Adaptive Automatic Threat Recogntion

AATR - Review

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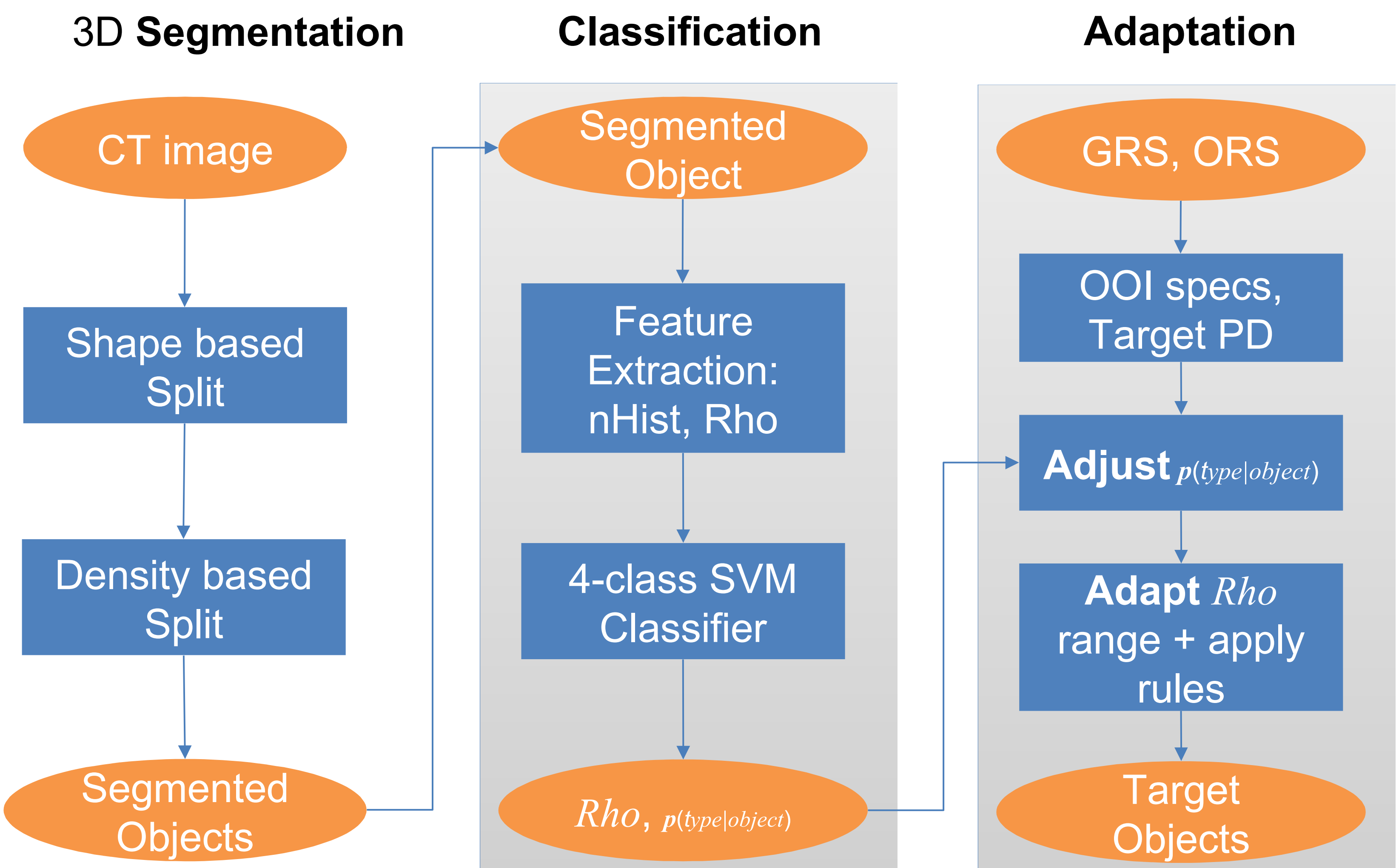
Overview



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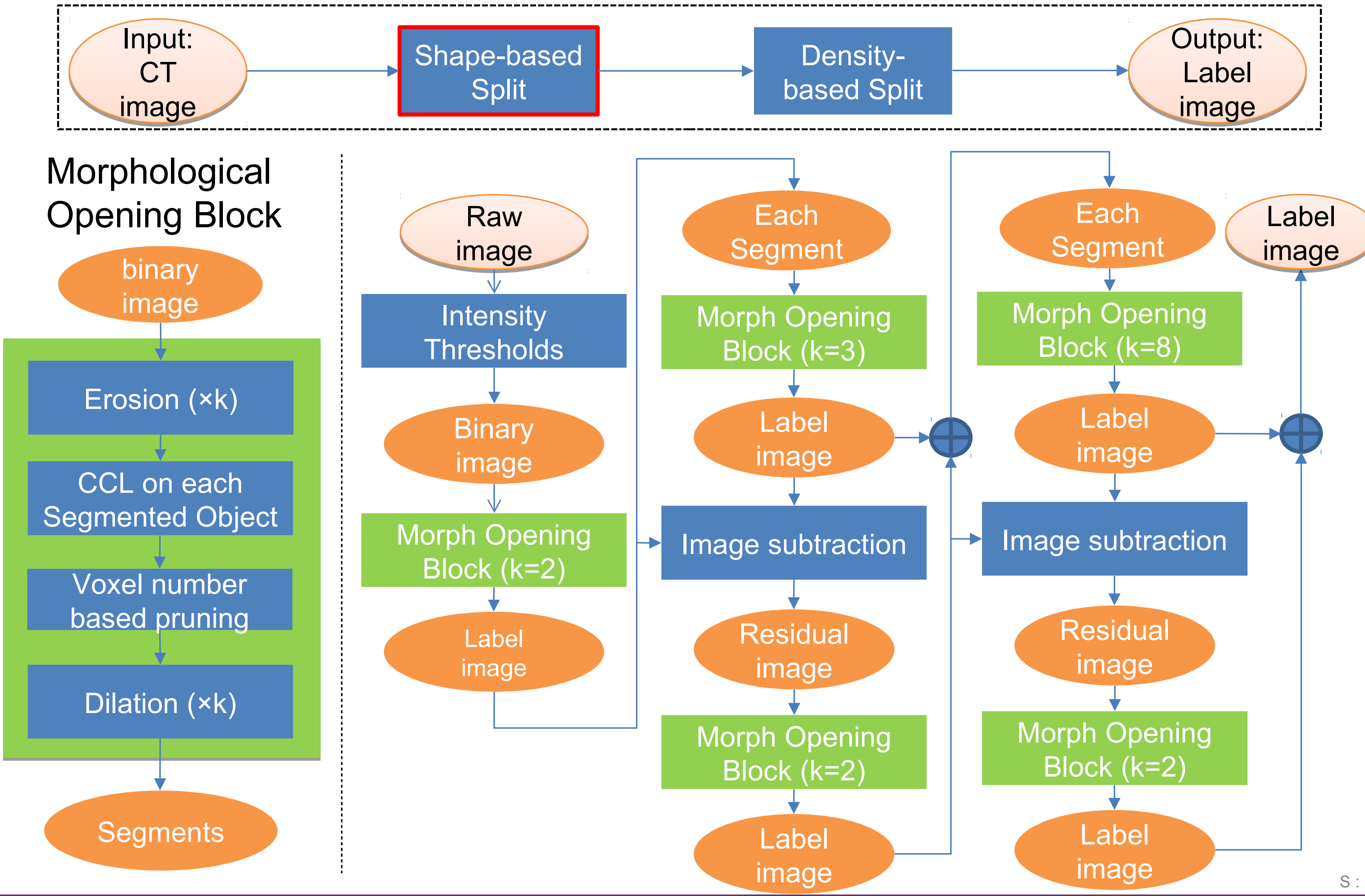
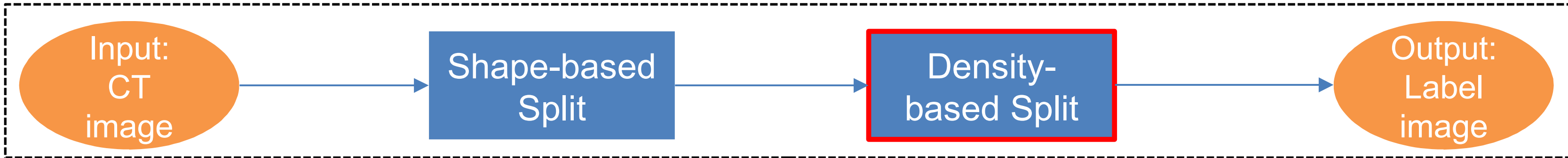
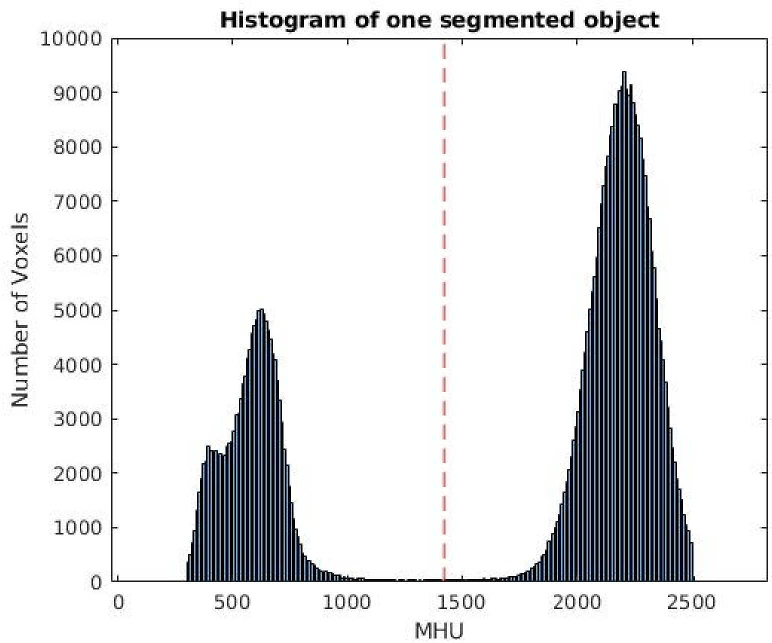
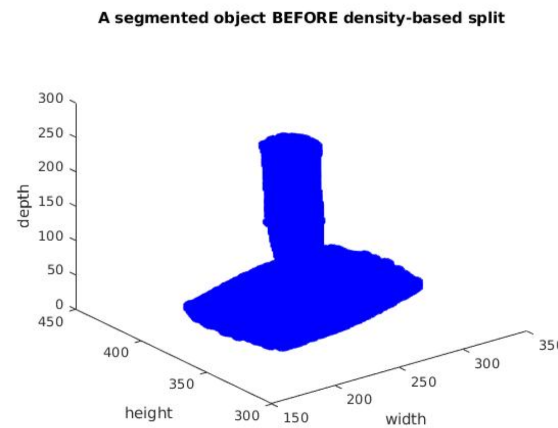
3D Segmentation: shape-based

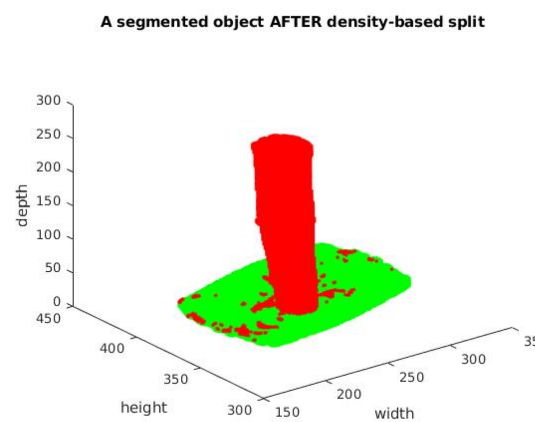


3D Segmentation: density-based

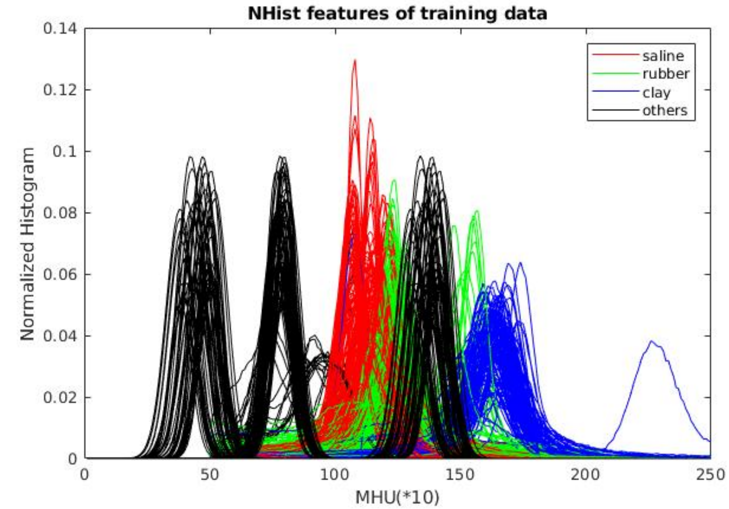








Classification



- **Four-Class Problem**
  - Saline, Rubber, Clay, Others
- **Features**
  - L2-normalized Histogram (nHist)
- **One-vs-All SVM (libsvm)**
  - Output Probability

    $p(saline|object)$

    $p(rubber|object)$

    $p(clay|object)$

    $p(others|object)$
- **Training**
  - Ground Truth Objects for Saline, Rubber and Clay
  - Synthesized nHist Features for New OOIs
    - Gaussian functions with randomly selected $\mu \in [minRho, maxRho]$, $\sigma \in [6,8]$

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Adaptation

- **Adjust the Density Range of OOIs:**

$$minRho = minRho * \alpha ,$$

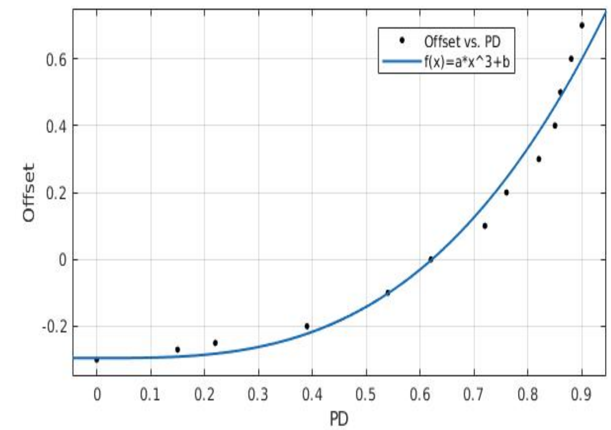
$$maxRho = maxRho / \alpha , \alpha \in (0,1].$$

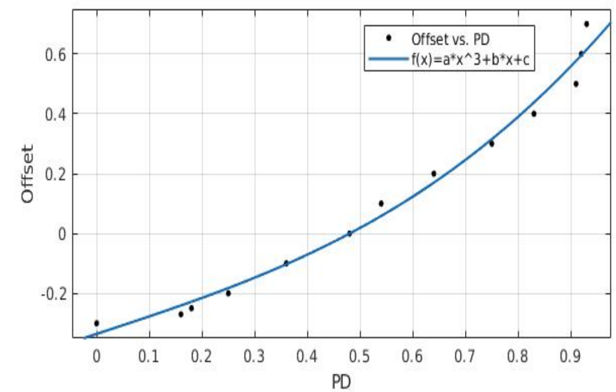
- **Adjust the Classifier Output Probability:**

$$p(OOI|object) = p(OOI|object) + Offset$$

$$Offset = f(PD_{OOI})$$

e.g., if saline is the target material, we **add a positive offset $f(PD_{OOI})$** to $p(saline|object)$, thus the segmented objects have better chance to be classified as saline than others.





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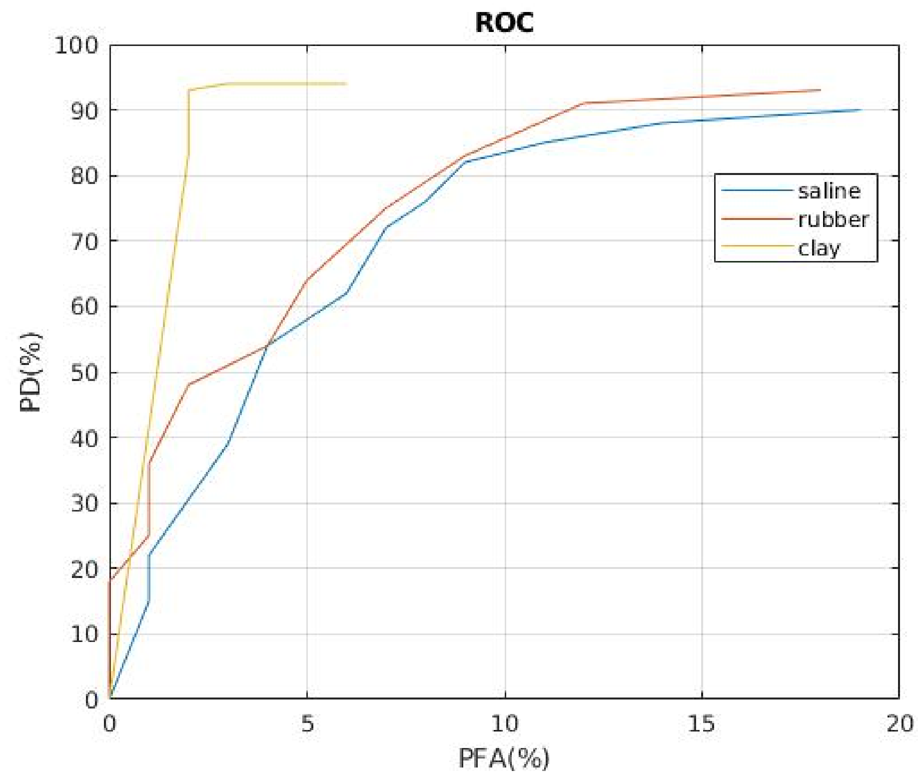
Results: ROC

- Based on AM2: ORS4, ORS5 and ORS6
- Highest PD
  - Saline: 90% (PFA:19%)
  - Rubber: 93% (PFA:18%)
  - Clay: 94% (PFA: 3%)
- PFA~=10%
  - PD(saline): 83%
  - PD(rubber): 85%
  - PD(clay): 94%



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Performer Training / TO4 Data

AM 1: AROC

OOI	Required PD [%]	Required PFA [%]	AATR PD [%]	AATR PFA [%]
S	0.7	0.02	0.73	0.07
S	0.8	0.05	0.82	0.1
S	0.85	0.08	0.85	0.12
S	0.9	0.1	0.88	0.14
S	0.95	0.2	0.9	0.22

AROC	0.87

AM 2: PD/PFA for Varying OOIs

OOI	Require d PD [%]	Required PFA [%]	AATR PD [%]	AATR PFA [%]
C,S,R	90	10	95	26
C	90	10	97	26
S	90	10	90	26
R	90	10	98	26

AM 3: Varing PD Weight

OOI	Required PD [%]	Required PFA [%]	AATR PD [%]	AATR PFA [%]
C,S	C:90, S:90	10	C:95, S:88	18
C,S	C:20, S:90	10	C:92, S:86	16
C,S	C:90, S:20	10	C:94, S:11	4

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	98	14	N/A	N/A
S	300	90	10	97	14	300 - 400	97
S	100	90	10	88	14	100 - 300	81

AM 5: PD/PFA for Varying Thicness

OOI	Min Thickness [mm]	Required PD [%]	Required PFA [%]	AATR PD [%]	AAT R PFA [%]	Incremental Thickness Rnge [mm]	AATR Incremental PD [%]
R	10	90	10	96	14	N/A	N/A
R	6.5	90	10	97	14	6.5 - 10	95
R	0	90	10	92	14	0 – 6.5	80

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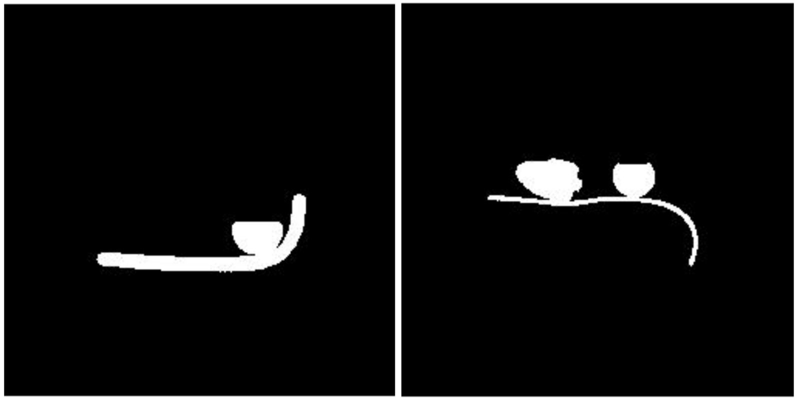
ALERT Testing / TO7 Data

AM 2: PD/PFA for Varying OOIs

OOI(s)	Required PD [%]	Required PFA [%]	AATR PD [%]	AATR PFA [%]
m1	90	10	76	12
m2	90	10	100	46
m3	90	10	92	15
m4	90	10	100	11

Future Work

- Improve Segmentation
  - Noise Removal (NLM)
  - Parameter tuning
- Improve Classification
  - Other features than nHist
  - One class for each new object
- Improve Adaptation
  - Consider the correlation between multiple OOIs if there exist
    - $f(PD_1)$ -> $f(PD_1;PD_2)$
    - $f(PD_2)$ -> $f(PD_2;PD_1)$



Segmentation Failure Examples (ssn=7,10)

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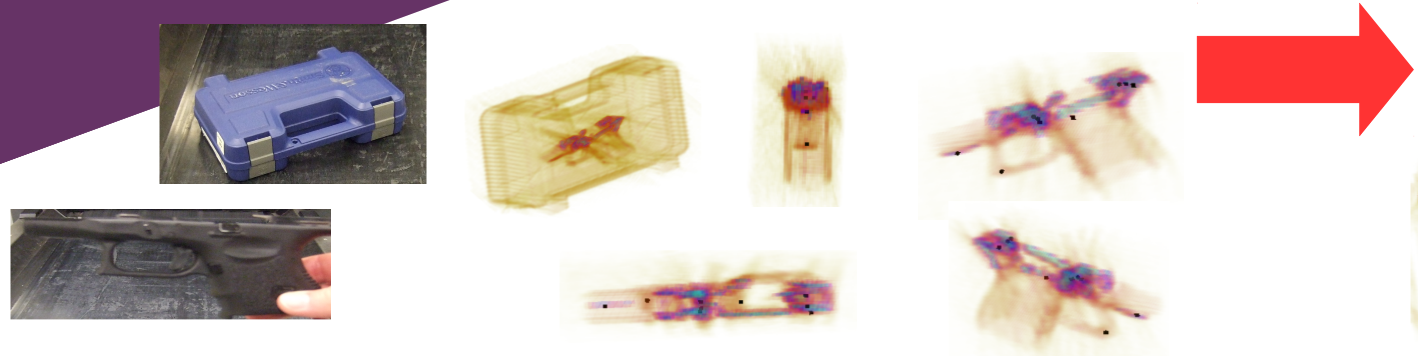
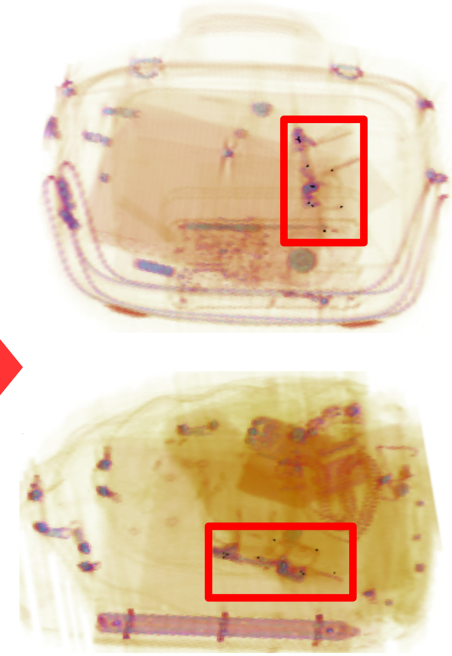
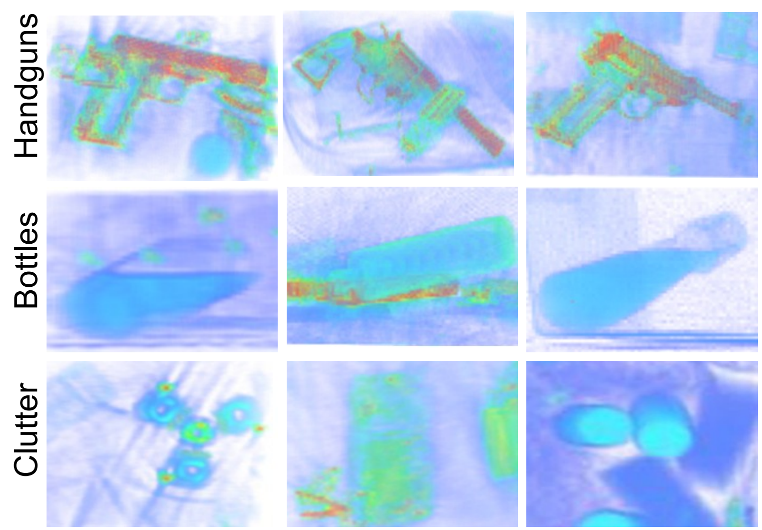
Object Detection & Classification in 3D CT





Single signature feature-point based **detection**: ~90% detection

[Flitton, Breckon, Megherbi - 2010]



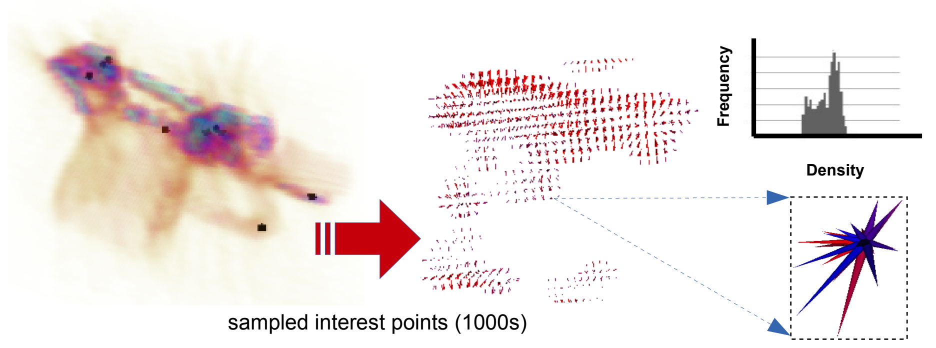
Working with:

“bag of visual words” generalized signature **classification** : ~98+% detection, low FP (<1%)

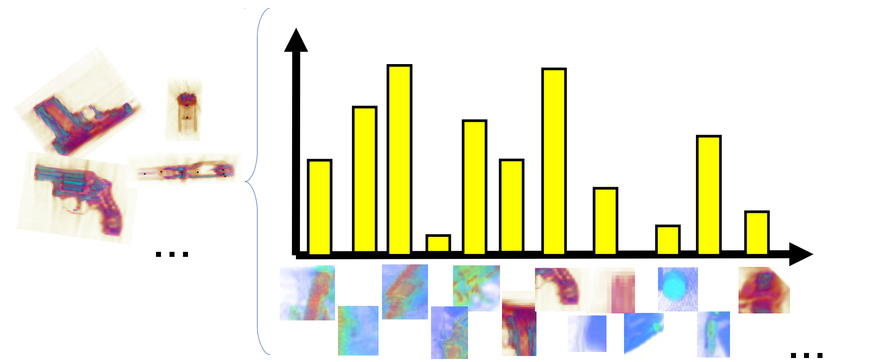
[Mouton, Breckon, 2014] [Mouton, Breckon 2015] [Flitton, Breckon 2015] [Flitton, Breckon 2012]

Some technical insight ….

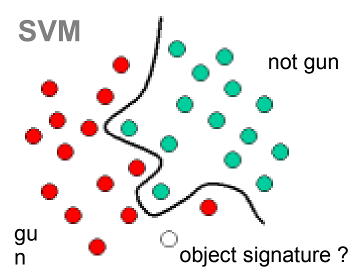
- **key-point** descriptors [video]

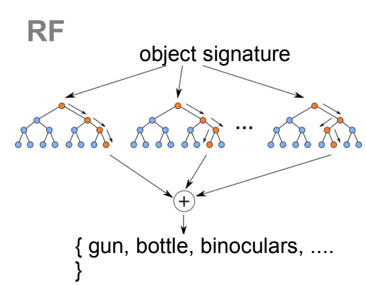


- **“bag of visual words” signature**
  - each object type represented as histogram of visual word occurrence



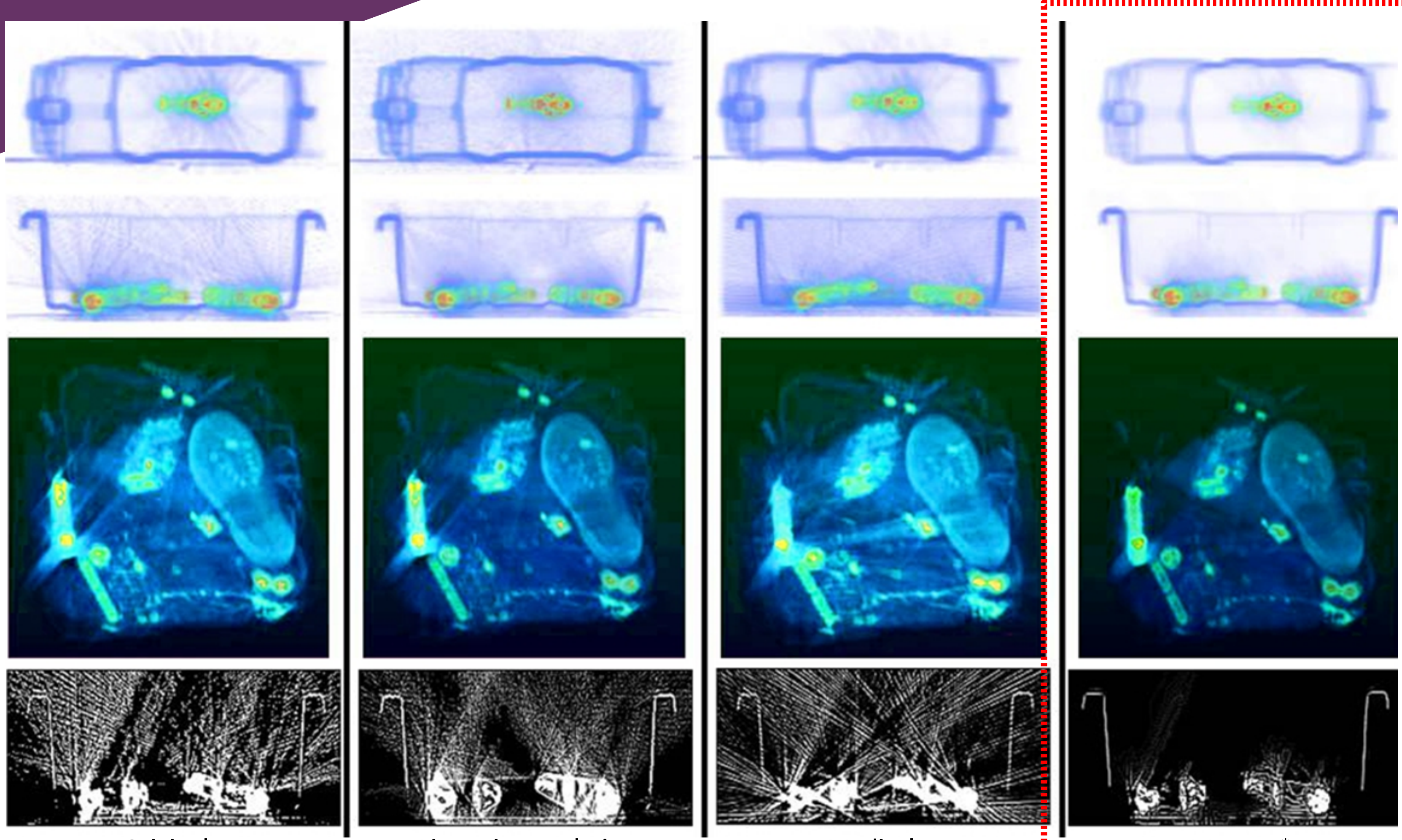
- **Machine Learning Classification:**
  - Support Vector Machine (SVM)
  - Random Forests (RF)





- Strongly **invariant: rotation**, **scale**, object **{occlusion | disassembly}**

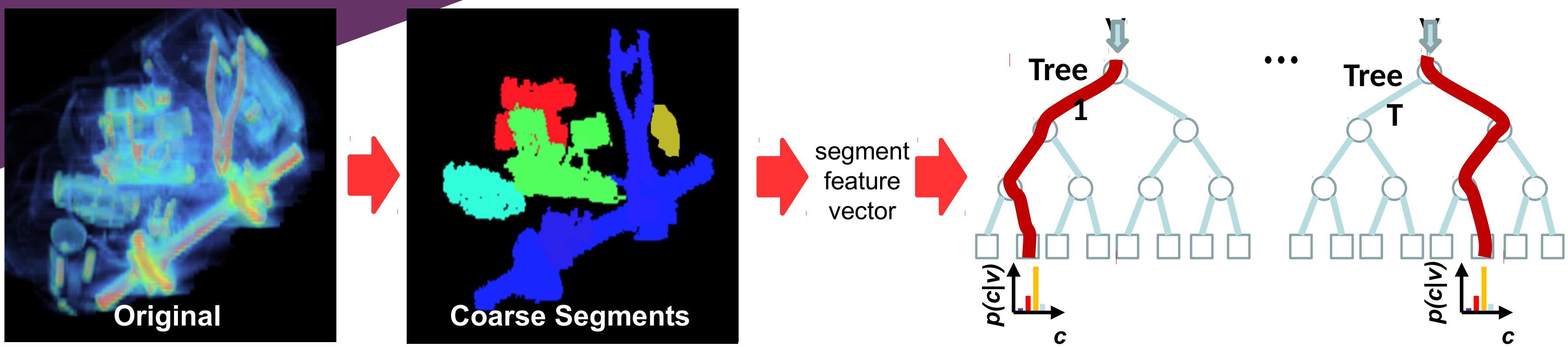
Noise (Metal Artefact) Reduction in 3D CT



Original | Linear interpolation | Medical | Mouton*

Metal Artefact Reduction - [Mouton, Breckon et al., 2013] [Mouton, Breckon et al., 2013].

Object Segmentation in 3D CT (dual energy)

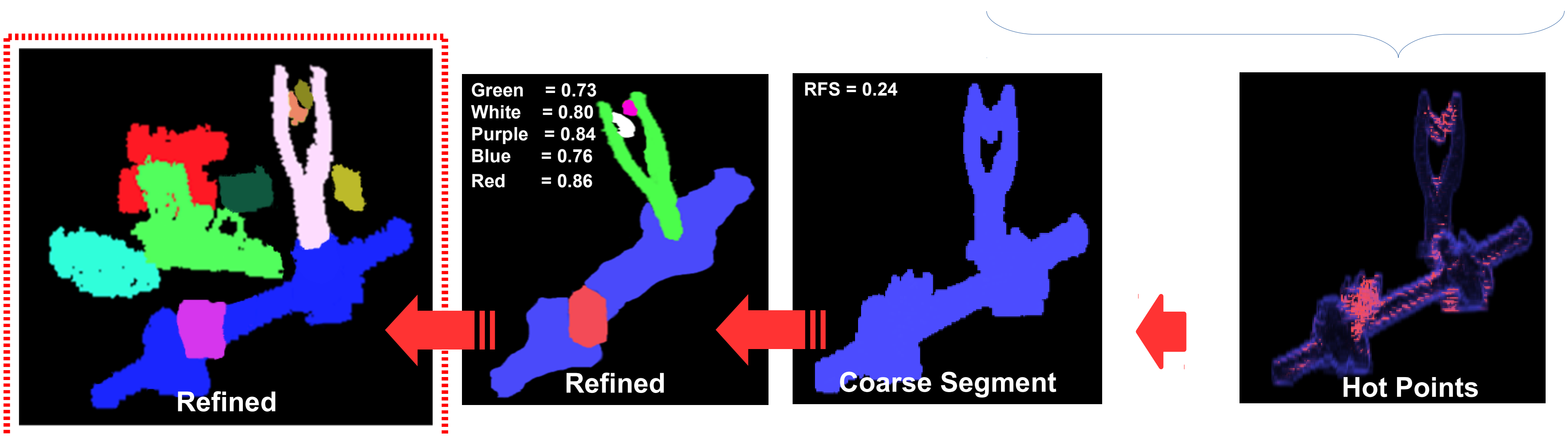


1. Coarse segmentation

Dual-energy CT materials-based discrimination

2. Quality Evaluation

Random Forest Score (RFS)

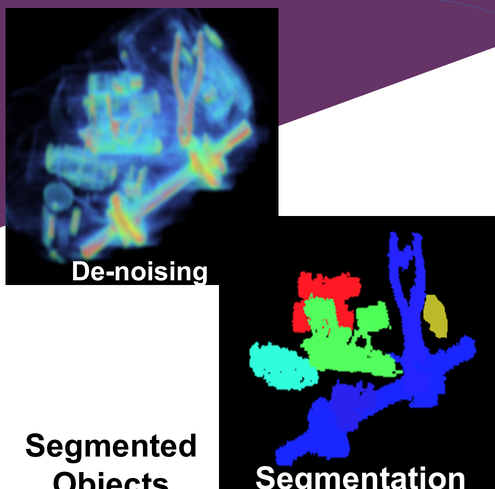


3. Random Forest Score (RFS) - guided refinement

Object partitioning at automatically detected fusion “hot points”

[Mouton, Breckon 2015]

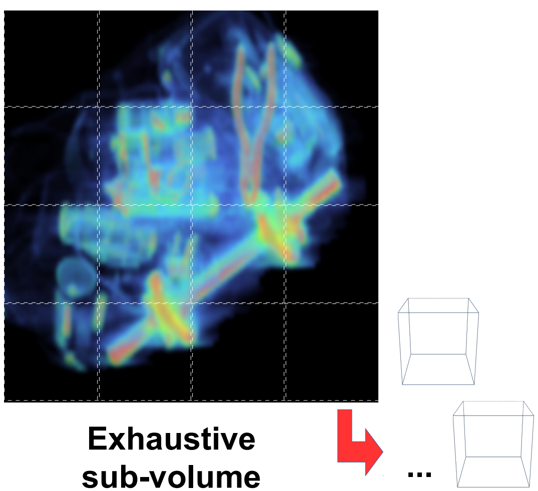
… which feeds back to object detection



Segmented Objects

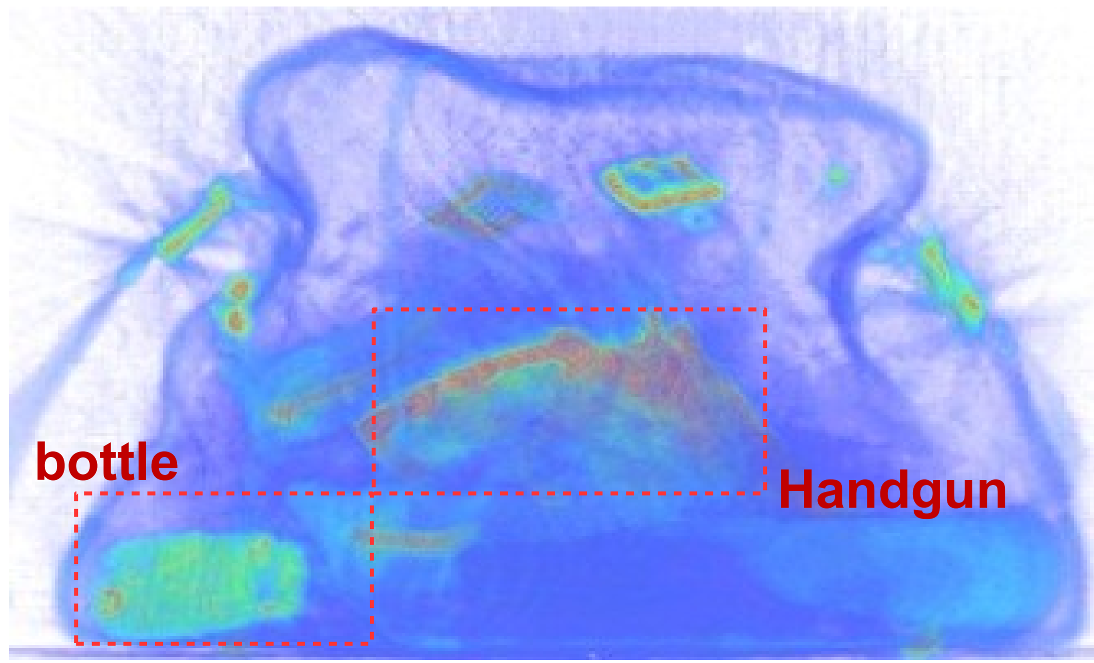
[Mouton, Breckon 2015]

Or:



Exhaustive sub-volume search

…



resolution 1.56 x 1.61 x 5 (mm)

Method	Class	True +	False +	Prec.
[Mouton, Breckon, 2014]	Handgun	99.71	0.28	0.990
	Bottle	98.88	0.60	0.987