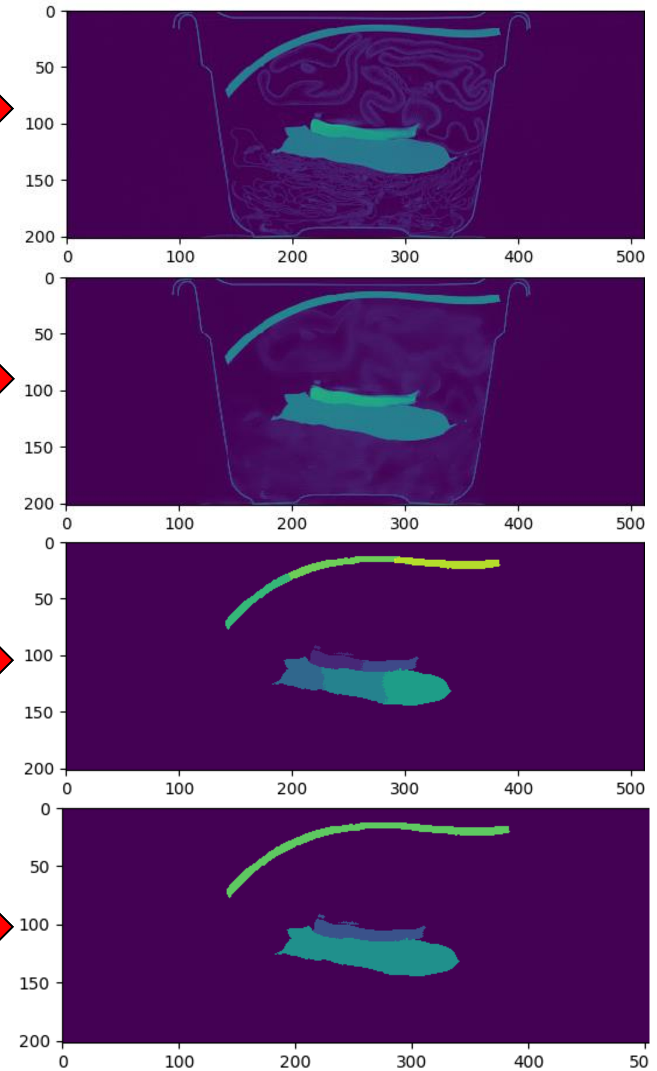
Supervoxel Segmentation

3D SLIC Over-Segmentation / Classification

Graph Partitioning

Normalized Cuts with Density-based RAG

GRS Output Image



Example: *I044.fits.gz* (*Slide 60*)

Technical Description
Implementation - ORS Classifier

ORS Classifier:

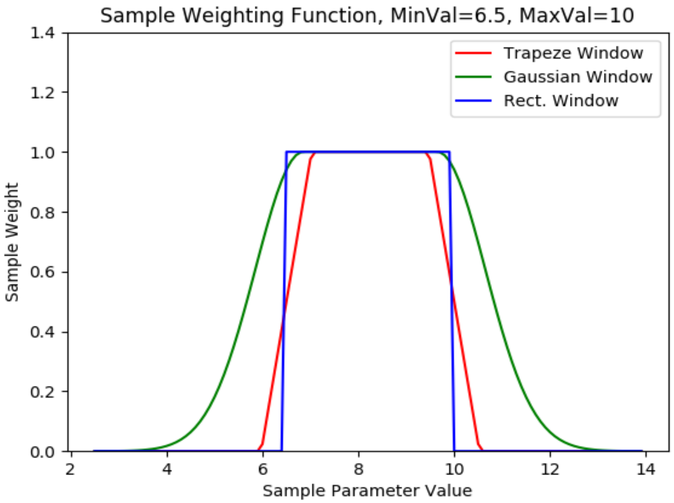
- Classifies the Candidates Blobs obtained from the ATR segmenter.
- *Type:* **Random Forest Classifier**
- *Features:* **Normalized Density Histogram + Thickness Vector**

Tuning for Varying ORS parameters - Dynamic Sample Weighting:

- Each training sample is weighted by comparing its feature value to the specified OOI feature range in the ORS.
- Weights are calculated for each ORS feature (*Mass*, *Thickness*, *Density*) using a **Gaussian Weighting Window**.

Example:

- Consider the OOI Thickness feature which is specified by ORS parameters ***ThicknessMin*** and ***ThicknessIncrement.***
- Using these values, a **Gaussian Weighting Window** is generated which calculates the weight for each training sample.
- The total sample weight for each sample is the product of the sample weights for all three ORS features (*Mass*, *Thickness*, *Density*).
- The classifier is then trained with these weighted samples:
  - The PD/PFA can be tuned by adjusting the standard deviation/spread of the weighting window (*to change PFA*) **OR**
  - The threshold used for the sample weights for bifurcating positive /negative samples in the dataset (*to change PD*).



Technical Description

Implementation - ORS Classifier

Tuning for Target PD / PFA:

$PD^{(1)}, PFA^{(1)}$ $\quad$ $PD^{(2)}, PFA^{(2)}$

Input CT Image → GRS Classifier, C1 → ORS Classifier, C2 → Output Label Image

C1: Supervoxel Classifier/Segmenter
C2: OOI Random Forest Classifier
PD: Probability of Detection
PFA: Probability of False Alarm

$$Target\ PD^{(T)} = PD^{(1)} PD^{(2)}$$
$$Target\ PFA^{(T)} = PFA^{(1)} PFA^{(2)}$$

$$\boxed{PD^{(2)} = \frac{PD^{(T)}}{PD^{(1)}}, \quad PFA^{(2)} = \frac{PFA^{(T)}}{PFA^{(1)}}}$$

Since $PD^{(1)}/PFA^{(1)}$ are fixed, target PD/PFA can be obtained by tuning PD/PFA for ORS classifier only.

The fixed values of PD/PFA for classifier C1 allow replacing the GRS classifier C1 with any ATR segmenter with a known PD/PFA, hinting at a method for extending an ATR system to AATR system.

In this project, PD/PFA are tuned by adjusting the thresholds on the sample weights or the Gaussian spread of the weighting function for the ORS classifiers.

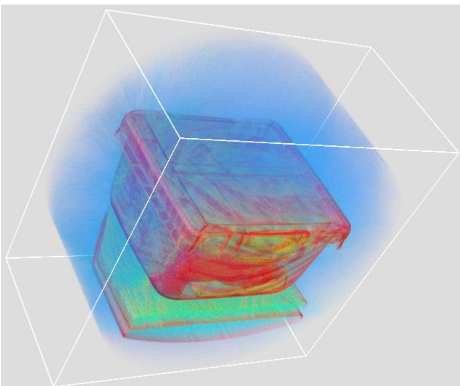
Tuning for Unknown OOIs:

- For an OOI specified with an unknown MOI, a classifier cannot be constructed from the dataset.
- Instead, **a normally distributed density histogram** is synthesized with a **mean and variance** derived from ORS values ***RhoMin, RhoMax***.
- The candidate blob is then classified by comparing its density histogram with the synthesized histogram.

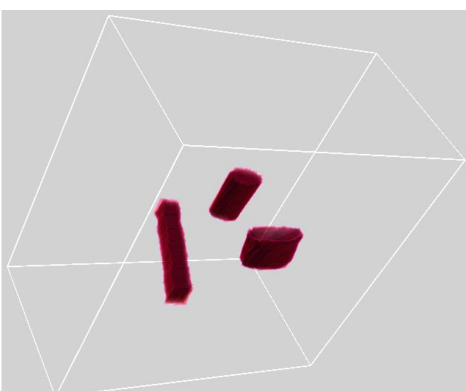
Example Illustration

TO-4 Sample: ***I026.fits.gz***

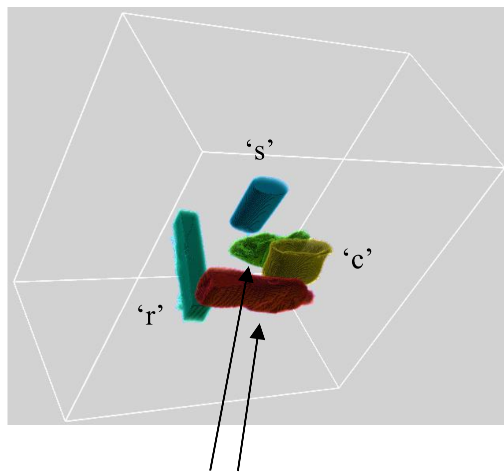
Input CT Image



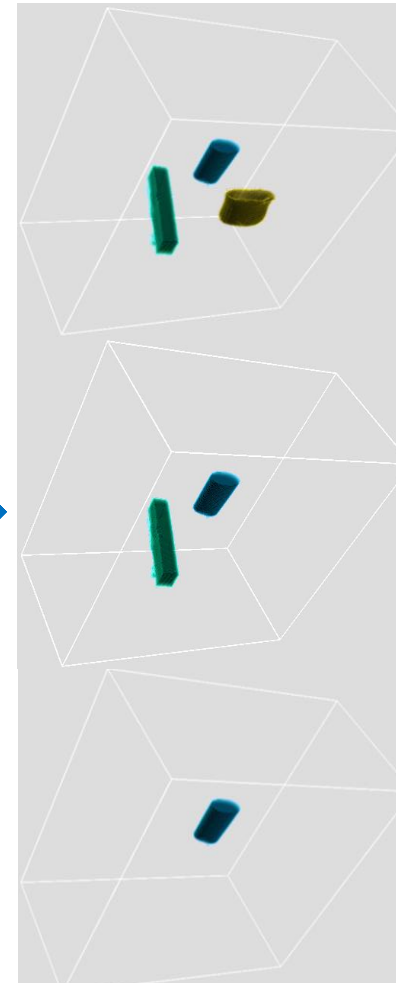
Ground Truth



GRS Classifier Output



False Alarms



AM2/ORS1 Classifier

OOIs: Saline, Rubber, Clay

AM2/ORS3 Classifier

OOIs: Saline, Rubber

AM2/ORS4 Classifier

OOIs: Saline

Inputs

GRS Output

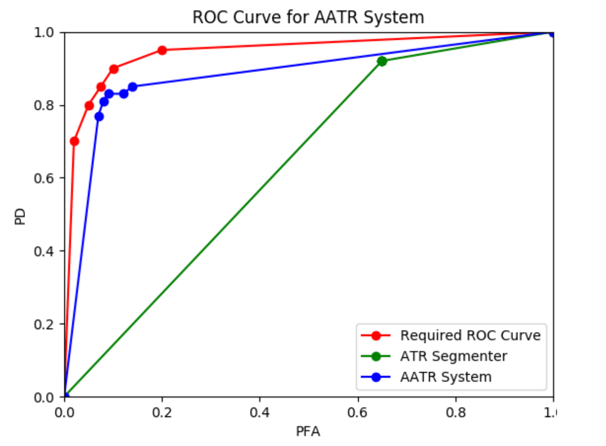
ORS Outputs

Technical Description

System Operation and Analysis

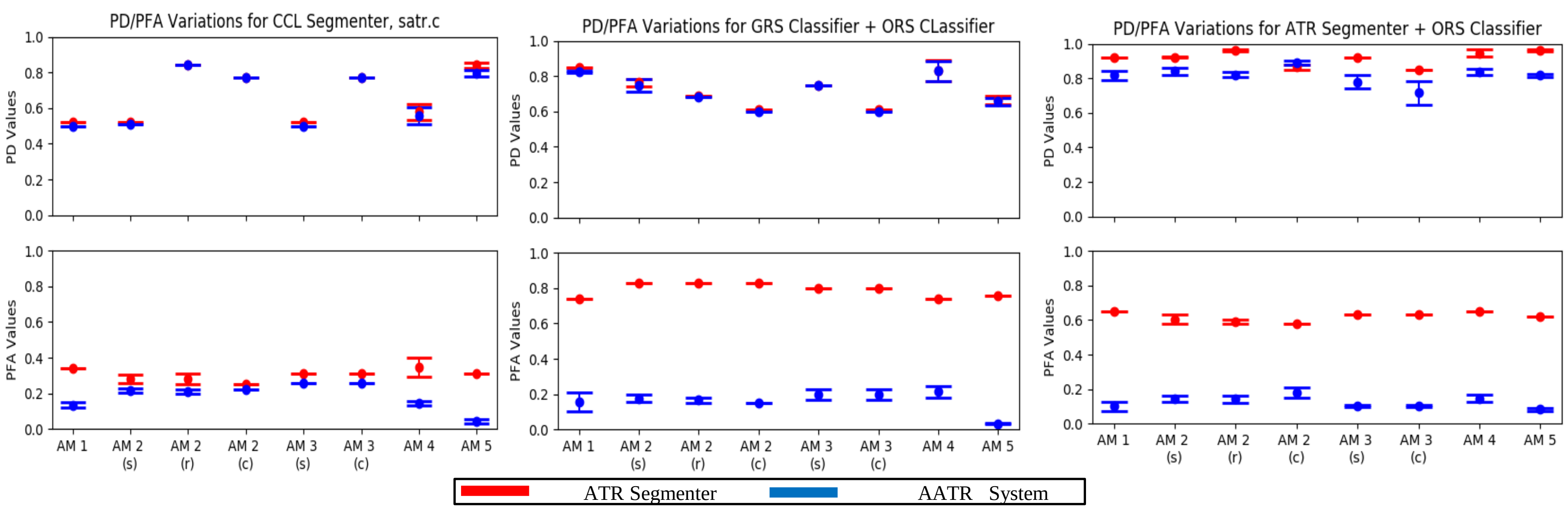
ROC Performance for Varying PD/PFA:

- Figure 1 shows the ROC curves obtained for ATR classifier with and without the cascade.
- Use of Dynamic Sample Weighting allows a better ROC performance in terms of tuning for PD and PFA.



Performance with and w/o Cascade:

- Response is shown for 5 Adaptability Metrics and 3 different ATR systems.
- Cascaded structure not only improves PFA but also keeps the standard deviation for the different parameters in check.
- **Why focus on standard deviation?** A more robust metric for Adaptability than the absolute values of PD and PFA.



Results

Performer Training / TO4 Data

AM 1: AROC

OOI	Required PD [%]	Required PFA [%]	AATR PD [%]	AATR PFA [%]
S	70	2	77	7.1
S	80	5	81	7.7
S	85	7.5	83	8.9
S	90	10	83	12
S	95	20	85	14

AROC	87.9

AM 2: PD/PFA for Varying OOIs

OOI	Required PD [%]	Required PFA [%]	AATR PD [%]	AATR PFA [%]
C,S,R	90	10	87	12
C	90	10	90	12
S	90	10	85	12
R	90	10	84	12

AM 3: Varing PD Weight

OOI	Req PD [%]	Req PFA [%]	AATR PD [%]	AATR PFA [%]
C,S	C:90, S:90	10	C: 81, S: 83	10
C,S	C:20, S:90	10	C: 65, S: 74	11
C,S	C:90, S:20	10	C: 69, S: 77	10

AM 4: PD/PFA for Varying Mass

OOI	Min Mass [g]	Required PD [%]	Required PFA [%]	AATR PD [%]	AATR PFA [%]	Incremental Mass Range [g]	AATR Incremental PD [%]
S	400	90	10	83	12	N/A	-
S	300	90	10	86	17	300 - 400	91
S	100	90	10	82	15	100 - 300	84

AM 5: PD/PFA for Varying Thickness

OOI	Min Thickness [mm]	Required PD [%]	Required PFA [%]	AATR PD [%]	AATR PFA [%]	Incremental Thickness Rnge [mm]	AATR Incremental PD [%]
R	10	90	10	83	7	N/A	-
R	6.5	90	10	81	9	6.5 - 10	89
R	0	90	10	81	9	0 – 6.5	74

ALERT Testing / TO7 Data

AM 2: PD/PFA for Varying OOIs

OOI (s)	Required PD [%]	Required PFA [%]	AATR PD [%]	AATR PFA [%]	AATR PD* [%]	AATR PFA* [%]
m1	90	10	27	13	26	13
m2	90	10	57	47	71	47
m3	90	10	38	28	38	28
m4	90	10	55	25	70	25

*** Lowered Precision and Recall thresholds, P = 0.1, R = 0.1**

Conclusion

Future Goals & Improvements

Dependency of PD Performance on the ATR Segmenter:

- The PD performance of the AATR system has an upper bound defined by the PD of the existing ATR system – the PD performance of the AATR system is only as good as the original ATR system though there are no constraints on the PFA of the ATR system.
- This is an important operating constraint for the extension of ATR to AATR systems using the cascaded structure.

Improving Response for Unknown OOIs:

- The AATR response for OOIs with unknown MOIs shows scope for improvement – although observing that the response is ameliorated with lowered requirements of Precision and Recall is an indication that this mainly depends on the choice of the ATR segmenter to be extended.

Testing for Adaptability on Different ATR systems:

- The response of the proposed Adaptive ATR system has been tested and verified for three ATR systems: (i) a simple CCL ATR segmenter, (ii) A GRS Supervoxel Classifier, and (iii) an ATR segmenter based on Graph Partitioning.
- Testing the validity of the system for other ATR systems can verify its usefulness in extending ATR systems to Adaptive ATR systems.

THANK YOU